Empirical Studies on Governance - Performance Interplay: The Investors' Perspective

Mohammed Zakriya

http://hdl.handle.net/10803/669238

DOCTORAL THESIS

Title	**Empirical Studies on Governance – Performance Interplay: The Investors' Perspective**
Presented by	**Mohammed Zakriya**
Centre	**Esade Business School**
Department	**Economics, Finance, and Accounting**
Directed by	**Dr. Ariadna Dumitrescu**

C. Claravall, 1-3 | 08022 Barcelona | Tel. 93 602 22 00 | Fax 93 602 22 49 | info@url.edu | www.url.edu

Abstract

This thesis aims to understand the relationship between corporate governance and performance by tracing its evolution over time and revisiting the methodological issues faced in measuring corporate governance. Empirical corporate governance literature shows that good governance stocks outperformed poor ones until investors' increased attention to governance information made this anomaly disappear. On the contrary, first part of this thesis reveals that poor governance stocks have outperformed good ones in recent years. To explain this novel result, we examine whether investors become aware of the risks associated with poor governance after the 2008 global financial crisis and integrate this information into their investment decisions. Empirical evidence supports this explanation. In the second part of the thesis, we propose an unequal-weighted measure of corporate governance using anti-takeover provisions. In comparison with existing measures of governance that employ equal weighting methodology, this is the first study to explore multiple unequal weighting methodologies. Results show that the relationship between governance and performance is better explained when individual anti-takeover provisions' heterogeneity is captured in the weights of the governance index. While the first two studies take the shareholders' view of corporate governance, the third study of this thesis takes a stakeholders' view by considering environmental, social and governance (ESG) characteristics together. Unlike prior literature that applies kitchen-sink measures of firms' ESG-orientation, this study introduces a selective approach to measure corporate sustainability as an ESG subset. We show that corporate sustainability is the main driver of ESG's relationship with financial performance. Overall, this thesis highlights the importance of governance and ESG information (and the way they are both measured) for both the firms and their investors. Governance is significantly related to performance and valuation, but conditional on the way it is mea-

sured. This, in turn, has important implications for managers, governance rating agencies, and regulators.

Acknowledgments

This thesis would not have been possible without endless support, constant encouragement, and utmost patience shown to me by my mentors, colleagues, family, and friends. I would like to thank them all for believing in me and helping me in pursuit of my dreams.

First and foremost, I owe all my current and future research accomplishments to my PhD supervisor Dr. Ariadna Dumitrescu. Thank you for taking me under your wings when I was unsure of the direction I wanted to head in. Your guidance, feedback, criticism, and help all through this journey have been invaluable. I may not have always been an easy PhD student to mentor, but you have always been an exemplary supervisor. I would especially like to thank you for your confidence and support during the difficult and demanding job market process.

Life in academia as a PhD candidate is less stressful if the research support system is strong. Thank you Dr. Vicenta Sierra, Dr. François Collet, Pilar Gállego, and Silvia Espin for your warmth and welcome that you have shown from day one. Special thanks to Cristina Costa, Ruth Babington, and Andrea del Pozo for being there to help me with all the bureaucratic documentations with regards to the FI-AGAUR grant. Relatedly, I acknowledge that this research has been financially supported by SUR (Secretaria d'Universitats i Recerca) of the DEC (Departament d'Economia i Coneixement) of the Government of Catalonia and European Social Fund (grants 2017-FI_B-00502, 2018-FI_B-00170 and 2019-FI_B2-00163).

My sincere gratitude to Dr. Javier Gil-Bazo for providing me the opportunity to do research assistance for him and to Dr. Rafael Zambrana for inviting me to NOVA SBE for my international research stay. Your words of wisdom and encouragement have been crucial in propelling my academic career. I would also like to thank Dr. Ioana Schiopu, Dr. Carolina Villegas-Sanchez, and other members of Group for Research in Economics and Finance at Esade for their help during my PhD. Special thanks to Dr. Vicente Bermejo, who is my co-author in a paper outside of this thesis, for continually supporting me during the job market process and advising me during different stages of my PhD.

Atieh, Eleu, and Menna, for their care and emotional support. Although I did not have many issues to vent about, but you were always there when I needed to. Esteban, Ferran, Josep Maria, Julia, Laia, Nour and Xiaoran for making the MRes year an unforgettable experience that I will always cherish. We met as strangers, but will remain an important part of each other's lives. To the rest of my Esade PhD family including Adria, Ali, Aman, Amer, Andreas, Anna, Asma, Averill, Ben, Dimitry, Eirine, Esther, Georges, Ignacio, Ira, Ipek, Khaled, Laura, Lina, Lucie, Lucrezia, Marco, Maria, Matteo, Mehdi, Mohammad, the two Nats, Obaid, Pooja, Rocio, Roy, Sahar, Shahzeb, Solange, and Vinicio. Thank you for all the "intellectual" conversations that we had over lunch or otherwise. You have all made this journey a memorable one.

My amazing friends from good old days who are now spread all around the world: Anita, Anu, Smitha, Nazia, Shweta, Sanjana, Sophia, Ahmed, Fahim, Nisar, Salim, Atheeq, Usman, Faizan, Gibran, Qaiser, Sawaf, and Saifan. You have played equally important roles in making me who I am. You have spent a lot of time with me during different stages of my life and supported me through and through in everything. Thank you for bearing with me and laughing at my peculiar jokes.

And, last but not least, a huge thanks to my family. To my parents, for showing me that love, belief, respect, hope, and kindness are second to none. Without your prayers and blessings, I won't have come this far. To my sisters and my brother, we have always had each other's back. Thank you.

Contents

List of Figures

List of Tables

CHAPTER 1
Introduction

1.1 An Overview

With multiple cases of bankruptcies amid financial crises witnessed in the last two decades, more and more investors are demanding improved governance structures. The use of good governance practices should translate into superior financial performances for firms and accordingly benefit its shareholders. However, are good governance firms actually creating more wealth than the poorly governed ones? The main focus of this dissertation is on studying how well the investors understand a firm's governance quality, and how do they react to it.

To begin with, this thesis examines whether investors can employ governance information to create investment strategies that can beat the markets. We do so by first examining if the disappearance of the relationship between governance and returns, shown in Bebchuk, Cohen, and Wang (2013), remains persistent after the 2007–2008 global financial crisis. Using anti-takeover provisions (ATPs) data from 1990 to 2018, we find that the disappearance of governance–returns relationship after 2001 is in fact temporary. Poor governance stocks outperform the good governance ones after 2008, in sharp contrast to the outperformance of good governance stocks seen in 1990s. The natural question then is what causes this change. We explore information flow-based explanation and find that a combination of investors' high prudence toward poor governance stocks and their increased awareness of investment horizon-based tailored governance preferences played an important role in the appearance of new governance–returns relation.

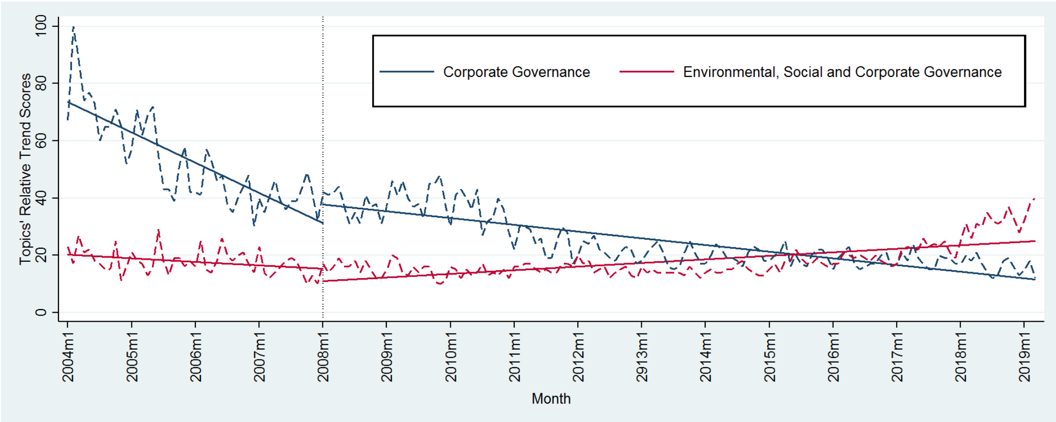
Next, this thesis highlights methodological issues in measuring corporate governance when ATPs are assigned equal weights (à la Bebchuk, Cohen, and Ferrell, 2009; Gompers, Ishii, and Metrick, 2003). As an alternative, we propose an unequal-weighted measure that accounts for the relevance and importance of its individual anti-takeover components. The results, using the ATPs data from 2007 to 2018, show that value implications for both the firms and their investors are quite different when the relevance of each ATP is identified and included as weights in the governance measure.

Lastly, this thesis considers a more holistic stakeholder view instead of shareholders' perspective captured by corporate governance characteristics such as ATPs. In recent years, the attention towards environmental, social and governance (ESG) information has increased considerably in comparison to the corporate governance characteristics. Figure 1.1 shows plots comparing corporate governance and ESG using Google Trends data. Similarly, from institutional

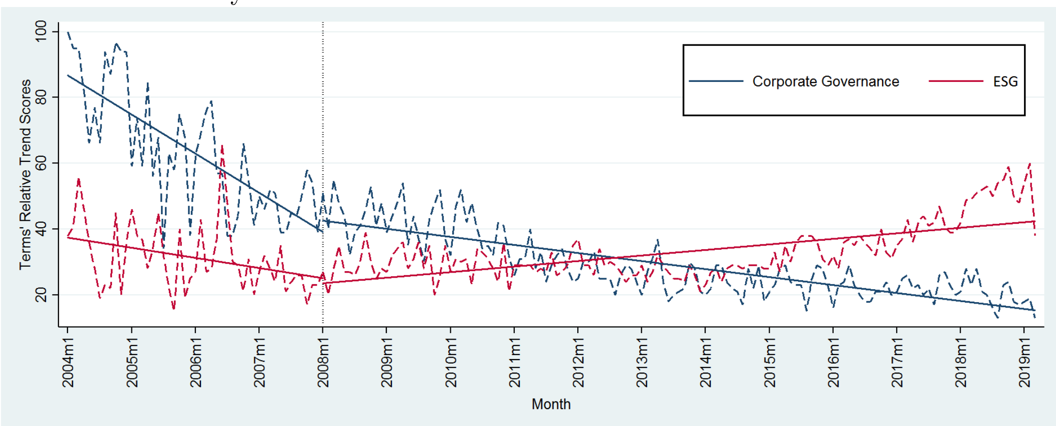
Figure 1.1 Corporate governance and ESG popularity trends

This figure compares the google trends for the topics (Panel A) and terms (Panel B) as available for comparison on Google Trends. The trend plots start in January 2004 and end in January 2019. The fitted trend lines are plotted separately for pre-2008 and post-2008 years (indicated by the dotted vertical line) to show the impact of global financial crisis on these topics and terms.

Panel A: Trends by Topics.



Panel B: Trends by Terms.



investors point of view as well, ESG integration in investment decisions have grown in recent years (Ailman et al., 2017). So, we examine measurement issues related to the ESG characteristics to determine what is essentially value relevant for both the firms and their investors. Our results show that only corporate sustainability-relevant ESG initiatives are important for corporate valuation.

1.2 Relevance and Background

Institutional investors consider corporate governance to be an important factor. On one hand, institutional investors intervene in the investee firms' governance through "voice" and "exit" (McCahery, Sautner, and Starks, 2016). On the other hand, institutional investors also react to firm's corporate governance quality when making their investment decisions. This is reflected by the fact that the market for corporate governance ratings has snowballed in last two decades with the institutional investors being their major clientÃĺle (Daines, Gow, and Larcker, 2010). Can these investors reliably use aggregate index measures or governance rankings to create investment strategies that generate abnormal returns? Can they also use these governance indices or rankings as a means of differentiating the good governance firms from the poorly governed ones? This study centrally focuses on these question while also revealing methodological and conceptual complexities that accompany the use of aggregated governance measures such as the G-Index (Gompers, Ishii, and Metrick, 2003), the E-Index (Bebchuk, Cohen, and Ferrell, 2009), and GovScore (Brown and Caylor, 2006), as well as the aggregated ESG measures (Dyck et al., 2018; Lins, Servaes, and Tamayo, 2017).

All across the globe, academic researchers as well as investment advisors have dedicated a lot of effort in trying to capture the governance quality of public companies using different measures (for e.g., Erkens, Hung, and Matos, 2012; Gao and Kling, 2008; Klapper and Love, 2004). Country-wide factors notwithstanding, studies on firm-specific characteristics in corporate governance have shown that features such as director ownership (Bhagat and Bolton, 2013), board characteristics (Eisenberg, Sundgren, and Wells, 1998) and other directorship aspects (Bushee, Carter, and Gerakos, 2013) are key to capture internal governance mechanisms and measure its quality. But instead of individual firm characteristics, the first two manuscripts presented in this dissertation explore firm-specific aggregated governance and their practical utility. Using cross-sectional variations in governance qualities of different publicly traded firms within a single country (i.e. United States), the aim is to assess whether the measures available to institutional investors—to differentiate and identify the good governance firms from poorly governed ones—are actually useful or not.

Similarly, in recent decades, there is an upsurge in interest shown towards firms' ESG quality (Edmans and Ioannou, 2019; Starks, 2009). While different streams of literature uses different names for the ESG-based measures (e.g., stakeholder welfare – Jiao, 2010, stakeholder-relations index – Borgers et al., 2013), they essentially reflect CSR performance (Buchanan, Cao, and Chen, 2018; Lins, Servaes, and Tamayo, 2017; Becchetti, Ciciretti, and Hasan, 2015; Becchetti, Ciciretti, and Giovannelli, 2013; Humphrey, Lee, and Shen, 2012). However, there is no clear consensus on whether ESG screens can create value for investors (Humphrey, Lee, and Shen, 2012; Fulton, Kahn, and Sharples, 2012). Thus, a part of this dissertation also sheds light on the benefits of ESG quality by accounting for the differential impacts that the individual ESG activities can have on firms' survival (Fatemi, Fooladi, and Tehranian, 2015).

As most of the governance and ESG data analyzed in this thesis are catered to institutional investors, our findings do not reflect the expectations of retail investors. However, this is not a major cause of concern as the objective is to see investors' behavior toward corporate governance and ESG information. Since the institutional investors can process governance and/or ESG signals better than the retail investors, they are more likely to exploit these signals in their investment decisions.

1.3 Corporate Governance

Corporate governance broadly refers to the policies and processes undertaken by companies to make sure that its business activities are focused towards mutual benefit of the corporation, its owners and the society at large within the existing legal setup. This expansive conceptualization of corporate governance has resulted in different streams of literature seeing it from different perspectives. Taking investors' perspective, corporate governance is aimed at ensuring timely corporate disclosures (or, transparency) and legal rights of shareholders (La Porta et al., 2000). Or, simply, it deals with companies' policies that assure investors of obtaining returns on their investments (Shleifer and Vishny, 1997).

1.3.1 Measuring Corporate Governance

Thus far, existing literature has identified multiple firm characteristics that can be indicative of effective corporate governance:

a. Ownership structure: Ownership structure, on its own has been widely investigated in different studies as a corporate governance practice. Using the agency theory as its backbone, research has shown that higher percentage ownership can lead to better board effectiveness and consequently, improved monitoring of firms (Chung and Lee, 2020; Crane, Koch, and Michenaud, 2019; Schmidt and Fahlenbrach, 2017).

b. Board of Directors (BoD) size and other attributes: BoD's experience, composition, structure and other features all have been suggested as governance practices that increase effectiveness of board monitoring (Cornelli and Karakaş, 2012; Eisenberg, Sundgren, and Wells, 1998; Hermalin and Weisbach, 1991).

c. BoD composition: There is a vast literature that has focused on the importance of independent directors within firms. As an indicator of corporate governance quality, many empirical papers have examined its effect along with other directors' characteristics on firm performances (e.g., Hu et al., 2020; Bhagat and Bolton, 2013; Bhagat and Black, 2001).

d. CEO Duality: By separating the management decisions from control, agency theory propagates reduction of agency costs and improvement of firm performance (Jensen and Meckling, 1976). However, empirical evidence relating CEO duality to firm performances have been far a few (Yang and Zhao, 2014; Boyd, 1995).

e. Audit Committee composition and attributes: Similar to BoD, Audit committees play a big role in ensuring accountability and transparency. The importance of having independent auditors and those who are committed to the cause by ensuring regular meetings, has been evidenced widely (Jiraporn, Singh, and Lee, 2009; Deli and Gillan, 2000).

f. Executive compensation arrangements: Several studies have examined CEO pays and other compensation arrangements such as bonuses and employee stock option plans for their effect on company performance (e.g., Cuñat, Gine, and Guadalupe, 2016; Larcker, Richardson, and Tuna, 2007).

g. Shareholder Voting: Any obstruction to the shareholder activism and/ or use of a provision that decreases their voting power is viewed in theory as opposed to good governance practice (Iliev et al., 2015; Cuñat, Gine, and Guadalupe, 2012; Gillan and Starks, 2000; Karpoff, Malatesta, and Walkling, 1996).

While some papers consider each of these characteristics separately, others use them together as multiple proxies for broadly representing corporate governance. Lo, Wong, and Firth (2010), for example, employ board independence, CEO Duality and audit committee compositions to show that good governance quality can deter earnings manipulations using related-party sales. Similarly, Core, Holthausen, and Larcker (1999) use the measures of board and ownership structures as proxies for corporate governance to show its effect on CEO compensation. While the list of characteristics presented above is not exhaustive, it covers most of the governance mechanisms that finance literature has studied. Of course, many more other firm-specific characteristics can directly or indirectly impact the monitoring of management by BoD and the shareholders (see Gillan, 2006 for a full review).

Notwithstanding the interest of shareholders, BoD, managers, and debtholders; other corporate participants such as the employees, suppliers and customers may also play a key role in its governance (Gillan, 2006). Each of these participants have contractual agreements with the firm that can eventually affect the shareholders' interests (Jensen and Meckling, 1976). Thus, the stakeholder view that also accounts for the environment (i.e., legal, political, community, etc.) is also important to get a robust picture of firms' governance quality (Gul et al., 2020; Jensen, 2001). For this reason, the investors' demand for firm's ESG data has rapidly grown in recent years (Van Duuren, Plantinga, and Scholtens, 2016; Bialkowski and Starks, 2016).

1.3.2 Anti-Takeover Provisions

Institutional investors' interest in corporate governance information grew manyfold with the failures that accompanied the corporate scandals of the early 2000s. The corporate bylaws and charter provisions are of particular interest to the investors as they can be employed by the management to potentially influence the market for corporate control (Ruback and Jensen, 1983). For example, staggered boards provision, which restricts board members' elections to occur in smaller groups, can deter potential takeover bids as the acquirer cannot take immediate control of the board. While such provisions can give more power to the board during takeover negotiations, they can also incentivize managerial entrenchment (Jarrell, Brickley, and Netter, 1988).

In theory, the presence of ATPs such as staggered board reduce firm value, due to their associated agency costs (Jensen and Meckling, 1976). Nevertheless, their incidence in firms has grown over the years as they have been shown to have positive effect on takeover bids (Sokolyk, 2011). Given the fact that the shareholders' proposals related to these provisions have grown over the years (Gillan and Starks, 2000), investors seem keen to influence the governance characteristics of their investee firms. Along with the presence of dual class stocks structure, ATPs such as the poison pills, staggered boards, blank-check preferred stock, limited ability to call special meetings or for written consent, and supermajority voting requirements are commonly identified as entrenching devices. For this reason, such ATPs have been voted down by the shareholders in majority of cases (Bebchuk, Cohen, and Ferrell, 2009).

Several papers have studied the impact of individual ATPs to show their importance for the firm and its investors. A series of papers starting with Bebchuk and Cohen (2005) and Faleye (2007), and followed by Cohen and Wang (2013), Amihud and Stoyanov (2017), Cremers, Litov, and Sepe (2017), Cohen and Wang (2017) and Daines, Li, and Wang (2018) have debated the effect of staggered boards on shareholder value. On one hand, staggered boards can promote managerial entrenchment and have negative effect on firm value, especially if they are present along with the poison pills, by preventing possible takeovers of loss-making firms (Bebchuk and Cohen, 2005). On the other hand, staggered boards could increase firm value by inhibiting managerial myopia when managers are free to pursue long-term goals without constant pressure from the board members (Cremers, Litov, and Sepe, 2017). Amihud, Schmid, and Solomon (2017) and Amihud, Schmid, and Solomon (2018) try to settle this debate by claiming that while the empirical evidence for both positive and negative effects of staggered boards on firm value may hold under specific conditions, overall this effect is statistically insignificant. Similarly, literature has widely debated other ATPs such as the golden parachutes (Bebchuk, Cohen, and Wang, 2014; Fich, Tran, and Walkling, 2013; Brusa, Lee, and Shook, 2009; Falaschetti, 2002) and poison pills (Heron and Lie, 2015; Bizjak and Marquette, 1998; Comment and Schwert, 1995; Ryngaert, 1988).

1.3.3 Corporate Governance Indices

Despite being insightful, studying each governance characteristic or ATPs separately cannot necessarily represent overall governance quality of the firms. Moreover, as shown previously, there is mixed empirical evidence when it comes to the benefits associated with each ATP individually. Hence, the need for aggregated corporate governance indices (Gompers, Ishii, and Metrick, 2003). Several governance indices have been conceptualized by commercial rating agencies and academic scholars. The degree to which these indices are good indicators of firms' governance quality can considerably constrain their practical applications (Bhagat, Bolton, and Romano, 2008). What separates most of these indices in terms of its construction, is mainly the corporate governance features that each of them combine (Black et al., 2017). While some indices have given relatively more importance to either internal governance features or external governance characteristics, there are others which combine both of these features in their composition (Beiner et al., 2006). However, all these indices employ equal weighted methodology, with the index formed as a sum of the presence of all the individual governance constituents. Although index weights are important, due to the complexities that arise when measuring them (Nerantzidis, 2018), very few scholars have attempted to construct unequal weighted indices.

Scholarly research on corporate governance indices and their construction was driven by the need to measure governance quality. Several rating agencies followed the suit by introducing their own proprietary indices based on their assessment criteria. These developments have led to a growing demand from both buy-side (i.e., institutional investors) and sell-side (i.e., firms themselves who want to signal their governance quality to investors) participants. Gompers, Ishii, and Metrick's (2003) G-Index was the first-of-a-kind company-specific aggregate measure of corporate governance constructed using ATPs. Higher G-Index values depicted more leeway for the managers to pursue their own interests (i.e., poor corporate governance). Subsequently, Bebchuk, Cohen, and Ferrell (2009) introduced E-Index using a subset of six indicators from the original G-Index provisions. These six takeover-defense provisions were identified for their ability to contribute "the most to managerial entrenchment" (hence, the name Entrenchment Index or E-Index). E-index constituted of staggered boards, limits to amend shareholder bylaws, supermajority requirements for mergers, limits to charter amendments, poison pills, and golden parachutes. Alternatively, Brown and Caylor (2006) introduced Gov-Score using more governance mechanisms than the ATP-focused G-Index and E-Index. By using a comprehensive set of 51 factors, Gov-Score was proposed to provide a better measure of corporate governance quality as it was not restricted to only the ATPs and included additional board composition and executive compensation indicators. In contrast, focusing on parsimony instead of exhaustivity, Cremers and Nair (2005) construct an Alternative Takeover Protection Index by considering only a set of three main ATPs.

In addition to those scholarly corporate governance indices, there are commercial rankings and indices by private research and advisory agencies that rate companies' governance qualities. For example, Institutional Shareholder Services (ISS), GovernanceMetrics International (GMI), Thomson Reuters, and The Corporate Library (TCL) have all been collecting data on a wide range of governance issues in order to provide investors, policymakers, and regulators with governance rankings. Daines, Gow, and Larcker (2010) show that commercial corporate governance ratings and indices do not necessarily measure what they ought to. This shows that the methodologies employed by these commercial rating agencies have further scope for improvements.

1.3.4 ESG Indices

Although the idea of ethical investing and social responsibility has been widely prevalent for many years (Graves and Waddock, 1994; Brown and Perry, 1994), research in this area was severely constrained by the lack of data on corporate social initiatives and controversies. While some of the early proponents were skeptical about the benefits of socially responsible investing (SRI), others considered that it is possible to be socially responsible and economically viable at the same time (Hamilton, Jo, and Statman, 1993). Hylton (1992) went as far as to declare that "more aggressively SRI is practiced, the more one would expect ethical investing to be economically unattractive." Corson and Van Dyck (1992), in contrast, show that ethical investing need not necessarily be harmful for investors as environmental and social activities may potentially just be a part of an extended set of firms' fundamentals.

More recently, ethical investing has gone mainstream and data providers such as MSCI KLD, Sustainalytics, Thomson Reuters, ISS, and Bloomberg have all started actively collecting ESG data and disseminating their ratings. In academic research, while some scholars prefer to use proprietary ESG ratings provided by these agencies (for e.g., Buchanan, Cao, and Chen, 2018; Liang and Renneboog, 2017; Ferrell, Liang, and Renneboog, 2016), others segregate all the available ESG data to measure ESG indices on their own (Dyck et al., 2018; Di Giuli and Kostovetsky, 2014; Kim, Li, and Li, 2014). In some cases, even individual ESG characteristics and proposals have been separately considered to study their financial outcomes (Flammer, 2015; Krüger, 2015; Dimson, Karakaş, and Li, 2015). While most evidence points to the benefits of ESG (or, CSR) performance for both the firms and their shareholders (Ferrell, Liang, and Renneboog, 2016; Flammer, 2015), its negative impact for certain stakeholders such as the debtholders (Dumitrescu, El Hefnawy, and Zakriya, 2019) has also been documented.

1.4 Dissertation Structure

This doctoral dissertation primarily focuses on governance–performance relationship by looking at it through investors' lens. The overall objective is to present three complete manuscripts that provide insights into different dimensions of this relationship: a) Whether and how investors react to the corporate governance signals, b) The corporate governance measure and its construction, and c) Broadening the governance perspective to include environmental and social factors to see how it affects investment outcomes. Thus, the dissertation is structured in the form of a monograph based on three related manuscripts.[1] While the central objective of the dissertation is to highlight the importance of governance information for investors, each of the three manuscripts are developed as standalone research papers that address each of the above three challenges that arise when studying investors' behavior toward governance information. Overall, these three manuscripts complement and contribute towards general understanding of how investors can benefit from certain intrafirm mechanisms that align the managements and shareholders, and/or other stakeholders interests.

The first manuscript documents the reappearance of governance pricing anomaly, and provides a possible explanation for the same using a natural experiment. The aim is to disentangle the possible managerial encroachment (i.e. managers benefiting at the expense of investors) and shareholder enrichment as outcomes of corporate governance signals. The second manuscript focuses on measuring the corporate governance quality itself by examining method-

[1]Please note that the references are provided at the end of each chapter. The limitations and future directions of research are discussed in the last chapter.

ological drawbacks in index construction when equal weights are assigned to underlying governance components. The aim is to draw attention towards the relevance and importance of the individual anti-takeover provisions. The third manuscript looks beyond corporate governance unidimensionality by including additional environmental and social initiatives into the mix to see how firm's sustainability can benefit its investors.

1.5 Objectives and Contributions of Each Manuscript

The central objectives and contributions for each of the three research projects presented in this dissertation are summarized as follows:

1.5.1 Study I: "Governance, Information Flow and Stock Returns"

This study identifies multiple structural breaks in the relationship between corporate governance and stock returns, and provides an investor-centric explanation for the second structural break.

<u>Contributions:</u> We contribute to the literature by showing that there are two structural breaks in the governance–returns correlation i.e. a) its disappearance, and b) its reappearance in the opposite direction. Using a natural experiment that captures the changes in institutional investors' governance preferences and its resultant impact on stock returns, we provide a possible explanation for the second structural break in the form of investor learning hypothesis. Under this hypothesis, beyond the initial learning or first break point, the repeated exposure to governance signals facilitates institutional investors to further appreciate the differences in good and poor governance firms, so that their expectations of returns from poor governance firms change. Our results from the natural experiment support this hypothesis. The proportion

of short-term investors increases in the poorly governed firms after the critical investor learning point. And, governance-based hedge portfolios show possible trading benefits from poor governance stocks, with the portfolio of these stocks consistently outperforming good governance portfolio beyond the investor learning point (i.e. January-2008). By evidencing the reappearance of governance pricing anomaly that was reported to have disappeared in the past, we also contribute to a growing literature that explores rational and behavior theories of asset pricing anomalies. Thus, in some ways, we also addresses market efficiency and its fragility.

1.5.2 Study II: "The Corporate Governance – Performance Puzzle: New Insights"

This study sheds light on the corporate governance–performance puzzle by exploring an unequally weighted governance index.

<u>Contributions:</u> Using a novel unequal-weighted approach that dynamically accounts for the heterogeneity of individual anti-takeover components, we show that our proposed "nG (new Governance) Index" is less prone to erroneous inferences than a comparable equal-weighted index (such as G-Index, E-Index etc.) is. Previous governance indices, being equal-weighted, did not possess requisite dynamism to trace the evolution of governance landscape that was induced by the government interventions and media influences. Given that recent research has shown that these indices are not associated with abnormal returns beyond the early 2000s, our findings reveal that when individual provision's weights are captured in an index, governance-based hedges can still generate abnormal returns for investors in recent years. Additionally, this study contributes by highlighting that the information content of all gover-

nance provisions are not the same.

1.5.3 Study III: "Sustain and Deliver: Capturing the Valuation Effects of Corporate Sustainability"

This study probes the environmental, governance and social characteristics to identify a *corporate sustainability* measure that can have implications for the value of the firms.

Contributions: In this study, we contribute to the literature by examining individual environmental, social and governance (ESG) factors that are commonly combined in the related literature to measure corporate social responsibility (CSR) or ESG performance. Inspired by the Bebchuk, Cohen, and Ferrell (2009) paper that introduces E-Index as a subset of G-Index introduced in Gompers, Ishii, and Metrick (2003), we identify a subset of ESG indicators that converge towards the concept of "corporate sustainability". This identified subset completely explains the CSR's valuation benefits, while also shedding some light on its stock market performance. In contrast, the remaining indicators have no impact on both the accounting- and stock market-based valuations of the firm. Since this is the first study to apply an industry-neutral selection of ESG indicators, it has implications for both the firms and their ESG-rating providers. By focusing attention on the sustainable aspects of ESG, managers can take value-relevant decisions and the rating agencies can provide value-enhancing investment advisory services.

1.6 Scholarly Contributions

The three articles presented in this dissertation are currently being revised for journal submissions. They have been presented in multiple international conferences and seminars in the last three years. The details about each of their authorship and conference presentations are summarized in Table 1.1. The first two manuscripts are co-authored with Dr. Ariadna Dumitrescu, and the third one is solo-authored.

Table 1.1 Scholarly contributions from the dissertation

Title	Authorship	Current Status	Conference/Seminar Presentations	Award Nominations/ Media Mentions
Governance, Information Flow, and Stock Returns	Ariadna Dumitrescu and Mohammed Zakriya	Working Paper, Journal submission planned for June 2020.	- 2019 Financial Management Association (FMA) Annual Meeting, New Orleans, U.S.A - 2019 Corporate Finance Day, Groningen, Netherlands - 2019 European Financial Management Association (EFMA) Annual Meetings, Azores, Portugal - 2019 FMA European Conference, Glasgow, Scotland - 2019 Finance Forum of Spanish Finance Association (AEFIN), Madrid, Spain - 2019 Financial Management & Accounting Research Conference (FMARC), Limassol, Cyprus - 2018 "Merton H. Miller" Doctoral Student Seminar, Milan, Italy	- Finalist for Larry Lang Corporate Finance Best Paper Award at the EFMA Annual Meeting, 2019 - Semifinalist for the Best Paper Awards at FMA Annual Meeting, 2019 - Featured in: "ESG, Firm Value, Governance", www.esginsights.dk, June 28, 2018
The Corporate Governance – Performance Puzzle: New Insights	Ariadna Dumitrescu and Mohammed Zakriya	Working Paper, Journal submission planned for October 2020.	- 2018 FMA European Conference, Kristiansand, Norway - 2017 Finance Forum of AEFIN, Barcelona - 2017 Financial Markets and Corporate Governance (FMCG) Conference, Wellington, New Zealand - 2017 Multinational Finance Society (MFS) Annual Conference, Bucharest, Romania - MDX Research Seminar, Middlesex University Dubai, U.A.E.	
Sustain and Deliver: Capturing the Valuation Effects of Corporate Sustainability	Mohammed Zakriya	Working Paper, Journal submission planned for June 2020.	- 2018 EFMA Annual Meetings, Milan, Italy - 2018 Finance Forum of AEFIN, Santander, Spain - 2018 FMCG Conference, Melbourne, Australia - National Securities Market Commission (CNMV) Seminar, Madrid, Spain - IÈSEG School of Management, Lille, France - NOVA SBE Brownbag Seminar, Lisbon, Portugal - NEOMA Business School, Paris, France.	- Nominated for Best Paper in Corporate Governance/Social Responsibility at the FMCG Conference, 2018

1.7 References

Ailman, C., Edkins, M., Mitchem, K., Eliopoulos, T., Guillot, J., 2017. The next wave of ESG integration: Lessons from institutional investors. Journal of Applied Corporate Finance 29 (2), 32–43.

Amihud, Y., Schmid, M., Solomon, S. D., 2017. Settling the staggered board debate. University of Pennsylvania Law Review 166, 1475.

Amihud, Y., Schmid, M., Solomon, S. D., 2018. Do staggered boards matter for firm value? Journal of Applied Corporate Finance 30 (4), 61–77.

Amihud, Y., Stoyanov, S., 2017. Do staggered boards harm shareholders? Journal of Financial Economics 123 (2), 432–439.

Bebchuk, L., Cohen, A., 2005. The costs of entrenched boards. Journal of Financial Economics 78 (2), 409–433.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22 (2), 783–827.

Bebchuk, L., Cohen, A., Wang, C. C., 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics 108 (2), 323–348.

Bebchuk, L., Cohen, A., Wang, C. C., 2014. Golden parachutes and the wealth of shareholders. Journal of Corporate Finance 25, 140–154.

Becchetti, L., Ciciretti, R., Giovannelli, A., 2013. Corporate social responsibility and earnings forecasting unbiasedness. Journal of Banking and Finance 37 (9), 3654–3668.

Becchetti, L., Ciciretti, R., Hasan, I., 2015. Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. Journal of Corporate Finance 35, 297–309.

Beiner, S., Drobetz, W., Schmid, M. M., Zimmermann, H., 2006. An integrated framework of corporate governance and firm valuation. European Financial Management 12 (2), 249–283.

Bhagat, S., Black, B., 2001. The non-correlation between board independence and long-term firm performance. Journal of Corporation Law 27, 231–274.

Bhagat, S., Bolton, B., 2013. Director ownership, governance, and performance. Journal of Financial and Quantitative Analysis 48 (01), 105–135.

Bhagat, S., Bolton, B., Romano, R., 2008. The promise and peril of corporate governance indices. Columbia Law Review 108, 1803–1882.

Bialkowski, J., Starks, L. T., 2016. SRI funds: Investor demand, exogenous shocks and ESG profiles. Unpublished working paper, `https://ir.canterbury.ac.nz/handle/10092/12492`.

Bizjak, J. M., Marquette, C. J., 1998. Are shareholder proposals all bark and no bite? Evidence from shareholder resolutions to rescind poison pills. Journal of Financial and Quantitative Analysis 33 (4), 499–521.

Black, B., De Carvalho, A. G., Khanna, V., Kim, W., Yurtoglu, B., 2017. Corporate governance indices and construct validity. Corporate Governance: An International Review 25 (6), 397–410.

Borgers, A., Derwall, J., Koedijk, K., Ter Horst, J., 2013. Stakeholder relations and stock returns: On errors in investors' expectations and learning. Journal of Empirical Finance 22, 159–175.

Boyd, B. K., 1995. CEO duality and firm performance: A contingency model. Strategic Management Journal 16 (4), 301–312.

Brown, B., Perry, S., 1994. Removing the financial performance halo from fortune's "most admired" companies. Academy of Management Journal 37 (5), 1347–1359.

Brown, L. D., Caylor, M. L., 2006. Corporate governance and firm valuation. Journal of Accounting and Public Policy 25 (4), 409–434.

Brusa, J., Lee, W. L., Shook, C., 2009. Golden parachutes, managerial incentives and shareholders' wealth. Managerial Finance 35 (4), 346–356.

Buchanan, B., Cao, C. X., Chen, C., 2018. Corporate social responsibility, firm value, and influential institutional ownership. Journal of Corporate Finance 52, 73–95.

Bushee, B. J., Carter, M. E., Gerakos, J., 2013. Institutional investor preferences for corporate governance mechanisms. Journal of Management Accounting Research 26 (2), 123–149.

Chung, K. H., Lee, C., 2020. Voting methods for director election, monitoring costs, and institutional ownership. Journal of Banking and Finance, 105738.

Cohen, A., Wang, C. C., 2013. How do staggered boards affect shareholder value? Evidence from a natural experiment. Journal of Financial Economics 110 (3), 627–641.

Cohen, A., Wang, C. C., 2017. Reexamining staggered boards and shareholder value. Journal of Financial Economics 125 (3), 637–647.

Comment, R., Schwert, G. W., 1995. Poison or placebo? Evidence on the deterrence and wealth effects of modern antitakeover measures. Journal of Financial Economics 39 (1), 3–43.

Core, J. E., Holthausen, R. W., Larcker, D. F., 1999. Corporate governance, chief executive officer compensation, and firm performance. Journal of Financial Economics 51 (3), 371–406.

Cornelli, F., Karakaş, O., 2012. Corporate governance of LBOs: The role of boards. Unpublished working paper, https://papers.ssrn.com/abstract_id=1875649.

Corson, B. C., Van Dyck, T., 1992. Socially responsible investing and financial return: Albatross or scapegoat? Journal of Investing 1 (2), 23–28.

Crane, A. D., Koch, A., Michenaud, S., 2019. Institutional investor cliques and governance. Journal of Financial Economics 133 (1), 175–197.

Cremers, K., Nair, V. B., 2005. Governance mechanisms and equity prices. Journal of Finance 60 (6), 2859–2894.

Cremers, K. M., Litov, L. P., Sepe, S. M., 2017. Staggered boards and long-term firm value, revisited. Journal of Financial Economics 126 (2), 422–444.

Cuñat, V., Gine, M., Guadalupe, M., 2012. The vote is cast: The effect of corporate governance on shareholder value. Journal of Finance 67 (5), 1943–1977.

Cuñat, V., Gine, M., Guadalupe, M., 2016. Say pays! shareholder voice and firm performance. Review of Finance 20 (5), 1799–1834.

Daines, R., Li, S. X., Wang, C. C., 2018. Can staggered boards improve value? Evidence from the massachusetts natural experiment. Unpublished working paper, Available at: http://ssrn.com/abstract=2836463.

Daines, R. M., Gow, I. D., Larcker, D. F., 2010. Rating the ratings: How good are commercial governance ratings? Journal of Financial Economics 98 (3), 439–461.

Deli, D. N., Gillan, S. L., 2000. On the demand for independent and active audit committees. Journal of Corporate Finance 6 (4), 427–445.

Di Giuli, A., Kostovetsky, L., 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. Journal of Financial Economics 111 (1), 158–180.

Dimson, E., Karakaş, O., Li, X., 2015. Active ownership. Review of Financial Studies 28 (12), 3225–3268.

Dumitrescu, A., El Hefnawy, M., Zakriya, M., 2019. Golden geese or black sheep: Are stakeholders the saviors or saboteurs of financial distress? Finance Research Letters, 101371.

Dyck, A., Lins, K. V., Roth, L., Wagner, H. F., 2018. Do institutional investors drive corporate social responsibility? International evidence. Journal of Financial Economics 131, 693–714.

Edmans, A., Ioannou, I., 2019. Future leaders, take note: finance and sustainability go together. Financial Times June 17, https://www.ft.com/content/54f96d4e-82ec-11e9-9935-ad75bb96c849.

Eisenberg, T., Sundgren, S., Wells, M. T., 1998. Larger board size and decreasing firm value in small firms. Journal of Financial Economics 48 (1), 35–54.

Erkens, D. H., Hung, M., Matos, P., 2012. Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. Journal of Corporate Finance 18 (2), 389–411.

Falaschetti, D., 2002. Golden parachutes: credible commitments or evidence of shirking? Journal of Corporate Finance 8 (2), 159–178.

Faleye, O., 2007. Classified boards, firm value, and managerial entrenchment. Journal of Financial Economics 83 (2), 501–529.

Fatemi, A., Fooladi, I., Tehranian, H., 2015. Valuation effects of corporate social responsibility. Journal of Banking and Finance 59, 182–192.

Ferrell, A., Liang, H., Renneboog, L., 2016. Socially responsible firms. Journal of Financial Economics 122 (3), 585–606.

Fich, E. M., Tran, A. L., Walkling, R. A., 2013. On the importance of golden parachutes. Journal of Financial and Quantitative Analysis 48 (6), 1717–1753.

Flammer, C., 2015. Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. Management Science 61 (11), 2549–2568.

Fulton, M., Kahn, B. M., Sharples, C., 2012. Sustainable investing: Establishing long-term value and performance. Unpublished working paper, http://ssrn.com/abstract=2222740.

Gao, L., Kling, G., 2008. Corporate governance and tunneling: Empirical evidence from China. Pacific-Basin Finance Journal 16 (5), 591–605.

Gillan, S. L., 2006. Recent developments in corporate governance: An overview. Journal of Corporate Finance 12 (3), 381–402.

Gillan, S. L., Starks, L. T., 2000. Corporate governance proposals and shareholder activism: The role of institutional investors. Journal of Financial Economics 57 (2), 275–305.

Gompers, P. A., Ishii, J. L., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118 (1), 107–155.

Graves, S. B., Waddock, S. A., 1994. Institutional owners and corporate social performance. Academy of Management Journal 37 (4), 1034–1046.

Gul, F. A., Krishnamurti, C., Shams, S., Chowdhury, H., 2020. Corporate social responsibility, overconfident CEOs and empire building: Agency and stakeholder theoretic perspectives. Journal of Business Research 111, 52–68.

Hamilton, S., Jo, H., Statman, M., 1993. Doing well while doing good? The investment performance of socially responsible mutual funds. Financial Analysts Journal 49 (6), 62–66.

Hermalin, B. E., Weisbach, M. S., 1991. The effects of board composition and direct incentives on firm performance. Financial Management, 101–112.

Heron, R. A., Lie, E., 2015. The effect of poison pill adoptions and court rulings on firm entrenchment. Journal of Corporate Finance 35, 286–296.

Hu, J., Li, S., Taboada, A. G., Zhang, F., 2020. Corporate board reforms around the world and stock price crash risk. Journal of Corporate Finance, 101557.

Humphrey, J. E., Lee, D. D., Shen, Y., 2012. Does it cost to be sustainable? Journal of Corporate Finance 18 (3), 626–639.

Hylton, M. O., 1992. Socially responsible investing: Doing good versus doing well in an inefficient market. American University Law Review 42, 1.

Iliev, P., Lins, K. V., Miller, D. P., Roth, L., 2015. Shareholder voting and corporate governance around the world. Review of Financial Studies 28 (8), 2167–2202.

Jarrell, G. A., Brickley, J. A., Netter, J. M., 1988. The market for corporate control: The empirical evidence since 1980. Journal of Economic Perspectives 2 (1), 49–68.

Jensen, M. C., 2001. Value maximization, stakeholder theory, and the corporate objective function. Journal of Applied Corporate Finance 14 (3), 8–21.

Jensen, M. C., Meckling, W. H., 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics 3 (4), 305–360.

Jiao, Y., 2010. Stakeholder welfare and firm value. Journal of Banking and Finance 34 (10), 2549–2561.

Jiraporn, P., Singh, M., Lee, C. I., 2009. Ineffective corporate governance: Director busyness and board committee memberships. Journal of Banking and Finance 33 (5), 819–828.

Karpoff, J. M., Malatesta, P. H., Walkling, R. A., 1996. Corporate governance and shareholder initiatives: Empirical evidence. Journal of Financial Economics 42 (3), 365–395.

Kim, Y., Li, H., Li, S., 2014. Corporate social responsibility and stock price crash risk. Journal of Banking and Finance 43, 1–13.

Klapper, L. F., Love, I., 2004. Corporate governance, investor protection, and performance in emerging markets. Journal of Corporate Finance 10 (5), 703–728.

Krüger, P., 2015. Corporate goodness and shareholder wealth. Journal of Financial Economics 115 (2), 304–329.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., Vishny, R., 2000. Investor protection and corporate governance. Journal of Financial Economics 58 (1), 3–27.

Larcker, D. F., Richardson, S. A., Tuna, I., 2007. Corporate governance, accounting outcomes, and organizational performance. Accounting Review 82 (4), 963–1008.

Liang, H., Renneboog, L., 2017. On the foundations of corporate social responsibility. Journal of Finance 72 (2), 853–910.

Lins, K. V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. Journal of Finance 72 (4), 1785–1824.

Lo, A. W., Wong, R. M., Firth, M., 2010. Can corporate governance deter management from manipulating earnings? Evidence from related-party sales transactions in china. Journal of Corporate Finance 16 (2), 225–235.

McCahery, J. A., Sautner, Z., Starks, L. T., 2016. Behind the scenes: The corporate governance preferences of institutional investors. Journal of Finance 71 (6), 2905–2932.

Nerantzidis, M., 2018. The role of weighting in corporate governance ratings. Journal of Management and Governance 22 (3), 589–628.

Ruback, R. S., Jensen, M. C., 1983. The market for corporate control: The scientific evidence. Journal of Financial Economics 11, 5–50.

Ryngaert, M., 1988. The effect of poison pill securities on shareholder wealth. Journal of Financial Economics 20, 377–417.

Schmidt, C., Fahlenbrach, R., 2017. Do exogenous changes in passive institutional ownership affect corporate governance and firm value? Journal of Financial Economics 124 (2), 285–306.

Shleifer, A., Vishny, R. W., 1997. A survey of corporate governance. Journal of Finance 52 (2), 737–783.

Sokolyk, T., 2011. The effects of antitakeover provisions on acquisition targets. Journal of Corporate Finance 17 (3), 612–627.

Starks, L. T., 2009. EFA keynote speech: "Corporate governance and corporate social responsibility: What do investors care about? What should investors care about?". Financial Review 44 (4), 461–468.

Van Duuren, E., Plantinga, A., Scholtens, B., 2016. ESG integration and the investment management process: Fundamental investing reinvented. Journal of Business Ethics 138 (3), 525–533.

Yang, T., Zhao, S., 2014. CEO duality and firm performance: Evidence from an exogenous shock to the competitive environment. Journal of Banking and Finance 49, 534–552.

CHAPTER 2

Governance, Information Flow, and Stock Returns

2.1 Abstract

We show that governance information is useful for investors but not as previously envisaged. Poor governance stocks outperform good governance ones after 2008. This novel reversal of the governance–returns relationship implies that its disappearance documented in Bebchuk, Cohen, and Wang (2013) is temporary. The revival of this relationship can be explained by sophisticated investors learning to recognize governance risks and becoming more prudent

after the global financial crisis. Consistent with this learning, we find that investors could have identified via *price* and *risk* channels that the poorly governed firms face higher uncertainty regarding their future earnings power after 2008. Furthermore, following the crisis, we observe that institutional investors update their governance preferences through information-induced learning.

2.2 Introduction

Does corporate governance matter for stock returns? Most investors would like to invest in good corporate governance stocks but perhaps not at the expense of shareholder returns. This issue is at the core of a recent debate about the role of corporate governance and corporate social responsibility in stock performance. In the past, firms with good corporate governance were associated with good stock performance (Gompers, Ishii, and Metrick, 2003). More recently, Edmans and Ioannou (2019) state "[t]he idea that companies and investors can both do good and do well is finding ever greater traction among executives, shareholders and wider society." As a result, large institutional investors have designed strategies to identify and invest in good corporate governance firms. The California Public Employees Retirement System (CalPERS), for example, devised its own list of effective governance practices and also used social activism to improve the performance of its investments.[2] However, Gillers (2019) reports in the Wall Street Journal that "[d]oubts about the strategy rose as Cal[PERS]' funding situation worsened in the decade after the 2008 financial crisis. A key sign came in December 2016 as retirement-system officials recommended the board drop its tobacco ban, citing the potential money lost.

[2]CalPERS is the largest public pension fund in the U.S. with $366 billion in assets as of June 2019 (Gillers, 2019) and is well known for creating the "Focus List," which contains companies with concerning or undesirable corporate governance practices. The fund worked with the listed companies to improve their performance creating a phenomenon known as the "CalPERS effect."

Staying out of the investments for 16 years had cost the fund more than $3.5 billion, a fund consultant calculated." Did CalPERS and other institutional investors realize the cost of ignoring poor governance stocks amid the funding crunch that accompanied the 2008 crisis?

This study analyses the evolution of governance–returns relationship to show that the poor governance stocks indeed cannot be ignored after 2008. In this period, poor governance firms are under-priced and a zero-investment strategy that goes long poor governance stocks and short good governance ones generates over 2.5% monthly risk-adjusted returns. This is a novel result that indicates a reversal of the governance–returns relationship. Before 2002, good governance stocks outperformed the poor governance ones (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009). Bebchuk, Cohen, and Wang (2013), however, show that the correlation between stock returns and corporate governance indices ceased to exist in the 2002-2008 period, and so also did any arbitrage opportunities for investors. Moreover, during the 2007-2008 financial crisis, good governance stocks performed poorly (Erkens, Hung, and Matos, 2012). We conjecture that the higher returns for poor corporate governance firms after 2008 may be driven by prices reflecting their high information asymmetry and the effect this had on institutional investors' demand. Consistent with this notion, we find that the price informativeness of good governance stocks increases and that of poor governance decreases after the disassociation period (2001-2008). This shows that information flow played an important role in making the governance–returns correlation reappear in the opposite direction. Furthermore, on exploring how institutional investors respond to these changes, we find that their governance preferences are affected by information-induced learning. After 2008, short-term (long-term) institutional ownership in poor (good) governance stocks is higher when compared to the dissociation years.

How did the 2008 financial crisis affect investors' attention to governance information? Attention is a key determinant of investment choice (Barber and Odean, 2008), and good corporate governance mitigates downside risk (Wang et al., 2015). Thus, we posit that, due to increased attention during the crisis period, investors realized that the increased volatility in the markets increases downside risk for poor governance firms. Sophisticated investors are most likely to identify this due to their superior data gathering and processing abilities. Some of these investors then used the information on downside risk together with the information about governance characteristics to design new investment strategies. This constitutes sophisticated learning. In other words, after the crisis-induced sophisticated learning, some of the investors become governance-motivated when they understand that the corporate governance continues to be a reliable signal for good corporate governance firms, but not so for the poor governance ones. This mechanism has been explored theoretically by Pastor, Stambaugh, and Taylor (2019) and Pedersen, Fitzgibbons, and Pomorski (2019), who show that environmental, social and governance (or, ESG) information and preferences are important for investment returns. When only a few investors use governance information, governance-based investment portfolios can generate abnormal returns and good governance stocks give higher returns (for e.g., during 1990s, as shown in Gompers, Ishii, and Metrick, 2003). Next, when this information becomes common to all investors, abnormal returns disappear (for e.g., after 2001, as in Bebchuk, Cohen, and Wang, 2013). However, unlike in the past, Pastor, Stambaugh, and Taylor (2019) predict that good (poor) governance stocks will give negative (positive) abnormal returns when the overall market sensitivity toward governance information is high. Pedersen, Fitzgibbons, and Pomorski (2019) similarly predict that when there are many governance-motivated investors in an economy, good governance stocks will have lower returns. Thus, our explanation for the recent reemergence of the relationship between governance and returns, and that too, remarkably in the opposite direction, are in line with these theoretical predictions.

In order to shed light on the evolving governance–returns relationship since the 1990s, we create governance-based hedge portfolios (see Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009) using the ISS governance provisions data. While this association disappears in 2001, further exploration reveals that another structural break exists in 2008, when the relationship reappears, albeit in the opposite direction.[3] We identify the two structural break points using Bebchuk, Cohen, and Wang (2013) approach, and use the Bai and Perron (1998) and Hatemi-J (2008) tests to confirm the two regime shifts. In recent years, we find that poor governance stocks have higher returns than the good governance ones. This outperformance of poor governance stocks after 2008 indicates that the sensitivity to governance information has increased after the financial crisis and that many sophisticated investors have adjusted their investments to this information (or, have become governance-motivated). Thus, to understand these two underlying mechanisms, we run multiple empirical tests and investigate whether investors learn, after 2008, that: (a) governance characteristics have become more informative, and (b) sophisticated investors are drawn to different sets of stocks based on their governance preferences.

We study the role of information flow in sophisticated learning by assessing if there is a systematic shift in the amount of information impounded in the prices of good and poor governance stocks across 2008. If there was indeed such a shift, investors, and more specifically, sophisticated investors, could

[3]All our main results and additional analysis employ the E-Index as a governance proxy, as this index can be reliably developed for the entire sample period. The change in ISS's data collection methodology after 2007 (that changed the number of anti-takeover provisions covered by ISS) makes the replication of the G-Index difficult after 2006.

have reacted to changes in price information by adjusting their expectations from poor governance stocks. We examine two underlying learning channels through which the informativeness of governance characteristics could have been identified by the investors. First, since good governance is related to the price informativeness (Lee, Chung, and Yang, 2016), we study the information content of good and bad governance stocks' prices and the changes that their price informativeness experiences across the two structural break points. More specifically, we capture the differences in investors' expectations of future firm growth rates and earnings prospects between well- and poorly-governed firms. Second, since the "no arbitrage" condition leads to a relation between the information flow rate and stock price volatility (Ross, 1989), we examine the impact of governance on idiosyncratic volatility and price non-synchronicity across the two structural breaks. While the first channel reflects the learning that is aided by information flows through the *price*, the second channel portrays the same experienced through the *risk*.

To investigate the price channel, we analyze the differences between the cross-sectional price informativeness of good and bad governance stocks. Our results support both the Bebchuk, Cohen, and Wang (2013) learning hypothesis for the first structural break and sophisticated learning across the second structural break. While price informativeness increased in the pre-2001 period for both good and bad governance stocks (through learning effects), there is a different trend in the post-2008 period. Poor governance stocks show a distinct decline in price informativeness after the second structural break point, whereas well-governed stocks show an upward trend for the same period. During the period of dissociation (i.e., between the two structural break points), price informativeness is statistically insignificant, implying stable information access across both well- and poorly-governed firms. We complement the results from cross-sectional measure of price informativeness using firm-specific information flow proxies, and again find evidence supporting sophisticated learning. More specifically, at the firm level, poor governance firms have greater information asymmetry and also show comparatively lower trading activity than well-governed ones after the second structural break.

To examine the risk channel, we study the firms' idiosyncratic volatility and stock price crash risk. Our results again support possible sophisticated learning, with bad governance firms being associated with higher idiosyncratic volatility in comparison with good governance ones in the post-2008 period. Additionally, we find that while the E-Index could not predict future stock price crash risk before 2008, there is a positive association between the two thereafter. This means that after the second structural break, poorly governed stocks with more entrenchment provisions have a higher likelihood of crashes. Jin and Myers (2006) show that "limited information affects the division of risk bearing between inside managers and outside investors." Combined with the evidence from the *price* channel tests, the results from the *risk* channel tests thus indicate that learning about the increased information asymmetry in poor governance firms could have made some investors become aware of the riskiness associated with these firms. As a result, these investors would have wisely adjusted their expectations of poor governance firms' future earnings power and associated risk premia in making their investment decisions.

Although the results from information-in-price tests lend credence to the existence of sophisticated learning, they do not shed light on the role of institutional investors in the appearance of a newer (i.e., negative) correlation between governance and returns. Institutional investors not only play an important role in the governance of investee firms (Gillan and Starks, 2000; McCahery, Sautner, and Starks, 2016), they also have their governance preferences (Bushee, Carter, and Gerakos, 2013). So, we next explore the evolving governance preferences of institutional investors around the 2008 financial crisis. We use a quasi-natural experiment to capture the changes in institutional investors' governance preferences and its resultant impact on stock returns. In 2007, Institutional Shareholder Services (ISS)—a leading corporate governance data provider used by institutional investors—changed its data collection and reporting methodology, which led to the faster dissemination of governance data on an annual basis than in previous years when governance data were made available to investors every two or three years. Since this exogenous shock occurs just before the second structural break in the governance–returns relationship, it provides an ideal setting within which to assess if investors learn to recognize the riskiness of poorly governed firms. Basically, our experimental test builds on the Grossman and Stiglitz (1980) and Hellwig (1980) theoretical models on informational efficiencies, as we aim to understand how informed sophisticated investors react to the quality of governance information and/or its noisiness through sophisticated learning.[4]

We examine the changes in short- and long-term institutional ownership across the second structural break point using the frequency of governance-information availability as a proxy for differential sophisticated learning among investors. While there is a significant decline in long-term institutional ownership among poor governance stocks after the second break point when there is faster dissemination of governance information to investors, short-term institutional ownership increases for poor governance firms. Our results support the idea that short-term investors seek returns by exploiting informational inefficiencies Yan and Zhang (2009). Long-term investors, meanwhile, choose good governance firms so that they can intervene through "voice," while they choose to "exit" when firms have poor governance structures (McCahery, Sautner, and Starks, 2016). In other words, the benefits from investing in good governance

[4]These models show that when it is costly to acquire information, prices cannot perfectly aggregate such information.

stocks arise in the form of lower monitoring costs, while foregoing short-term gains (Bebchuk, Brav, and Jiang, 2015).

In addition to merely exploring and explaining the negative association between governance and stock returns, our findings contribute to a broader body of the literature that studies information-based trading strategies and/or long-run event studies. From an asset pricing perspective, we draw attention to a possible anomaly (see Schwert, 2003). This is especially important as the anomaly in focus was shown to have disappeared after 2001. While the disappearance of financial anomalies has been widely studied, few studies have highlighted their possible reappearance. In some ways, our study also reflects the tensions and complementarities between the rational and behavioral theories of financial anomalies (Brav and Heaton, 2002). We show that while learning does involve the recalibration of governance information by rational investors, the additional uncertainties accompanying information asymmetry induce sophisticated learning that allows investors to exploit fresh arbitrage opportunities. Additionally, we contribute to the larger market efficiency literature (see Fama, 1991). Our findings are consistent with those of Brown, Harlow, and Tinic (1988), as we show that investors' risk and returns adjust to new information, especially for poor governance structures after market prices have corrected for the differences between well-governed and poorly governed firms (i.e., after the initial learning period). Alternatively, the relatively high idiosyncratic risk and lower price informativeness of poorly governed firms after the second break point may also be indicative of the ambiguity premium (Epstein and Schneider, 2008).

The rest of this study is organized as follows. Section 2.3 discusses sophisticated learning. Section 2.4 describes the data and variables. Section 2.5 makes a case for the two structural breaks or regime shifts in the governance–returns relationship. Next, Section 2.6 explores the price and risk channels to assess the importance of information flow for sophisticated learning. Section 2.7 applies a quasi-natural experiment to understand the short- and long-term institutional investors' behavior toward governance information, and Section 2.8 summarizes our main results and concludes.

2.3 Sophisticated Learning

Investors are constantly seeking information that can help them *beat* the markets (French, 2008). Moreover, they are sensitive to managerial entrenchment (E-Index), as the presence of entrenching anti-takeover provisions within firms exposes them to possible information asymmetry when managers are better shielded from takeover threats (Bebchuk, Cohen, and Ferrell, 2009). We expect investors' sensitivity to such governance provisions to be heightened when they are exposed to extreme downside events such as the global financial crisis. Thus, we define sophisticated learning as the governance-centric learning experienced by sophisticated investors when they exercise high prudence towards poor governance stocks on facing the stock market free fall in 2008. The underlying rationale is that some investors learn to better adapt to market conditions after the financial crisis so that they make more informed investment decisions using governance information than other market participants.

Using a theoretical model, Pedersen, Fitzgibbons, and Pomorski (2019) show that investors' sensitivity to governance (or, ESG) information can explain the existence and disappearance of abnormal returns, and predict that investors' governance preferences will drive the governance-based portfolios' performance in the future. When only a few investors use governance scores, portfolios based on these scores have higher returns than an average portfolio that ignores them (à la Gompers, Ishii, and Metrick, 2003). Subsequently, when all investors employ governance information, but they do not have specific governance preferences, abnormal returns disappear (as in Bebchuk, Cohen, and

Wang, 2013). However, Pedersen, Fitzgibbons, and Pomorski (2019) show that when investors have ESG preferences, they are willing to pay a premium for good ESG stocks. Pastor, Stambaugh, and Taylor (2019) model governance-motivated investors in a market that is highly sensitive to governance information. They show that poor governance stocks have positive abnormal returns in equilibrium if all investors have governance preferences.

Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) propose that many market participants in the 1990s did not understand the importance of governance provisions, thus creating opportunities for institutional investors to obtain abnormal returns. As a consequence, Chung and Zhang (2011) find a positive relationship between institutional ownership and governance structures for the same period. However, increased attention toward these provisions over time resulted in the disappearance of abnormal returns from governance-based hedge portfolios (Bebchuk, Cohen, and Wang, 2013). We conjecture that a change in investors' governance preferences took place around 2008. During the global financial crisis in 2007–2008, firms with better governance characteristics and higher institutional ownership performed poorly in terms of their stock returns (Erkens, Hung, and Matos, 2012). This would have led to an increased prudence toward governance provisions among informed institutional investors. Thus, the learning that accompanies such increased scrutiny should have created additional investment opportunities for these investors after the financial crisis, hence, affecting the demand for good/bad governance stocks.

As institutional investors have comparatively superior information-gathering and -processing power, they can identify potential sources of information asymmetries and agency problems faster. Beyond the critical sophisticated learning point, we expect short- and long-term institutional investors to react differently to governance signals. While the myopic view of short-term investors will make poor governance stocks lucrative for them, long-term investors will be attracted to good governance firms (Nesbitt, 1994). From firms' perspective, stock prices are influenced by investors' liquidity needs (Chang, Chen, and Zolotoy, 2017). Thus, the impact of firms' governance structures on institutional ownership and subsequent liquidity pressures should jointly influence their stock returns. In other words, although governance risk may affect stock returns through liquidity risk (see Dumitrescu, 2015; Back et al., 2018), it is not captured through the same in its entirety. Hence, the markets at large may not really factor in governance risks. In the long run, however, such governance-based abnormal returns opportunities should disappear, with the market learning process eventually eliminating any governance-related information asymmetry. Hence, while the returns accompanying sophisticated learning do dwell upon market inefficiency in the short run, it does not rule out the possible return to efficient market conditions in the future.[5]

We expect learning among institutional investors to be driven by either one or all of the following three conditions. First, investors' risk attitudes and returns expectations are known to change around financial crises (Weber, Weber, and Nosić, 2012). This implies that investors may have become more prudent after the 2007–2008 financial crisis. Second, governance information was previously not made available to investors in a consistent and reliable manner. However, investment planning should have improved with ISS standardizing its governance reporting practices. Lastly, informed institutional investors are in a better position to react to newer information than uninformed investors and hence should demand higher returns when investing in high private information firms

[5] From a different and more rational standpoint, the sophisticated learning hypothesis does not necessarily assume complete market inefficiency or suggest purely investor-centric learning. Since we mimic the passive market portfolio by only controlling for some well-known risk factors, such learning may even be experienced by investors and all other market participants alike, as long as they can factor additional governance risk into their investment decisions.

(Easley and O'Hara, 2004). This would also entail the governance–returns relationship being affected by a reliable information flow.

The aforementioned effect of the financial crisis on investor behavior and stock prices cannot be ignored (Muir, 2017). In our tests of the sophisticated learning involving quasi-natural experiment, since our focuses on investee firms, we can control for the 2007–2008 financial crisis under the assumption that it had similar impacts on both treatment and control firms. However, our tests on the price and risk channels of learning merely assume that institutional investors must have readjusted their portfolios after the crisis due to increased diligence and prudence. Two opposing catalysts drive these post-crisis readjustments: the improved accuracy of analysts' assessments of a firm's riskiness (Joos, Piotroski, and Srinivasan, 2016) and the decline in the accuracy of earnings forecasts (Sidhu and Tan, 2011). Moreover, Mondria and Quintana-Domeque (2013) and Bekaert et al. (2014) show that international investors pay more attention to "macroeconomic fundamentals" during a crisis period. In other words, the country's economic stability becomes more important than the individual firm's characteristics. Together, these factors would have contributed to sophisticated learning. While these are important explanatory drivers from investors' perspective, much of our analyses in this study aim to understand investees' firm-specific drivers.

2.4 Data and Measures

We draw the data for anti-takeover provisions from the ISS governance database, the stock returns, prices, and volumes from the Center for Research in Stock Prices (CRSP) database, firm-specific fundamentals and controls from COMPUSTAT, and the Fama-French and Liquidity Factors from WRDS. Additional data for the probability of informed trading (PIN), as used by Brown and Hillegeist (2007), were obtained from Stephen Brown's website. The main sample includes firms whose governance data are reported by ISS and excludes all firms with dual class stocks as these have governance structures that differ from single class stock firms (Gompers, Ishii, and Metrick, 2009).

2.4.1 Governance Data

We focus on the governance data published by ISS (formerly IRRC-Riskmetrics), which reports the anti-takeover provisions of S&P 500 and other large Fortune 500 companies to its customers (i.e., institutional investors). ISS's governance rankings and related data assess the takeover protection mechanisms in sample firms using the documents and forms filed with the U.S. Securities and Exchange Commission as well as other publicly available information from annual reports and proxy statements. Using these anti-takeover provisions as a proxy for the shareholder–manager relationship, Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) present the G-Index and E-Index, respectively.[6] ISS's governance data collection and reporting methodology as well as its frequency have changed over time. Before 2007, almost 30 governance provisions and state-based statutes were reported for sample firms every two to three years. Since 2007, however, ISS has published its anti-takeover provisions data annually, which cover about 25 provisions and state laws. Thus, to ensure comparison across the years, we use the E-index (Bebchuk, Cohen, and Ferrell, 2009) as our main corporate governance indicator, as it can be measured over the entire sample period from 1990 to 2018.[7]

While Bebchuk, Cohen, and Ferrell (2009) construct the E-index as the man-

[6]Anti-takeover provisions along with other governance characteristics such as ownership, board features, and auditing requirements from ISS data are also used by Brown and Caylor (2006) to create another measure of corporate governance (i.e., Gov-Score). However, these data have only been made available by ISS for a limited time since 2001.

[7]Although we cannot construct the G-Index across the entire sample period, as its scale would differ between the pre-2007 and post-2007 years, we do use a normalized G-Index score, or *G-Proxy*, to test the robustness of all our results.

agerial entrenchment subset from within the G-Index using pre-2007 ISS data, it can still be created for the new ISS dataset, as four of the six entrenchment provisions (i.e., staggered boards, limits to shareholder bylaw amendments, poison pills, and golden parachutes) were retained, even after 2007. The remaining provisions on the supermajority requirement for mergers and charter amendments are included by assessing the reported voting percentage requirements for these. We examine how the distribution of each of the six E-Index provisions is affected by using a balanced panel sample comprising the last three and first three governance data releases of the two ISS datasets (i.e., 2002, 2004, and 2006, and 2007, 2008, and 2009 respectively). We only find that the indicator representing golden parachutes shows a distinct decline from 78.7% in 2006 to 52.7% in 2007, but recovers to 81.4% in 2009. Nevertheless, to ensure that our results are not driven by this trend in the presence of golden parachutes, we also test the robustness of all our results by excluding golden parachutes.

Table 2.1 shows the summary statistics for the E-Index across our sample for each year in which the ISS governance data were published. There is a distinct trend for both the mean value of the E-Index and its standard deviation across the years. We find that the average governance structures have worsened over time and the cross-sectional variations among the governance structures have also reduced. Figure 2.1 also shows that the change in ISS's data collection methodology in 2007 does not seem to distinctly affect the E-Index. The monotonic trends of the increasing average E-Index values and its declining cross-sectional variations are maintained before and after 2007. Over the 29-year period, our sample comprises more than 40,800 firm-year observations of governance scores.

Table 2.1 E-Index across the years

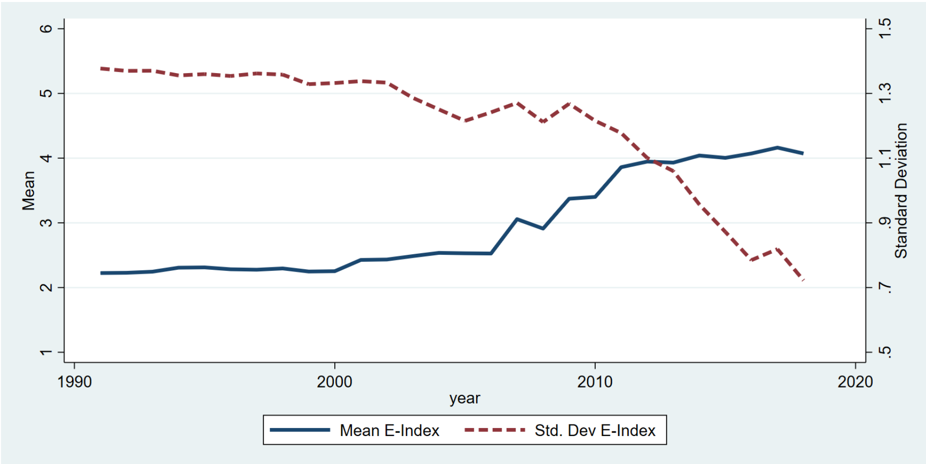
This table summarizes the presence of entrenchment provisions (using E-Index) in our sample for each of ISS data publication years. Dual class stocks are left out. For details on each of the E-Index provisions, see Bebchuk, Cohen, and Ferrell (2009). The dashed line indicates change in ISS data collection methodology.

Year	Mean	SD	Minimum	Median	Maximum	Number
1990	2.2177	1.3826	0	2	6	1346
1993	2.3114	1.3548	0	2	6	1336
1995	2.2966	1.3420	0	2	6	1369
1998	2.2609	1.3245	0	2	6	1702
2000	2.4390	1.3055	0	2	6	1665
2002	2.4802	1.2877	0	3	6	1668
2004	2.5333	1.2457	0	3	6	1759
2006	2.4933	1.2354	0	3	6	1711
2007	3.0521	1.2923	0	3	6	1556
2008	2.9653	1.2303	0	3	6	1528
2009	3.2910	1.2456	0	3	6	1519
2010	3.3311	1.2214	1	3	6	1492
2011	3.7785	1.2331	1	4	6	1458
2012	3.8182	1.1627	1	4	6	1419
2013	3.8492	1.1038	1	4	6	1386
2014	3.8943	1.0347	1	4	6	1372
2015	4.0202	0.8416	1	4	6	1291
2016	4.0723	0.7981	1	4	6	2580
2017	4.1634	0.8183	1	5	6	2347
2018	4.1054	0.7013	1	4	6	2169
Full Sample^{+}	2.9107	1.4145	0	3	6	40819

$^{+}$The full sample here includes firms' last E-Index values for intermediate years when the governance data was not issued by ISS. For example, the firms' E-Index scores in 1990 are replicated for the years 1991 and 1992.

Figure 2.1 Evolution of E-Index and its cross-sectional variation over time

This figure shows the plots of average E-Index scores from 1990 to 2018 along with its standard deviations. As in the Table 2.1, when governance data was not issued by ISS for a year, the previous E-Index score for each firm is carried forward.



2.4.2 Stock Returns and Other Data

We also use in our analysis data on monthly returns for the period 1988 to 2019 obtained from the CRSP database for all the firms in the governance dataset. We thus, ensure the availability of two additional years before and one after the governance data. This allows us to compute the lagged controls (e.g., past returns) and/or calculate future portfolio returns. We additionally use daily returns from CRSP database to measure crash risk and idiosyncratic volatility. For all the sample firms, we also use the annual balance sheet data to measure price informativeness and other firm-specific controls. Lastly, institutional ownership is obtained from Thomson Reuters institutional holdings 13f filings data, with the ownership proportions computed for short- and long-term investors separately.

2.4.3 Price Informativeness and Information Flow Measures

We construct the price informativeness measure using the estimation procedures use by Bai, Philippon, and Savov (2016). We first regress future earnings on market valuations for each of the years, with multiple time horizons (i.e., using future earnings at one-, two-, three-, and five-year intervals). The current period's earnings and industry sector controls are used to measure publicly available information as in Bai, Philippon, and Savov (2016). The industry controls also take into account different investment opportunities available during booms and busts (Li and Li, 2016):

$$\frac{E_{j,t+i}}{A_{j,t}} = a_{t,i} + b_{t,i} ln\left(\frac{MV_{j,t}}{A_{j,t}}\right) + c_{t,i}\frac{E_{j,t}}{A_{j,t}} + d_{t,i}S_{j,t} + \epsilon_{j,t,i}, \tag{2.1}$$

where $E_{j,t}$, $MV_{j,t}$, and $A_{j,t}$ are the annual earnings, market values, and total assets of firm j in year t, respectively. $S_{j,t}$ is a sector dummy using the one-digit SIC code. For each group of firms (i.e., good and poor governance), we obtain coefficients for each year t and time horizon i. Finally, price informativeness (PRI) is computed as a product of the cross-sectional standard deviation (σ_t) of the main regressor, namely, $MV_{j,t}/A_{j,t}$, and its coefficient's estimate from the above equation using:

$$PRI_{t,i} = b_{t,i} * \sigma_t\left(ln\frac{MV_{j,t}}{A_{j,t}}\right). \tag{2.2}$$

While this measure helps us trace the cross-sectional price informativeness of good and poor governance firms from a holistic perspective, it does not reveal how the information flows within individual firms are influenced by governance structures. Thus, we also compute firm-specific information flow measures to examine whether any systematic difference exists across the structural breaks. We use the two measures from Ferreira and Laux (2007): share turnover ($TURN$) and the probability of informed trading (PIN) following Easley, Hvidkjaer, and O'hara (2002).

2.4.4 Idiosyncratic Volatility and Crash Risk Measures

Ferreira and Laux (2007) show a persistent negative association between the G-Index and idiosyncratic volatility. Similarly, Andreou et al. (2016) show that a wide array of corporate governance mechanisms (e.g., institutional ownership, CEO stock options, percentage of outside directors with stock ownership, and board size) can help predict future stock price crashes. Thus, to explore sophisticated learning through the risk channel, we apply two firm-specific risk measures: stock price crash risk and idiosyncratic volatility.

We begin by estimating firm-specific weekly returns W from the residuals obtained by regressing weekly firm returns in an expanded index model as suggested by Hutton, Marcus, and Tehranian (2009):

$$r_{j,t} = \alpha_j + \beta_{a,j} * r_{m,t-2} + \beta_{b,j} * r_{m,t-1} + \beta_{c,j} * r_{m,t} + \beta_{d,j} * r_{m,t+1} + \beta_{e,j} * r_{m,t+2} + \epsilon_{j,t}, \tag{2.3}$$

where $r_{j,t}$ is firm j's Wednesday-to-Wednesday return for week t, and $r_{m,t}$ is the CRSP value-weighted market index return for the same week. To control for infrequent trading, we introduce one- and two-week lagged and forward market returns. We calculate firm-specific weekly returns as $W_{j,t} = ln(1 + \epsilon_{j,t})$ to correct for the skewed residuals $\epsilon_{j,t}$.

We measure crash risk using $CRASH$ that indicates whether a firm has experienced at least one crash week in a given year (Hutton, Marcus, and Tehranian, 2009). The crash week is defined as the one in which the firm-specific return $W_{j,t}$ declines by more than 3.09 standard deviations below the average $W_{j,t}$ in that year.[8] We use several additional crash risk proxies for robustness. $CRASHNUM$ is defined as the number of crash weeks experienced by a firm

[8]The 3.09 standard deviation threshold picks up the lowest 5% of $W_{j,t}$ for any year. We use 10% or 1% thresholds as a robustness check and see no difference in our main findings for $CRASH$.

in a given year. $JUMP$ measure stock price up-movements (Hutton, Marcus, and Tehranian, 2009) i.e., using an indicator of whether firm-specific $W_{j,t}$ rises by more than 3.09 standard deviations above the average $W_{j,t}$ in that year. Finally, following Chen, Hong, and Stein (2001), we compute two alternative measures negative conditional skewness $NCSKEW$ and down-to-up volatility $DUVOL$.

For idiosyncratic volatility, we aim to capture more variation by considering monthly measures unlike the crash risk measures, which are estimated on a yearly basis. For each month, we run the estimation of a slightly modified version of Equation 2.3 considered for the crash risk measures. In this case, we consider daily stock returns $r_{j,t}$ for each firm without the lead and lag market returns, and estimate R^2 on a monthly basis. As in the literature (e.g., Ferreira and Laux, 2007), idiosyncratic volatility is then computed through a logistic transformation as

$$IDIOSYN = ln\left(\frac{1-R^2}{R^2}\right). \tag{2.4}$$

2.4.5 Investment Horizon Measures

We identify short- and long-term institutional investors following the procedure in Harford, Kecskes, and Mansi (2018). For each investor in a given year, we measure the proportion of each stock that is no longer held in the investor's portfolio in comparison to the amount of that stock held three years ago.[9] This turnover measure is in the interval [0,1]. Next, we compute a weighted average turnover measure for each investor based on its investment portfolio weights for each year. Finally, investors are classified into short- and long-term groups based on their average turnover. Corresponding approximately to the lowest quartile of the turnover distribution, investors with 35% or lower

[9]In addition to three-year portfolio turnover, we employ two-year turnover in a robustness check.

average turnover are categorized as long term, while the rest form the short-term investor group (for more details, see Nguyen, Kecskés, and Mansi, 2020).

2.4.6 Summary Statistics

Table 2.2 summarizes the mean, median, standard deviation, and total number of available observations for each of the main variables other than stock returns, market returns, and related risk factors. We first present these statistics for the full sample and then separately for the governance–returns association years (1990–2000), dissociation years (2001–2007), and negative association years (2008–2018), as indicated at the top of the table. Panel A covers all the variables introduced to measure price informativeness. There is no visible trend for these variables across the three time periods. Panels B and C show all the firm-based information flow and risk measures. Whereas PIN increases on average over these three periods, turnover activity $TURN$ shows a declining trend on average. Lastly, Panel D presents all the control variables. Many of the variables associated with firm size show a characteristic rise over the years. This is expected because many of the firms in our sample are consistently reported by ISS and have grown during these years.

2.5 The Association, Dissociation, and Reassociation of Governance and Returns: A Case of Two Structural Breaks

2.5.1 Identification Strategy

Using the long-run event study methodology, we trace the two extreme governance portfolios (i.e., Democracy or Good Governance with E-Index = 0, and Dictatorship or Bad Governance with E-Index = 5 | 6) along with the governance hedge portfolio (long Democracy/short Dictatorship) over a 26-year

Table 2.2 Descriptive statistics

This table presents the mean, standard deviation (SD), median and the number of observations (N) for all of the main variables and controls. The summary statistics are reported first for the full sample, and then, separately for the governance–returns association years (1990-2000), dissociation years (2001-2007) and negative association years (2008-2018) as indicated on top of the table. Panel A covers all variables introduced to measure price informativeness as explained in Section 2.4.3 Panels B and C show all the firm-based information flow and risk measures, whereas Panel D presents all the control variables. All variables are computed from COMPUSTAT Annual and CRSP daily/monthly data (see Appendix 2.A.1 for more details). Except for *TURNOVER* and *IDIOSYN* which are recorded at monthly frequency, all other variables are observed on annual basis.

		Full Sample				1990-2000				2001-2007				2008-2018			
		Mean	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**
Panel A: Variables for Price Informativeness																	
Earnings Over Asset	E_t/A_t	0.067	0.156	0.074	58564	0.076	0.137	0.082	27288	0.065	0.139	0.071	13489	0.055	0.191	0.066	17787
1 Year Future Earnings Over Assets	E_{t+1}/A_t	0.084	0.194	0.083	52301	0.091	0.226	0.090	26097	0.086	0.129	0.079	12159	0.071	0.174	0.073	14045
2 Year Future Earnings Over Assets	E_{t+2}/A_t	0.103	0.358	0.091	47243	0.108	0.467	0.097	24908	0.104	0.147	0.086	10983	0.092	0.18	0.083	11352
3 Year Future Earnings Over Assets	E_{t+3}/A_t	0.128	0.552	0.100	42729	0.133	0.727	0.105	23727	0.125	0.176	0.096	9876	0.119	0.148	0.093	9126
5 Year Future Earnings Over Assets	E_{t+5}/A_t	0.180	1.356	0.119	35533	0.201	1.741	0.127	21264	0.158	0.248	0.112	7962	0.139	0.241	0.104	6307
Market Value Over Assets (in logs)	$\ln(MV_t/A_t)$	-0.217	1.120	-0.129	58486	-0.255	1.187	-0.195	27242	-0.146	1.020	-0.049	13476	-0.214	1.085	-0.107	17768
Panel B: Firm-based Information Flow Variables																	
Monthly Share Turnover	*TURN*	0.171	0.192	0.117	431005	0.110	0.162	0.060	150983	0.183	0.198	0.127	136372	0.223	0.198	0.169	143650
Probability of Informed Trading*	*PIN*	0.162	0.084	0.145	38938	0.190	0.086	0.175	19623	0.142	0.071	0.127	15548	0.100	0.052	0.093	3767
Panel C: Firm Risk Variables																	
Idiosyncratic Volatility (in logs)	*IDIOSYN*	2.243	2.291	1.794	757735	2.952	2.262	2.490	156982	1.570	1.907	1.160	138769	2.203	2.339	1.765	461984
Crash Risk	*CRASH*	0.266	0.442	0.000	74233	0.209	0.407	0.000	32324	0.298	0.457	0.000	19105	0.318	0.466	0.000	22804
Price Jump	*JUMP*	0.274	0.446	0.000	74233	0.257	0.437	0.000	32324	0.254	0.435	0.000	19105	0.315	0.464	0.000	22804
Negative Conditional Skewness	*NCSKEW*	0.068	1.160	0.046	74001	0.018	1.055	-0.002	32182	0.103	1.181	0.072	19048	0.110	1.274	0.099	22771
Down-to-Up Volatility	*DUVOL*	0.022	0.449	0.023	73822	0.006	0.429	0.006	32092	0.026	0.451	0.029	19000	0.040	0.472	0.044	22730
Panel D: All Control Variables																	
Return on Equity	*ROE*	0.001	0.510	0.000	56337	0.007	0.276	0.000	24922	-0.004	0.590	0.000	14132	-0.005	0.673	0.000	17283
36 Months Variance for ROE	*vROE*	0.059	2.450	0.000	55642	0.006	0.165	0.000	22988	0.144	4.241	0.000	15284	0.056	1.830	0.000	17370
Leverage	*LEV*	0.196	0.207	0.152	57422	0.187	0.198	0.141	25601	0.191	0.202	0.144	14425	0.214	0.223	0.174	17396
Market Value (in logs)	*SIZE*	7.002	1.710	6.916	56747	6.427	1.663	6.346	25168	7.290	1.549	7.158	14183	7.599	1.635	7.492	17396
Market to Book (in logs)	*MB*	4.528	2.836	3.794	56329	4.130	2.684	3.410	24914	4.789	2.877	4.085	14131	4.889	2.941	4.192	17284
Return on Asset	*ROA*	0.103	0.157	0.112	57422	0.113	0.140	0.121	25601	0.102	0.132	0.106	14425	0.088	0.194	0.102	17396
Dividend Dummy	*DD*	0.513	0.500	1.000	63590	0.526	0.499	1.000	26931	0.457	0.498	0.000	16770	0.543	0.498	1.000	19889
Age (in logs)	*AGE*	4.919	1.107	5.159	61201	4.712	1.182	4.970	25559	4.961	0.996	5.050	16193	5.155	1.041	5.371	19449
Share Turnover YOY Difference	*DIFTURN*	0.367	9.700	0.119	66095	0.397	5.480	0.114	27141	0.586	15.830	0.339	17937	0.141	6.572	-0.118	21017
Average Return	*AVG*	-0.002	0.013	-0.002	74233	-0.003	0.014	-0.002	32324	-0.002	0.014	-0.001	19105	-0.002	0.010	-0.001	22804
Return Volatility	*SIGMA*	0.056	0.038	0.045	74111	0.062	0.041	0.052	32243	0.055	0.040	0.044	19079	0.048	0.032	0.039	22789
Opacity	*OPQ*	0.214	0.193	0.180	63462	0.222	0.178	0.165	25667	0.214	0.221	0.690	14132	0.214	0.218	0.176	23663

* The full sample for probability of informed trading (*PIN*) spans 1993-2010 as obtained from Stephen Brown's Database
.

period.[10] This allows us to locate the exact point (points) of the structural break (breaks) in the time series for abnormal returns using Quandt likelihood ratios. To estimate unknown structural breaks, we use the supremum of the likelihood ratios (Andrews, 1993) in three stages. We first run the sup-Wald test for the entire sample to identify the first break point. By design, with 15% trimming applied, the procedure identifies only the first structural break point, which usually provides the largest F-statistic because of the approximated asymptotic distribution. Next, we run the same test by restricting the sample months after the first break to locate the second break point. Lastly, we run confirmation tests following Clemente, Montañés, and Reyes (1998) and Bai and Perron (1998), specifically with the two structural break tests of Hatemi-J (2008).[11]

Put differently, we apply the Andrews (1993) tests for unknown structural breaks twice (to identify each break) by running time-series regressions and looking for statistically significant breaks in the αs or risk-adjusted returns. We calculate abnormal returns using Carhart (1997) four factor model adding the liquidity factor (Pástor and Stambaugh, 2003). We use other alternative asset pricing for robustness checks. The main specification is as follows:

$$\begin{split} R_t = \alpha + (\Delta\alpha) * POST + \beta_1 * RMRF_t + \beta_2 * SMB_t + \beta_3 * HML_t + \\ \beta_4 * MOM_t + \beta_5 * LIQ_t + \varepsilon_t, \end{split} \tag{2.5}$$

where R_t is the governance-based hedge portfolio return for month t, $POST$ is an indicator used to measure structural break, $RMRF_t$ is the excess return

[10] When the minimum value of E-Index is not '0', the next lowest value i.e., '1' is used to identify the Democracy stocks.

[11] Since we want to identify breaks only in the alphas or constants, we use single structural break estimation twice. Bai and Perron (2003) use multiple structural break estimation techniques as they seek structural breaks for both slopes and trends. Nevertheless, we employ these estimations as a more stringent robustness check to detect the second structural break.

of the market portfolio, SMB_t is the size factor, HML_t is the book-to-market factor, MOM_t is the momentum factor, and LIQ_t is the liquidity factor. This model allows us to statistically locate the exact points in time when the two regime shifts occur for α.

Similar to Bebchuk, Cohen, and Wang (2013), we identify the possible "critical learning" point using 36-month rolling alphas to determine when gradual learning is complete. For sophisticated learning, we apply a similar gradual process assumption and determine the end point of sophisticated learning using a rolling estimation. For each governance-based hedge portfolio, we estimate the 36-month rolling abnormal returns or alphas and identify (a) the month in which abnormal returns are consistently statistically insignificant and (b) the exact month in which abnormal returns are again consistently significant. While the statistical estimation using the Quandt (1960) method identifies the critical points of the structural breaks or regime shifts, the rolling estimation method pinpoints the last possible points for the two learning phases (Bebchuk, Cohen, and Wang, 2013).[12]

2.5.2 Results

We start by estimating the first structural break, which is the month in which the F-statistic for a break was the largest in the entire sample of 26 years. Panel A in Table 2.3 summarizes the first break points identified by both the Quandt method using 15% trimming and the 36-month rolling returns method. The estimated break points for the first structural break in the table are similar to those shown by Bebchuk, Cohen, and Wang (2013) for both the equal- and the value-weighted portfolios. To identify the second break point, we repeat the F-statistic test by excluding the time period before the first structural

[12] Assuming that market learning and sophisticated learning is completed within three years.

Table 2.3 The two structural breaks in governance–returns association

In this table, Panel A reports the two break points in governance–returns relationship as identified using the Andrews (1993) Quandt tests and the 36-month rolling methods. The results follow both equal-weighted (EW) and value-weighted (VW) governance hedge (long Democracy/ short Dictatorship) portfolios wherever indicated. Hedge portfolios are rebalanced whenever new data is made available by ISS. Monthly portfolio returns are loaded on five factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM) and liquidity (LIQ). Our final estimates for each break point are also shown. Panel B, alternatively, reports abnormal returns (α s or Alphas) by running Equation 2.5 with additional structural break (SB) variables in place of POST. All estimations use White (1980) robust standard errors (in parentheses). In the 2 SB model, the dissociation period (2001-2007) is taken as the benchmark, with each of the association and negative association periods represented by SB1 Dummy (for 1990-2000) and SB2 Dummy (for 2008-2018) respectively. In the 1 SB model, a single variable takes the value of '-1' for pre-dissociation period and '+1' for post-dissociation years. The benchmark remains the same as before. We also control for the sensitivities of each of the five factors on the SB dummies by including their interactions in these estimation. Significance levels at 10%, 5%, and 1% are shown using *, ** and *** respectively.

Panel A: The break points				
	1st break point		2nd break point	
	VW	EW	VW	EW
Quandt LR Method	July-2000	November-2000	January-2008	February-2008
36-month Rolling Method	February-2003	June-2002	July-2008	December-2008
Estimated point:	January-2001		January-2008	

Panel B: Alphas and the two structural breaks				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	0.0012	0.0005	-0.0067**	-0.0003
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0076**	0.0068*	-0.0184***	-0.0078***
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0262***	-0.0073*		
	(0.008)	(0.005)		
Observations	340	340	340	340
R-squared	0.26	0.23	0.24	0.20
p-Value	0.00	0.00	0.00	0.00

break. The estimated second break points using the equal- and value-weighted portfolios are just one month apart (i.e., January 2008 and February 2008).

Using the 36-month rolling returns method as well, the identified break points for the first structural break are similar to those of Bebchuk, Cohen, and Wang (2013). For the second structural break, interestingly, the estimated end points for sophisticated learning are either July 2008 (for the value-weighted portfolio) or December 2008 (for the equal-weighted portfolio). This suggests that sophisticated learning is much quicker than the Bebchuk, Cohen, and Wang (2013) learning during the first structural break. To ensure that the effects of learning are separated as early as possible, and therefore the sophisticated learning point can be estimated within a larger window, we identify the first break point as January 2001. For the second break point, we consider the earliest point in time found by both the applied methods (across the two portfolios), as this point essentially identifies the first instance of sophisticated learning and the governance–returns' negative association in our sample. Confirmatory tests using the Bai and Perron (1998) and Hatemi-J (2008) estimations—with the slightly modified specifications of Equation 2.5 that allow for multiple breaks—show that the second structural break is close to that in our previous analysis.

Figure 2.2 confirms our two structural break hypothesis by showing that there are indeed three distinct phases in the evolution of average 36-month future abnormal returns: (a) a monotonically increasing trend, (b) an almost flat trend, and (c) a decreasing trend. The dotted vertical lines superimposed on this figure are the two structural break points. As expected, these appear a few months after the trend shifts, since the plots represent future returns. Along with the value- and equal-weighted governance hedge portfolios, we additionally plot the industry-adjusted value- and equal-weighted returns by adjusting each stock's returns using the 48-industry mean of Fama and French (1997) classification. This helps us alleviate concerns about industry clustering driving the governance–returns relationship, as expressed by Johnson, Moorman, and Sorescu (2009) and Giroud and Mueller (2011). While the industry adjustment does drastically suppress the excess returns for the equal- and value-weighted portfolios during the association and dissociation years, the declining

Figure 2.2 Returns from governance trading strategies

This figure shows the plots of the cumulative excess returns generated from a long good governance/ short bad governance hedge portfolio using the E-Index. For each month, future 36-month average abnormal returns are computed using rolling five-factor regressions that account for the three Fama and French (1993) factors, namely, market, size, and book-to-market, along with the Fama-French momentum factor and Pástor and Stambaugh (2003) liquidity factor. These monthly abnormal returns are then compounded over the months beginning September 1990 and ending December 2018. The previous month market capitalization-weighted or value-weighted (VW), and the equal-weighted (EW) portfolios are both considered. Additionally, to account for product market competition, industry-adjusted returns (IA) using the 48-industry classification of Fama and French (1997) are shown. The vertical dotted lines on the plot represent the two identified structural break points.

returns are consistent across all the portfolios after 2008. This suggests that the sophisticated learning is robust to industry clustering and product market competition.

To assess the changes in abnormal returns for the three time periods separated by the two aforementioned structural break points: 1990–2000, 2001–2007, and 2008–2018, we consider two variations of the model in Equation 2.5 (Panel B of Table 2.3). In the first model, we consider 2001–2007 (or the dissociation years) to be the benchmark and include two structural break (SB) dummies: one indicating the pre-dissociation period and the other representing the negative association years. In the second model, we again consider 2001–2007 to be the reference period, but include a single structural break variable coded -1 for the pre-dissociation years and +1 for the post-dissociation period. While both these estimations provide the different abnormal returns for the governance-based strategies over and above the zero alpha during the dissociation years, the first variant breaks them down into two components and the second one measures the average excess alphas during the two association periods (i.e., both pre- and post-dissociation).

Using the two structural break variables, we find that the E-Index-based value-weighted (equal-weighted) hedge portfolio alphas are statistically significant, producing +76 (+68) basis points and almost -2.6% (-0.7%) monthly risk-adjusted returns in the pre- and post-dissociation periods, respectively. Expectedly, the reference period alpha is statistically insignificant, confirming the dissociation between governance and returns. The negative abnormal returns for our governance hedge point out the reversal of the long/short positions (i.e., long Dictatorship and short Democracy) to generate zero-investment gains in the post-dissociation years. The second estimation in Panel B of Table 2.3, with one structural break variable, shows the net association effect across the two governance–returns association periods. For the value-weighted (equal-weighted) portfolio, this effect is 184 (78) basis points, statistically significant at 1%. Even when we use alternative asset pricing models instead of the five factors shown in Equation 2.5, the coefficients retain their statistical and economic significance (see Appendix 3.A.4).

2.6 The Role of Information Flow

The first structural break point can be explained either with the learning hypothesis (Bebchuk, Cohen, and Wang, 2013) or using the available investment and divestiture options across governance structures (Li and Li, 2016). However, as we show that the association between governance and returns undergoes another structural change, the second break point needs to be further examined. We start by investigating if information flow played any role in helping investors recognize governance risk around the second break point. We look at two broad channels: (a) the price price channel and (b) the risk channel.

2.6.1 Sophisticated Learning Through Price Channel

To explore the price channel, we first employ the price informativeness measure of Bai, Philippon, and Savov (2016) that captures the ability of stock prices to predict future earnings. Under the sophisticated learning hypothesis, investors realize the inherent governance risk of bad governance firms compared with good governance ones. Thus, the focus is on information asymmetry between the firm and its investors. Such asymmetry would expectedly be larger for poor governance firms with more anti-takeover provisions (or higher managerial entrenchment). Therefore, we expect the price informativeness of good governance stocks to be greater than that of poor governance stocks and this difference to be driven by the decreasing price informativeness of poor governance firms after the second structural break point.

While price informativeness does shed light on the information asymmetry trends between good and bad governance firms, it provides no insights into firm-level changes. Thus, we complement the price informativeness tests with additional firm-based information flow measures. Since we are interested in identifying whether within-firm governance changes influence firms' information flow to investors, we employ a fixed effects panel regression to find any systematic differences in the way changes in managerial entrenchment affect the information flow across the two structural breaks.

2.6.1.1 *Estimation Models*

With multiple complementary tests, we assess how information-in-price may have driven sophisticated learning. To compare the trends, we split our sample into good governance and poor governance firms using the median E-Index as the cutoff for each year. We then compute the welfare-based aggregate price informativeness (PRI_t) for each group separately over different expectation horizons (as explained in Section 2.4.3). Finally, we regress the price informativeness values (with various investment horizons) on the dummies representing pre-dissociation ($SB1$) and post-dissociation years ($SB2$) to examine the trends for each group. This means that the 2001–2007 period (or the dissociation years) is captured by the constant term. The following model is run separately for the price informativeness of good and bad governance firms:

$$PRI_t = A_1 + B_1(SB1_t) + C_1(SB2_t) + \varepsilon_t. \tag{2.6}$$

We additionally run a similar regression using the differences in price informativeness between the two groups as a dependent variable to quantify the differential trend.

To capture the average effects of the association years against the dissociation years, we use an alternative specification. We model 2001–2007 as the reference time period, but include a single SB variable coded -1 for the pre-dissociation years and +1 for the post-dissociation years. In this specification, we include a dummy EI that represents poor governance (above the median E-Index):

$$PRI_t = A_2 + B_2(SB_t) + C_2(EI_t) + C_2(SB_t * EI_t) + \varepsilon_t. \tag{2.7}$$

Second, to reaffirm that sophisticated learning through price is not merely an aggregative process, we focus on the firm-specific information flow measures.

For the firm-based information flow measures ($FPRI_{j,t}$), which are either PIN or $TURN$ as defined in Section 2.4.3, we use the following specification:

$$FPRI_{j,t+1} = A_3 + B_3(E{-}Index_{j,t}) + C_3(X_{j,t}) + \varepsilon_{j,t}, \qquad (2.8)$$

where $X_{j,t}$ includes all the standard controls used in Ferreira and Laux (2007) and Hutton, Marcus, and Tehranian (2009).[13]

2.6.1.2 Results

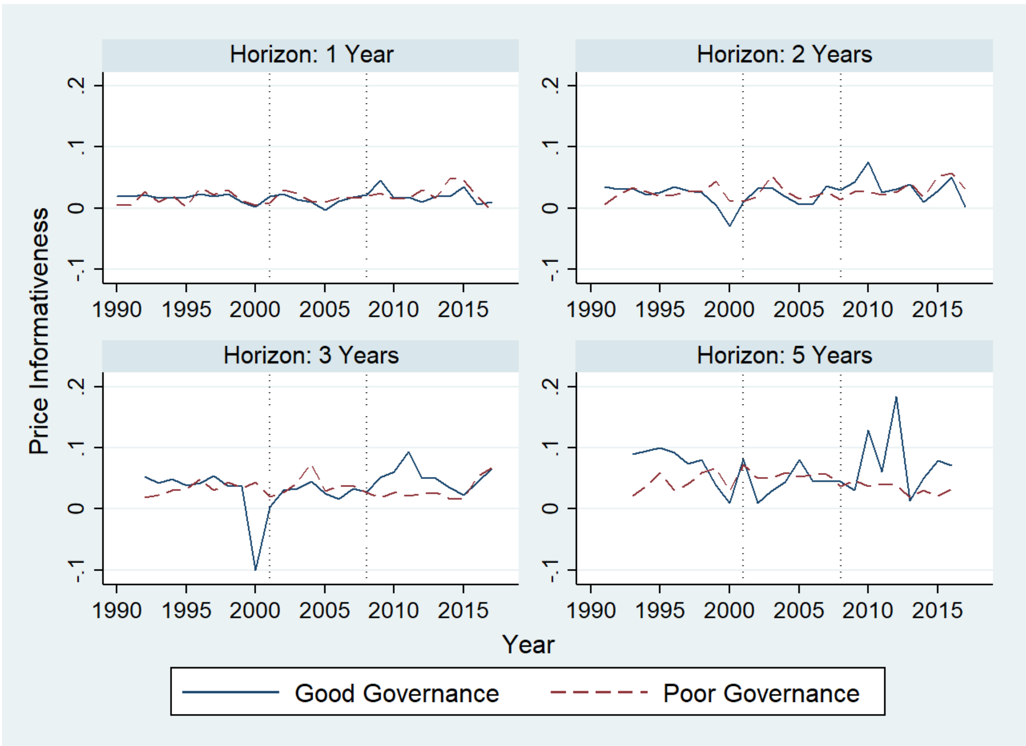
We compare the price informativeness of our sample firms grouped into good and poor governance categories using the median E-Index in each year, and the results are presented in Figure 2.3. The two groups follow a similar trend of slightly positive price informativeness with the one-year earnings forecast horizon across all three periods (i.e., association, dissociation, and negative association), which are separated by the vertical dotted lines in this figure. However, for the remaining three horizons, a common pattern emerges between the good and poor governance groups in the post-dissociation period (i.e., 2008–2018). After the second structural break, the price informativeness of good governance stocks largely lies above that of poor governance ones. Additionally, over the longer horizons of three and five years, poor governance stocks tend to show declining price informativeness after 2008. To gain more insights into this trend and the differences between these two groups, we estimate regression Equations 2.6 and 2.7.

In Panel A of Table 2.3, we focus on the dummy variable representing the years after the second break point (i.e., $SB2$). While there is no difference in the relative price informativeness of good and poor governance firms over the short horizon, a consistent trend is found for the medium to long hori-

[13] See Appendix 2.A.1 for the definitions of all these control variables.

Figure 2.3 Governance and price informativeness

This figure compares the price informativeness of good and poor governance firms grouped by the median E-Index cutoff for each year. For each group, price informativeness (PRI) is separately computed by first using Equation 2.1 to obtain the information coefficient (tracing $ln(MV/A)$) and then substituting this coefficient into Equation 2.2 for each year. Each of the subplots represents the different forecasting horizons considered (represented by i in Equation 2.2). The same are indicated at the top of each subplot, with the vertical dotted lines representing the two structural break points (i.e., January 2001 and January 2008).



zons. For the three- and five-year horizons, the price informativeness of poor governance stocks during 2008–2018 decreases, whereas that of good governance ones increases in comparison to the dissociation years. The differential effect (i.e., good – poor PRI) for each of these horizons shows a monotonic increasing trend, implying that the price informativeness of poor governance stocks worsens in terms of future earnings predictability with longer horizons compared with good governance stocks. The results in Panel B confirm our findings in Panel A that most of the changes in price informativeness appear after the second structural break point. When we combine the two structural breaks into a single structural break variable, only price informativeness over the three-year horizon picks up a consistent governance-based differential effect across the two structural breaks.

To gather more fine-grained insights into the price channel, Table 2.5 reports the firm-based information flow measures (i.e., $TURN$ and PIN) in relation to the E-Index across the two structural breaks. Model 1 uses simple ordinary least squares (OLS) with industry fixed effects and Model 2 controls for firm heterogeneity by including firm fixed effects in a panel regression. For both $TURN$ and PIN, we see a distinct shift in the E-Index coefficients across the second structural break, especially with the firm fixed effects. Note that $TURN$ is measured monthly, while PIN is available on a yearly basis. Before 2008 an increasing E-Index would entail increased trading activity ($TURN$) for an average firm, however the direction of this relationship reverses after 2008. For PIN, the findings are directionally opposite to those for $TURN$. Increasing anti-takeover E-Index provisions increases PIN after second break point in contrast to its effect on PIN before the same point.

The systematic differences between the dissociation and post-dissociation years for both aggregate price informativeness and the firm-based information flow measures indicate an increase in information asymmetry for poor governance

Table 2.4 Price informativeness and the two structural breaks

This table shows the coefficients and Newey and West (1994) standard errors (in parentheses) with five lags for time series regressions of price informativeness around the two structural breaks. In Panel A, Bai, Philippon, and Savov (2016) price informativeness measure is computed separately for good governance and poor governance firms separated by the median E-Index (=3 for years < 2010, and 4 otherwise). Additionally the difference in price informativeness between good and poor governance firms is also taken for each year and regressed over the two structural break (SB) variables each representing the pre-dissociation (1990-2000) and post-dissociation (2008-2018) periods. Panel B considers pooled regressions of price informativeness for good and poor governance firms by applying a single structural break variable that is defined as in Table 2.3. Statistical significance at 10%, 5%, and 1% respectively are denoted by *, **, and ***.

Panel A: Price informativeness and governance using two structural break (SB) variables

Horizon	1 year			2 years			3 Years			5 Years		
	Good	Poor	Good - Poor	Good	Poor	Good - Poor	Good	Poor	Good - Poor	Good	Poor	Good - Poor
Constant (2001 to 2007)	0.0129***	0.0164***	-0.0036**	0.0232***	0.0248***	-0.0016	0.0336***	0.0382***	-0.0046	0.0600***	0.0497***	0.0103
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)	(0.005)	(0.007)	(0.006)	(0.003)	(0.010)
$SB1$	0.0041	-0.0010	0.0051	-0.0033	-0.0019	-0.0015	-0.0075	-0.0061	-0.0014	0.0037	-0.0025	0.0062
	(0.003)	(0.002)	(0.003)	(0.007)	(0.003)	(0.008)	(0.011)	(0.004)	(0.016)	(0.012)	(0.004)	(0.020)
$SB2$	0.0073**	0.0066**	0.0007	0.0108*	0.0086**	0.0022	0.0190***	-0.0061	0.0251***	0.0165*	-0.0191***	0.0356***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)	(0.009)	(0.005)	(0.006)	(0.010)	(0.009)	(0.003)	(0.012)
Observations	28	28	28	27	27	27	26	26	26	24	24	24
p-Value	0.09	0.05	0.28	0.16	0.02	0.94	0.00	0.32	0.05	0.20	0.00	0.01
R-squared	0.14	0.13	0.01	0.15	0.02	0.01	0.14	0.17	0.11	0.04	0.14	0.11

Panel B: Price informativeness and governance using a single structural break (SB) variable

Horizon	1 year	2 years	3 Years	5 Years
Constant (2001 to 2007)	0.0171***	0.0259***	0.0378***	0.0670***
	(0.001)	(0.003)	(0.005)	(0.006)
SB	0.0015	0.0070	0.0130**	0.0055
	(0.002)	(0.004)	(0.006)	(0.008)
EI	0.0014	0.0013	-0.0040	-0.0247***
	(0.002)	(0.004)	(0.006)	(0.007)
$SB * EI$	0.0022	-0.0018	-0.0147**	-0.0128
	(0.002)	(0.005)	(0.007)	(0.008)
Observations	56	54	52	48
p-Value	0.12	0.01	0.00	0.00
R-squared	0.08	0.10	0.11	0.11

Table 2.5 Firm-specific information flow and the two structural breaks

This table lists the results obtained for regressions of trading activity $TURN$ and information asymmetry i.e. probability of informed trade PIN on E-Index. The full sample period is segregated around the two structural breaks and separate regressions are run for each of the association, dissociation and negative association periods shown in the table by their respective time periods. For both $TURN$ (Panel A) and PIN (Panel B), we report OLS (Model 1) and firm fixed effects (Model 2). Standard firm-based controls as suggested in Ferreira and Laux (2007) are included. Additional industry-wide controls using Fama and French (1997) 48 industry classification are present in Model 1 with firm clustered standard errors shown in parentheses. The coefficients for constant and industry dummies are omitted. See Appendix 2.A.1 for definitions of all controls. Significance levels at 10%, 5%, and 1% respectively are shown using *, **, and ***.

Panel A: TURN	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2018	1990 - 2000	2001 - 2007	2008 - 2018
E-Index	**0.0003**	**0.0273*** **	**-0.1911*** **	**0.0023*** **	**0.1494*** **	**-0.0705** **
	(0.000)	**(0.005)**	**(0.021)**	**(0.001)**	**(0.011)**	**(0.028)**
ROE	-0.0180***	-0.0063	-0.0179	0.0003	0.0181	0.0348
	(0.001)	(0.010)	(0.015)	(0.003)	(0.021)	(0.057)
$vROE$	0.0009	0.0023**	0.0183***	-0.0084***	-0.0020	0.0058
	(0.002)	(0.001)	(0.006)	(0.002)	(0.003)	(0.009)
LEV	-0.0175***	-0.0129	0.1353***	0.0029	0.2496***	0.3407*
	(0.003)	(0.028)	(0.039)	(0.005)	(0.075)	(0.194)
MB	0.0081***	0.0041*	-0.0153***	-0.0020***	0.0026	-0.0615***
	(0.000)	(0.002)	(0.004)	(0.000)	(0.007)	(0.016)
$SIZE$	0.0116***	0.1582***	0.5236***	0.0201***	0.0796***	-0.1302***
	(0.000)	(0.009)	(0.038)	(0.001)	(0.016)	(0.038)
AGE	-0.0163***	0.0313***	0.0675***	0.0153***	0.4915***	0.1713**
	(0.001)	(0.006)	(0.011)	(0.001)	(0.035)	(0.067)
DD	-0.0727***	-0.1694***	-0.4788***	-0.0209***	0.0888**	-1.1124***
	(0.001)	(0.020)	(0.115)	(0.002)	(0.037)	(0.088)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	141776	99639	162734	141776	99639	162734
R-Squared	0.146	0.020	0.017	0.001	0.001	0.001
Number of Groups				2053	2419	2810
Panel B: PIN	Model 1			Model 2		
	1993 - 2000	2001 - 2007	2008 - 2010	1993 - 2000	2001 - 2007	2008 - 2010
E-Index	**-0.0036*** **	**-0.0034*** **	**0.0038*** **	**-0.0052*** **	**-0.0029*** **	**0.0037** **
	(0.000)	**(0.000)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.002)**
ROE	0.2100	-0.2540***	-0.0001**	-0.0080	0.2270***	-0.1390
	(0.132)	(0.007)	(0.002)	(0.158)	(0.008)	(0.161)
$vROE$	0.0001	0.0000	0.0001	0.0000	-0.0002*	0.0002
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
LEV	-0.0046	0.0045	-0.0024	-0.0201***	0.0128**	-0.0109
	(0.005)	(0.004)	(0.005)	(0.008)	(0.005)	(0.018)
MB	-0.0052***	-0.0012***	-0.0006	-0.0054***	-0.0038***	-0.0020*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
$SIZE$	-0.0291***	-0.0269***	-0.0179***	-0.0286***	-0.0231***	0.0065***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
AGE	-0.0004	0.0010	-0.0000	-0.0182***	-0.0256***	-0.0027
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)
DD	0.0080***	0.0015	0.0016	0.0061*	-0.0007	-0.0041
	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.008)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	8551	8426	2076	8551	7234	2076
R-Squared	0.416	0.558	0.440	0.361	0.426	0.217
Number of Groups				1683	1829	1341

firms after 2008. Market prices and trading activity can communicate this change to investors if they are alert and receptive to such signals.

2.6.2 Sophisticated Learning Through Risk Channel

Although price information flow and volatility have a close relationship (Ross, 1989), they are two distinct channels for sophisticated learning. The investors' portfolios are not only sensitive to the earnings information in price (Hamburger and Kochin, 1972), but also to the stock price volatility (Ferreira and Laux, 2007). Thus, in this section, we examine the ability of the E-Index to predict firms' risk and show how it evolved across the two structural break points. We find that there are systematic differences in firms' riskiness relative to governance changes across the two structural breaks.

2.6.2.1 Estimation Model

We use two main measures of firm-specific risk ($FR_{j,t}$) for each firm j in a given year or month t, namely, idiosyncratic volatility (*IDIOSYN*, monthly) and crash risk (*CRASH*, yearly):

$$FR_{j,t+i} = A_4 + B_4(E\text{−}Index_{j,t}) + C_4(X_{j,t}) + \varepsilon_{j,t}. \tag{2.9}$$

For the model using *IDIOSYN*, the firm-specific controls $X_{j,t}$ are similar to those used for the firm-based information flow measures in Ferreira and Laux (2007), whereas for the one using *CRASH*, we identify the controls from Hutton, Marcus, and Tehranian (2009), An and Zhang (2013), and Kim, Wang, and Zhang (2016). For idiosyncratic volatility, we consider 12-month forward values or $i = 12$, whereas for crash risk, $i = 1$. We additionally control for accounting opacity in both these firm risk regressions. With the annual *CRASH* measure, the year fixed effects are also included to control for unobservable time trends. The models estimated here are similar to those used for the firm-based information flow measures, as we divide the full sample into three subsamples around the two structural breaks.

While relative idiosyncratic volatility (*IDIOSYN*) captures firm-specific risk by accounting for the covariance of a firm's stock returns with market returns, stock price crash risk (*CRASH*) captures the skewness of returns distributions through the presence of extreme negative outliers. Stock price crashes are generally a result of managerial bad news hoarding (Jin and Myers, 2006). In the short run, managers have the freedom to choose to hide or divulge firms' bad performance, and they tend to show a preference toward withholding it (Kothari, Shu, and Wysocki, 2009). However, when the downside risk exposure grows beyond managers' control in consecutive bad periods, the sudden release of accumulated bad news results in a crash.

2.6.2.2 Results

Table 2.6 reports the results of the pooled regressions (Model 1) and firm fixed effects panel regressions (Model 2) for our two main firm-specific risk measures (i.e., *IDIOSYN* and *CRASH*). To compare and contrast the predictive ability of governance or the E-Index on these measures across the structural breaks, we subdivide the sample into three periods: 1990–2000, 2001–2007, and 2008–2018. Panel A shows the results for idiosyncratic volatility. For both the pooled and the fixed effects models, there is a significant change in the coefficients of the E-Index before and after sophisticated learning (i.e., around the second structural break point). During 1990–2000 and 2001–2007, future idiosyncratic volatility is negatively associated with the E-Index both in cross-sectional terms (Model 1) and within firm terms (Model 2). However, this relationship turns positive for 2008–2018. Since *IDIOSYN* is a relative measure (see Equation 2.4), the coefficients of the E-Index can be interpreted as a decline in idiosyncratic volatility by 13.42% (5.91%) for each extra adoption (cross-sectional change) of the E-Index provision during the dissociation years. Sophisticated learning opportunities are reflected in the post-dissociation years with idiosyncratic volatility increasing by 8.93% (8.80%) for each E-Index differential change within (across) firms. From 1990–2000 to 2001–2007 (i.e., across the first break point), the negative association with the E-Index is persistent for idiosyncratic volatility and increases in magnitude for both Models 1 and 2.

Similarly, crash risk also shows a distinct shift in relation to the E-Index from 2001–2007 to 2008–2018. Since *CRASH* is a dummy variable indicating a stock price crash in a given year, we estimate a pooled logit (Model 1) and panel logit with firm fixed effects (Model 2) in Panel B of Table 2.6. During the dissociation years, the coefficients of the E-Index are statistically insignificant, indicating no relation with crash risk (for both regression models). On the contrary, the E-Index shows a statistically significant (at 1%) and positive relation with future stock price crash risk during the post-dissociation years. We estimate the marginal effects of the E-Index on future *CRASH* to establish the economic significance of the coefficients from the pooled logit and panel logit models by fixing all control variables at their means. Every additional E-Index provision is found to increase crash likelihood by 1.16% ($p < 0.01$) in cross-sectional terms (Model 1) and 0.05% ($p < 0.10$) for within-firm changes (Model 2). The lower effect for the within-firm adoption of anti-takeover provisions is understandable because, in our sample, the proportion of firms with changing E-Index values over time is much lower than those with a constant E-Index (especially when the sample is divided around the two structural breaks).

Just as for idiosyncratic volatility, crash risk also shows no distinct shifts around the first structural break. Furthermore, the marginal effects during both the pre-dissociation (1990–2000) and the dissociation (2001–2007) periods are not statistically different from zero. This indicates that there is no

Table 2.6 Firm-specific risk and the two structural breaks

This table shows results obtained for relative idiosyncratic volatility (*IDIOSYN*) and firm specific crash risk (*CRASH*) on E-Index across the association, dissociation and negative association years as indicated by their respective time periods. In Panel A, we report results for *IDIOSYN* using OLS (Model 1) and firm fixed effects (Model 2) with all controls similar to those used in Table 2.4, and an additional control for opacity (*OPQ*) introduced (Hutton, Marcus, and Tehranian, 2009). Panel B reports results for *CRASH* using logit (Model 1) and panel firm fixed effects logit (Model 2). When firm fixed effects are not considered (i.e. Model 1), we control for industry characteristics using Fama-French 48 industry classification dummies and use firm clustering to report standard errors and corresponding z or t statistics. The coefficients for constant and industry/year dummies are left out. See Appendix 2.A.1 for definitions of all control variables. *, **, and *** represent significance levels for 10%, 5%, and 1% respectively.

Panel A: Idiosyncratic Volatility	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2018	1990 - 2000	2001 - 2007	2008 - 2018
E-Index	**-0.0217*** **	**-0.0591*** **	**0.0880*** **	**-0.0565*** **	**-0.1342*** **	**0.0893*** **
	(0.006)	**(0.005)**	**(0.005)**	**(0.019)**	**(0.011)**	**(0.008)**
ROE	0.0387**	0.0312*	-0.0140	0.0655	0.0139	0.0452**
	(0.017)	(0.017)	(0.010)	(0.051)	(0.030)	(0.019)
vROE	-0.0131	0.0000	-0.0033	0.0285	-0.0090**	-0.0018
	(0.018)	(0.001)	(0.002)	(0.034)	(0.004)	(0.003)
LEV	0.1193**	0.1764***	0.5401***	-0.0233	-0.1005	0.8446***
	(0.054)	(0.042)	(0.031)	(0.108)	(0.082)	(0.060)
MB	-0.0332***	-0.0189***	0.0260***	0.0124	-0.0152**	-0.0087*
	(0.004)	(0.003)	(0.002)	(0.010)	(0.008)	(0.005)
SIZE	-0.3632***	-0.2112***	-0.1665***	-0.3580***	-0.2448***	0.1798***
	(0.005)	(0.005)	(0.004)	(0.016)	(0.017)	(0.011)
AGE	-0.0560***	-0.0604***	-0.0825***	-0.2326***	-0.2809***	0.6077***
	(0.013)	(0.010)	(0.006)	(0.031)	(0.036)	(0.021)
DD	0.1311***	-0.1851***	-0.1104***	0.0771	0.0844**	0.0891***
	(0.022)	(0.017)	(0.012)	(0.054)	(0.040)	(0.026)
OPQ	0.0367***	0.0219***	0.0435***	0.0624***	0.0506***	0.0208***
	(0.004)	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	78098	91747	142593	78098	91747	142593
R-Squared	0.082	0.079	0.066	0.057	0.038	0.014
Number of Clusters/Groups	1278	1966	2697	1278	1966	2697
Panel B: Crash Risk	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2018	1990 - 2000	2001 - 2007	2008 - 2018
E-Index	**0.047***	**0.022**	**0.057*** **	**0.087**	**-0.016**	**0.083*** **
	(0.027)	**(0.023)**	**(0.019)**	**(0.090)**	**(0.082)**	**(0.030)**
DIFTURN	0.044**	0.021***	0.028***	0.036***	0.016**	0.024***
	(0.017)	(0.006)	(0.005)	(0.012)	(0.006)	(0.004)
AVG	12.765**	15.705***	1.329	-12.187	-13.217**	-20.072***
	(5.316)	(4.384)	(3.660)	(7.501)	(5.501)	(4.140)
SIGMA	3.005*	0.140	4.045***	-4.829	-4.229**	1.685
	(1.688)	(1.398)	(1.172)	(3.033)	(1.990)	(1.525)
LEV	0.384*	0.194	-0.239**	0.022	-0.293	-0.033
	(0.220)	(0.179)	(0.111)	(0.521)	(0.373)	(0.229)
SIZE	0.045*	-0.047**	0.021	0.506***	0.417***	0.640***
	(0.026)	(0.022)	(0.016)	(0.098)	(0.093)	(0.058)
MB	0.048***	0.025**	0.013	-0.018	0.001	0.025
	(0.018)	(0.012)	(0.008)	(0.051)	(0.035)	(0.019)
ROA	0.711*	0.488*	0.611***	1.244	0.508	0.297
	(0.384)	(0.267)	(0.190)	(0.811)	(0.548)	(0.346)
NCSKEW	0.022	0.094***	0.046**	-0.251***	-0.207***	-0.104***
	(0.046)	(0.033)	(0.023)	(0.053)	(0.036)	(0.022)
OPQ	0.062***	0.051***	0.0208***	0.0413***	0.0265***	0.0120***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	5265	6295	11342	4131	5436	12112
Pseudo R-Squared	0.036	0.021	0.027	0.038	0.023	0.026
Number of Clusters/Groups	928	1366	2532	587	988	1442

Table 2.7 Alternative firm risk measures and the two structural breaks

This table presents the coefficients and standard errors (robust/clustered by firms as in Table 2.4 Models 1 and 2) using alternative firm risk measures i.e. negative conditional skewness (NCSKEW - Panel A), down-to-up volatility (DUVOL - Panel B), number of CRASHes experienced by a firm in a year (CRASHNUM - Panel C) and an indicator if the firm specific weekly return shows a price jump (JUMP) in a year. All controls in Table 2.6 are used. Additionally, for DUVOL and NCSKEW, past three years values of the same are included to partially control for autocorrelation and reverse causality. Model 1 in Panels A and B apply OLS regressions, with Panel C using Tobit regression and Panel D employing Logit regression. Model 2 controls for firm heterogeneity by including firm-fixed effects. *, **, and *** represent significance levels for 10%, 5%, and 1% respectively.

Model 1			Model 2		
1990–2000	2001–2007	2008–2018	1990–2000	2001–2007	2008–2018
Panel A: NCSKEW					
0.0106	0.0059	0..0468***	0.0248	0.0121	0.0617***
(0.011)	(0.011)	(0.010)	(0.042)	(0.039)	(0.016)
Panel B: DUVOL					
0.0045	-0.0046	0.0185***	0.0034	-0.0067	0.0235***
(0.004)	(0.004)	(0.004)	(0.016)	(0.014)	(0.006)
Panel C: CRASHNUM					
0.0346	0.0174	0.0418***			
(0.021)	(0.017)	(0.014)			
Panel D: JUMP					
-0.0313	-0.0140	-0.0106	-0.0309	-0.0503	-0.0444
(0.026)	(0.023)	(0.019)	(0.087)	(0.094)	(0.029)

learning-induced effect of the E-Index on crash risk in these periods.

Robustness Checks: We use alternative measures of crash risk as a robustness check (Table 2.7) and find that our previous result indicating the predictive ability of the E-Index for future price crashes after second break point remains consistent across all these alternative measures. Additionally, we test whether the effect of the E-Index is symmetrically observed across price crashes and jumps. Using the price $JUMP$ indicator, we see that the E-Index does not show a similar marginal effect as on $CRASH$. This indicates that while poor governance (Model 1) as well as deteriorating governance structures (Model 2) do marginally influence future stock price crash risk in recent years, the opposite is not true; in other words, neither good governance nor improving governance structures explain stock price jumps.

Overall, our findings support the sophisticated learning hypothesis and show that firm-specific risk is another possible channel through which alert investors may have learnt to appreciate the governance risk difference between low and high E-Index firms.

2.7 The Role of Investors' Governance Preferences: An Indicative Experiment

The analysis we performed identifies the second break point and studies the role of information flow. However, it does not identify underlying mechanisms. One possible mechanism is explained by Pedersen, Fitzgibbons, and Pomorski (2019) and Pastor, Stambaugh, and Taylor (2019) highlighting the role of institutional investors and their governance preferences on stock returns. To investigate this, we provide some evidence regarding the behavior of institutional investors around the second break using a quasi-natural experiment.

2.7.1 Identification Strategy

In this experiment, our identification strategy exploits the change in ISS's data collection and reporting methodology in 2007. Although IRRC (the governance data provider) was taken over by ISS in 2005, its methodology was not immediately affected. In 2007, when ISS introduced new specifications for collecting the data on takeover defenses, which required annual reviews of firms' charters and bylaws, a newer methodology was adopted. We proxy for sophisticated learning using the change in ISS's data reporting frequency, which is a source of exogenous variation in the governance information available to institutional investors. The main underlying assumptions are that investors are not aware which firms' governance data will be reported for 2007 and do not plan their governance-based investment strategies in advance. It may be argued that if some institutional investors do actively seek governance information to plan their trading strategies, they may obtain such information on their own—even before it is provided by ISS. If this is indeed true, then these investors will trade on governance information beforehand, thereby eliminating any potential gains from the informational advantage that ISS's new data reporting methodology provides. In other words, the attenuation accompanying such pre-shock trading makes it harder for us to observe the sophisticated learning effect (because of relatively conservative estimates), thus enhancing our identification.

The change in ISS's governance reporting methodology offers us a good quasi-experimental setting that can isolate institutional investors' reaction to governance information, and comes with several advantages. First and foremost, firms whose information was not updated in 2007 (control firms, or Slow group henceforth) and those that had a new set of information in 2007 (treatment firms, or Fast group) are mutually exclusive, ensuring that the two groups are clearly categorized. Second, considering that ISS issues governance data independently, both sets of treatment and control firms are largely unaware of which group they fall into. This eliminates any potential intra-firm sources of endogeneity. Third, we can safely assume a roughly random assignment of firms to the two groups because there are no reasons to believe that ISS favors reporting some firms' governance provisions over others.[14] From the institutional investors' perspective, this also means that they were largely unaware of which firms' information was to be updated in 2007 and which was not. Fourth, as an extension of the previous point, ISS's decision to cover a specific firm's anti-takeover provisions should largely be independent of the firm's past institutional ownership and returns. Fifth, although the frequency and timing with which ISS released the governance data (which were previously issued

[14] Nevertheless, we do tackle selection concerns by using propensity-score-matched groups.

at two- or three-year intervals) was inconsistent, the timing and frequency remained consistent for the last three reports. This would have allowed investors to plan their investment strategies using governance information with certainty. Lastly, the inconsistencies in past reporting frequency allows for possible placebo tests, which can strengthen the validity of our inferences.

Institutional investors can benefit more from faster information dissemination. This benefit will be more prevalent for the group of firms whose governance data were reported in 2006 and updated in 2007. As mentioned earlier, we call this the Fast group, which represents treatment firms. By contrast, firms covered by ISS in 2006 but not reported in 2007 are allocated to the Slow group. In our setting, the Slow group thus includes control firms that induce comparatively slower sophisticated learning, as their reporting frequency and accompanying investment strategy are similar to those employed with past ISS (or, IRRC) publications (i.e., portfolios being reset every two to three years). Since most firms covered by ISS in 2006 are updated with the 2007 information, we find that the treatment group (2,086) is much larger than the control group (395).[15] When we look at the number of firms in extreme portfolios (i.e., *Democracy* with E-Index = 0 and *Dictatorship* with E-Index = 5 | 6) for each group, the trend remains the same (i.e., 399 firms in the treatment group and 55 in the control group). Importantly, we also ensure that the ISS coverage in 2007 is independent of firm-specific attributes such as size, profitability, and age by using propensity score matching.

[15]The governance index scores change little over time. Within the treatment group, only 505 firmsâĂŹ (i.e., 25% of the sample) E-Index scores change in the treatment period from 2006 to 2007. This proportion is slightly higher than the past governance updates from ISS (approximately 21% of firmsâĂŹ E-Index scores changed in the governance datasets of 2004 and 2006). However, it is still much smaller than the proportion of changes observed for 2010 (51%) and 2015 (74%).

2.7.1.1 Estimation Model

To assess whether and how institutional investors adjust their investment portfolios based on governance structures, we focus on the changes in short- and long-term institutional ownership during the experimental window (2006 to 2009). Overall, institutional ownership has increased on average over the years. However, since our experimental setting focuses on a shock to the governance information flow, we seek to identify how short- and long-term institutional investors across the treatment and control groups react differently to changes in the frequency and quality of governance reporting. In general, short-term investors tend to seek mispriced stocks (Derrien, Kecskés, and Thesmar, 2013). Thus, after 2008 when poor governance stocks are mispriced, we expect these investors to maximize their short-term gains by aggressively investing in these stocks. On the contrary, long-term investors actively intervene in their portfolio firms (McCahery, Sautner, and Starks, 2016). Hence, they prefer to exit poor governance firms and stay invested in good governance ones to maximize their long-term performance.[16] To capture this different behavior for each group of institutional investors across the treatment and control firms, we segregate the four-year experimental window into pre- and post-learning periods of two years each. We then estimate the overall treatment effect on short- and long-term institutional ownership (termed SIO and LIO, respectively) using triple difference (DDD) analysis. We subdivide the sample into good and poor governance firms by using the dummy variable EI that represents the above- and below-median E-Indices for each year t. Two additional dummy variables,

[16] It is important to note that our classification of short- and long-term investors applies three-year investment horizon (see Section 2.4.5), whereas subsequent tests on abnormal returns in Appendix 2.A.2 consider monthly returns for portfolios that are rebalanced annually. However, as the investor classification considers a continuum of proportions of long-term shares held (i.e., 0 to 1), both sets of investors, in principle, can invest in the governance-hedge that we use to assess abnormal returns.

$SB2$ and $Treat$, represent the post-learning period (2008 onward) and treatment firms, respectively. The institutional ownership variable IO is either SIO or LIO depending on the investment horizon:

$$\begin{aligned} IO_{j,t} = A_0 + B_{0,1} * EI_{j,t} + B_{0,2} * SB2_{j,t} + B_{0,3} * Treat_{j,t} + B_{0,4} * EI_{j,t} * SB2_{j,t} \\ + B_{0,5} * EI_{j,t} * Treat_{j,t} + B_{0,6} * SB2_{j,t} * Treat_{j,t} \\ + B_{0,7} * EI_{j,t} * SB2_{j,t} * Treat_{j,t} + C_0 * X_{j,t} + \epsilon_{j,t}. \end{aligned} \tag{2.10}$$

We aim to identify how SIO and LIO react to changes in EI for treatment firms compared with control firms after the second structural break. Accordingly, the interaction of EI with $SB2$ and $Treat$ gives us the DDD coefficient of interest (i.e., $B_{0,7}$). The controls $X_{j,t}$ include size (market capitalization), age, leverage, return on assets, Tobin's Q, dividend yield, share price, monthly turnover, past returns, and volatility as in Yan and Zhang (2009) and Chung and Zhang (2011).

2.7.1.2 Internal Validity

There are two potential threats to the internal validity of our experimental inferences. First, as mentioned earlier, the control group is smaller than the treatment group and selection biases, which confound the outcomes of an experiment when treatment and control firms have significantly different characteristics, may also drive our results. For example, if size is such a factor, larger firms may be more likely to be covered by ISS's governance publications (becoming treatment firms), and in turn these firms may also have exaggerated influences from governance structures than smaller control firms. We tackle these selection concerns using a propensity-score-matched treatment group that identifies comparable firms for each control group firm matched on size (log of total assets), profitability (return on assets), and leverage (debt to assets). Second, sophisticated learning may not be unique to the second structural break. In other words, similar sophisticated learning trends may exist in other periods. We conduct placebo DDD tests to verify that this is not the case by first identifying similar ISS reporting frequency-centric control and treatment groups in another period and then running a pre-post analysis across alternative placebo break points.

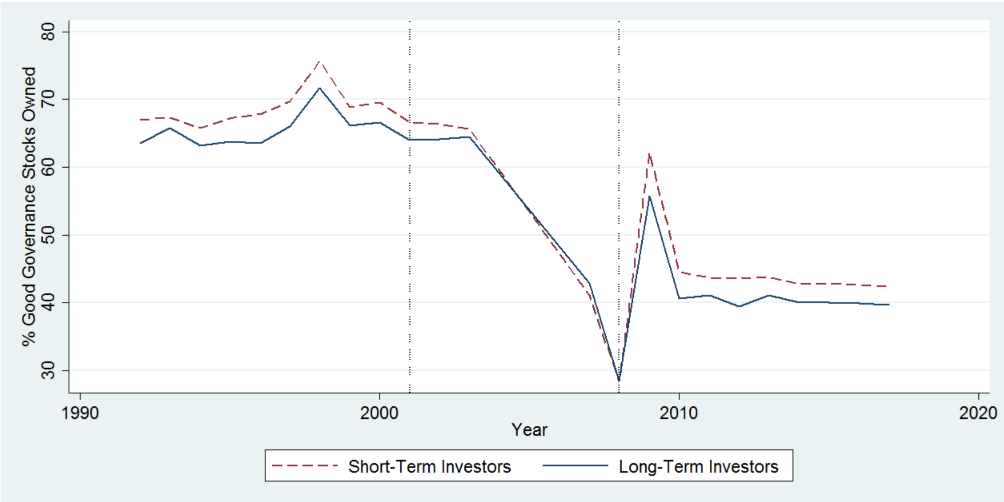
2.7.2 Preliminary Evidence

The corporate governance provision data became available annually to institutional investors from 2007 onward. How did they adjust their investments to the more timely dissemination of governance signals? The sophisticated learning hypothesis predicts that institutional investors' learning experience is higher when governance information is disseminated to them at a faster pace (on an annual basis) than the older IRRC reporting practices (biennial or triennial). Owing to such learning, institutional investors (both short- and long-term ones) would have readjusted their investment portfolios to benefit from the subsequent informational advantage. As shown by Yan and Zhang (2009), we expect this informational advantage to be better exploited by short-term investors.

To show the differences in preferences for governance structures between short- and long-term institutional investors, Figure 2.4 compares the average proportion of good governance stocks held by each investor type for each year in our sample period. We divide firms into good and poor governance stocks by considering the median E-Index cutoff for each year. The plots indicate a general trend of long-term investors preferring more good governance stocks than short-term ones. While the average preferences for both investor types overlap between the two structural breaks, the difference reappears after the second structural break. Interestingly, while both short- and long-term investors had the majority of their investment in good governance stocks before

Figure 2.4 Institutional investors and the two structural breaks

This figure shows the plots of the proportion of good governance stocks held by short- and long-term institutional investors. All the sample firms were grouped into good and poor governance stocks around the median E-Index for each year. For each institutional investor, the proportion of good governance stocks in its portfolio is then computed as the total good governance stock value divided by the total portfolio value at the end of each year. Finally, the cross-investor value-weighted mean proportions are computed for each of the two investor types. The two structural break points are represented using vertical dotted lines.

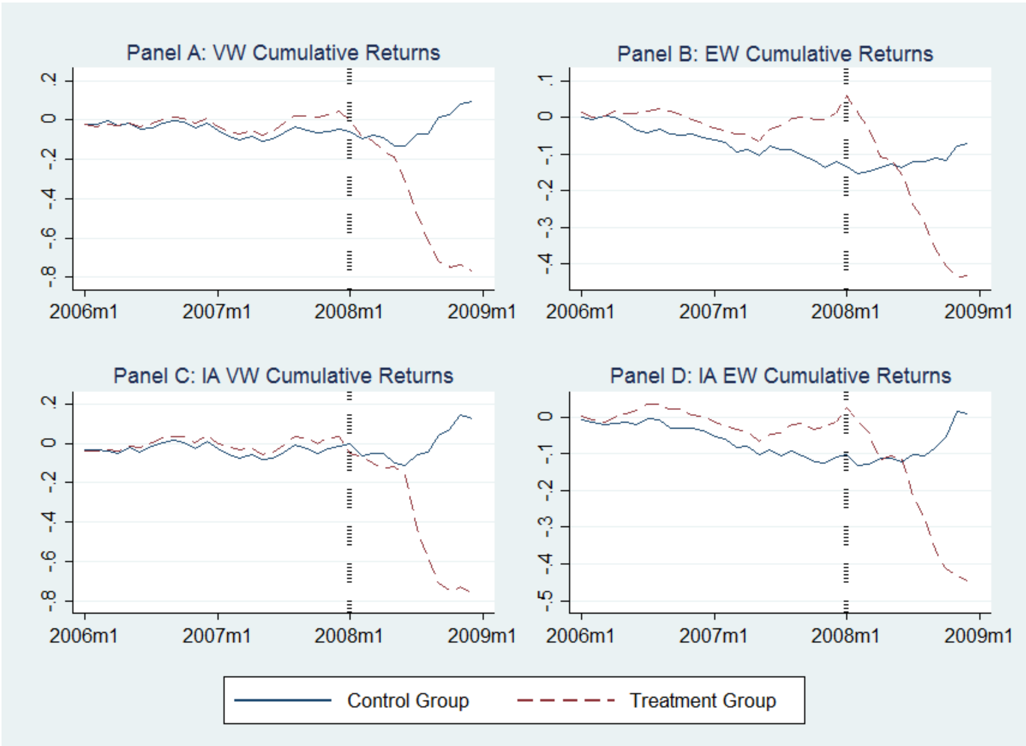


the first structural break, they both show much lower average propensities for the good governance stocks after the second structural break. Between the two breaks, there is a sharp decline in the institutional ownership of good governance stocks, seemingly driven by two factors. First, learning-induced rebalancing makes good governance stocks less attractive to investors. Accordingly, investors' choices are independent of the governance characteristic (50%) around 2006. Second, a further decline accompanies the increased investor prudence during the crisis years (see Section 2.3).

Figure 2.5, meanwhile, compares the raw cumulative returns, using various long good governance/short bad governance portfolios, between control (Slow) and treatment (Fast) firms. Panels A and B show the value-weighted and equal-weighted E-Index governance hedge portfolios, respectively, whereas Panels C and D show the same by adjusting each firm's returns using the Fama-French

Figure 2.5 Returns from governance trading strategies around the second structural break

This figure shows the plots of the cumulative returns generated for control (Slow) and treatment (Fast) firms using various long good governance/ short bad governance hedge portfolios constructed with the E-Index. For each month, we compute compounded hedge portfolio returns from January 2006 (the first month of our DiD period). Both value-weighted (VW)and equal-weighted (EW) portfolios are shown. Additionally, industry-adjusted returns (IA) using the Fama and French (1997) 48-industry classification are shown to control for product market competition and industry clustering. The vertical dotted lines on the plots represent the critical sophisticated learning point (i.e., January 2008).



48-industry means to control for product market competition and industry clustering. Across all four plots, whereas cumulative hedge portfolio returns from the control group remain almost flat and close to zero, those from the treatment group drop after the sophisticated learning point (marked by the dotted vertical line in the figure). In fact, the trend between the two groups is directionally opposite, with the governance hedge portfolios of control firms showing positive and increasing returns. These plots support the validity of our experimental setting.

Despite the preliminary evidence presented in Figures IV and V, there is a need to statistically examine the sophisticated learning phenomenon for the experimental period. Thus, to study the changes around the second structural break point while eliminating possible biases from extraneous confounders, we estimate the Equation 2.10.

2.7.3 Experimental Results

Table 2.8 shows the results for the DDD estimations using firms' institutional ownership classified into short and long term based on their investment horizons (Panels A and B use three- and two-year turnover periods, respectively). All the DDD estimations use the E-Index dummy (EI).[17] The baseline results show that while short-term institutional investors increase their ownership (SIO) of poor governance stocks on average after the second structural break point, the long-term institutional ownership (LIO) of poor governance stocks decreases after the same point. This is reflected by the coefficients of the DDD terms, which are statistically significant for both SIO and LIO, but in the opposite directions.

Next, we ensure equivalent control and treatment firms using nearest neighbor propensity score matching with a 0.001 caliper. Firms in the control group are matched based on size of assets, operating performance (i.e., return on assets), and leverage to obtain a comparable treatment firm. Panel A in Table 2.9 summarizes the key characteristics for each group before and after the matching. The three firm characteristics used sufficiently balance the treatment and control groups, even across the additional dimensions, as shown in Table 2.9.[18] The economic and statistical significance of the matched DDD

[17]The statistical significance of the DDD terms remains the same when the true E-Index scores are used in place of the E-Index dummy. However, we prefer to report the results for EI in Table 2.8 to allow us to interpret and compare good and bad governance firms.

[18]Only the E-Index means are different between the two groups. The mean value is higher

Table 2.8 Does sophisticated learning affect the institutional ownership?

This table reports the triple difference (DDD) estimation results for short- and long-term institutional ownership (shown as SIO and LIO respectively) for the experimental period 2006 to 2009. Panels A and B show the results for both SIO and LIO with the institutional ownerships categorized using three- and two-year portfolio horizons respectively. All models are estimated using Equation 2.10 controlling for size (log of market capitalization), age (in logs), leverage, return on assets (ROA), Tobin's Q, dividend yield, share price, monthly turnover, past returns (in logs) and volatility. See Appendix 2.A.1 for further details on control variables. Robust standard errors, clustered by firms, are shown in parentheses. Structural Break Dummy (SB2) represents the post-dissociation years in the baseline and propensity score (PS) matched DDD models. Placebo DDD 1 employs the year 2000 as a dummy structural break and placebo DDD 2 applies the first structural break year 2001. PS matched DDD employs nearest-neighbor logit using a 0.001 calliper to match one treatment firm for each control firm in each of the years in our experimental period. Significance levels for 10%, 5%, and 1% are shown using *,**, and *** respectively.

Panel A: Investor horizons defined using last three year portfolio turnover

	Baseline DDD		PS Matched DDD		Placebo DDD 1		Placebo DDD 2	
	SIO	LIO	SIO	LIO	SIO	LIO	SIO	LIO
EI	0.2520	0.7722	0.2763	0.8537	-0.0094	0.0101	0.0034	0.0428**
	(0.250)	(0.779)	(0.278)	(0.866)	(0.013)	(0.025)	(0.010)	(0.020)
$SB2$	0.0196	-0.1016**	0.0109	-0.1193**	-0.0009	-0.0227	-0.0175	-0.0155
	(0.016)	(0.047)	(0.020)	(0.059)	(0.007)	(0.015)	(0.012)	(0.031)
$Treat$	0.0031	-0.0262	0.0168	0.0318	-0.0068	-0.0101	-0.0053	-0.0084
	(0.013)	(0.038)	(0.028)	(0.086)	(0.006)	(0.012)	(0.004)	(0.008)
$EI * SB2$	0.0488***	-0.0665***	0.0458***	-0.0696**	0.0097	0.0449	-0.0031	0.0220
	(0.009)	(0.021)	(0.011)	(0.028)	(0.013)	(0.031)	(0.031)	(0.047)
$EI * Treat$	0.0131	0.0167	0.0168	0.0316	0.0038	0.0246*	0.0056	0.0301**
	(0.010)	(0.026)	(0.018)	(0.052)	(0.007)	(0.014)	(0.006)	(0.012)
$SB2 * Treat$	0.0214*	-0.1202***	0.0327***	-0.0921***	-0.0009	-0.0164	-0.0038	0.0415***
	(0.013)	(0.035)	(0.011)	(0.030)	(0.006)	(0.013)	(0.004)	(0.009)
$\boldsymbol{EI * SB2 * Treat}$	**0.0369*** **	**-0.0813** **	**0.0395*** **	**-0.0701** **	**0.0094**	**0.0201**	**0.0055**	**0.0618** **
	(0.012)	**(0.034)**	**(0.011)**	**(0.029)**	**(0.008)**	**(0.016)**	**(0.006)**	**(0.013)**
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3480	3480	2685	2685	2549	2549	2596	2596
R-squared	0.010	0.010	0.012	0.012	0.159	0.283	0.159	0.309

Panel B: Investor horizons defined using last two years portfolio turnover

	Baseline DDD		PS Matched DDD		Placebo DDD 1		Placebo DDD 2	
	SIO	LIO	SIO	LIO	SIO	LIO	SIO	LIO
EI	0.1843	0.5228	0.2017	0.5733	-0.0132	0.0139	0.0014	0.0478**
	(0.165)	(0.519)	(0.182)	(0.572)	(0.009)	(0.025)	(0.007)	(0.020)
$SB2$	0.0512***	-0.1003**	0.0451**	-0.1193*	-0.0077	-0.0213	-0.0224***	-0.0014
	(0.016)	(0.050)	(0.020)	(0.063)	(0.006)	(0.016)	(0.008)	(0.032)
$Treat$	0.0101*	-0.0140	0.0155	0.0158	-0.0090*	-0.0014	-0.0028	-0.0055
	(0.006)	(0.018)	(0.012)	(0.036)	(0.005)	(0.013)	(0.003)	(0.009)
$EI * SB2$	0.0701***	-0.0665***	0.0677***	-0.0770**	-0.0009	0.0551*	0.0041	0.0261
	(0.009)	(0.025)	(0.011)	(0.032)	(0.010)	(0.032)	(0.036)	(0.061)
$EI * Treat$	0.0204***	0.0090	0.0253**	0.0211	-0.0001	0.0356**	0.0062	0.0368***
	(0.006)	(0.017)	(0.011)	(0.032)	(0.005)	(0.016)	(0.004)	(0.013)
$SB2 * Treat$	0.0494***	-0.1149***	0.0587***	-0.0972***	-0.0068	-0.0152	-0.0050	0.0528***
	(0.011)	(0.035)	(0.010)	(0.028)	(0.005)	(0.014)	(0.003)	(0.009)
$\boldsymbol{EI * SB2 * Treat}$	**0.0612*** **	**-0.0722** **	**0.0635*** **	**-0.0708** **	**0.0007**	**0.0270**	**0.0027**	**0.0732** **
	(0.012)	**(0.036)**	**(0.011)**	**(0.033)**	**(0.006)**	**(0.017)**	**(0.004)**	**(0.013)**
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4561	4561	3584	3584	2549	2549	2596	2596
R-squared	0.008	0.008	0.010	0.009	0.173	0.280	0.174	0.307

Table 2.9 Summary statistics for unmatched and matched samples

This table reports the averages of important firm characteristics for the treatment and control group firms along with the differences in their means. For definitions of each of these characteristics, see Appendix 2.A.1. Panel A considers the full E-Index sample employed for short- and long-term institutional ownerships, whereas Panel B includes only the sub-sample consisting of Democracy and Dictatorship firms used for assessing the abnormal returns. The propensity score and matching employs log of assets, return on assets (ROA) and leverage (LEV). For the mean differences, significance levels at 10%, 5%, and 1% are represented using *,**, and *** respectively.

Panel A: Full E-Index Sample (2006–2009)

	Unmatched			Matched		
	Control	Treatment	Difference	Control	Treatment	Difference
ln(assets)	6.979	7.865	-0.886***	7.295	7.308	-0.013
ROA	0.053	0.116	-0.064***	0.099	0.097	0.002
LEV	0.227	0.185	0.043***	0.211	0.222	-0.011
Tobin's Q	2.096	2.115	-0.019	1.984	2.023	-0.039
CAPEX/TA	-3.681	-3.65	-0.031	-3.576	-3.631	0.056
R&D/TA	0.742	0.093	0.649***	0.052	0.055	-0.003
Annual Returns	-0.081	-0.044	-0.037**	-0.062	-0.061	-0.001
Propensity Score	0.744	0.824	-0.080***	0.786	0.786	0.001
E-Index	1.938	2.784	-0.846***	1.906	2.758	-0.851***

Panel B: Democracy & Dictatorship Sample (2006–2008)

	Unmatched			Matched		
	Control	Treatment	Difference	Control	Treatment	Difference
ln(assets)	7.338	8.22	-0.882***	7.361	7.629	-0.268
ROA	0.099	0.115	-0.016	0.101	0.094	0.007
LEV	0.221	0.193	0.027	0.201	0.196	0.005
Tobin's Q	1.889	1.956	-0.068	1.901	1.889	0.012
CAPEX/TA	-3.564	-3.641	0.077	-3.546	-3.678	0.132
R&D/TA	0.027	0.031	-0.004	0.025	0.039	-0.014
Annual Returns	-0.02	-0.102	0.082	-0.028	-0.104	0.076
Propensity Score	0.787	0.836	-0.049***	0.792	0.802	-0.01
E-Index	0.407	4.064	-3.656***	0.423	4.215	-3.792***

estimators remains the same as in the baseline estimations.

We additionally test the validity of our experiment using placebo sophisticated learning points, as shown in Table 2.8. We first locate similar treatment and control firms at a different point in time (in this case, taking the 1998–2001 period instead of 2006–2009). While the IRRC report for 1995 lasted three years, the IRRC governance report in 1998 was applicable for two years. We thus consider firms with information updated in 2000 to be the placebo treatment and those without such new information to be the placebo control. Both the DDD terms for SIO and LIO are statistically insignificant for this test (placebo DDD 1). Lastly, we check if a similar sophisticated learning effect is visible across the first structural break by including 2001 as the learning year within the same experimental setting as placebo DDD 1. For this test (placebo DDD 2), there is again no significant changes for SIO, whereas LIO has a DDD coefficient with the opposite sign to that in the baseline DDD. However, the positive influence of the E-Index on LIO has to be interpreted with caution, as the application of placebo learning in 2001 affixes the E-Index for four consecutive years (1998 to 2001) for control firms.

Overall, the results in Table 2.8 support the existence of the sophisticated learning effect through the informational advantages that accompany faster information dissemination. Our results indicate a preference for poor governance stocks among short-term investors after 2008. Meanwhile, long-term investors prefer to exit poor governance stocks after the same year. This finding is consistent across the two short- and long-term institutional investor classifications.[19]

---

for the treatment group than the control group, which shows that increased anti-takeover provisions within firms did not necessarily prevent these firms from making such information available to ISS. Additionally, the median E-Index across both these groups is the same.

[19]In unreported analyses, we also apply the classification of short- and long-term investors proposed by Yan and Zhang (2009) using the portfolio turnover in the last four quarters and obtain similar results to those reported in Table 2.8.

We run supplementary analyses to test whether (a) governance-based hedge portfolios that employ these treatment and control groups show a distinct shift in abnormal returns beyond 2008 (see Appendix 2.A.2), and (b) a combined governance and information timeliness (double-sorted) hedge portfolio could have generated abnormal returns (see Appendix 2.A.3). The results from both these tests confirm that information flow plays an important role in the relationship between governance and returns after 2008. Lastly, we also show that our results are not driven by the applied five-factor asset pricing model using other alternative models. The coefficients of the sophisticated learning effect remain stable across all the alternative pricing models employed.

2.8 Conclusion

In his seminal paper, Fama (1998) examines several asset pricing anomalies and shows that "anomalies are chance results" and "apparent overreaction of stock prices to information is about as common as underreaction." Our tests of the sophisticated learning, to a certain extent, build on this stock price overreaction/underreaction mechanism and show that the governance–returns anomaly is indeed fragile. This fragility is displayed by the initial disappearance of the governance–returns association and then its reappearance. The association reappears when institutional investors with different investment horizons adapt their investment strategies by considering governance-related risks.

We show that the governance–returns relation disappeared after 2000, as shown in Bebchuk, Cohen, and Wang (2013), but it subsequently reappears in the opposite direction (i.e., showing a reversal of the hedge position) from 2008 onward. The disappearance of this relation is explained by the market participants' learning to include governance information in their decisions.[20] The

[20]Alternatively, Li and Li (2016) show that the governance–returns relation over time

reappearance of this relation is explained by sophisticated learning. Specifically, sophisticated learning represents institutional investors' ability to understand governance risk, which other market participants, as well as the markets at large, do not yet recognize. Consistent with sophisticated learning, we find evidence that after 2008 price information and risk channels may communicate governance risk. While medium- and long-run price informativeness declined for poor governance stocks after 2008, it increased for good governance stocks. With respect to firms' risk measures, we find that poor governance stocks are more likely to face future stock price crashes and have higher future idiosyncratic volatility. Both these trends with regards to price information flows and firm risks were not visible in the dissociation period. Hence, we posit that investors that learned about governance risk after the first structural break point, may have identified governance-based investment opportunities that subsequently appeared.

Furthermore, we provide additional insights on sophisticated learning by exploring the role of institutional investors and their governance preferences in propagating the new (or, negative) governance–returns relation. Using a quasi-natural experiment set around an exogenous shock to governance information availability, we show that investors may have benefited from learning (after the second structural break point) by better adjusting their investment portfolios and corresponding returns expectations. Our results indicate that firms' corporate governance structures influence the institutional investors' holding period. In other words, when we look at firms' ownership patterns, the proportion of short-term investors increases in poorly governed firms after the

---

can be explained by the economic conditions (i.e., booms or busts) faced by each firm's industry. Hence, the pre-2000s governance–returns anomaly is not robust when investment and divestiture options are accounted for. However, hedge reversal and sophisticated learning seem robust to such industry-wide factors. We do not directly test such economic conditions or investment options, but do control for them by adjusting the returns of each firm by its industry's mean returns.

critical sophisticated learning point. Long-term investors are known to reduce managerial rent extraction and improve governance (Harford, Kecskes, and Mansi, 2018). This, along with our findings on their recently revitalized preference for well-governed firms, suggests a reinforcing mechanism that benefits these investors through lowered monitoring costs. On the contrary, trading profits seem to attract short-term investors to poor governance stocks in lieu of forgoing the long-term monitoring benefits.

Daines, Gow, and Larcker (2010) show that corporate governance rankings do not provide any useful information for shareholders (in 2005–2007). Our results confirm that indeed during the dissociation years, no useful information was provided to investors through governance data and rankings. However, we find that governance indices can be informative for investors and that this information content changes across the two identified structural breaks. In fact, such governance information can be used by investors to develop investment strategies that can generate abnormal returns after 2008. From this perspective, our results neither indicate market inefficiency nor suggest sophisticated learning solely for the institutional investors. Our passive investment strategy only controls for some of the well-known risk factors, whereas the market may yet be pricing the unobservable *governance risk* that we fail to account for as it has not yet been measured (Fama, 1998). However, as a word of caution, since corporate governance itself encompasses a variety of underlying monitoring and auditing mechanisms, it is highly unlikely that such governance risk becomes completely priced by markets, thus continually creating investment opportunities such as the one documented herein.

2.9 References

An, H., Zhang, T., 2013. Stock price synchronicity, crash risk, and institutional investors. Journal of Corporate Finance 21, 1–15.

Andreou, P. C., Antoniou, C., Horton, J., Louca, C., 2016. Corporate governance and firm-specific stock price crashes. European Financial Management 22 (5), 916–956.

Andrews, D. W., 1993. Tests for parameter instability and structural change with unknown change point. Econometrica 61 (4), 821–856.

Back, K., Collin-Dufresne, P., Fos, V., Li, T., Ljungqvist, A., 2018. Activism, strategic trading, and liquidity. Econometrica 86 (4), 1431–1463.

Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66 (1), 47–78.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18 (1), 1–22.

Bai, J., Philippon, T., Savov, A., 2016. Have financial markets become more informative? Journal of Financial Economics 122 (3), 625–654.

Barber, B. M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21 (2), 785–818.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22 (2), 783–827.

Bebchuk, L., Cohen, A., Wang, C. C., 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics 108 (2), 323–348.

Bebchuk, L. A., Brav, A., Jiang, W., 2015. The long-term effects of hedge fund activism. Columbia Law Review 115 (5), 1085–1155.

Bekaert, G., Ehrmann, M., Fratzscher, M., Mehl, A., 2014. The global crisis and equity market contagion. Journal of Finance 69 (6), 2597–2649.

Brav, A., Heaton, J. B., 2002. Competing theories of financial anomalies. Review of Financial Studies 15 (2), 575–606.

Brown, K. C., Harlow, W. V., Tinic, S. M., 1988. Risk aversion, uncertain information, and market efficiency. Journal of Financial Economics 22 (2), 355–385.

Brown, L. D., Caylor, M. L., 2006. Corporate governance and firm valuation. Journal of

Accounting and Public Policy 25 (4), 409–434.

Brown, S., Hillegeist, S. A., 2007. How disclosure quality affects the level of information asymmetry. Review of Accounting Studies 12 (2-3), 443–477.

Bushee, B. J., Carter, M. E., Gerakos, J., 2013. Institutional investor preferences for corporate governance mechanisms. Journal of Management Accounting Research 26 (2), 123–149.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52 (1), 57–82.

Chang, X., Chen, Y., Zolotoy, L., 2017. Stock liquidity and stock price crash risk. Journal of Financial and Quantitative Analysis 52 (4), 1605–1637.

Chen, J., Hong, H., Stein, J. C., 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. Journal of Financial Economics 61 (3), 345–381.

Chung, K. H., Zhang, H., 2011. Corporate governance and institutional ownership. Journal of Financial and Quantitative Analysis 46 (1), 247–273.

Clemente, J., Montañés, A., Reyes, M., 1998. Testing for a unit root in variables with a double change in the mean. Economics Letters 59 (2), 175–182.

Cremers, K. M., Nair, V. B., John, K., 2009. Takeovers and the cross-section of returns. Review of Financial Studies 22 (4), 1409–1445.

Daines, R. M., Gow, I. D., Larcker, D. F., 2010. Rating the ratings: How good are commercial governance ratings? Journal of Financial Economics 98 (3), 439–461.

Derrien, F., Kecskés, A., Thesmar, D., 2013. Investor horizons and corporate policies. Journal of Financial and Quantitative Analysis 48 (6), 1755–1780.

Dumitrescu, A., 2015. Corporate governance, disclosure and market liquidity. Unpublished working paper, Available at: http://ssrn.com/abstract=1356204.

Easley, D., Hvidkjaer, S., O'hara, M., 2002. Is information risk a determinant of asset returns? Journal of Finance 57 (5), 2185–2221.

Easley, D., O'Hara, M., 2004. Information and the cost of capital. Journal of Finance 59 (4), 1553–1583.

Edmans, A., Ioannou, I., 2019. Future leaders, take note: finance and sustainability go together. Financial Times June 17, https://www.ft.com/content/54f96d4e-82ec-11e9-9935-ad75bb96c849.

Epstein, L. G., Schneider, M., 2008. Ambiguity, information quality, and asset pricing. Journal of Finance 63 (1), 197–228.

Erkens, D. H., Hung, M., Matos, P., 2012. Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. Journal of Corporate Finance 18 (2), 389–411.

Fama, E. F., 1991. Efficient capital markets: II. Journal of Finance 46 (5), 1575–1617.

Fama, E. F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49 (3), 283–306.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33 (1), 3–56.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics 43 (2), 153–193.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies 29 (1), 69–103.

Ferreira, M. A., Laux, P. A., 2007. Corporate governance, idiosyncratic risk, and information flow. Journal of Finance 62 (2), 951–989.

French, K. R., 2008. Presidential address: The cost of active investing. Journal of Finance 63 (4), 1537–1573.

Gillan, S. L., Starks, L. T., 2000. Corporate governance proposals and shareholder activism: The role of institutional investors. Journal of Financial Economics 57 (2), 275–305.

Gillers, H., 2019. Calpers' dilemma: Save the world or make money? Wall Street Journal June 16, https://www.wsj.com/articles/calpers-dilemma-save-the-world-or-make-money-11560684601.

Giroud, X., Mueller, H. M., 2011. Corporate governance, product market competition, and equity prices. Journal of Finance 66 (2), 563–600.

Gompers, P. A., Ishii, J., Metrick, A., 2009. Extreme governance: An analysis of dual-class firms in the United States. Review of Financial Studies 23 (3), 1051–1088.

Gompers, P. A., Ishii, J. L., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118 (1), 107–155.

Grossman, S. J., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. American Economic Review 70 (3), 393–408.

Hamburger, M. J., Kochin, L. A., 1972. Money and stock prices: The channels of influences. Journal of Finance 27 (2), 231–249.

Harford, J., Kecskes, A., Mansi, S., 2018. Do long-term investors improve corporate decision making? Journal of Corporate Finance 50, 424–452.

Hatemi-J, A., 2008. Tests for cointegration with two unknown regime shifts with an application to financial market integration. Empirical Economics 35 (3), 497–505.

Hellwig, M. F., 1980. On the aggregation of information in competitive markets. Journal of Economic Theory 22 (3), 477–498.

Hutton, A. P., Marcus, A. J., Tehranian, H., 2009. Opaque financial reports, r 2, and crash risk. Journal of Financial Economics 94 (1), 67–86.

Jin, L., Myers, S., 2006. R2 around the world: New theory and new tests. Journal of Financial Economics 79 (2), 257–292.

Johnson, S. A., Moorman, T. C., Sorescu, S., 2009. A reexamination of corporate governance and equity prices. Review of Financial Studies 22 (11), 4753–4786.

Joos, P., Piotroski, J. D., Srinivasan, S., 2016. Can analysts assess fundamental risk and valuation uncertainty? An empirical analysis of scenario-based value estimates. Journal of Financial Economics 121 (3), 645–663.

Kim, J.-B., Wang, Z., Zhang, L., 2016. CEO overconfidence and stock price crash risk. Contemporary Accounting Research 33 (4), 1720–1749.

Kothari, S. P., Shu, S., Wysocki, P. D., 2009. Do managers withhold bad news? Journal of Accounting Research 47 (1), 241–276.

Lee, C., Chung, K. H., Yang, S., 2016. Corporate governance and the informational efficiency of prices. Financial Management 45 (1), 239–260.

Li, D., Li, E. X., 2016. Corporate governance and costs of equity: Theory and evidence. Management Science 64 (1), 83–101.

McCahery, J. A., Sautner, Z., Starks, L. T., 2016. Behind the scenes: The corporate governance preferences of institutional investors. Journal of Finance 71 (6), 2905–2932.

Mondria, J., Quintana-Domeque, C., 2013. Financial contagion and attention allocation. Economic Journal 123 (568), 429–454.

Muir, T., 2017. Financial crises and risk premia. Quarterly Journal of Economics 132 (2), 765–809.

Nesbitt, S. L., 1994. Long-term rewards from shareholder activism: A study of the ?CalPERS effect? Journal of Applied Corporate Finance 6 (4), 75–80.

Newey, W. K., West, K. D., 1994. Automatic lag selection in covariance matrix estimation. Review of Economic Studies 61 (4), 631–653.

Nguyen, P.-A., Kecskés, A., Mansi, S., 2020. Does corporate social responsibility create shareholder value? The importance of long-term investors. Journal of Banking and Finance 112.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111 (3), 642–685.

Pastor, L., Stambaugh, R. F., Taylor, L. A., 2019. Sustainable investing in equilibrium. Tech. rep., National Bureau of Economic Research.

Pedersen, L. H., Fitzgibbons, S., Pomorski, L., 2019. Responsible investing: The ESG-efficient frontier. Unpublished working paper, Available at: http://ssrn.com/abstract=3466417.

Quandt, R. E., 1960. Tests of the hypothesis that a linear regression system obeys two separate regimes. Journal of the American Statistical Association 55 (290), 324–330.

Ross, S. A., 1989. Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance 44 (1), 1–17.

Schwert, G. W., 2003. Anomalies and market efficiency. In: Constantinides, G., Harris, M., Stulz, R. (Eds.), Handbook of the Economics of Finance. Vol. 1. Elsevier, pp. 939–974.

Sidhu, B., Tan, H. C., 2011. The performance of equity analysts during the global financial crisis. Australian Accounting Review 21 (1), 32–43.

Wang, L.-H., Lin, C.-H., Fung, H.-G., Chen, H.-M., 2015. Governance mechanisms and downside risk. Pacific-Basin Finance Journal 35, 485–498.

Weber, M., Weber, E. U., Nosić, A., 2012. Who takes risks when and why: Determinants of changes in investor risk taking. Review of Finance 17 (3), 847–883.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 817–838.

Yan, X., Zhang, Z., 2009. Institutional investors and equity returns: Are short-term institutions better informed? Review of Financial Studies 22 (2), 893–924.

2.A Appendices

2.A.1 Definitions of the Control Variables

SIZE: The market value of equity (in logs) either for each month or year.

ROE: Net income divided by the book value of common stock i.e. the sum of book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

vROE: Variance of ROE over last 36 months.

AGE: Log transformation of firm age measured as the months that firm is listed on CRSP database (as per the end of each calendar year).

LEV: Long term debt (Compustat data item 9) / Total assets (Compustat data item 6). Alternative measure of leverage (Long term debt/ Total equity) was used for robustness check.

MB: Log of the ratio of the CRSP market value of common equity to its book value. Book value of common equity is the sum of book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

DD: A dummy variable indicating if the firm pays dividends.

ROA: Return on Assets calculated as the operating income divided by end of the year total assets (Compustat data item 6). We use operating income before depreciation (Compustat data item 13) in the numerator.

DIFTURN: It is the difference of mean monthly share turnover for current year t and the mean monthly share turnover of prior year $t-1$. For each firm-month, the monthly share turnover is the ratio of corresponding trading volume to the total shares outstanding.

AVG: The average firm specific weekly return $W_{j,t}$ (see Section 2.4.4) for a given firm in a year.

SIGMA/Volatility: Volatility or standard deviation of specific weekly return

$W_{j,t}$ for a given firm over that year.

OPQ: Discretionary accruals that indicate opacity as measured by Hutton, Marcus, and Tehranian (2009) using a three year moving sum of the absolute value of discretionary accruals calculated with modified Jones model.

Tobin's Q: Following Bebchuk, Cohen, and Ferrell (2009), computed as market value (MV) of assets divided by book value (BV) of assets (Compustat data item 6) with the MV of assets being: (BV of assets + MV of common stock) – (BV of common stock + deferred taxes). Corresponding industry-adjusted (SIC 2-digit) values are obtained using industry median Tobin's Q values.

TURN: Measures liquidity using the volume of trade for the firm's common equity recorded in the calendar year divided by 12 (in logs).

Share Price: Firm's share price as on the last trading day of a calendar year.

2.A.2 Applying the Experimental Setting on Abnormal Returns

We employed the experimental setting explained in Section 2.7 to assess if the returns on governance-hedge portfolios differ between the treatment and control groups. Simply put, we empirically test the preliminary results shown in Figure 2.5 using a difference-in-differences (DiD) design. With respect to abnormal returns, the time window chosen for our experiment lasts from January 2006 (when the *last* old IRRC methodology-based governance data were published) to December 2008 (which covers the end date of possible investment strategy using the *first* set of new ISS methodology-based governance data). Since our identification strategy for returns focuses on governance-based hedge portfolios over this three-year window, while assuming a persistent investment strategy using the available governance data, we employ the calendar-time portfolio approach to obtain the risk-adjusted abnormal returns. This approach follows a similar rationale to the long-run method in Section 2.5, but with the event window shortened to three years instead of 26 years. We find that, on average, Democracy stocks underperform Dictatorship stocks in terms of raw returns. This difference is more pronounced in the Fast group than in the Slow group, suggesting that learning investors benefit from the faster reporting of governance data. This variation in returns, in tandem with the long-run event study used to obtain abnormal returns for the governance hedge portfolios in each group, lays the basis for us to identify the causal estimates for governance-based sophisticated learning on stock returns. While testing for differences in raw returns or abnormal returns for governance portfolios across the treatment and control groups can identify the effect of reporting frequency and better information quality on stock returns, it does not provide any insights into the second structural break. Our sophisticated learning hypothesis predicts that investors only learn to appreciate the governance risk of high E-Index firms after the second structural break point (i.e., January 2008). Hence, to capture the sophisticated learning effect, we divide the 36-month period into a 24-month pre-learning period and 12-month post-learning period. With this, we thus have the ideal backdrop for a DiD setup that captures both the time trend (i.e., before vs. after) and the treatment effect in the interaction term.

For abnormal returns, the DiD design has the following specification with observations for each month:

$$R_{J,t} = \alpha + \pi_1 SB2_t + \pi_2 Treat_J + \pi_3 SB2_t * Treat_J + \gamma F_t + \varepsilon_t, \tag{2.11}$$

where $R_{J,t}$ denotes the hedge portfolio returns for a certain group J of firms in month t, $SB2$ indicates the period after the second break point or the months following sophisticated learning, and $Treat$ is a dummy indicating if portfolio J is composed of firms from the Fast (treatment) or Slow (control) group. Our main coefficient for this model is thus π_3, which shows the DiD interaction effect, namely, the effect on the abnormal returns of the treated portfolio due to sophisticated learning. As in Equation 2.5, we control for some of the common risk factors that can explain the time series of a market or passive portfolio returns. Similar to Section 2.5.1, we include the market, size, book-to-market, momentum, and liquidity factors for F_t in this model.[21] For abnormal returns, we account for the numerical differences in the two groups by increasing the number of firms in the control group using a median E-Index-based classification of Democracy and Dictatorship firms.[22]

Table 2.10 shows the main results of our DiD estimation for abnormal returns. To test the validity of our experiment, we first run Model 1, which estimates only π_1 and π_2; that is, it ignores the interaction term in Equation 2.11. Panel A shows that the treatment group-based portfolio generates significantly different abnormal returns than the control group one on average for both the equal-weighted and the value-weighted portfolios. Additionally, there is a statistically significant change in returns across the second structural break for both these portfolios. In Model 2 with the DiD term included, the estimation results strongly support the existence of the sophisticated learning phenomenon, as only the interaction term remains statistically significant.

In Panel B of Table 2.10, we correct for the differences in the number of firms in the Democracy and Dictatorship portfolios between the treatment and control groups by expanding the portfolio classification for control group firms using the median E-Index. The results, especially when it comes to the DiD term, remain largely the same in terms of both the magnitude and the statistical significance of the coefficient. Next, in Panel C, we ensure equivalent control and treatment firms in each portfolio using nearest neighbor propensity score

[21] Other asset pricing models are again used for the robustness checks.

[22] Using such broad criteria, Democracy firms are redefined as $E - Index \leq 3$ and Dictatorship firms as those with $E - Index > 3$. This results in an almost equal number of firms in both the Fast and the Slow groups.

Table 2.10 Does sophisticated learning Drive the negative governance–returns association?

This table reports the Difference-in-Differences (DiD) estimation results for average main effects (Model 1) and average treatment effects (Model 2) using various governance-based hedge portfolios excess returns. All models are estimated using Equation 2.11 controlling for market, size, book-to-market, momentum and liquidity factors. Robust standard errors are shown in parentheses. Structural Break (SB2) Dummy represents the post-dissociation year 2008. Treat is a dummy representing Fast group as defined in Section 2.7.1.1. Baseline estimation in Panel A considers extreme portfolios in the Fast (treatment) and Slow (control) groups by hedging long Democracy (E-Index=0) short Dictatorship (E-Index=5|6). Panel B augments the results of Panel A by ensuring larger control group whereby the two extreme portfolios are redefined around the median E-Index=3 (included in the Dictatorship portfolio). To correct for the possible selection bias, Panel C employs nearest-neighbor logit propensity score (PS) matching using a 0.001 calliper to match one treatment firm for each control firm. Here, hedge portfolios are defined as in Panel A. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: Baseline Difference-in-Differences (DiD) estimation

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0426***	-0.0183*	0.0211	0.0100
	(0.015)	(0.010)	(0.018)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0058
	(0.013)	(0.006)	(0.007)	(0.004)
$\boldsymbol{SB2 * Treat}$			**-0.1275*** **	**-0.0566*** **
			(0.030)	**(0.013)**
Observations	72	72	72	72
R-squared	0.25	0.15	0.49	0.40

Panel B: DiD estimation with median-based control group portfolios

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0283*	-0.0212**	0.0495***	0.0068
	(0.016)	(0.010)	(0.017)	(0.010)
$Treat$	-0.0400***	-0.0183***	0.0119*	0.0004
	(0.014)	(0.006)	(0.008)	(0.004)
$\boldsymbol{SB2 * Treat}$			**-0.1555*** **	**-0.0560*** **
			(0.028)	**(0.016)**
Observations	72	72	72	72
R-squared	0.22	0.16	0.56	0.37

Panel C: DiD estimation with propensity score (PS) matched treatment group

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0353	-0.0029	0.0514***	0.0225
	(0.023)	(0.018)	(0.018)	(0.022)
$Treat$	-0.0359**	0.0075	0.0219	0.0244
	(0.017)	(0.014)	(0.014)	(0.016)
$\boldsymbol{SB2 * Treat}$			**-0.1734*** **	**-0.0507* **
			(0.035)	**(0.030)**
Observations	72	72	72	72
R-squared	0.15	0.08	0.43	0.11

matching with a 0.001 caliper. As was the case for institutional ownership, the matched groups are equivalent for extreme portfolio firms as well (see Panel B in Table 2.9). The economic and statistical significance of the matched DiD estimator is similar to the baseline DiD estimate.

Table 2.11 reports additional robustness tests for the main results of the DiD estimation shown in Table 2.10. While the results in Panels B and C of Table 2.10 strengthen the validity of our results by increasing the power (Panel B: increased control group) and eliminating selection bias (Panel C: propensity matching with the control group), we do not have a case of high power and low selection bias together. In Panel A of Table 2.11, we combine the wider median-based portfolios with propensity score matching to overcome this. Once again, the results support the sophisticated learning hypothesis, especially for the value-weighted portfolios. The loss of significance for the equal-weighted portfolio may be driven by some of the matched characteristics explaining the variations in returns. The magnitudes of the coefficients are also smaller, indicating that this is a much sterner test of our experiment because the difference between Democracy and Dictatorship firms is much smaller with the median-based division.

We carry out additional validity tests in our experimental setting by running placebo DiD estimations (see Panels B and C of Table 2.11). Panel B considers a three-year timeframe as in all the previous DiD estimations, considering arbitrary sophisticated learning in 2000 within an estimation period from 1998 to 2000. Panel C, on the contrary, includes the returns for 2001 (the learning structural break year) to assess whether a similar sophisticated learning effect exists, albeit with a possible reversal of direction. Across both placebo test specifications, the DiD terms are insignificant, providing further credence to our main result that sophisticated learning from governance information was experienced only in 2008.

Table 2.11 Robustness for sophisticated learning and negative governance–returns Association

This table reports the robustness tests for the main Difference-in-Differences (DiD) estimation results shown in Table 2.10. The average main effects (Model 1) and average treatment effects (Model 2) using various governance-based hedge portfolios excess returns are shown accordingly with robust standard errors given in parentheses. All models are estimated using Equation 2.11 controlling for market, size, book-to-market, momentum and liquidity factors. Structural Break Dummy represents the post-dissociation year (SB2 or 2008) in Panel A, the placebo year (2000) in Panel B, and the dissociation year (SB1 or 2001) in Panel C. Treat is a dummy representing Fast group as defined in Section 2.7.1.1. Panel A employs the PS matched sample while using the hedge portfolios defined around the median E-Index as in Table 2.10 Panel B, but for both control and treatment groups. For the placebo tests, i.e. Panels B and C, hedge portfolios are defined exactly as in Table 2.10 Panel A (i.e. with the control group's extreme portfolios divided around the median E-Index=3). The significance levels at 10%, 5%, and 1% are represented using *,**, and *** respectively.

Panel A: DiD estimation with PS matched treatment group using median-based portfolios

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	0.0156**	0.0055	0.0357***	0.0081
	(0.007)	(0.005)	(0.012)	(0.008)
$Treat$	-0.0036	-0.0047	0.0098*	-0.0030
	(0.005)	(0.003)	(0.005)	(0.003)
$\boldsymbol{SB2 * Treat}$			**-0.0402*** **	**-0.0052**
			(0.012)	**(0.009)**
Observations	72	72	72	72
R-squared	0.30	0.18	0.43	0.17

Panel B: Placebo DiD estimation

	Model 1		Model 2	
	VW	EW	VW	EW
$PlaceboSB$	-0.0174	0.0123	0.0021	-0.0003
	(0.016)	(0.017)	(0.028)	(0.028)
$Treat$	0.0334*	-0.0058	0.0465**	-0.0142
	(0.017)	(0.015)	(0.022)	(0.016)
$\boldsymbol{PlaceboSB * Treat}$			**-0.0392**	**0.0252**
			(0.035)	**(0.034)**
Observations	72	72	72	72
R-squared	0.10	0.26	0.11	0.26

Panel C: Placebo DiD estimation around first structural break (2001)

	Model 1		Model 2	
	VW	EW	VW	EW
$SB1$	0.0155	0.0018	0.0397	0.0052
	(0.021)	(0.019)	(0.038)	(0.033)
$Treat$	0.0213	-0.0075	0.0334*	-0.0058
	(0.016)	(0.013)	(0.017)	(0.015)
$\boldsymbol{SB1 * Treat}$			**-0.0485**	**-0.0068**
			(0.040)	**(0.032)**
Observations	96	96	96	96
R-squared	0.01	0.13	0.02	0.12

2.A.3 Abnormal Returns from Sophisticated Learning: The Governance Risk Premium

As an additional supplementary analysis, we extend the findings from the previous DiD experiment to examine how a fully informed investor may potentially benefit from exploiting both the governance data and its timing, or in other words, complete sophisticated learning. We model this using the five factor model as shown in Equation 2.5, but taking the returns from information timeliness hedge of the governance hedge portfolios. Alternatively put, our hypothetical investment strategy involves going long Slow governance hedge (Democracy – Dictatorship) and shorting the Fast one. In some ways, this strategy mimics double-sorted portfolio hedging when the stocks are sorted both by their E-Index values and its availability (or frequency). Hence, we expect the abnormal returns from such a strategy to essentially represent the sophisticated learning premium, especially beyond the second structural break point. As a word of caution, the proposed investment strategy is actually impractical in our DiD experimental period as the investors were unaware in advance as to which stocks' governance data will be updated for the year 2007. For this reason, the premium measures using abnormal returns from our double-sorted hedge may be inflated by informational biases.

Table 2.12 presents possible premia for investors' learning using both the value-weighted and equal-weighted portfolios. In Panel A, we see that a long Slow governance hedge and short Fast one would have generated 4.38% (26 bps) premium for value-weighted (equal-weighed) portfolios. These results are robust to alternative asset pricing models (see Table 2.15). When the investment horizons are restricted to annual periods, in Table 2.12 Panel B, we find that much of the governance risk premium is generated soon after the second structural break i.e. in the year 2008. For both the value-weighted and equal-weighted portfolios, such sophisticated learning premia are statistically significant beyond 5% levels.

Table 2.12 Governance, sophisticated learning and returns

This table shows the coefficients and standard errors (in parentheses) of five-factor regression using three factors of Fama and French (1993) i.e. market (RMRF), size (SMB), book-to-market (HML) along with the momentum factor (UMD) and Pástor and Stambaugh (2003) liquidity factor (LIQ). The dependent variable is monthly returns from an information-based hedge on governance-based portfolios i.e. long Slow information governance hedge / short Fast information governance hedge. The governance hedge is set up through zero-investment trading strategy that buys good governance stocks and shorts bad governance ones. For the Fast stocks, portfolios get reset in the beginning of each year when new governance data is available, while the Slow stocks employ governance information of year 2006 as ISS did not report updated governance data for this group. Panel A considers the full DiD horizon period, whereas Panel B consider annual investment horizons. *,**, and *** respectively represent significance levels at 10%, 5%, and 1%.

Panel A: Full DiD horizon (2006 to 2008)

Portfolios	α	$RMRF_t$	SMB_t	HML_t	MOM_t	LIQ_t	R^2
Value-weighted							
Slow	0.0131	-0.2603	0.4403	-1.4691***	-0.0909	-0.6047	0.330
	(0.009)	(0.222)	(0.517)	(0.506)	(0.269)	(0.366)	
Fast	-0.0307***	0.5675*	-1.6650**	-1.7338***	-0.2836	0.4351	0.462
	(0.011)	(0.316)	(0.653)	(0.613)	(0.387)	(0.404)	
Slow – Fast Hedge	0.0438***	-0.8278*	2.1053**	0.2648	0.1927	-1.0398	0.298
	(0.016)	(0.409)	(0.964)	(0.959)	(0.518)	(0.646)	
Equal-weighted							
Slow	-0.0107	-0.5234	1.0687*	-1.3621*	-0.3394	0.2853	0.120
	(0.013)	(0.335)	(0.622)	(0.721)	(0.443)	(0.340)	
Fast	-0.0132**	0.0314	-0.1183	-0.5257*	-0.3731	0.3583	0.153
	(0.005)	(0.174)	(0.286)	(0.304)	(0.224)	(0.243)	
Slow – Fast Hedge	0.0026	-0.5547	1.1869*	-0.8364	0.0337	-0.0730	0.093
	(0.014)	(0.393)	(0.653)	(0.792)	(0.481)	(0.458)	

Panel B: Annual investment horizons

Portfolios	2006	2007	2008
Value-weighted			
Slow	0.0477	0.0286	0.0621***
	(0.027)	(0.026)	(0.016)
Fast	-0.0123	-0.0124	-0.0836**
	(0.007)	(0.010)	(0.031)
Slow – Fast Hedge	0.0601*	0.0410	0.1458***
	(0.025)	(0.023)	(0.043)
Equal-weighted			
Slow	-0.0224	0.0125	0.0090
	(0.028)	(0.035)	(0.016)
Fast	-0.0052	-0.0065	-0.0578***
	(0.005)	(0.006)	(0.020)
Slow – Fast Hedge	-0.0172	0.0189	0.0668**
	(0.030)	(0.315)	(0.029)

2.A.4 Alternative Asset Pricing Models

We check the robustness of all our results that employ five factor model presented in Equation 2.5 by using alternative asset pricing models. We apply capital asset pricing model (CAPM), the three-factor model (Fama and French, 1993), the five-factor model (Fama and French, 2016) and the variations of these Fama-French (FF) models with the Pástor and Stambaugh (2003) liquidity factor included. The Cremers, Nair, and John (2009) takeover factor was also considered, but left out due to lack of data availability for recent years.

Table 2.13 Robustness check for Table 2.3 using alternative factor models

This table summarizes results when alternative asset models are considered in Table 2.3 Panel B by running different factors and factor combinations in Equation 2.5 with additional structural break (SB) variables. All estimations use White (1980) robust standard errors (in parentheses). For variable definitions, see Table 2.3. Significance levels at 10%, 5%, and 1% are shown using *, ** and *** respectively.

	2 SB Variables		1 SB Variable	
Panel A: CAPM				
	VW	EW	VW	EW
Alpha	-0.0053	-0.0019	-0.0102***	-0.0028
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0107**	0.0065	-0.0173***	-0.0069**
	(0.005)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0238***	-0.0077		
	(0.009)	(0.006)		
Panel B: Fama-French 3 factors				
	VW	EW	VW	EW
Alpha	0.0011	0.0003	-0.0065**	-0.0008
	(0.004)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0105***	0.0084**	-0.0204***	-0.0085***
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0289***	-0.0085		
	(0.009)	(0.006)		
Panel C: Fama-French 3 factors + liquidity factor				
	VW	EW	VW	EW
Alpha	0.0008	-0.0001	-0.0065	-0.0009
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0109***	0.0087**	-0.0197***	-0.0082**
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0260***	-0.0070		
	(0.008)	(0.006)		
Panel D: Fama-French 5 factors				
	VW	EW	VW	EW
Alpha	0.0003	0.0041	-0.0039	0.0008
	(0.003)	(0.002)	(0.003)	(0.002)
SB1 Dummy	0.0116***	0.0046	-0.0227***	-0.0092***
	(0.004)	(0.003)	(0.004)	(0.003)
SB2 Dummy	-0.0308***	-0.0139**		
	(0.008)	(0.006)		
Panel E: Fama-French 5 factors + liquidity factor				
	VW	EW	VW	EW
Alpha	0.0019	0.0028	-0.0038	0.0007
	(0.003)	(0.002)	(0.003)	(0.002)
SB1 Dummy	0.0125***	0.0058*	-0.0220***	-0.0089***
	(0.004)	(0.003)	(0.004)	(0.003)
SB2 Dummy	-0.0284***	-0.0119**		
	(0.008)	(0.006)		

Table 2.14 Robustness check for Table 2.10 using alternative factor models

This table summarizes results using alternative asset models for main DiD estimation result in Table 2.10 (Panel A). White (1980) robust standard errors are shown in parentheses. For variable definitions, see 2.10. Average main effects (Model 1) and average treatment effects (Model 2) are shown using either the equal-weighted (EW) or value-weighted(VW) governance-based hedge portfolios. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

	Model 1		Model 2	
Panel A: CAPM				
	VW	EW	VW	EW
$SB2$	-0.0561***	-0.0162*	0.0077	0.0120*
	(0.019)	(0.009)	(0.014)	(0.006)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275***	**-0.0565***
			(0.032)	**(0.014)**
Panel B: Fama-French 3 factors				
	VW	EW	VW	EW
$SB2$	-0.0421***	-0.0184*	0.0216	0.0099
	(0.015)	(0.010)	(0.018)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.007)	(0.004)
$SB2 * Treat$			**-0.1275***	**-0.0565***
			(0.030)	**(0.014)**
Panel D: Fama-French 3 factors + liquidity factor				
	VW	EW	VW	EW
$SB2$	-0.0425***	-0.0181*	0.0212	0.0101
	(0.014)	(0.010)	(0.017)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0058
	(0.013)	(0.006)	(0.007)	(0.004)
$SB2 * Treat$			**-0.1275***	**-0.0566***
			(0.030)	**(0.014)**
Panel D: Fama-French 5 factors				
	VW	EW	VW	EW
$SB2$	-0.0329*	-0.0180	0.0309	0.0103
	(0.018)	(0.011)	(0.020)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275***	**-0.0566***
			(0.029)	**(0.014)**
Panel E: Fama-French 5 factors + liquidity factor				
	VW	EW	VW	EW
$SB2$	-0.0299*	-0.0158	0.0338	0.0124*
	(0.016)	(0.011)	(0.021)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275***	**-0.0566***
			(0.029)	**(0.014)**

Table 2.15 Robustness check for Table 2.12 using alternative factor models

This table reports alphas (αs) when alternative asset pricing models are used in the Panel A of Table 2.12. For variable definitions and other details, see Table 2.12. Abnormal returns from long / short strategies based on governance information (Fast vs Slow) on the E-Index hedge (long Democracy short Dictatorship) using both equal-weighted (EW) and value-weighted (VW) portfolios are shown. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

VW			EW		
Slow	Fast	Slow – Fast	Slow	Fast	Slow – Fast
Panel A: CAPM					
0.0072	-0.0314**	0.0344*	-0.0089	-0.0126**	0.0036
(0.010)	(0.012)	(0.018)	(0.012)	(0.005)	(0.013)
Panel B: Fama-French 3 factors					
0.0069	-0.0285***	0.0311*	-0.0102	-0.0123**	0.0021
(0.009)	(0.010)	(0.018)	(0.011)	(0.006)	(0.012)
Panel C: Fama-French 3 factors + liquidity Factor					
0.0128	-0.0315***	0.0446***	-0.0116	-0.0143**	0.0026
(0.009)	(0.010)	(0.016)	(0.013)	(0.005)	(0.013)
Panel D: Fama-French 5 factors					
-0.0003	-0.0160*	0.0159*	-0.0186	-0.0063	-0.0122
(0.008)	(0.009)	(0.013)	(0.011)	(0.005)	(0.011)
Panel E: Fama-French 5 factors + liquidity Factor					
0.0056	-0.0212**	0.0294**	-0.0175	-0.0087*	-0.0088
(0.008)	(0.009)	(0.013)	(0.013)	(0.005)	(0.012)

CHAPTER 3

The Corporate Governance–Performance Puzzle: New Insights

3.1 Abstract

This study presents the "nG (new Governance) Index", an unequal-weighted measure of corporate governance that dynamically captures the heterogeneity of its individual antitakeover components, as an alternative to the equal-weighted G-Index, E-Index, and Gov-Score proposed in the related literature. Our findings show that all antitakeover provisions do not equally contribute to the firms' corporate governance quality, and our proposed nG-Index there-

fore traces the governance–performance relationship more persistently than an equal-weighted measure does. Further analysis reveals that an nG-Index based zero-investment hedge, going long on a poor governance portfolio and shorting the good governance one, would generate an abnormal return of over 1.33% per month, or about 16% per year. In contrast, a comparable hedge using equal-weighted index shows no significant abnormal returns. Moreover, we find that the heterogeneity of antitakeover provisions is important to show the investors' underreaction to good governance signals and their attentiveness to the riskiness associated with poorly governed firms.

3.2 Introduction

"Goodness is the only investment that never fails."

–Henry David Thoreau

Firms that employ good corporate governance mechanisms should outperform poorly governed ones. However, do they actually perform better? Do better internal and external governance practices translate into superior performance and higher equity valuations? Do stock prices and the corresponding returns factor in the firm's corporate governance quality? These are some of the questions that have baffled corporate governance scholars over last three decades, who made several attempts to investigate the governance–performance relationship empirically. However, empirical tests of this relationship are difficult due to the complexities in measuring corporate governance itself. The underlying fundamental question is: *How do we differentiate well-governed firms from poorly governed ones?*

To measure corporate governance, identifying its constituent mechanisms is a big challenge. The existing literature discusses several mechanisms to put a check on managers to avoid agency problems and provide better governance. These include higher monitoring by the board of directors, having large (or institutional) shareholders, using an appropriate financial structure, and through takeover threats (or antitakeover provisions, ATPs hereafter) and proxy battles.

In this study, we focus on segregating various ATPs and their use for managerial entrenchment to harm shareholders, to assess how well they measure firms' corporate governance quality. Our main contribution to the literature is in the form of a unique measure of corporate governance that captures the heterogeneity of its individual antitakeover components. To this end, we propose that stock markets can best capture the differences in firms' governance quality, and thus use contemporaneous returns-based models to identify the importance of individual ATPs. More specifically, we capture the weights from past contemporaneous relationships (i.e., between lagged or out-of-sample ATPs and returns) to apply them for each year's index construction. Previously conceptualized measures such as the Governance Index (G-Index, Gompers, Ishii, and Metrick, 2003), Entrenchment Index (E-index, Bebchuk, Cohen, and Ferrell, 2009), Corporate Governance Index (CGI, Beiner et al., 2006), and Gov-Score (Brown and Caylor, 2006), all of which assign equal weights to each of its antitakeover components, have the composite index as a sum of all such provisions present in a firm. On the contrary, for the first time, we can identify the importance and relevance of each provision as represented by their weights in each year. Furthermore, we apply our measure to study the relationship between governance and future abnormal returns.

In general, good corporate governance practices that align owners' and management's interests should benefit both the firm and its investors (see Shleifer and Vishny, 1997 for a full review). This is true for both internal and external governance (Acharya, Myers, and Rajan, 2011). The presence of frictions between owners and managers, and accompanying agency problems, can influence managerial decisions and risk taking (Fama, 1980; Fama and Jensen, 1983). Managers have and will always tend to have a strong inclination and incentive to expropriate firms' assets to undertake projects that benefit themselves at the expense of shareholders (Jensen and Meckling, 1976; Stein, 1989). This, in turn, affects both the firms' value and their cost of capital.[23] While the valuation effect is driven by intra-firm power dynamics (Rajan and Zingales, 1998) and managerial rent extraction (Shleifer and Vishny, 1989), which can influence investors' expectations of future cash flows (Jensen, 1986), the cost of capital effect is driven by monitoring and auditing costs (Lombardo and Pagano, 2002; Dumitrescu, 2015), which influence investors' expected risk premium (Chen, Chen, and Wei, 2009). When shareholders vote against an ATP, they expect market monitoring (through the threat of hostile takeover) to counter agency risks, forcing managers to undertake projects that add value to the firm, and hence resulting in better firm performance and subsequently increasing shareholders' wealth (Stein, 1988).

To evidence the benefits of good governance, using measures such as the G-Index and E-Index (constructed from ATPs prevalent in the sample firms during the 1990s and early 2000s) researchers show a positive relationship between governance and measures such as firm value, operating performance, and future abnormal returns. However, recent studies indicate that this relationship has disappeared or weakened over time (Erkens, Hung, and Matos, 2012; Bebchuk, Cohen, and Wang, 2013). We propose that the disappearance of the governance–performance relationship maybe due to the inability of previously conceptualized governance indices to successfully measure corporate governance beyond the early 2000s. Because all the previous indices were

[23] Williamson (1988) elaborates the contractual problems from such conflicts of interest using transaction cost economics and agency theory. Regardless of whether adopting the ex-ante approach in agency theory (DeAngelo and Rice, 1983) or the ex-post view of transaction cost economics (Williamson, 1998), harmonized contractual relations using appropriate governance structures should benefit the firm.

constructed by assigning equal weights to all available ATPs, they did not possess requisite dynamism to capture the subsequent evolution of the governance landscape as newer government interventions and media influences shaped it.

Do the weights of individual provisions really matter? Studies that employ voting data on individual ATPs show that these provisions are related to abnormal returns. Cuñat, Gine, and Guadalupe (2012), for example, show that passing of governance proposals can create value for shareholders, albeit within a shorter event window (i.e., most abnormal returns are generated on the day that the governance proposal passes). Additionally, this effect is more profound for provisions included in the G-Index. Alternatively, using the same index, Bebchuk, Cohen, and Wang (2013) show that the increased attention to corporate governance led to the disappearance of the association between governance indices and abnormal returns after the year 2000. Thus, the persistence in this relationship for individual provisions, despite the disappearing association for aggregate indices, may indicate pure learning effects seen only in the long run. In other words, increased attention to governance over the years has limited the benefits of governance provisions to a shorter window for investors (as Cuñat, Gine, and Guadalupe, 2012, 2016 show), since markets now adjust more quickly to the differences in firms' governance. However, besides learning, it also indicates potential flaws in the governance indices, which possibly restrict their ability to represent governance quality when the importance or weights of individual provisions are ignored.

To begin with, using ATPs that can jeopardize shareholders' rights, we introduce an index that dynamically measures firms' corporate governance quality. Using a dynamic weighted methodology allows us to overcome the implicit drawbacks of the previous indices elaborated earlier. Our goal is to identify the right mix of ATPs within the composite measure for each year. Using the new unequally weighted method, we find evidence that of the 19 ATPs available in the ISS database, certain provisions (such as unequal voting rights, limited ability to amend bylaws, etc.) warrant higher weights than other provisions do to better reflect governance quality. We also find that some provisions, such as golden parachutes and a supermajority requirement to amend charters, do not capture governance quality or become irrelevant with time. Having multiple indicators for the same governance mechanism (for example, special meetings and supermajority requirement for these meetings) allows us to show that each of the sub-dimensions for a given ATP does indeed require different weights within a governance index. We also evaluate alternative dynamic variable selection and/or weight extraction methodologies including machine learning algorithms. To compare the unequally and equally weighted (Gompers, Ishii, and Metrick, 2003) methodologies, we introduce an equal-weighted modified Governance Index (mG-Index) along with our unequal-weighted new Governance Index (nG-Index) using the same 19 provisions.

After introducing the nG-Index, we hypothesize that this unequally weighted index should track a firm's governance quality much better than the mG-Index does. On comparing the two indices in how they capture the governance–performance relationship, we see that the nG-Index shows more persistent and statistically significant results than the equally weighted mG-Index does. Our findings show that good governance measured by the nG-Index is significantly related with superior firm value measured by Tobin's Q, as Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) also show. In other words, firms with good governance structures (i.e., lower nG scores) had significantly higher firm valuations than those with bad governance structures in our sample period. The mG-Index traces this relationship on an annual basis weakly, with statistical significance shown only for 1 of the 9 years examined. Our nG-Index, on the other hand, retains its explanatory power for 5 of the 9 years. The results from fixed effects and system generalized method of moments (GMM) regressions also lend stronger support to the nG-Index than for the mG-Index. This is important because for our sample, using an equally weighted index would suggest very low or even zero difference between the Tobin's Q values of firms with good and bad governance, which is not the case when using an unequally weighted index. We also note that the coefficients obtained with the mG-Index are largely biased upwards, as Cuñat, Gine, and Guadalupe (2012) suggests.[24] While the nG-Index indicates that the absence of all 19 provisions would result in an increase of about 0.75 units in Tobin's Q, the mG-Index indicates that there would be an increase of 3.55 units in Tobin's Q.

To identify a causal link between the nG-Index and Tobin's Q, we exploit an exogenous shock to the firms' corporate governance quality caused by the adoption of Revlon ruling in the state of Maryland (for details, see Cain, McKeon, and Solomon, 2017). The Revlon ruling affects potential hostile takeover bids by enforcing the directors to accept only the most reasonable of the available prices, which in turn impacts the effectiveness of ATPs. Our results from this quasi-experimental setting corroborate the findings from the panel and GMM regressions, i.e. the changes in nG-Index does cause changes in Tobin's Q for the treatment firms.

We further assess the nG and mG indices in relation to operating performance measures such as return on assets (ROA), return on equity (ROE), and net profit margin (NPM). Across these measures, the nG-Index shows greater consistency in reflecting the superior operating performance of well-governed firms. Bhagat, Bolton, and Romano (2008) and Bhagat and Bolton (2009) show a similar positive and significant association between governance and operating

[24] Cuñat, Gine, and Guadalupe (2012) mention the upward bias of estimates for abnormal returns for the governance portfolio returns in Gompers, Ishii, and Metrick (2003), but do not assess bias in firm values or Tobin's Q.

performance for the G-Index, E-Index, and Gov-Score as well in the pre-2007 period. However, in our sample period (i.e., 2007 to 2015), while the nG-Index has a negative relationship with all the three operating performance measures, the mG-Index has an opposite association with ROE. From this, an important implication is that using the nG-Index to measure governance quality allows us to judge the management of well governed firms in terms of their operating outcomes or profit margins, which is not always the case for an equal-weighted index.[25]

Good governance being related to superior firm value and better operating performance does not necessary imply that our index should be associated with future abnormal stock returns because market prices are expected to reflect and correct for any differences in firms' governance. However, we find that corporate governance is an important factor to consider in investment decisions, since a zero-investment strategy based on the nG-Index shows potential to yield abnormal returns. We construct portfolios each year by grouping all available firms into nG-Index-based governance deciles. Our analysis reveals that buying the bottom 5th percentile stocks (bad governance portfolio) and selling the top 5th percentile stocks (good governance) generates an abnormal return of 1.33% per month or about 16% per year in our sample period. In contrast, a similar zero-investment hedge using mG-Index-based governance portfolios shows no statistically significant abnormal returns consistent with the findings of Bebchuk, Cohen, and Wang (2013).

We further run supplementary tests to investigate whether the proposed nG-Index can predict future stock price crashes and if it can track future benefits of good governance. This gives us further insights on the importance of index weights for investment decisions by examining the governance related risk-

[25] The triple difference estimations exploiting the Revlon ruling in Maryland additionally reveal a causal relation between nG-Index and two of the operating performance measures.

return tradeoffs. Our analysis reveals that the nG-Index reflects high riskiness associated with poorly governed firms as they do show a higher likelihood of a future stock price crashes. On the contrary, mG-Index based classification of good and poor governance firms fails to show a significant relationship with future price crashes. Additionally, only nG-Index based hedge portfolios show that investors can potentially benefit from good governance signals in the long-run.

The rest of this study is structured as follows. Section 3.3 presents the governance–performance puzzle and the testable hypotheses. Section 3.4 describes the data, new index construction, and provides a preliminary evaluation of our proposed index. Section 3.5 presents the empirical models and results for the outlined governance–performance relations. Next, Section 3.6 discusses the importance and relevance of our findings. Lastly, Section 3.7 summarizes and concludes.

3.3 The Governance–Performance Puzzle

Since the 1990s, research on corporate governance centers largely around individual governance-related firm characteristics (such as CEO Duality, Director Ownership, etc.) and its outcomes, or around aggregated measures of corporate governance, that is, governance indices (for a detailed review, see Maskara, Maskara, and Aggarwal, 2013). With respect to the latter, most of the literature on governance indices construction is motivated by the fact that these indices are correlated with firm value measures (i.e., Tobin's Q), operating performance measures (such as ROA, ROE, and profitability ratios), and abnormal stock returns (e.g., Gompers, Ishii, and Metrick, 2003). In other words, firms with good governance practices as per their governance scores had superior firm values and operating performance, while also generating higher abnormal returns for their investors. However, despite the consistent evidence on the positive relationship between firm values and good governance in subsequent literature (Bebchuk, Cohen, and Ferrell, 2009), the relationship with abnormal returns puzzlingly disappeared beyond the early 2000s, partly due to investor learning (Bebchuk, Cohen, and Wang, 2013; Erkens, Hung, and Matos, 2012). The same disappearance occurred for operating performance measures as well (Bhagat and Bolton, 2013).

3.3.1 Do We Need a New Governance Index?

To explain the aforementioned disappearance of the association between ATP-based indices (such as the G-Index, E-index, etc.) and the performance measures beyond the 1990s, we argue that the advent of various corporate scandals in the early 2000s and the consequent regulatory interventions caused a considerable change in the global corporate governance landscape. Static corporate governance indices do not capture this evolution because they give equal importance to all available ATPs, rendering them incapable of measuring governance quality well in changing times. Note that each governance provision does not exist in isolation. This means that post-2002 (with regulations in place such as the Sarbanes-Oxley Act, SOX henceforth), the increased importance of some of the previously optional provisions may have had a cascading effect on other provisions as well, due to the newer regulatory mandates (Bhagat and Bolton, 2013). Expectedly, such regulatory changes should affect how firms attend to their governance provisions. With regulatory changes making some of the previously optional provisions compulsory (hence, limiting their ability to capture governance variability), their contribution as an indicator of good governance would have disappeared. Thus, we seek to provide a better understanding of the key ATPs that are appropriate to construct a corporate governance index, even after the wide acceptance of such regulatory changes.

Most prior studies exploring the governance–performance relation largely used either the G-Index or E-Index from governance data before 2007. Our governance index, in addition to allowing for heterogeneity in individual provisions, uncovers the governance–performance relationships for 2007 to 2015. Essentially, using the ATPs, we want to introduce a governance index that is dynamic and can retain its explanatory power, even in recent years. The revival of interest in corporate governance research recently could be ascribed to the 2008 Global Financial Crisis, as regulators and investors began looking for better means of monitoring internal governance mechanisms. Executive compensation was one of the key factors responsible for the reckless risk exposure at financial institutions that led to the crisis. Consequently, newer codes and regulations have been introduced, giving shareholders a non-binding say-on-pay with respect to executive compensation arrangements. For this reason, the present regulatory advancements and ever-growing shareholder activism were directed towards clipping the wings of the companies that employ poor governance mechanisms. Using an alternative governance index that factors in this evolution in corporate governance will enable us to examine the changing relevancies of all governance provisions that constitute the nG-Index, and see how certain provisions have either gained or lost importance as an indicator of governance quality.

Another explanation for the disappearance of the governance–performance relation in recent years could be that the ATPs on their own should not be operationalized into one single construct, as such indices ignore other important governance dimensions. Beiner et al. (2006) raised a similar question when they use the CGI with five additional variables instead of only relying on the aggregated CGI measure. However, we follow an approach that differs from that of Beiner et al. (2006), as we do not seek to introduce more variables to increase the explanatory power of corporate governance on performance, but instead focus on identifying the relative importance of each available variable or provision. We propose that the information content of the ATPs' relative importance can enrich and revive the relevance of governance indices. Why adopt only ATPs and not other governance aspects, such as ownership patterns, director characteristics (independence, diversity, etc.), shareholder activism, executive compensations, and more? As we consider the investor's point of view, the idea is to rely on data that is readily available to investors in a single place to create a comprehensive measure of governance quality. Undoubtedly, including the aforementioned additional aspects into the mix would make the governance measure richer and more reliable, but it comes at the expense of the parsimony and simplicity essential for constructing an index.

Recent research applying aggregate governance measures employs ATP-based governance ratings and rankings provided by commercial research firms. These studies widely assume that these rankings are reliable and provide a clear indication of good versus poor governance practices within their sample firms because commercial agencies have superior access to firm-level governance data and better resources than academic scholars do (Schnyder, 2012). However, the relationship between these ratings and firm performance measures show inconsistent results (Daines, Gow, and Larcker, 2010), implying that even commercially available governance rankings do not represent firms' governance qualities well enough. To analyze firms' governance prior to 2006, academic researchers continue to apply the G and E indices because their reliability has been empirically tested. The same cannot be said for governance research that uses the latest aggregated or index data as –in almost all cases– commercial governance rating agencies do not reveal the methodological details for the approaches they use in their rankings. Thus, there is a need to study the latest governance dataset (in our case, data on ATPs) to assess whether we can organize it into a measure that has a higher methodological transparency than commercial indices to provide academic scholars the opportunity to test them empirically, and that investors could possibly use to assess firms' governance quality. We present one such measure in the form of the nG-Index. Apart from the aforementioned benefits to the academic community and investors, there is additional scope to apply a similar and more objective unequally weighted approach even in commercial governance rankings.[26]

3.3.2 Relationship Between Governance and Firm Performance

Governance can affect both the firm's value and operating performance positively or negatively (Gompers, Ishii, and Metrick, 2003). On the one hand, a weaker governance structure implies weaker shareholder rights and that even underperforming managers can continue without having fear of being fired. Furthermore, lesser shareholder involvement entails lesser requisite transparency, meaning that even the better managers within these firms will undertake value diminishing activities like shirking, leading to higher agency costs and declining performance. On the other hand, with weaker governance mechanisms in place, managers have more security and are encouraged to take less risky investment projects (Shleifer and Vishny, 1989). This, in turn, would result in better firm performance. Improving governance by adopting a shareholder-friendly provision (or dropping an ATP) would increase managers' accountability, thereby increasing the likelihood that managers will focus on immediate rather than long-term performance in order to signal their intent.

Much of the empirical evidence indicates that there is indeed a positive relationship between governance and firm value and operating performance.[27]

[26] Most commercial governance rankings tend to use subjective weights identified from 'expert' opinions.

[27] Some studies, such as those by Hermalin and Weisbach (1991) and Bhagat and Black (2001) show negative or no relationship between governance and Tobin's Q, but these usually focus on a specific governance attribute such as board characteristics or director independence instead of an aggregate governance measure.

Even in our sample period, we expect that the firms that demonstrate good governance quality according to the nG-Index will show relatively higher firm values and better operating performance than poorly governed firms will. The direction of this governance–performance causality could be questioned, nevertheless, as one can also argue that the firms with higher market valuations have a higher likelihood of employing superior governance mechanisms because they have more capital, lower costs of capital, better access to external sources of financing, and more investment prospects (Durnev and Kim, 2005; Klapper and Love, 2004). While our initial analysis will rely on the governance–performance *correlation*, and not *causation*, to assess how well governance quality is measured, we do shed some light on causality in subsequent analyses.

We hypothesize that if our governance index truly reflects the sample firms' governance quality, it will show consistent relationships across multiple performance measures and model specifications. Supposing that some operating performance measures (ROE, ROA, or NPM) indicate significant positive correlations with governance, while others show negative relationships, we argue that the lack of consistent results would be driven largely by the presence of measurement errors within the governance index. We do not presume that there is no possibility of having a negative governance–performance relationship, as in the alternative argument above. However, even a negative relationship would more reliably reflect the true effect of governance mechanisms only if the results are consistent across multiple performance measures.

3.3.3 Relationship Between Governance and Stock Returns

With respect to the effect of governance on investors, much of academic research focuses on the existence of abnormal stock returns for good governance portfolios vis-à-vis poor governance ones. Although initial studies such as Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) show a significant positive relationship between abnormal returns and governance, subsequent studies (Core, Guay, and Rusticus, 2006; Bebchuk, Cohen, and Wang, 2013; Gu and Hackbarth, 2013; Cremers and Ferrell, 2014) show that this correlation disappeared in the post-2000 period as market participants and investors learned to apprise governance scores in their investment decisions.

Gompers, Ishii, and Metrick (2003) provide two sets of explanations for the positive governance–returns association. First, poor governance creates agency costs (as seen for other firm performance measures previously), and in the 1990s, investors tended to underestimate these costs, resulting in stock performance falling below their expectations. Second, governance may have been correlated with returns merely due to the high degree of correlations with other risk factors that caused abnormal stock returns in the 1990s. Due to the endogeneity problem, it is difficult to prove the causal explanation. However, using a regression discontinuity design (RDD), Cuñat, Gine, and Guadalupe (2012, 2016) show that adopting a governance proposal does cause a significant increase in shareholder value. These RDD studies, however, consider short event-windows and the significant positive returns occur within the first two days of a governance proposal being passed.

Bebchuk, Cohen, and Wang (2013) and Cremers and Ferrell (2014), using the G-Index and E-Index, empirically show the disappearance of the governance–abnormal returns association over the years. Does market wisdom explain this puzzling disappearance completely, or is it an indication of changing investor expectations from poorly governed firms? While increasing media attention and research coverage of governance is indeed one of the factors behind this disappearing relationship, and hence the learning hypothesis (Bebchuk, Cohen, and Wang, 2013) cannot be questioned, we argue that the measurement ability of governance indices declined over the years, leading to measurement errors and the classical errors-in-variables problem. Thus, the results tend to have an upward bias due to inherent threats to construct validity (i.e., the degree to which these governance indices actually measure what they purport to measure), with a major threat being the equal weights assigned to individual ATPs/factors in their operationalizations. To put it differently, the "learning hypothesis" that Bebchuk, Cohen, and Wang (2013) proposes is true not only for investors, but is also true for regulators, as policy makers grew wiser in terms of the actions and interventions they force upon poorly governed firms. Such interventions and regulatory changes should affect how companies attend to their governance provisions and their priorities for each of them. The older indices (G-Index, E-Index, etc.) do not account for the changing relevance of individual provisions, in turn restricting their ability to measure governance. Thus, the lack of relevance weights in these indices would lead to biased results in the correlation and regression coefficients shown in literature (especially after big scandals in the 2000s and the passing of SOX), due to the attenuation effect, or "regression dilution."

Core, Guay, and Rusticus (2006) report that the outperformance of good governance stocks over poor governance ones is not seen beyond the year 2000, stating, "abnormal stock returns for firms with weak shareholder rights are somewhat greater than returns for strong governance firms." They suggest that the previous outperformance (i.e., before 2000) of good governance stocks is merely a case of "shareholders rights anomaly ... connected to ... new economy pricing anomaly of the (late) 1990s." This is the underlying presumption for also possibly expecting a negative association between governance and returns.

3.3.4 Endogeneity in Governance–Performance Relationships

When studying the outcomes of corporate governance, it is difficult to draw causal inferences by ruling out reverse causality and the possible effects of parallel confounding or unobservable variables. In recent years, several studies (Cuñat, Gine, and Guadalupe, 2012, 2016; Chemmanur and Tian, 2017) assess the outcomes of ATPs using RDDs, which can provide causal estimates. However, RDDs using pass votes on ATPs' removal can only establish the outcomes for individual provisions when they are randomly dropped around the vote share pass window. Such studies essentially measure the impact on the firm when a certain provision is dropped and governance improves. With index measures, it is difficult to examine causality with RDD because indices tend to look at the available ATPs in aggregate.

In light of these arguments, we thus first try to tackle endogeneity concerns in our governance–performance specifications using a dynamic panel GMM (Wintoki, Linck, and Netter, 2012).[28] GMM is superior to ordinary least square (OLS) and fixed-effects (FE) models because it wholly controls for simultaneity, the effect of past governance structures on firm outcomes, and additional unobserved firm-level heterogeneity [see (Schultz, Tan, and Walsh, 2010) and (Wintoki, Linck, and Netter, 2012) for methodology, econometric rationale, and other details]. Moreover, previous studies employing GMM to capture the governance–performance relationship largely conclude that there is no causal relation between them in spite of the statistically significant association observed with OLS and FE specifications. Thus, the estimates from GMM provide a good preliminary acid test to alleviate endogeneity concerns

[28] The advantage of using GMM for a governance index is that this method identifies instruments internally from within the panel data itself. With difficulties in spotting exogenous sources of variations to develop instrumental variables for indices, GMM provides a solution by using past performance and governance data to instrument for the contemporaneous outcomes of governance.

in our setting.

Finding an exogenous shock, which substantively affects governance quality as measured using an aggregated index, is a big challenge to employ ideal identification strategies such as a natural experiment or difference-in-differences. Despite this, we next obtain additional causal estimates by exploiting the timing of the adoption of Delaware ruling of Revlon Inc case, which had an effect on firms' corporate governance characteristics by enforcing directors to only accept "best" price whenever there is a takeover bid. This exogenous ruling has an impact on takeover markets by restricting the directors from accepting offers for management buyouts, leveraged buyouts, or friendly takeovers whenever an offer price is lower than an acceptable market value. Although this ruling came out in the state of Delaware in 1986, it was only accepted or rejected within other states in later years. In our sample period, Maryland adopts the Revlon ruling in November 2009. This allows us to take the firms based in Maryland as the treatment firms (which faced an external shock to their governance) and the ones based in Delaware as control firms (since much of the regulatory or legal interventions in Delaware happened in 1980s). The final treatment effect is then computed using triple difference estimation (DDD or diff-in-diff-in-diff) which gives us the resultant impact on TobinâĂŹs Q or other performance measures, when there are changes in the nG-Index between the pre-2009 and post-2010 years, and also between the Maryland- and Delaware-based firms. We additionally check the validity and robustness of our results using placebo tests and propensity score matching.

3.3.5 Governance and the Risk-Return Tradeoff

Firms with higher agency risks are more prone to future stock price crashes (Andreou et al., 2016; Kim and Zhang, 2016). With greater agency risks, managers are more likely to take suboptimal investments (Bebchuk and Stole, 1993) and aim to maximize short-term benefits and incentives (Stein, 1989). However, this information asymmetry cannot be maintained to conceal bad news for long, as markets eventually learn about it, resulting in a significant decline in stock prices or a crash (Kim and Zhang, 2016). In a similar vein, when markets experience declining trends, firms with accumulated hidden information tend to have bigger negative return outliers (Hong and Stein, 2003). In conjunction with the learning hypothesis (Bebchuk, Cohen, and Wang, 2013), investors and market participants must have became more aware of governance provisions after the year 2000. This means that with time, they must have also learnt to identify poor governance stocks as high agency risk firms. If indeed governance index weights are irrelevant for assessing such risks, then both equal- and unequal-weighted index should show similar influence of governance on price crashes.

Good governance should pay off for investors in the long run (McCahery, Sautner, and Starks, 2016). In other words, if the stock market impounds only part of the available governance information in the stock prices, returns from good governance stocks in the short run will be subdued. However, in the long run, shareholders of good governance firms will earn higher returns as all of the information is impounded over the years. If governance index weights do not matter for future returns, then both equal- and unequal-weighted index should track this benefit of good governance to investors. Through these two mechanisms, we aim to provide preliminary insights on how index weights can also impact risk-return tradeoffs associated with corporate governance.

3.4 Data and Methodology

3.4.1 The Data

The data we use in our analysis are largely taken from three main sources available in the WRDS database: Institutional Shareholder Services (ISS) for the governance data on ATPs, Standard and Poor's COMPUSTAT annual database for accounting data to measure performance variables and firm-level controls, and the Center for Research in Security Prices (CRSP) monthly data for stock prices and returns. We also collected additional Fama-French four factors and liquidity factors from the WRDS.

Before 2006, ISS (then IRRC-Riskmetrics) published data on firm-level governance provisions every 2 to 3 years. These data were taken from inputs such as proxy statements, annual reports, charters and bylaws, and other SEC filings. The provisions data were typically collected for large Fortune 500 or S&P 500 companies that institutional investors requisitioned to assess the takeover protection mechanisms that these companies employed. ATPs are a proxy for the shareholder–manager relationship. For this reason, Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) use similar data to conceptualize the G-Index and E-Index, respectively. Brown and Caylor (2006) also use the same pre-2007 dataset to create the Gov-Score, which includes additional governance characteristics from other ISS data. However, with a change in the data collection methodology after 2007, these indices have grown obsolete because there are only 19 distinct provisions in the new ISS governance dataset, unlike the previous data that had 22 takeover-related provisions and an additional 6 state-mandated takeover statutes.[29] The new data collection system introduced in 2007 includes an initial review of every company's bylaws and charters and other SEC filings on a yearly basis. The governance data we include in our analysis encompasses an average of 1100

[29] The E-index (Bebchuk, Cohen, and Ferrell, 2009) can still be created for new ISS dataset because the information on all six entrenchment provisions (i.e., staggered boards, limits to bylaw amendments, limits to charter amendments, poison pills, golden parachutes, and supermajority requirement for mergers) are available. However, note that Bebchuk, Cohen, and Ferrell (2009) identifies these provisions as a subset of the existing G-Index to show that the E-index has superior explanatory power than the G-Index does. Thus, applying the E-index to the new governance data, which has a different set of provisions, may give misleading results.

companies for each year from 2007 to 2015, with a total of 10,190 firm-year governance observations.

3.4.1.1 Governance Data

The ISS governance dataset has 21 antitakeover characteristics and an additional 8 “opt-outs” (representing whether the company opted out of certain state laws concerning takeover-related features such as fair price, poison pill, director duties, etc.). We combine the 8 opt-outs into a single variable that measures whether the company opted out of any of the takeover provisions, in turn restricting the available shareholder rights. Of the 21 ATPs, three variables are related to a majority vote requirement for a director’s election, so we combine these and present them as a single supermajority requirement. We drop the provision related to *Carve-Out Contest*, as it is essentially reflected in the aforementioned supermajority requirement for a director’s election, thus making it redundant. Table 3.1 summarizes the selected ISS provisions (for more details on these and the full list of other available ISS governance provisions, see Appendix 3.A.1).

As in Gompers, Ishii, and Metrick (2003), we categorize all provisions into 5 distinct groups: those that delay hostile takeovers (*Delay*), those related to voting (*Vote*), those that protect director’s rights (*Protection*), other ATPs (*Other*), and those related to opt-outs from state laws. This categorization provides only a means of comparison between the provisions in the G-Index to those used to construct the nG-Index. We retained the four voting provisions for the G-Index (i.e., Blank check, staggered board, special meeting, and written consent) in the same group in our dataset as well, with two additional provisions assessing a supermajority requirement to call for special meeting or to take action by written consent. Similarly, we included two additional provisions (supermajority to amend charters and to amend bylaws) in the pro-

Table 3.1 Governance provisions from the ISS database

This table summarizes the presence of ATPs in the sample covered by ISS from 2007 to 2015. For details on each of these provisions, see Appendix 3.A.1. The provisions are classified into the five categories as presented in Gompers, Ishii, and Metrick (2003). Firms with dual-class stocks are left out of the final sample.

Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Number of firms	1329	1359	1387	1386	1381	1403	1420	1409	1417
Delay Provisions									
Blank check preferred stock	92.02%	91.76%	92.00%	92.21%	93.48%	93.73%	93.87%	93.40%	93.65%
Staggered board	56.21%	54.01%	51.84%	50.22%	46.05%	43.62%	40.56%	37.33%	34.65%
Special meeting	44.70%	45.47%	46.14%	47.19%	48.15%	49.25%	53.31%	54.36%	55.54%
Written consent	42.14%	41.94%	41.38%	44.23%	58.29%	58.37%	57.82%	58.98%	58.93%
Supermajority–special meeting	3.09%	3.24%	3.24%	3.03%	2.68%	2.57%	2.82%	2.91%	2.82%
Supermajority–written consent	19.41%	20.68%	20.19%	19.34%	31.72%	32.57%	32.82%	33.29%	33.24%
Protection Provisions									
Golden parachutes	52.22%	34.07%	81.40%	83.41%	84.00%	84.11%	84.51%	84.32%	79.46%
Resignation requirement^{+}	-	68.29%	64.38%	59.96%	55.03%	46.47%	40.35%	34.14%	28.51%
Voting Provisions									
Bylaws	84.88%	86.53%	87.53%	88.17%	88.49%	88.74%	88.52%	88.22%	88.99%
Charter	86.98%	89.26%	90.70%	91.70%	92.54%	94.73%	95.28%	97.23%	97.81%
No cumulative voting	91.95%	92.27%	92.29%	93.00%	94.06%	94.23%	94.44%	94.68%	95.13%
No secret voting	88.19%	87.71%	86.09%	86.00%	86.82%	86.89%	87.39%	87.51%	87.65%
Supermajority for merger	32.66%	31.13%	29.27%	30.09%	36.71%	32.00%	20.99%	18.38%	18.14%
Supermajority–amend charter	54.85%	55.63%	55.37%	54.83%	54.67%	53.60%	53.17%	53.09%	52.43%
Supermajority–amend bylaws	40.56%	40.77%	39.87%	40.69%	40.33%	39.77%	38.66%	39.25%	38.81%
Unequal voting	0.53%	0.52%	0.43%	0.51%	0.51%	0.21%	1.48%	1.21%	0.78%
Other Provisions									
Fair price	12.04%	13.10%	15.07%	16.16%	13.61%	13.26%	12.89%	12.42%	12.28%
Poison pill	39.13%	34.95%	27.54%	21.50%	17.02%	13.97%	10.92%	10.01%	7.62%
State Laws^{++}									
Opt outs from state laws	0.00%	15.08%	12.91%	13.20%	0.00%	0.00%	0.00%	0.00%	0.00%

$^{+}$ No data were collected on the resignation requirement provision by ISS in 2007.
$^{++}$ The ISS governance dataset contains information on opt-outs chosen by firms for 8 separate laws, which are combined here into a single dummy variable measuring whether any of the opt-outs were selected or not.

tection provisions for the new dataset. There are fewer provisions (only two, fair price and poison pill) that are retained within the other provisions group. Following Gompers, Ishii, and Metrick (2003) and related literature (Bebchuk, Cohen, and Ferrell, 2009; Bebchuk, Cohen, and Wang, 2013) we leave out companies with dual-class stocks because they have governance characteristics that are incomparable with companies having a single class stock. While the presence of certain provisions, such as special meeting, written consent, and its supermajority requirement, no cumulative voting requirement and limited ability to amend the charter increased over the years in our sample; the incidence of other provisions such as a supermajority requirement for a merger, poison pills, and resignation requirements declined over the same period. This supports our argument that such an evolving corporate governance landscape needs an index construction methodology that considers the relative importance of specific provisions that contribute more to governance quality than others.

Similar to the within-firm clustering Gompers, Ishii, and Metrick (2003) show for governance provisions from 1990 to 2000, we find that most of the positive pairwise correlations amongst these 19 provisions are statistically significant from 2007 to 2015. Since ISS governance data (and its previous versions from IRRC-Riskmetrics) cover a wide variety of firms in terms of size, age, and other characteristics, we expect minimal or no sampling bias and systematic bias. Similarly, we do not see survivorship bias affecting our analysis as we employ panel regressions in most cases, and we cannot explain the results of all the governance–performance relationship variations considered therein by the disappearance of a few firms from the ISS dataset.

To build a governance dataset for constructing the nG-Index, we coded ISS data based on the presence or absence of each individual provision. Much of the coding rules follow the procedures specified in Gompers, Ishii, and Metrick

(2003), with only the criteria for supermajority provisions changed. These supermajority requirements were coded 1 when more than 66% voting was required for the respective governance provision.[30] Although most of the provisions restricted shareholders, as Gompers, Ishii, and Metrick (2003) show, there were two exceptions: ability to have secret ballot and cumulative voting. We code these for their absence as an indicator of poor governance, unlike the rest remaining provisions for which we code presence as 1 [Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) use similar exceptions in their indices].

3.4.1.2 Performance and Returns Data

We extracted all performance-related firm characteristics from COMPUSTAT annual data for the firms in the governance data sample. As in the prior literature, we compute Tobin's Q to measure firm value and measure operating performance using ROA, ROE, and NPM. We calculated additional control variables such as size, book-to-market, leverage, and so on using standard procedures in the literature (for details on these variables and their underlying calculations, see Appendix 3.A.2). Table 3.2 Panel A gives the summary statistics for all performance-related variables along with the controls.

We collected monthly returns from CRSP for all firms and years represented in the governance dataset. Additionally, for each firm, we included data for at least 2 years prior to the availability of governance data to measure additional lagged returns-based controls. Table 3.2 Panel B summarizes the returns-based variables in our study. Note that whenever monthly returns are used with the

---

[30] Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) allow for a supermajority to be considered when a 51% voting requirement is in place. However, with a more precise definition of supermajority, we expect it to contribute less to measurement error. We use the 51% simple majority criteria in place of the 66% supermajority as a robustness check for our main findings and see no major differences in the two results.

Table 3.2 Descriptive statistics for performance and returns variables

This table presents the mean, standard deviation, range extremes, and the number of observations for all main performance variables, returns variables, and controls from 2007 to 2015. Panel A covers all variables included in either the firm value–governance or operating performance–governance regressions on an annual basis. These variables are computed from COMPUSTAT data. For details on the composition of these variables, see Appendix 3.A.2. Panel B shows brief statistics on the returns related variables to analyze the stock returns–governance relationship at a monthly frequency. Inputs for these variables were sourced from CRSP. For more details, see Appendix 3.A.3.

Panel A:

Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
Tobin's Q	2.17	1.18	-0.97	1.86	15.23	10190
ROA	0.12	0.11	-2.6	0.12	1.18	10190
NPM	0.05	0.88	-66.8	0.07	6.65	9156
ROE†	23.84	62.37	-6.98	1.59	429	7618
Size (Log of Total Assets)	8.08	1.67	4	7.95	14.76	10190
Altman's Z	1.69	1.5	-42.16	1.63	14.3	10190
Leverage	0.19	0.18	0	0.17	2.88	10190
Log of CAPEXTA	-3.75	1.39	-11.65	-3.54	-0.35	9569
S&P Dummy	0.32	0.47	0	0	1	10190
Delaware Dummy	0.45	0.5	0	0	1	10190
Log of Age	5.45	0.74	1.61	5.51	6.47	9990
Log of Book-to-Market	-4.3	2.66	-15.06	-3.68	1.63	8462
(R&D + Adv. Exp.)/Total Assets	0.03	0.06	0	0.01	0.96	10190

Panel B:

Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
Returns	0.0094	0.1116	-0.9544	0.0101	1.9917	119857
Log Past 2-Month returns	0.0075	0.1611	-3.5224	0.0194	1.9076	119809
Log Past Quarter returns	0.0145	0.1949	-2.6216	0.0309	1.8235	119719
Log Past Semi-Annual returns	0.0319	0.2822	-3.0894	0.0587	2.3305	119430
Log of Book-to-Market	-4.5	2.77	-15.17	-3.83	2.78	119517
Log of Dollar Volume traded	20	1.66	12.24	19.98	25.35	119860
Log monthly Closing Price	3.39	0.79	-4.37	3.45	7.4	119840
Log Market Value (Size)	7.89	1.52	0.78	7.74	13.13	119853
Log Two-Year returns	-2.88	1.23	-9.7	-2.74	3.26	66202
Yield	0.02	0.04	0	0.01	1.67	118693
Sales Growth	1.16	0.43	-0.57	1.11	13.98	118946

† Winsorized at 5% on both tails due to the presence of extreme outliers.

governance and performance data in regressions, the annual variables are held constant for each fiscal year.

3.4.2 Dynamic Weighting Methodologies

We employ multiple indexing methodologies that aim to capture the dynamism that each of the constituent ATPs show over the years. In all our approaches we start with the basic premise that it is the market, who best understands the importance of individual ATPs and prices this in the stock returns. Cuñat, Gine, and Guadalupe (2012) show that firms' stock prices do react to their shareholders' acceptance or rejection of ATP proposals. Thus, while we assume strong stock market efficiency for ATPs cross-sectionally, we do not necessarily presume ATPs to be risk factors. This can be explained by the fact that the relevance of individual ATPs are fundamentally derived from their presence or absence in each of the sample firms up to the measurement year, and hence varies over time. Moreover, ATPs merely represent firm characteristics, and not all firm characteristics can necessarily be treated as systematic risk factors (Pukthuanthong, Roll, and Subrahmanyam, 2018).

Our index construction methodology primarily relies on the Sharpe's (1992) technique, commonly identified as returns-based style analysis. Its initial application was to identify asset allocation weights to construct mutual fund portfolios that maximize their returns. We apply a slightly modified algorithm using similar constrained regressions to identify governance factor weights on individual firms' returns. Our model reflects the restrictive ability of ATPs on shareholders' wealth, with an additional constraint capturing the negative relationship between the number of existing governance provisions within the firm and its raw returns. While the relationship of governance indices with stock returns has disappeared (Bebchuk, Cohen, and Wang, 2013), the impact of individual ATPs on returns remains (Cuñat, Gine, and Guadalupe, 2012).

By applying the modified Sharpe's (1992) methodology, we aim to capture each of the ATPs' influences on the stock returns, and then use this information to construct a more precise and informed aggregate index. In other words, the idea is to show that weights extracted from "past realized returns" have important information about individual governance provisions that can help us identify a monotonic contemporaneous relationship between governance and performance.

As an alternative, we employ a methodology that considers a slightly different variable selection approach in place of weight identification/extraction. But, importantly, variable selection algorithm in our application can also be viewed as a weight extraction tool with the ATP weights restricted to 0s (exclusions) and 1s (inclusions) in the index construction. Thus, we check if a machine learning algorithm can identify important ATPs that are cross-sectional predictors of stock returns. More specifically, we apply Least Absolute Shrinkage and Selection Operator (LASSO) technique (Tibshirani, 1996) on the same regression model that we constrain with an economic condition using Sharpe's (1992) technique. Chinco, Clark-Joseph, and Ye (2019) state that while "LASSO uses a statistical rule rather than economic intuition to identify predictors, the predictors it identifies are nevertheless associated with economically meaningful events" when it comes to returns. We aim to test if this is true for ATPs by extracting the relevant subset of ATPs that can predict stock returns and then using them to measure corporate governance. We also considered a partial least square (PLS) framework to identify important ATPs using returns as instruments in a three-pass regression filter (3PRF) using an approach similar to that used in Huang et al. (2015). However, extracting relevant ATPs using their covariance with stock returns does not allow for identifying dynamic weights since one of the passes in 3PRF is aimed at capturing time-series variation. For this reason, we focus only on LASSO estimation as an alternative to baseline identification using Sharpe's (1992) methodology.

After applying the two main approaches, we compare them on the basis of their out-of-sample predictive power. Accordingly, the weight extraction or ATP selection that results in best predictability for out-of-sample returns, is selected to measure corporate governance as a linear combination of the identified ATPs.

3.4.2.1 Baseline Methodology to Extract Index Weights

A similar returns-based model for extracting factor weights using constrained regressions is popular in the asset pricing literature (Heston and Rouwenhorst, 1994; Bekaert, Hodrick, and Zhang, 2009) and comes with several additional advantages.[31] First, assuming efficient markets, stock returns are least subject to endogeneity problems, unlike other outcomes of governance provisions. Second, data on stock returns is available with much higher frequency than accounting-based measures like ROA, ROE, or Tobin's Q are, allowing us to capture more variations. Third, causal estimates were established for contemporaneous returns in relation to individual governance provisions in recent years (for short event-windows) in Cuñat, Gine, and Guadalupe (2012). Finally, having a model that is structurally similar to the one used in Sharpe's (1992) provides us with plausible tools to assess the fit of this model for our purpose.

Unlike regular OLS regressions, a linearly constrained least squares (CLS) combines one or more linearity constraints within the least square problem. The same OLS objective remains – to minimize the error sum of squares –

[31] In an unreported analysis, we additionally test the robustness of our factor weights by considering other accounting-based performance measures to extract weights in place of returns. Over 75% of weights that accounted for the 5 most relevant provisions in our returns-based model remained the same, even in an ROA-based model. We found similar outcomes with Tobin's Q.

but with an additional condition imposed on some or all of the independent variables. The main purpose of using constrained regression is to account for coexisting provisions that results in biased coefficient estimates (due to multicollinearity), especially since our main factor variables are binary. In our sample, multiple ATPs have very high and statistically significant correlations of up to 0.48. With constrained regression that sets the sum total of coefficients to a constant, we are able to marginally correct for this bias (see Appendix 3.A.5 for details).

Factor models are common in investment theory and in asset pricing models, with the following general form:

$$\tilde{R}_i = \sum_{j=1}^{n} \lambda_{ij} F_j + \varepsilon_i, \tag{3.1}$$

where λ_{ij} represents the sensitivities of each factor j to the returns on an asset i. For asset pricing, the fundamental assumption that the factors are uncorrelated with the error term ε_i follows by definition. The Sharpe's (1992) asset allocation problem was a special case of the generic factor model, with each factor representing the individual asset's returns and the factor sensitivities λ constrained to sum to 1 (i.e., 100%).[32] However, when considering governance factors or provisions, it is important to control for all other omitted variables that may be separate from the error term as a direct influence on returns. Accordingly, we include essential controls such as firm size, book-to-market ratio, growth rate, liquidity, past price, and past returns.[33] Additionally, we assume

[32] Sharpe's model was based on the underlying assumption that asset allocation explains most of the variations in any well-diversified investment portfolio. With the sensitivities constrained to 100%, the measured component (for factors or assets) represents a style attribute and the error component forms the selection attribute.

[33] These controls are largely similar to those in the Fama-MacBeth return regressions in Gompers, Ishii, and Metrick (2003) that considers controls from Brennan, Chordia, and Subrahmanyam (1998), Shleifer and Vishny (1994), and Morck and Yang (2001).

that the error terms for each firm are uncorrelated with the other error terms (i.e., $\rho(\varepsilon_i, \varepsilon_j) = 0$). As a modified model to extract factor weights based on Equation 3.1, we use the following model:

$$log\widetilde{R_i} = \sum_{j=1}^{n} \lambda_{ij} F_j + \sum_{k=1}^{m} \gamma_{ik} X_{ik} + \varepsilon_i, \tag{3.2}$$

where λ_{ij} represents the sensitivities of each provision (or factor F) to the firm's returns, X are the controls with corresponding sensitivities γ, and the error is ε. The monthly returns for each stock i is given by $log\widetilde{R_i}$ (log returns). We assume that the individual factors are uncorrelated with the controls and the error term (although the index created from these factors would eventually have correlations with other firm characteristics that we include as controls X). Thus, the first component in this model expectedly measures the governance attribute, the second component controls for the firm characteristics, and the error term captures all unobservables that are uncorrelated with the first two components.

Since we define the absence of ATPs as 1 to maintain consistency with the approaches in prior literature, such as Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009), we expect a negative relationship between the overall governance attribute (first component) and the contemporaneous returns. In other words, firms with poor governance practices (having *more* ATPs) should perform poorly on stock markets in terms of realized returns (Cuñat, Gine, and Guadalupe, 2012, 2016). Accordingly, the constraint is that the factor weights (or sensitivities λ) sum to -1. That is:

$$\sum_{j=1}^{n} \lambda_j = -1. \tag{3.3}$$

This constraint requires a cautious interpretation. We do not assume that the log returns move linearly with the governance measure. Depending on the individual factor weights, the presence or absence of the provision would drive the stock returns down by the margin identified by the constrained regression coefficients. Thus, here, we only presume the sign of this relationship based on the restrictive abilities of the ATPs with respect to shareholder rights, and backed by empirical evidences available in the literature. The sum weight of 1 for factors ensures that the total weights do not exceed 100% and are distributed as per their contribution to the contemporaneous returns–governance relationship.[34] One could argue that if a poorly governed firm has all 19 ATPs in place, and drops all of them to become an extremely well-governed firm the very next month, our measurement would imply an increase of 100% in the stock returns. In practice, however, this extreme condition is impossible to verify, as such large-scale changes in governance provisions do not occur. Moreover, in any constrained regression, the overall objective remains the same as in the OLS, that is, to minimize squared deviations, with an additional constraint applied on the coefficients. This means that changing the magnitude of the constraint would not really change the relative measures of the coefficients.[35]

For constrained regressions, we can assess the model fit and the strength of the applied constraint or restriction by comparing the two root mean squared error (RMSE) values, that is, with and without the constraint (Bekaert, Hodrick, and Zhang, 2009). If the RMSE shows only a marginal change with the application of constraint, then the constrained regression fits the data as well

[34] The exact dates for each annual meeting are available in the governance data, which is updated in the beginning of each year for the provisions applied in the previous year. For ease of constructing the index, however, we consider the provisions as stable through the calendar year without accounting for the meeting dates. Accordingly, for a given year, the logged monthly returns we obtained from CRSP are regressed on the governance data observed during that calendar year.

[35] For example, using "-2" or "-3," or even "-1/2" as the constraint instead of "-1" would merely change the magnitude of the coefficients, but not their relative weights, that is, make the coefficients either twice, thrice, or half of their respective values obtained using "-1" as a constraint.

as the unconstrained regression.[36]

We present the coefficients of the unconstrained and constrained regressions in Table 3.3. The last two columns show the coefficients for the complete dataset. We see that applying our constraint on the contemporaneous returns–governance provisions regression only marginally increases the RMSE from 0.107 to 0.119. This increase of 11% in the RMSE is very low compared to the change in RMSE with other possible restrictions or constraints. Every year, we run regressions inclusive of all past governance and returns information available up to that year. This serves two purposes. First, it ensures richness in the data as we move ahead in time to provide a better picture of the relationship between each of the governance provisions and returns. This is essential for our purpose of weight extraction because our criterion is to choose weights in accordance with each of the provisions' importance and relevance as a contributor to shareholders' wealth. Second, it enables us to trace the evolution of each provision's contribution to our proposed nG-Index.

For each year, at least 15 of the 19 provisions remain statistically significant contributors to returns. Through 2007 to 2015, while some of the provisions lost importance as contributors to returns, others gained prominence. For this reason, it is important to continue using all available provisions data when using such unequal-weighted indices. Though one of the provisions, i.e. supermajority requirement to amend the charter, does not show a significant relationship with returns until 2014, it eventually shows some effect on returns in 2015, albeit with a positive coefficient. Beyond 2009, the provision for golden parachutes becomes statistically irrelevant. Singh and Harianto (1989) show

[36] In an asset allocation case, the asset classes contribute significantly to portfolio returns (translating into large a R^2 value), especially for well-diversified portfolios. However, with the governance factor weights, the R^2 values are comparatively lower, as there are many additional unobservable firm characteristics (that directly or indirectly affect the firm's raw returns); in other words, the explanatory power of the model is not very high.

Table 3.3 Constrained and unconstrained regressions

This table presents the coefficients of all 19 provisions obtained using the regression in Equation 3.2 constrained by Equation 3.3 for each year. The unconstrained regression coefficients are presented for the full sample inclusive of firms in 2015 in the last column. The dependent variable is stock returns (in log) for month 't,' while all 19 provisions are independent variables. The standard controls include volume, past returns, size, value, and others, as shown in Appendix 3.A.3. Standard errors are given in parenthesis with the significance levels at 10%, 5%, and 1% indicated using * , **, and ***, respectively.

	Constrained Coefficients									Unconstrained
Provisions	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2015**
Golden parachutes	-0.0083**	-0.0089***	-0.0047**	0.0013	-0.0006	0.0010	-0.0001	-0.0011	-0.0011	0.0102***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fair price	-0.0254***	-0.0226***	-0.0160***	-0.0149***	-0.0135***	-0.0122***	-0.0134***	-0.0134***	-0.0138***	-0.0026*
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Resignation Req.	-0.0000***	-0.0253***	-0.0163***	-0.0117***	-0.0138***	-0.0126***	-0.0138***	-0.0145***	-0.0135***	-0.0009
	(0.000)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unequal Voting	-0.6332***	-0.5859***	-0.5836***	-0.5692***	-0.5502***	-0.5782***	-0.4950***	-0.4593***	-0.4655***	0.0015
	(0.012)	(0.012)	(0.010)	(0.009)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)
No secret voting	-0.0223***	-0.0189***	-0.0122***	-0.0127***	-0.0141***	-0.0119***	-0.0158***	-0.0184***	-0.0180***	0.0053***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
No cumulative voting	-0.0364***	-0.0350***	-0.0398***	-0.0405***	-0.0425***	-0.0372***	-0.0415***	-0.0441***	-0.0429***	-0.0026
	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Staggered Board	0.0013	0.0065**	0.0068**	0.0071***	0.0077***	0.0059***	0.0036**	0.0028**	0.0028**	0.0012
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SM - Merger	-0.0330***	-0.0357***	-0.0278***	-0.0244***	-0.0144***	-0.0135***	-0.0185***	-0.0173***	-0.0147***	-0.0033***
	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SM - Consent	-0.0070*	-0.0088**	-0.0167***	-0.0183***	-0.0167***	-0.0142***	-0.0146***	-0.0143***	-0.0138***	-0.0011
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
SM - Sp. Meeting	-0.0539***	-0.0669***	-0.0754***	-0.0862***	-0.0949***	-0.0919***	-0.1138***	-0.1217***	-0.1200***	0.0028
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
SM - Bylaws	-0.0174***	-0.0137***	-0.0140***	-0.0140***	-0.0141***	-0.0127***	-0.0134***	-0.0141***	-0.0152***	-0.0016
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
SM - Charter	-0.0009	-0.0004	0.0008	0.0002	0.0005	0.0008	0.0011	0.0009	0.0021*	-0.0000
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Poison Pill	-0.0026	-0.0020	-0.0033	-0.0079***	-0.0081***	-0.0085***	-0.0102***	-0.0114***	-0.0110***	0.0019*
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sp. Meetings	-0.0659***	-0.0724***	-0.0834***	-0.0936***	-0.1005***	-0.0967***	-0.1184***	-0.1265***	-0.1247***	0.0003
	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Written Consent	-0.0196***	-0.0137***	-0.0188***	-0.0217***	-0.0226***	-0.0199***	-0.0212***	-0.0209***	-0.0206***	-0.0019*
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Bylaws	-0.0145***	-0.0268***	-0.0280***	-0.0291***	-0.0310***	-0.0297***	-0.0344***	-0.0355***	-0.0356***	-0.0014
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
No Blank Check	-0.0423***	-0.0452***	-0.0449***	-0.0435***	-0.0461***	-0.0421***	-0.0446***	-0.0454***	-0.0443***	-0.0048**
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Opt Outs	-0.0000***	-0.0077**	-0.0053**	-0.0032*	-0.0054**	-0.0084***	-0.0154***	-0.0201***	-0.0217***	0.0002
	(0.000)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Charter	-0.0186***	-0.0165***	-0.0172***	-0.0179***	-0.0197***	-0.0183***	-0.0208***	-0.0258***	-0.0285***	0.0024
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
No. of observations	6728	13524	19496	25330	34274	42431	49478	58059	65547	65547
Adj. R-squared										0.051
RMSE	0.101	0.143	0.148	0.142	0.135	0.128	0.124	0.121	0.119	0.107

that firms adopting golden parachutes experience greater takeover threats than the firms that do not. Similarly, Bebchuk, Cohen, and Wang (2014) show that until 2006, firms that adopted golden parachutes showed negative abnormal returns. Our results indicate that beyond 2009, this trend disappeared. Examining the incidence of this provision in our sample (Table 3.1) shows that beyond 2009, few proposals on golden parachutes were adopted and the numbers remain stable over the years. Whereas the diffusion of golden parachutes was fast over the previous years, making it a red flag for investors, investors began to accept them as a neutral governance mechanism in recent years (for details on the diffusion process of golden parachute agreements, see Fiss, Kennedy, and Davis, 2012).

In contrast, we see that poison pills show an opposite trend. They remain irrelevant to shareholder returns until 2009, but become statistically significant in the subsequent years. This trend is important to discuss because poison pill is one of the six most significant provisions of the 24 G-Index provisions when Bebchuk, Cohen, and Ferrell (2009) proposed the E-index. While the G and E indices included poison pills as an important constituent of corporate governance measures, the unequally weighted methodology applied here shows that its importance does not remain constant over time, with instances where the provision is statistically insignificant as a contributor to returns and, in turn, the corporate governance measure. Another important finding in Table 3.3 is with respect to the staggered board provision, which shows a consistently positive effect on stock returns. Bebchuk and Cohen (2005) show that staggered boards have a negative effect on firm value. Additionally, as it is for poison pill, the E-index treats the presence of staggered boards as an indicator of low governance quality. While staggered boards may have a negative effect on firm value, as the literature suggests, there has been very little or no evidence of it impacting stock returns.[37] We show that staggered board tends to show a positive effect on stock returns in recent years. One possible explanation for investors benefiting from this antitakeover provision could be based on the findings in Guo, Kruse, and Nohel (2008) showing that the de-staggering of boards provides immediate returns (within three days), but this effect wanes in the subsequent period. Essentially, staggered boards destroy shareholder value on their adoption, but as investors realize with time that the threat of takeover is low, it turns beneficial. Additionally, our aim here is to assess whether staggered board is a significant indicator of corporate governance or not, and we find that it is indeed significant over our sample period.

Several governance mechanisms represented in our data have multiple indicators. This allows us to assess if the assigned weights are actually relevant and practical. For instance, special meetings and written consent provisions both have an additional indicator of supermajority requirements. With most governance aspects captured by these provisions themselves, the additional supermajority indicators should have a considerable yet marginal governance effect, and thus show relatively lower coefficients. We see that this is indeed true for all such provisions.

On the whole, we see that the coefficient weights for factors from constrained regressions are a good representation of each provision's contribution to corporate governance. We also find that the relative importance of provisions, which previous index construction methodologies ignore, can be important when measuring the real impact of governance characteristics.

[37] Bebchuk, Coates IV, and Subramanian (2002) show that shareholder returns were reduced by 8-10% during 1996 to 2000, when the target firms being acquired had "effective" staggered boards. In our study, we merely consider the presence of staggered board provisions.

3.4.2.2 Alternative Methodology

In our LASSO application for ATP selection, we use Equation 3.2 to minimize the following function:

$$\sum_{i=1}^{N}\left(log\widetilde{R_i}-\sum_{j=1}^{n}\lambda_{ij}F_{ij}-\sum_{k=1}^{m}\gamma_{ik}X_{ik}\right)^2+\Lambda_1\left(\sum_{j=1}^{n}|\lambda_{ij}|+\sum_{k=1}^{m}|\gamma_{ik}|\right). \quad (3.4)$$

The terms associated with Λ_1 represent our LASSO-penalty for the OLS estimation captured by the first term.[38] Thus, the LASSO technique here essentially selects a subset of ATPs (F_{ij}) that explains the returns best in comparison to a full model that includes all the 19 ATPs.

Commonly, variable selection can be done one variable at a time using stepwise regression. However, employing an advanced variable selection technique such as the LASSO comes with several advantages. First, LASSO is effective in identifying the relative importance of predictors or factors to omit irrelevant variables. Second, LASSO is specifically designed to maximize in-sample predictive ability. Third, it can be customized to use up-to-date information for every year, so that dynamic selection is applied for ATPs. Fourth, LASSO estimation works even in the presence of multicollinearity. Last, it requires fewer iterations and, hence, is faster when there are many variables to choose from.

In Table 3.4, we report the ATPs selected from LASSO estimations in each year of our sample period when all 19 ATPs are included as predictors of returns using Equation 3.2. All the controls X are the same as those used in the baseline methodology shown in the Section 3.4.2.1. For each year, we introduce all prior sample years data along with the estimation year. The LASSO-selected

[38] With only 19 ATPs to select from, alternative algorithms such as ridge regression or elastic net estimation showed similar results as LASSO.

Table 3.4 LASSO estimations

This table presents the summary of ATPs that are selected when LASSO estimations are used on Equation 3.2 for each year. The dependent variable is stock returns (in log) for month 't,' while all 19 provisions are independent variables along with standard controls including volume, past returns, size, value, and others, as shown in Appendix 3.A.3. For each year, the estimations consider all data available up to the focal year to provide dynamic ATP selection. In-sample R-squared values for the selected model that minimizes Extended Bayesian Information Criterion (EBIC) are also provided.

Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Golden parachutes			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fair price	Yes					Yes		Yes	Yes
Resignation Req.		Yes	Yes		Yes	Yes	Yes	Yes	Yes
Unequal Voting				Yes	Yes	Yes	Yes		
No secret voting			Yes	Yes	Yes	Yes	Yes	Yes	Yes
No cumulative voting				Yes	Yes	Yes		Yes	
Staggered Board					Yes	Yes			
SM - Merger			Yes	Yes	Yes	Yes	Yes	Yes	Yes
SM - Consent									
SM - Sp. Meeting	Yes		Yes			Yes	Yes	Yes	Yes
SM - Bylaws									
SM - Charter					Yes	Yes			
Poison Pill		Yes	Yes		Yes	Yes			Yes
Sp. Meetings									
Written Consent	Yes				Yes	Yes			
Bylaws	Yes								
No Blank Check					Yes	Yes	Yes	Yes	Yes
Opt Outs									
Charter				Yes	Yes	Yes	Yes	Yes	Yes
In-sample R-squared	0.069	0.072	0.062	0.061	0.053	0.054	0.056	0.054	0.053

ATPs subset varies over time confirming the results from Table 3.3, that the explanatory power of each of the ATPs toward returns are not constant. With LASSO, the number of selected ATPs varies from as few as 2 in 2008 to as many as 14 in 2012.

The in-sample R-squared values across the sample for LASSO-selected ATPs remain comparable to those obtained using OLS regressions. For example, the R-squared for the year 2015 is the same as that shown for unconstrained regression (or OLS) in Table 3.3. Moreover. when we compare the out-of-sample predictive power of LASSO selected ATPs to the weights identified with Sharpe's (1992) method, we find that LASSO underperforms consistently across the years. Thus, we employ the weights identified from constrained regression in Table 3.3 to construct the unequal-weighted governance index.

3.4.3 The Two Indices for Comparison

3.4.3.1 The New Governance Index

The new governance (nG) index is a simple weighted sum of individual provisions coded as 1 for each provision that empowers managers and limits shareholders' say, and 0 if the provision is absent. Similar coding for presence/ absence of ATPs were used to construct the G and E indices (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009). Some provisions, such as those measuring supermajority requirements for certain firm decisions, were specifically designed from the available data to capture poor governance mechanisms (see Appendix 3.A.1 for more details). The weights attached to each of the 19 factors were extracted using the methodology explained in previous section. For every year, we determined the weights based on the data available up to that specific year. This was essential to avoid recency bias and to ensure that the index captures the essence of each provision's evolution with time. Using all available data to construct the index also ensured richness in the data and reduced the effects of survivorship bias. The index composition for each firm j in year t can be summarized as:

$$nG_{j,t} = |\sum_{i=1}^{19} w_{i_t} F_{i_{j,t}}|, \tag{3.5}$$

where $nG_{j,t}$ is the new governance (nG) index for firm j in year t, w_{i_t} is the individual factor i's weight for each year t, and we define $F_{i_{j,t}} \in \{0, 1\}$ as above for each provision factor. We set the weights $w_{i_t} = \lambda_{i_t}$ for all factors except $w_{i_t} = 0$ when the factors were statistically insignificant (at $\alpha = 0.10$)

Table 3.5 Annual summary statistics for the new Governance (nG) Index

This table shows the summary statistics for the new governance (nG) index over time. The nG-Index is computed using the 19 provisions in Table 3.1 using the method detailed in Section 3.4.2.1. The index values presented here are in percentages for ease of interpretation. Higher values for the nG-Index indicates lower governance quality, and vice versa. The last row provides the summary statistics for the entire sample. Firms with dual class stocks are excluded.

Year	Number of Firms	Mean	Standard Deviation	Minimum	5th percentile	Median	95th percentile	Maximum
2007	1020	24.38	5.53	10.00	18.21	24.55	28.88	96.41
2008	1071	27.63	5.58	12.48	21.53	27.54	32.34	95.84
2009	1113	26.31	5.35	13.99	20.55	26.06	31.67	94.83
2010	1161	28.35	5.30	14.37	23.36	28.19	32.09	97.55
2011	1164	29.01	5.19	17.99	24.04	28.52	33.50	97.23
2012	1187	26.57	3.63	17.07	22.22	26.45	30.27	82.82
2013	1202	31.28	6.53	19.54	26.12	30.55	35.37	95.77
2014	1236	33.25	5.88	22.32	28.04	32.67	37.66	95.20
2015	1036	32.63	4.70	22.09	28.22	32.34	36.69	93.64
Total	10190	28.90	6.06	10.00	22.07	28.52	35.68	97.55

in the constrained regressions.[39] Our examination of the statistically insignificant coefficients revealed that most had very low and sometimes negligible magnitudes, which again backed our assumption that these provisions were irrelevant for that year in differentiating a well governed firm from a poorly governed one. As a robustness check, we also created indices for each year by including all weights, regardless of their statistical significance ($w_{i_t} = \lambda_{i_t}$ for all factors) and found that it had a very high correlation ($\rho = 0.9768$) with our index, showing that omitting certain irrelevant factors from the index for specific years does not lead to any significant loss of information.

The constructed index, thereby represents the degree to which management is able to restrict shareholders' rights by ensuring the existence of ATPs within

[39] This is not a mere heuristic approximation. With the factors beings statistically insignificant, we cannot reject the hypothesis that their weights are 0. Hence, the rule applies.

these firms. Table 3.5 summarizes the key characteristics of our governance index. The true nG-Index scores are on a scale of 0 to 1, with 0 characterizing the lack of ATPs or better governance quality (the G and E indices have a similar scale of 0 for good governance to higher values for poor governance). We see that, on average, the governance quality of firms in our sample worsened over the years. We see the same from the minimum scores seen for each year as well. However, the highest degree of bad governance for each year shows no such monotonic trend. For most, the mean scores lie on the right side of the median scores, showing that the governance ratings using the nG-Index generally have a positively skewed distribution. We also provide the 5th and 95th percentile scores because this formed the criteria to identify good and poor governance portfolios when examining abnormal returns.

3.4.3.2 The Modified Governance Index

To establish the advantages of an unequal-weighted index over an equal-weighted index and to demonstrate its superior ability to track governance quality, we also created an index using the same 19 provisions by assigning them equal weights of 1; that is, setting $w_{i_t} = 1$ in the right-hand-side of Equation 3.5. We do this to stay consistent with the method followed in prior literature to compose the G-Index, E-Index, Gov-Score, and so on. Since most of the available provisions are similar to those used in the G-Index, albeit smaller in number, we refer to this index as the modified Governance (mG) index.

$$mG_{j,t} = \sum_{i=1}^{19} F_{i_{j,t}}, \tag{3.6}$$

where Fs are the individual factors or provisions explained before. We use the exact same factor codings as those for the nG-Index. Most of the key characteristics of mG are similar to those observed for nG in Table 3.5, but on a different scale of 0 to 19.

3.4.4 Relationship Between the New and Old Indices

We used the mG-Index as a close proxy for the G-Index and additionally created a similar close proxy for the E-Index using the currently available set of ATPs. Table 3.A.1 of the Appendix reports the correlations amongst these indices. The corresponding proxies for the two existing indices (G-Index and E-Index) have a correlation of 0.72, which is similar to that reported in Bebchuk, Cohen, and Ferrell (2009). However, the nG-Index has a statistically significant correlation of 0.37 with the G-Index proxy and 0.13 with the E-Index. While this does show that the E-Index contributes considerably to the G-Index, it contributes significantly less to the unequally weighted index. This is understandably because the E-Index, by construction, consists of the most relevant elements from within the G-Index provisions, but at the expense of 75% of the remaining elements that also have a substantial and even higher correlation to the G-Index (Bebchuk, Cohen, and Ferrell, 2009). Moreover, these correlations also indicate the possibility that certain provisions in the E-Index may have become irrelevant within the new set of provisions for which data is collected and reported by ISS beyond 2007.

The nG-Index understandably retains a higher correlation with the G-Index than the E-Index proxy because it includes all of the available ATPs. The low correlation of 0.37 between the equally and unequally weighted indices may also indicate a considerable amount of information loss when the relative importance of individual provisions is ignored.

Since our first set of empirical tests focus on assessing the ability of the nG-Index as a measure of governance quality, in the next section, we draw comparisons between the nG and mG indices and make a case for nG-Index. Subsequently, we examine the abnormal returns' relationship with the investment portfolios created using the nG-Index to assess investor returns from a governance-based hedge.

3.5 Corporate Governance–Performance Relationship

We study the relationship between corporate governance and various performance measures using both the nG- and mG-Index to then compare the results and examine their respective explanatory powers. For testing the nG-Index's association with the firm values and operating performances, we use out-of-sample construction of the index (i.e. replacing w_{i_t} by $w_{i_{t-1}}$ in Equation 3.5) to ensure that the results are free from in-sample bias. The in-sample problem for these performance measures can be summarized as follows. If current ATPs are included as a determinant of returns to obtain the factor weights, these weights will be correlated with current returns and hence should essentially be related to firm values and operating performances. This may result in overfitting that drives the statistical significance for the nG- against the equally weighted mG-Index. The said problem is not existent when we study the abnormal returns from governance portfolios, because these portfolios are constructed by sorting the sample firms using last year's nG-Index values.

3.5.1 Firm Value and Corporate Governance

Most studies investigating the governance–firm value association use Tobin's Q as the proxy for firm value.[40] Therefore, for ease of comparison between our results and those in the prior corporate governance literature, we study the effect of corporate governance on firm value by using Tobin's Q as the dependent variable. We account for industry-wide variations in firm value

[40] In relation to aggregated governance indices as well as specific governance characteristics such as board diversity (Carter, Simkins, and Simpson, 2003), board size (Eisenberg, Sundgren, and Wells, 1998), executive compensation (Mehran, 1995), and ownership structures (Cho, 1998).

by generating an industry-adjusted Tobin's Q with respect to the industry median values. The industry-adjusted Tobin's Q based on mean was also explored, but the median-based industry-adjusted Tobin's Q was preferred, as Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) suggest. The model specifications for the Tobin's Q on corporate governance regressions were variations of the following baseline model:

$$Q_{j,t} = a_1 + b_1 * G_{j,t} + c_1 * X_{j,t} + \epsilon_{j,t}, \tag{3.7}$$

where $Q_{j,t}$ is Tobin's Q (in all cases, industry-adjusted using the industry-median Tobin's Q) for firm j in year t, and $X_{j,t}$ are the corresponding firm-based controls. $G_{i,t}$ is either the nG scores or mG scores for firm j in a given year. Standard controls identified from prior literature included size (firm's assets), Altman's Z-scores (measuring financial distress; see Altman, 1968), volume of shares traded (a proxy for liquidity), leverage, capital expenditures/total assets ratio (CAPEXTA), and a Delaware incorporation dummy. Many studies use these controls in examining the corporate governance–firm value association (such as Bhagat and Bolton, 2008, 2009; Bebchuk, Cohen, and Ferrell, 2009). Bhagat and Bolton (2008) use Altman's Z-scores as an instrumental variable to control for endogeneity. However, many recent studies indicate a direct relationship between financial distress as measured by Altman's Z-score and the firm value or Tobin's Q (Güner, Malmendier, and Tate, 2008; Allayannis, Lel, and Miller, 2012). For this reason, we introduce Altman Z-score as a control for financial distress in our specification. We also reviewed each of these controls from the literature to identify the expected sign of their relationships with Tobin's Q. We included firm assets, volume traded, and CAPEXTA in the models using logarithmic transformations, as these variables were positively skewed with long tails.

The governance index literature suggests multiple variations of Equation 3.7.

However, there is an overall agreement that a classic OLS is not sufficient. Thus, we look at two variants of this regression equation. First, as Gompers, Ishii, and Metrick (2003) suggest, we use a variant of Fama and MacBeth (1973) method by assessing the statistical significance of cross-sectional regressions for each year and across years. Second, since the nG scores vary with both time and year, we examine the Tobin's Q and governance relationship by running a fixed effects (FE) panel regression to control for unobserved firm heterogeneity (Bebchuk, Cohen, and Ferrell, 2009). However, on a cautionary note, within-firm governance characteristics change very little over time, and thus the FE estimates may be attenuated if they mostly capture time-series variations (Gompers, Ishii, and Metrick, 2003). So, to account for time-trends, we include additional year dummies in the FE model and isolate only the effect of changes in the governance score (nG or mG) on Tobin's Q.

Table 3.6 summarizes the outcomes for the first variation of the Tobin's Q regressions (i.e., annual estimates). We see a significant relationship between both nG and mG with Tobin's Q when we consider the time-series averages (last row). However, a closer examination of the annual cross-sectional regressions show the superiority of nG over mG. The unequally weighted nG has statistically significant coefficients (at $p<0.10$) for more years in the sample period than the equally weighted mG does. We consider two alternative models to check these annual regression estimates: first, Model 1 in Table 3.6 considers only the four controls used in Gompers, Ishii, and Metrick (2003); second, Model 2 includes additional controls as Bebchuk, Cohen, and Ferrell (2009) and Bhagat and Bolton (2008) suggest. Comparing the adjusted R-squared for both index measures shows no considerable difference in their explanatory powers. However, with more controls in the regression (Model 2), five of the nine years for nG show statistical significance, while we see the same for mG in only one of the years. Overall, we see here that better governance (lower

Table 3.6 Annual regressions for Tobin's Q on governance

This table shows the results obtained by running regressions of Tobin's Q on the new Governance (nG) and modified Governance (mG) indices for each year in our sample. Model 1 considers Tobin's Q with the two indices using only the four controls in Gompers, Ishii, and Metrick (2003), i.e., log of assets, log of firm age, Delaware dummy, and S&P500 dummy. Model 2 extends Model 1 by additionally controlling for ROA, Altman's Z, leverage, and log of capital expenditures. For details on the definition of each variable, see Appendix 3.A.2. All regressions use industry-adjusted Tobin's Q calculated as Tobin's Q minus the median Tobin's Q for that industry (segregated using Fama and French (1997) 48 industry classification). For each year, the corresponding coefficients and robust standard errors from cross-sectional regressions are reported accordingly. The time-series coefficients and standard errors (using Fama and MacBeth, 1973 methodology) are given at the bottom of the table. The coefficients for constant and controls are left out. Significance levels are represented by *, **, and *** for 10%, 5%, and 1%, respectively.

Year	Number of Observations	(1)		(2)	
		nG-Index	mG-Index	nG-Index	mG-Index
2007	1001	-0.8959**	-0.0319*	-0.4772	-0.0073
		(0.392)	(0.017)	(0.371)	(0.014)
2008	1050	-0.8080**	-0.0179	-0.6150*	-0.0044
		(0.384)	(0.013)	(0.373)	(0.012)
2009	1092	-1.3295***	-0.0373**	-0.9159**	-0.0197
		(0.403)	(0.013)	(0.339)	(0.012)
2010	1137	-0.9954**	-0.0299**	-0.5314	-0.0055
		(0.445)	(0.015)	(0.357)	(0.017)
2011	1140	-1.1504**	-0.0364**	-0.7414**	-0.0051
		(0.503)	(0.015)	(0.352)	(0.013)
2012	1161	-1.5539*	-0.0439**	-0.6706	-0.0178
		(0.822)	(0.015)	(0.573)	(0.013)
2013	1176	-1.2348**	-0.0633**	-0.5816*	-0.0211
		(0.411)	(0.019)	(0.353)	(0.016)
2014	1207	-1.4874**	-0.0645**	-1.3352**	-0.0524**
		(0.524)	(0.022)	(0.564)	(0.025)
2015	1026	-1.1441*	-0.0475**	-0.7451	-0.0352
		(0.614)	(0.024)	(0.508)	(0.023)
Mean	9388	-1.1777***	-0.0414***	-0.7348***	-0.1872***
		(0.085)	(0.005)	(0.087)	(0.005)

nG scores) is associated with higher firm values (Q). The last row in Table 3.6 shows that a 100% decline in the nG score (i.e., from 1 to 0) will result in approximately 0.74 units increase in firm value measured by Tobin's Q. In contrast, every 1 unit decline in mG score (on a scale of 0 to 19), increases Tobin's Q by 0.19 units. For comparison, we transformed the units for mG into same scale as for nG and find that a 100% decrease in the mG score (i.e., from 19 to 0) increases the firm value measure Tobin's Q by only 0.35 units.[41] Since the presence of measurement error in the independent variable can lead to biased estimates, the lower impact on Q indicates the downward bias in these results, which the fact that individual cross-sectional regressions for each year had mostly insignificant coefficients for mG also confirms.

With the nG-Index being a better indicator of firms' governance quality than the mG-Index is, we expect more consistency for its coefficients in the annual Tobin's Q regressions. Our findings confirm that the nG-Index indeed consistently shows that good governance is significantly related with superior firm value in both time-series and cross-sectional models. This is not the case with the mG-Index, which has a significant coefficient only for the time-series average.

Regardless of the results above, there is still a chance that the mG-Index is equally as good as the nG-Index is in measuring governance quality, if not better. Although the observations in the sample were *exactly the same* in both cases, the effect of firm characteristics on the two measures are *different* because many firm characteristics are controlled in creating the nG-Index (in the constrained regressions), which is not the case with mG. This leaves a possibility that these firm characteristics interact with the error term and distort our

[41] We did this by creating a new variable, calculated as $[mG_1 = (19 - mG)/19]$ to normalize to the same scale as nG scores, and then running the Fama-MacBeth variant of the Q on the governance regression in Equation 3.7.

results. To tackle this, we considered the next variation of regressions using the firm FE model. Table 3.7 reports the results from these regressions for both indices.

We essentially see a similar pattern as that from the annual regressions. Good governance firms (with lower nG scores) perform significantly better than those with poor governance quality (i.e., high nG scores) do. However, when we consider firm fixed effects, only the nG-Index shows a statistically significant relationship between governance and firm value. The alternative mG-Index shows no statistically significant relationship between good governance and firm value, with the coefficient's sign (+) being opposite to our expectation (–). The model fits, as the R-squared values indicate, because all nG regressions are marginally better than those seen for the mG-Index. These results enforce our inferences from Table 3.6 that the nG-Index, being a better indicator of governance quality, shows a more persistent relationship with firm value (i.e., Tobin's Q) than the mG-Index does.

As Section 3.3.4 explains, we further analyze the relationship between the two indices and Tobin's Q using a dynamic system GMM as a preliminary control for endogeneity. We first assessed if past firm values affect the current firm value. Models 4 and 5 in Table 3.7 show the results. This is important to understand whether we can indeed use past firm values as instruments for present governance structures. Subsequently, we drop the recent two lags and include the next two lags to capture the dynamism between governance and firm value in the panel GMM estimator. Wintoki, Linck, and Netter (2012) show that such instruments are exogenous and that including two lags is sufficient for governance–performance relationships. Model 6 reports the system GMM estimation. Similar to the assumption in Wintoki, Linck, and Netter (2012), we consider all regressors besides the year dummies and firm age to be endogenous. The results show that even after accounting for simultaneity,

Table 3.7 OLS, panel, dynamic OLS and system GMM regressions for Tobin's Q on governance

This table shows the results obtained by running multiple regression models for Tobin's Q on the new Governance (nG) and modified Governance (mG) indices. Model 1 considers Tobin's Q with the two indices without any controls. Model 2 improves on Model 1 by including the additional controls shown in the table. Model 3 shows the results with firm fixed effects. Models 4 and 5 improve on the static OLS Models 1 and 2 by introducing past firm values for two and four years respectively, along with the industry fixed effects. Model 6 supplements Model 3 using system GMM. First set of columns (1 to 6) report the coefficients and robust standard errors when using the nG-Index, and the next set shows the results for the mG-Index. For details on nG and mG calculations, see Section 3.4.3. For calculations and details on rest of the variables, see Appendix 3.A.2. All regressions use industry-adjusted Tobin's Q calculated as Tobin's Q minus the industry-median Tobin's Q using the Fama and French (1997) 48 industry classification. The coefficients for constant and year / industry dummies are left out for brevity. Robust standard errors are given in parenthesis below the coefficients, while their significance at 10%, 5%, and 1% are shown by *, **, and *** respectively. Additional test results for the system GMM, including AR(1), AR(2) and Hansen tests, are shown in terms of p-value. The instruments include both the level and difference equations of all regressors lagged at $t-3$ and $t-4$.

	Static OLS		Panel FE	Dynamic OLS		System GMM	Static OLS		Panel FE	Dynamic OLS		System GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
nG (–)	**-1.0517*** (0.150)**	**-0.7742*** (0.142)**	**-0.3351** (0.149)**	**-0.1693** (0.086)**	**-0.1588* (0.089)**	**-4.9897* (3.045)**						
mG (–)							**-0.0297*** (0.005)**	**-0.0183** (0.006)**	**0.0107 (0.007)**	**-0.0065** (0.003)**	**-0.0063* (0.003)**	**-0.0098 (0.027)**
ROA		4.5149*** (0.597)	1.1247*** (0.124)	1.0807*** (0.270)	0.9959*** (0.256)	0.2050 (1.490)		4.6239*** (0.570)	1.3624*** (0.121)	1.1001*** (0.261)	0.9917*** (0.256)	1.7226 (1.250)
Size		-0.2071*** (0.015)	-0.3209*** (0.029)	-0.0682*** (0.008)	-0.0634*** (0.007)	0.1869 (0.143)		-0.2054*** (0.015)	-0.3567*** (0.027)	-0.0662*** (0.008)	-0.0648*** (0.008)	-0.0436 (0.089)
Age		-0.0944*** (0.016)	-0.2214*** (0.050)	0.0286*** (0.010)	0.0299*** (0.010)	-0.1433 (0.080)		-0.0935*** (0.015)	-0.2359*** (0.045)	0.0252*** (0.010)	0.0283*** (0.010)	-0.0110 (0.045)
Altman's Z		-0.0320** (0.016)	0.0824*** (0.017)	-0.0004 (0.009)	-0.0022 (0.009)	0.1977 (0.259)		-0.0373** (0.016)	0.0758*** (0.016)	-0.0019 (0.009)	-0.0020 (0.009)	-0.0422 (0.124)
Leverage		-0.9190*** (0.135)	-1.0972*** (0.087)	-0.2706*** (0.076)	-0.2432*** (0.076)	-0.2587 (0.515)		-0.9635*** (0.128)	-0.9584*** (0.081)	-0.3123*** (0.076)	-0.2435*** (0.076)	-0.3140 (0.352)
CAPEX / Assets		-0.0539*** (0.014)	0.0845*** (0.014)	-0.0088 (0.011)	-0.0094 (0.011)	-0.0698 (0.082)		-0.0564*** (0.014)	0.0797*** (0.014)	-0.0077 (0.010)	-0.0095 (0.011)	-0.0179 (0.059)
S&P500		0.5282*** (0.045)	0.3642*** (0.053)	0.1474*** (0.021)	0.1344*** (0.020)	-0.3893 (0.319)		0.5178*** (0.041)	0.3679*** (0.048)	0.1425*** (0.020)	0.1330*** (0.020)	-0.1083 (0.181)
Delaware Dummy		0.0082 (0.024)	-0.0687** (0.027)	-0.0062 (0.014)	-0.0050 (0.014)	-0.0287 (0.076)		0.0073 (0.022)	-0.0550** (0.027)	0.0023 (0.014)	-0.0070 (0.015)	0.0365 (0.063)
Tobin's Q (t–1)				0.7579*** (0.038)	0.7503*** (0.040)	0.1586 (0.224)				0.7457*** (0.035)	0.7505*** (0.040)	0.4932** (0.185)
Tobin's Q (t–2)				0.0075 (0.026)	-0.0491 (0.035)	0.2348 (0.147)				0.0100 (0.024)	-0.0494 (0.035)	0.0856 (0.100)
Tobin's Q (t–3)					0.1157*** (0.030)						0.1157*** (0.030)	
Tobin's Q (t–4)					-0.0285 (0.021)						-0.0286 (0.021)	
Year Effects	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm/Industry Fixed Effects	No	No	Firm	Industry	Industry	Firm	No	No	Firm	Industry	Industry	Firm
Number of observations	9170	8445	8445	9341	8132	8341	10190	9388	9388	9276	8132	9276
R-Squared	0.003	0.322	0.189	0.748	0.758		0.003	0.321	0.185	0.748	0.758	
Number of Groups			1472			1393			1472			1453
Number of Instruments						36						37
AR(1) / AR(2) Test (p-value)						0.503 / 0.019						0.061 / 0.052
Hansen J Test (p-value)						0.000						0.000

possible reverse causality, and unobservable heterogeneity, there exists a statistically and economically significant relationship between nG-Index and firm value. When we use the equal-weighted mG-Index instead, the GMM estimate becomes statistically insignificant. This reaffirms our earlier inference that the nG-Index has superior explanatory power to the mG-Index, since our proposed index provides causal estimates for the relationship between corporate governance and firm value, while the equal-weighted measure fails to do so.

3.5.1.1 Robustness

We further ran in-sample tests for all regressions in this section to affirm that our results are not driven by the out-of-sample period weights assigned for the nG-Index. The results remain the same, even with an alternative in-sample construction of the nG-Index that assigns the current year's weight to each provision in any given year (Appendix Table 3.14). Alternatively, we fixed the weights from year 2007, and applied it across the years 2008 to 2015 and again found that the results remain robust (untabulated). However, without dynamism the information on each ATPs becomes obsolete over time, and the statistical significance and magnitude of the coefficients decline. We additionally ran a horse-race regression by including the E-Index and several measures of active ownership to see if our index retains its explanatory power when we control for other governance characteristics. The nG coefficient estimates continue to show strong and consistent effects on Tobin's Q (see Appendix Tables 3.15 and 3.16).

3.5.1.2 Quasi-Natural Experiment

Despite the system GMM estimation results indicating a causal link between nG-Index and Tobin's Q, there remains a need to further explore a cleaner identification that can isolate the true influence of governance (as measured

Table 3.8 Do changes in nG-Index cause changes in Tobin's Q?

This table reports the Diff-in-Diff-in-Diff (DDD) estimation results for average main effects (1), main effects + average first interaction effects (2), and full model with all main and interaction effects (3) for the impact of changes in governance on Tobin's Q. All models are estimated using Equation 3.8 controlling for the same firm characteristics as those introduced in Table 3.7 (except the Delaware dummy, which becomes redundant by the definition of Control and Treatment firms). Robust standard errors are shown in parenthesis. ΔnG represents the annual change in nG-Index values for a firm. $Post$ indicates years after Revlon ruling is passed in Maryland (i.e. beginning 2010) and $Treat$ is a dummy representing Maryland-based firms, where Delaware-based firms are taken as control group. Baseline DDD estimation in Panel A considers the Maryland and Delaware firms as is. Propensity score (PS) matched DDD estimation considers a comparable Delaware firm matched on log of assets, return on assets and leverage, for every Maryland firm in a given year (using nearest-neighbor match with a 0.001 calliper). Panel B validates the results of Panel A by running placebo treatments. First placebo test assumes placebo treatment group for firms based in the state of Ohio, and the second test modifies the baseline DDD estimation by considering placebo $Post$ (beginning 2011). All models include industry and year fixed effects. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: Baseline and Propensity Score (PS) Matched DDD estimations

	Baseline DDD			PS Matched DDD		
	(1)	(2)	(3)	(1)	(2)	(3)
ΔnG	0.1963	-0.0499	0.0562	0.2354	-4.7860	-2.4677
	(0.184)	(0.688)	(0.713)	(0.378)	(3.087)	(2.717)
$Post$	-0.0480	-0.0575*	-0.0615*	0.0625	0.1708	0.1819
	(0.031)	(0.032)	(0.033)	(0.148)	(0.149)	(0.152)
$Treat$	-0.0210	-0.1243	-0.1936*	-0.0715	-0.1835	-0.2472*
	(0.056)	(0.113)	(0.108)	(0.077)	(0.131)	(0.129)
$\Delta nG * Post$		0.2953	0.1803		5.2824*	2.9667
		(0.710)	(0.734)		(3.111)	(2.734)
$\Delta nG * Treat$		-1.6503	-8.4209*		-0.3432	-7.7447
		(2.471)	(4.620)		(2.957)	(5.649)
$Post * Treat$		0.1206	0.2281*		0.1521	0.2502*
		(0.122)	(0.119)		(0.141)	(0.138)
$\Delta nG * Post * Treat$			**11.1171****			**11.1314***
			(5.102)			**(6.516)**
Observations	4831	4831	4831	506	506	506
R-squared	0.031	0.031	0.033	0.168	0.178	0.189

Panel B: Placebo DDD tests

	Placebo Treated State (Ohio)			Placebo Post-Treatment (2011)		
	(1)	(2)	(3)	(1)	(2)	(3)
ΔnG	0.2491	0.5462	0.4668	0.1963	-0.6044	-0.5582
	(0.168)	(0.686)	(0.800)	(0.184)	(0.389)	(0.391)
$Post$	-0.1055***	-0.1009***	-0.1019***	-0.0600*	-0.0411	-0.0426
	(0.033)	(0.035)	(0.035)	(0.033)	(0.034)	(0.034)
$Treat$	0.0032	0.0105	0.0156	-0.0210	-0.0231	-0.0596
	(0.024)	(0.056)	(0.058)	(0.056)	(0.089)	(0.100)
$\Delta nG * Post$		-0.3578	-0.2668		1.0864**	1.0401**
		(0.683)	(0.819)		(0.425)	(0.427)
$\Delta nG * Treat$		-0.0525	0.2425		-1.3847	-4.4612
		(0.416)	(0.861)		(2.518)	(4.332)
$Post * Treat$		-0.0097	-0.0164		-0.0235	0.0328
		(0.061)	(0.063)		(0.097)	(0.109)
$\Delta nG * Post * Treat$			**-0.4578**			**6.2700**
			(0.929)			**(4.800)**
Observations	4929	4929	4929	4831	4831	4831
R-squared	0.030	0.030	0.030	0.031	0.032	0.032

by nG-Index) on the firm values. We exploit the acceptance of Revlon ruling in the state of Maryland as an exogenous shock to corporate governance (see Section 3.3.4) and run a DDD estimation as follows:

$$\Delta Q_{j,t} = a_{1,1} + b_{1,1} * \Delta G_{j,t} + b_{1,2} * Post_{j,t} + b_{1,3} * Treat_{j,t} + b_{1,4} * \Delta G_{j,t} * Post_{j,t} \\ + b_{1,5} * \Delta G_{j,t} * Treat_{j,t} + b_{1,6} * Post_{j,t} * Treat_{j,t} \\ + b_{1,7} * \Delta G_{j,t} * Post_{j,t} * Treat_{j,t} + c_{1,1} * X_{j,t} + \epsilon_{j,t}, \tag{3.8}$$

where $Post$ is a dummy variable indicating the years after the introduction of Revlon ruling in the state of Maryland. $Treat$ is a dummy variable taking a value of one for the firms based out of Maryland and zero for firms registered in the state of Delaware. Firms' pre-existing ATPs are known to bias the estimates when using state-based antitakeover rulings for identification (Karpoff and Wittry, 2018). To overcome this, we model the changes in nG-Index as $\Delta G_{j,t}$, i.e. the change in nG-Index experienced by a firm j from year $t-1$ to t, and accordingly measure the impact on Tobin's Q as $\Delta Q_{j,t}$, which is again computed as a first difference of time-series of industry-adjusted Q. All the controls $X_{j,t}$ remain the same as in Equation 3.7, except for the Delaware dummy that is already controlled for in $Treat$.

Our main coefficient of interest is $b_{1,7}$ that captures the resultant change in TobinâĂŹs Q when there are changes in the nG-Index between the pre-2009 and post-2010 years, and also between the Maryland- and Delaware-based firms. Table 3.8 shows the regression results for our triple difference estimation. The overall treatment effect of changes in nG-Index on Tobin's Q is represented by the triple interaction term shown in the table. The results indicate that there is a statistically significant positive effect of changes in nG-Index on Tobin's Q: essentially, changes in Tobin's Q are greater after the passing of Revlon ruling in Maryland, and relative to Delaware firms.

The result for the triple difference term largely remains the same both in terms of the magnitude and statistical significance even with propensity score (PS) matched control group. For each Maryland-based firm, we identify an equivalent Delaware-based control firm using nearest neighbor PS matching with a 0.001 calliper matched on the size of assets, operating performance (i.e. ROA) and leverage. Panel B in Table 3.8 shows additional validity tests for our quasi-experimental shock by running a couple of placebo DDD estimations. We first take a placebo treatment state (Ohio) in place of Maryland, and find that the DDD effect is statistically indistinguishable from zero. Next, for our original treatment state (i.e. Maryland), we assume a placebo treatment date (2010 instead of 2009) and check if the DDD estimate is insignificant. The results from both these placebo estimations affirm the internal validity of our causal inference from baseline DDD model.

3.5.2 Operating Performance and Corporate Governance

The relationship between operating performance and governance indices was studied using multiple measures of operating performance, such as ROA, ROE, NPM, and sales growth (Gompers, Ishii, and Metrick, 2003; Bhagat and Bolton, 2008, 2009; Brown and Caylor, 2009). Core, Guay, and Rusticus (2006) examine the operating performance–governance index relationship using the G-Index and show that "firms with weak shareholder rights [proxied using the G-Index] exhibit significant operating underperformance". Most subsequent studies on governance impacts on operating performance use ROA as its preferred proxy. We use three measures: ROA, ROE, and NPM, to represent operating performance and assess how consistently the two governance measures (nG and mG) relate to them. Our basic model specification to estimate the relationship between operating performance and governance is similar to that used for firm value in the previous section, but with the operating performance proxies (i.e., ROA, ROE, or NPM) as the dependent variable.

$$OP_{j,t} = a_2 + b_2 * G_{j,t} + c_2 * X_{j,t} + \epsilon_{j,t}, \tag{3.9}$$

where $OP_{j,t}$ is either industry-adjusted ROA, ROE, or NPM using the industry-median values for firm j in year t and $X_{j,t}$ are the corresponding firm-based controls. $G_{j,t}$ is either the mG or nG scores for firm j across years t in the sample period. Most of our control variables here are the same as those used in the Tobin's Q regressions with an addition of log of book-to-market ratio following the methods in (Giroud and Mueller, 2011). We leave out Altman's Z due to its definition (as it has operating performance as one of its constituents). For the ROA and ROE regression models, we exclude leverage and CAPEXTA as controls because they would lead to greater endogeneity concerns for the reason that they include either assets or equity in their computations.[42] Additionally, we include a variable capturing research and development (R&D) expenses and advertising expenses for the NPM regression as a ratio of sum-total of these two expenses to total assets.[43]

Table 3.9 shows the results for various operating performance measures using using median regressions with block bootstrapped standard errors, as operating performance data show some degree of autocorrelation, which would lead to bias in both the time-series and panel regressions. An alternative process suggested in the literature (e.g., Brown and Caylor, 2009) corrects for this autocorrelation by including a one-period lagged operating performance measure (the same as the dependent variable); however, this process may still lead to some bias because it only considers a lag-one autocorrelation.

[42] This is not an issue for NPM, which is a sales or revenue based measure.

[43] For similar concerns as those for excluding leverage and CAPEXTA, we cannot use this control for the ROA or ROE regressions.

Table 3.9 Regressions for operating performance on governance.

This table summarizes several variations of the median (minimum absolute deviation) regressions that specify operating performance as depending on the nG and mG indices for the entire sample. For both nG and mG, the respective expected signs for their coefficients are shown in parenthesis. The results for the operating performance measures ROA, ROE, and NPM are shown in Panels A, B, and C, respectively. Model 1 considers the operating performance measure with the two indices without any controls. Model 2 improves on model 1 by including size (log of assets), age (in logs), book-to-market ratio (in logs), and dummies for S&P500 and Delaware incorporation as controls. For the NPM regressions, we additionally control for capital expenditure along with R&D and advertising expenses. Model 3 includes year fixed effects. For further details and the calculations for each variable, see Appendix 3.A.2. All regressions use industry-adjusted operating performance measures calculated as ROA (ROE or NPM) minus the median ROA (ROE or NPM) for that industry using the Fama-French Fama and French (1997) (FF) 48 industry classification. The first set of models report the coefficients and robust standard errors for the nG measure of governance and the next set show the same for the mG measure. Models 2 and 3 considered block bootstrapping with 200 bootstraps to estimate standard errors. The coefficients for constant, controls, and year dummies are omitted. Significance levels are represented by *, **, and *** for 10%, 5%, and 1%, respectively.

Panel A: ROA as the performance measure

	(1)	(2)	(3)	(1)	(2)	(3)
nG (–)	-0.0174**	-0.0166**	-0.0195**			
	(0.008)	(0.006)	(0.009)			
mG (–)				-0.0011***	-0.0019***	-0.0020***
				(0.000)	(0.000)	(0.000)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	9170	7368	7368	10190	8276	8276

Panel B: ROE as the performance measure

	(1)	(2)	(3)	(1)	(2)	(3)
nG (–)	-1.1335*	-4.1191***	-3.2665***			
	(0.605)	(1.187)	(1.166)			
mG (–)				-0.0272***	0.1564***	0.1148**
				(0.011)	(0.055)	(0.050)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	6785	6630	6630	7615	7442	7442

Panel C: NPM as the performance measure

	(1)	(2)	(3)	(1)	(2)	(3)
nG (–)	-0.0493***	-0.0378***	-0.0452***			
	(0.016)	(0.014)	(0.013)			
mG (–)				-0.0021***	-0.0015***	-0.0017***
				(0.000)	(0.000)	(0.000)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	9156	7368	6950	9156	7805	7805

For ROA and NPM, both nG and mG show that good governance quality is significantly related to better operating performance. Bhagat and Bolton (2008, 2009) show similar results. However, in the full model 3, the effect on NPM (0.04 units increase) is double that for ROA (0.02 units) for the nG-Index. In contrast, the effect of mG-Index on ROA is marginally more than that on NPM. We cannot compare these coefficients in absolute terms because the two indices operate on different scales (0 to 1 for nG and 0 to 19 for for mG). However, the transformed scale for the mG index shows that the effect size using both indices are almost similar, that is, 0.045 units for nG and 0.038 units for mG.[44] The results for ROE differ from those seen for the other two operating performance measures. While the nG-Index shows a statistically significant relationship with ROE, indicating that good governance leads to improved operating performance, the mG-Index results in a coefficient in contrast to our expectation; that is, good governance as measured using the mG-Index would lead to a decline in operating performance measured by ROE.

Again, overall, we see that the unequally weighted nG-Index is a better indicator of firms' governance quality than the mG-Index is. Using the nG-Index, we find an association between good governance and superior operating performance consistently across all three measures. The mG-Index shows significant relationships with operating performance as well, albeit an opposite sign for ROE (i.e., well-governed firms have a lower ROE than poorly governed ones). Assuming that the mG-Index measures governance well, poorly governed firms outperform well-governed firms in terms of net profits made available to equity shareholders. This would contradict the inferences drawn from the other operating performance measures. Consequently, we deduce that unless some other variable drives this directional change, this is a sufficiently clear indication of measurement error in the mG-Index.

[44] We find this result using the same normalized mG index as for Tobin's Q.

3.5.2.1 Robustness

As for the Tobin's Q regressions, we ran in-sample tests for all regressions and each operating performance measure as a robustness check. This test shows that our results are not driven by the out-of-sample period weights assigned for the nG-Index, as even with the alternative in-sample nG-Index construction, the results remain same (see Appendix Table 3.17). Similarly, the results remain robust even by applying the fixed weights of year 2007 for the sample period 2008 to 2015 (untabulated).

3.5.2.2 Quasi-Natural Experiment

To account for endogeneity, we further ran causal estimations for nG-Index on all the three operating performance measures using changes in ROA, ROE or NPM as a dependent variable in place of ΔQ in Equation 3.8. Results were largely similar to that seen for Tobin's Q earlier, with the DDD effect for Revlon ruling in Maryland indicating a strong and statistically significant causal relationship between nG-Index and two of the operating performance measures (i.e. ROA and NPM, see Appendix Table 3.18).

The results for both firm value and operating performance reveal the same reliability issues with the mG-Index. Overall, poor governance firms (with higher nG or mG scores) significantly underperform good governance firms (low scores) in our sample period. However, only the nG-Index shows a consistent relationship between governance and both firm value and operating performance.

3.5.3 Stock Returns and Corporate Governance

One of our primary motivations for conceptualizing the unequally weighted nG-Index was the disappearing premium in terms of abnormal returns seen in good governance firms vis-à-vis the bad governance ones. If, indeed, the disappearance of the abnormal returns–governance association was only for the reasons given according to Bebchuk, Cohen, and Wang (2013) learning hypothesis, our index would corroborate their findings by showing that there is no investment strategy possible based on our governance index to beat the markets. However, if, in addition to learning by market participants, the disappearing association is also a result of low construct validity of the G and the E indices, then long-short strategies using portfolios constructed with our index will result in either gains or losses, albeit lower than those seen in the 1990s (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009). We test this by dividing the sample for each year in deciles based on their nG scores, with 'Decile 1' (or Democracy) representing good governance firms and 'Decile 10' (or Dictatorship) having the poorly governed firms. This good to bad governance classification of portfolios is similar to those that Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) use. The yearly division of deciles serves two specific purposes. First, it enables us to ensure that we draw deciles using the latest nG index scores when they are available at the beginning of each year.[45] Second, it allows us to reset the portfolios each year as and when new information becomes available.

We form the governance portfolio deciles by first sorting the individual firms in our sample based on their nG-Index scores, with the 1st decile containing firms with low nG-Index scores in the previous year, and the 10th decile comprising bad governance firms with high nG-Index scores. We could select these portfolio deciles using quantiles to break the 10 groups down. With equal-sized groups using quantile breaks, however, we find that the difference

[45] Note that, in essence, we consider lagged governance (nG) scores to see if investors can use this information at its availability to make abnormal returns using long-short governance portfolios. The weight extraction procedure in Section 3.4.2, on the other hand, employs contemporaneous governance provisions.

between the first and tenth decile scores is not significantly large enough to show differences in their governance qualities. Another reason that we do not use quantile breaks is the positive skewness seen for nG-Index, as more firms are concentrated in the better governance (or lower nG-Index) region. Additionally, these governance scores are not unique for each firm, as in the case of the G and E indices, meaning that there could be several firms with the same governance scores, making it difficult to decide which ones to include in which decile if they lie at the decile thresholds. Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) have similar unequal portfolio quantiles, that is, deciles for the G-Index and sextiles for the E-Index.

The top 5 percentile governance firms are those with nG-scores of less than 0.21 (or 21%), whereas we assign the worst 5 percentile governance rank to those with nG-scores of more than 36%. We divide the remaining 90 percentile firms among the remaining 8 portfolios such that the intermediate range of nG-scores (between the two extreme portfolios) are equally divided amongst them.[46]

We first examine whether the abnormal returns vary with governance deciles over our entire sample using the methodology that Gompers, Ishii, and Metrick (2003) suggest. However, unlike Gompers, Ishii, and Metrick (2003), we consider the Fama-French momentum factor in place of the Carhart (1997) momentum factor along with the Fama and French (1993) three factors. In addition, in the past few years, corporate governance scholars investigated the relationship between corporate governance and stock market liquidity (for example, Chung, Elder, and Kim, 2010). For this reason, we include the Pástor

[46] In terms of nG% scores ranging from 21% or more for Decile 1 to 36% or less for Decile 10, this would mean dividing the 15% difference equally amongst the remaining 8 portfolios such that each portfolio has a range of scores = 15%/8 = 1.875%.

and Stambaugh (2003) liquidity factor within our returns model:

$$R_t = \alpha + \beta_1 * RMRF_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * LIQ_t + \epsilon_t, \tag{3.10}$$

where R_t is the excess return for a certain portfolio in month t, the three standard Fama-French factors are $RMRF_t$ (excess market returns over the risk-free rate), SMB_t (Small minus Big), and HML_t (High minus Low) representing the market, size, and value effects for time t with the additional MOM_t factor capturing the momentum effect and LIQ_t representing the value-weighted traded liquidity factor for month t. Although the literature contains considerable discussion on the ability of these factors to assess risk and performance, we follow Gompers, Ishii, and Metrick (2003) argument that these factors can depict a passive investment strategy, so that the intercept α represents the abnormal returns from an active portfolio. We also consider the recent five-factor model that Fama and French (2016) propose, which includes additional investment and profitability factors. However, as Fama and French (2016) mention, including these additional factors makes HML redundant. In other words, keeping parsimony in mind, the returns variations captured by the HML factor would more or less explain the impact of the investment and profitability factors. Additionally, since we focus on attributing governance to portfolio performance, the momentum and liquidity factors would be more pertinent for corporate governance than the profitability and investment factors.

Table 3.10 summarizes the key attributes of the individual decile portfolios. The first column shows the average nG-Index value for each portfolio by year. The next two columns show the average monthly excess returns and the 5-factor alphas using the model in Equation 3.10 for the value-weighted portfolios. The remaining two columns show the same excess monthly returns and alphas for the equal-weighted portfolios. We see that the abnormal returns

Table 3.10 nG-Index based trading strategies and their abnormal returns

This table provides the result for a five-factor regression (Fama and French (1993) of three factors along with their momentum factor and Pástor and Stambaugh (2003) liquidity factor) for each decile portfolio created from the nG-Index. The alphas and mean excess returns are shown using both value- and equal-weighted portfolios. These portfolios are reset when new data is available at the beginning of each year. The monthly portfolio returns for each decile are regressed over factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM), and liquidity (LIQ) for White (1980) standard errors. The stocks in deciles 1 and 10 represent the Democracy and Dictatorship Portfolios, respectively, identified as per the criteria in parenthesis. For deciles 2 to 9, equal intervals are assigned for the remaining nG-Index range. For 2015, there were no stocks categorized in decile 1, so the stocks in the next highest group, decile 2, were assigned to the Democracy portfolio. Significance at 10%, 5%, and 1% are indicated by *, **, and ***, respectively.

		Value-weighted		**Equal-weighted**	
Portfolios	Mean nG-Index	Alpha	Excess Returns	Alpha	Excess Returns
Democracy – Dictatorship		-1.333**	-1.233	-0.316	-0.275
		(0.623)		(0.405)	
Decile 1 (Democracy)	0.189	-0.954**	-0.345	0.010	0.729
($0 \leq$ nG < 0.21)		(0.490)		(0.306)	
Decile 2	0.221	-0.393	0.238	-0.181	0.550
		(0.443)		(0.244)	
Decile 3	0.239	-0.359*	0.621	-0.093	0.637
		(0.226)		(0.159)	
Decile 4	0.257	-0.181	0.452	0.100	0.818
		(0.153)		(0.108)	
Decile 5	0.276	0.231**	0.849	.295***	1.021
		(0.111)		(0.099)	
Decile 6	0.293	0.011	0.679	0.237	0.953
		(0.188)		(0.147)	
Decile 7	0.312	-0.117	0.533	0.206	0.848
		(0.197)		(0.000)	
Decile 8	0.331	0.006	0.622	0.271	0.973
		(0.320)		(0.283)	
Decile 9	0.349	1.267***	1.669	1.400**	1.929
		(0.462)		(0.558)	
Decile 10 (Dictatorship)	0.488	0.378	0.888	0.326	1.004
($0.36 <$ nG ≤ 1)		(0.414)		(0.258)	

or alpha estimates for all decile portfolios using both the monthly returns of the equal- and value-weighted portfolios follow an increasing trend from the Democracy portfolio to the Dictatorship portfolio. The democracy portfolio (decile 1) distinctly underperforms the Dictatorship portfolio (decile 10). We see this outperformance of Dictatorship portfolio over the Democracy portfolio for both mean excess returns and abnormal returns. In the first row, we include the results of estimating the regression model specification in Equation 3.10 by taking the returns from the hedged portfolio (long Democracy and short Dictatorship) on the right-hand side. From a preliminary analysis of the alphas and mean excess returns for the two extreme portfolios, we expect this hedge portfolio to return a negative alpha, implying a possible reversal of the long-short positions. However, we retain the long-short hedge strategy as in previous studies (e.g., Gompers, Ishii, and Metrick, 2003; Core, Guay, and Rusticus, 2006; Giroud and Mueller, 2011) for ease of comparison.

For this hedged model, α is about -16% per annum (or -1.33% per month) for the value-weighted portfolios and about -3.8% per annum (-0.32% per month) on the equal-weighted portfolios. The negative abnormal returns on our governance hedge is statistically significant at the 5% level for the value-weighted portfolios. This result is markedly different from that in Gompers, Ishii, and Metrick (2003), of around $+8.5\%$ and in Bebchuk, Cohen, and Ferrell (2009), of about $+14\%$ for value-weighted portfolios in the 1990s, showing that stock returns over our sample period were negatively related to governance (i.e., lower returns for better governance stocks). The negative alpha indicates that swapping the buy/sell positions in the assumed hedge portfolio, i.e., going long on poor governance firms and short on good governance ones, should have yielded about 16% returns per year using the value-weighted portfolios. The corresponding equal-weighted hedge does not have statistically significant returns.[47] The statistically significant outperformance of the decile 10 (Dictatorship) portfolio over the decile 1 portfolio (Democracy) is also a powerful indicator of the strength of our proposed hedge because the remaining performance attribution differences based on risk factors (market, size, book-to-market, momentum, and liquidity) are either less significant or insignificant. Additional analysis using portfolios created with the mG-Index, show markedly different results to those in Table 3.10, as there are no economically or statistically significant magnitudes of abnormal returns possible.

From the individual portfolio decile summaries in Table 3.10, we see that the value-weighted portfolios have mostly negative alphas (with the top 4 deciles all having negative alphas) for the first 5 deciles, while 4 of the higher 5 deciles (6 to 10) have positive alphas. This shows that, collectively, portfolios of poor governance stocks tend to outperform passive investment strategies, while portfolios composed of good governance stocks tend to underperform the same. The results are similar for the equal-weighted portfolios as well, with less statistically significant alphas than those for the value-weighted investments. This is consistent with the new hedge seen for our sample period and follows the directionally opposite trend to portfolio performance in the 1990s reported by Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009).

3.5.3.1 Robustness Checks

We next carried out additional robustness checks on the hedge portfolio's abnormal returns to emphasize the validity of our findings. We follow a two-pronged strategy here. First, we considered alternative portfolio constructions to those in Table 3.10 to rule out the possibility that the results are not driven

[47] A closer examination of the individual deciles shows that the outperformance of poor governance stocks is largely driven by Decile 9 (which has significant αs). Thus, with a wider selection criteria for extreme portfolios, both the equal- and value-weighted hedge portfolios become statistically significant.

by the nG-Index criteria applied for the portfolio division or other characteristics such as industry membership, firm size, or year of returns. Table 3.19 of the Appendix shows the results for this robustness check. Second, we analyze portfolio returns using alternative risk-factor models to check if the results change when we add new factors or remove others. If the alphas remain consistent in all alternative asset pricing models, we can rule out the potential that the results are model driven. Additionally, alternative risk factor models allow us to see if the five factors we use in our performance attribution analysis explains the hedge portfolios best. The Table 3.20 in the Appendix reports the results for these alternative asset pricing models.

Table 3.19 includes some modifications to the governance-hedged portfolio by varying the nG-Index criteria in the selected deciles (see Bebchuk, Cohen, and Ferrell, 2009) and in subsamples (see Gompers, Ishii, and Metrick, 2003).[48] We use the Fama and French (1997) 48 industry classification to obtain the industry-adjusted monthly returns for each firm by adjusting for the industry median returns for each month. Additionally, to assess how hedged portfolios behave if we use the equally weighted mG-Index to construct the portfolios in place of the nG-Index, we show the corresponding abnormal returns for a long-short mG-Index hedge.

For each portfolio construction variant in Table 3.19, we apply the same five-factor model for performance attribution in Equation 3.10. In addition to the abnormal returns or alphas, we report the mean excess returns for each Democracy–Dictatorship hedge portfolio. These checks allow us to see if the choice of cutoff (i.e., rows 2 to 4), industry membership (row 5), or time effects (rows 6 and 7) may drive the results. We create additional Democracy–

[48] We show results using (a) the same 5/95 percentile as in our primary decile portfolios with the criterion limits changing every year, (b) newer 2/98 percentile rules held constant for all years, and (c) equal sized deciles or 10 quantiles.

Dictatorship hedges by combining more than 1 extreme deciles from our baseline portfolio (row 1) to show the monotonic decline in abnormal returns as the portfolio sizes in the extremes are increased by including more firms from the center of the nG-Index distribution (rows 8 and 9 – see Bebchuk, Cohen, and Ferrell, 2009 for additional inputs on these variations). Last, as in the last row of Table 3.19, we assess how the inferences would differ if we use the equal-weighted mG-Index in place of the nG-Index.

For most of the portfolio variants, the potential gains from both the value-weighted and equal-weighted hedges are economically large. The only cases for which the abnormal returns fall below 1 basis point are the cases with equal-sized deciles or 10 quantiles (row 4) and when we use the mG-Index to construct the portfolios (row 10). These results corroborate our previous findings. Using equal-sized deciles does not provide a good hedge because the extreme portfolios have very little difference between them, and because the positive skewness of the nG-Index scores affect them. The results for the mG-Index, once again, show that the equally weighted methodology may not truly measure the firm's governance quality. We find statistical significance for alphas in five of the variants for the nG-Index based value-weighted hedge portfolios.

When we adjust the cutoffs for Democracy and Dictatorship portfolios each year (row 2), the value-weighted hedge portfolio remains statistically significant at the 10% level. However, when we make the cutoffs smaller (to increase the differences between the extremes), the abnormal returns from the hedged portfolios become statistically insignificant. This result, combined with those in row 4 indicate that making cutoffs too small or too big are detrimental to these governance-based hedges.

Table 3.20 shows the estimates of abnormal returns for the long good governance–short poor governance strategy using alternative asset pricing models. We do this mainly to test whether using different factors or factor combinations affect our main results in Table 3.10. We use the capital asset pricing model (CAPM), three-factor model of Fama and French (1993), five-factor model of Fama and French (2016), and variants of these Fama-French (FF) models with the Pástor and Stambaugh (2003) liquidity factor included.[49] For the value-weighted hedge portfolio, the abnormal returns range from -1.31% per month to -1.49% per month, and are all significant at the 5% level. This shows that our main result indicating that investors could potentially gain abnormal returns by reversing the more conventional Democracy–Dictatorship hedge position is true, even when we consider alternative asset pricing models. Moreover, the FF four factor + liquidity model that we substantively selected to assess these abnormal returns seem to give the most conservative estimates of the various asset pricing models tested (with only the CAPM giving an alpha lower than our estimate). For the equal-weighted portfolio hedge, in fact, the alpha for our baseline model is the lowest amongst all models tested.

Overall, we find that our inference from nG-Index sorted portfolios is robust and that investors could have potentially made abnormal returns by going long on poor governance stocks and short on good governance stocks, especially by investing in value-weighted portfolios.

3.5.4 Are the Index Weights Really Important for Investors?

We ran further empirical tests to examine how important are index weights for investors by considering the risk-return tradeoffs related to governance. First, we assess if poor governance firms are indeed riskier for investors by studying the differences in stock price crash risks associated with good governance firms

[49] We also considered the Cremers, Nair, and John (2009) takeover factor and Carhart (1997) momentum factor for this robustness check. However, data on the takeover factor is available only until 2003. We expect that the FF momentum factor (MOM) factor to be closely related to Carhart (1997) up-minus-down (UMD) because it is constructed by including stock momentum sorts along with firm size sorts.

vis-à-vis poor governance firms. If governance weights are indeed important for investors' downside risk, future stock price crash should be related only to the nG- and not the mG-Index. Next, we checked the implication of applying nG-Index scores to portfolio segregation after 2 and 3 years of the information being available to investors. If investors do not capture the benefits of good governance signals in the period immediately following the availability of governance information (as we see in the previous section), the subsequent period abnormal returns for long good governance–short bad governance hedge portfolios should be higher. As more time passes, investors would react favorably to the good governance stocks as they start to understand the benefits of good governance signals. If, again, the index weights are essential for investors future returns associated with good governance, only nG-Index should capture this relation and not the mG-Index.

3.5.4.1 Future Stock Price Crash Risk and Corporate Governance

Can corporate governance, measured using the nG-Index, be used to identify firms with future low performances and corresponding stock price crash risk? In this section, we address this central question.

Using the nG-Index as a proxy for corporate governance and corresponding agency risk, we expect firms that have high nG scores (i.e., demonstrating poor governance practices) to show a higher propensity of facing stock price crashes in the near future; that is, in the next year. We measure firm-specific weekly returns W as the logarithmic transformation of the residual obtained from running weekly returns for each firm in an expanded index model regression following Hutton, Marcus, and Tehranian (2009):

$$r_{j,t} = \alpha_j + \beta_{1j} * r_{m,t-2} + \beta_{2j} * r_{m,t-1} + \beta_{3j} * r_{m,t} + \beta_{4j} * r_{m,t+1} + \beta_{5j} * r_{m,t+2} + \epsilon_{j,t}, \tag{3.11}$$

where $r_{j,t}$ is firm j's Wednesday-to-Wednesday return in week t, $r_{m,t}$ is the corresponding CRSP value-weighted market index for the same week t. To allow for nonsynchronous trading, we include additional two week lead and lag terms for market index returns. Next, using the residual $\epsilon_{j,t}$ from the above equation, we obtain the firm-specific weekly return as $W_{j,t} = ln(1 + \epsilon_{j,t})$.

To measure crash risk, we use four variables identified from prior literature (Chen, Hong, and Stein, 2001; Jin and Myers, 2006; Kim, Wang, and Zhang, 2016): CRASH, CRASHNUM, NCSKEW, and DUVOL. When a firm-specific weekly return $W_{j,t}$ falls by more than 2.98 standard deviations below the average firm-specific weekly return (FSWR) for that calendar year, we identify it as a crash week. We set this limit to pick the lowest 10% of the FSWR distribution in that year. The first measure CRASH is a dummy variable that takes value 1 if the firm undergoes at least one crash week in a given year, while the second measure CRASHNUM counts the number of crash weeks experienced by each firm in a given year.

The other two measures are negative conditional skewness (NCSKEW) and down-to-up volatility (DUVOL) as defined in the prior literature (for formulae and calculations, see Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009). While NSCKEW looks at the ratio of the third moment difference in FSWR and its average to its standard deviation in a given year, DUVOL considers weeks with above-average FSWR separately from those with below-average FSWR and computes the log ratio of the down and up movement's standard deviations. These four measures of crash risk are regressed in either OLS, logit, or tobit models with the following generic specification:

$$CR_{j,t+1} = A + B * G_{j,t} + C * X_{j,t} + \epsilon_{j,t} \tag{3.12}$$

where $CR_{j,t+1}$ is either $CRASH$, $CRASHNUM$, $NCSKEW$, or $DUVOL$

for each year $t+1$ as defined above and $G_{j,t}$ is either a dummy indicating poor governance (above average nG-score that year) or the nG-Index scores themselves depending on the regression model used.

When $CRASH$ and $CRASHNUM$ are the dependent variables, we run logit and tobit regressions, respectively, with the poor governance dummy as the main explanatory variable. Since the crash frequency is much lower than that for non-crash events, we can identify the likelihood of a crash better with a dichotomous classification for governance. In other words, using the nG-Index itself instead of a governance dummy would lead to this model being underidentified. To capture predictability, we always use one-year forward dependent variables in all regressions. From the previous literature on crash risk, we identify controls, $X_{j,t}$, such as the difference in investor opinions $DIFTURN$ (Hong and Stein, 2003), the average FSWR or AVG, return volatility or $SIGMA$, and additional firm controls such as firm $SIZE$, market to book ratio MB, leverage LEV, ROA ROA, and opacity based on accruals $OPAQUE$ (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009). For regressions with $CRASH$ and $CRASHNUM$, we also control for past crash risk by including $NCSKEW$ in the model. For the OLS regressions involving $NSCKEW$ and $DUVOL$, we include up to three period lagged values of dependent variables as controls to partially account for reverse causality and endogeneity (Kim, Wang, and Zhang, 2016).

Table 3.11 shows the results for each of the tobit, logit, and OLS regressions with corresponding dependent variables. For $CRASHNUM_{j,t}$, we use the tobit regression because it measures the number of crash weeks in a year t experienced by firm j. Using the tobit regression allows us to model crashes better, as it imposes only left censoring for firms that do not experience crashes, where $CRASHNUM_{j,t} = 0$. For the binary variable $CRASH_{j,t}$, logit modeling allows to implement the likelihood of experiencing one or more crashes in year t.

Table 3.11 Future stock price crash risk and governance

This table shows the results obtained by running various regressions for crash risk measures on a dummy that represents poor governance. For each of the dependent variables CRASHNUM, CRASH, NCSKEW and DUVOL, column 1 (column 2) represents firms with nG (mG) scores greater than the average nG-Index (mG-Index) for the entire sample in that year. All regressions control for year and industry fixed effects. For industry classifications, we employ Fama and French (1997) 48 industries. All regressions use firm clustering to report standard errors (shown in parentheses) and the corresponding z or t statistics. Regression models for each dependent variable are specified in the table. The coefficients for constant and industry/year dummies are left out. See Appendix 3.A.4 for the definitions of all variables, including controls. Significance levels are represented by *, **, and *** for 10%, 5%, and 1%, respectively.

Regression:	**Tobit**		**Logit**		**OLS**			
Dependent:	**$CRASHNUM_{t+1}$**		**$CRASH_{t+1}$**		**$NCSKEW_{t+1}$**		**$DUVOL_{t+1}$**	
	(nG)	(mG)	(nG)	(mG)	(nG)	(mG)	(nG)	(mG)
Poor Governance	**0.091****	**0.020**	**0.123****	**0.026**	**0.069****	**0.010**	**0.024****	**0.002**
	(0.035)	**(0.036)**	**(0.049)**	**(0.049)**	**(0.027)**	**(0.028)**	**(0.010)**	**(0.010)**
$DIFTURN_t$	0.021***	0.021***	0.028***	0.028***	0.000	0.001	0.000	0.000
	(0.003)	(0.003)	(0.005)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
AVG_t	0.902	0.773	2.448	2.337	12.723***	12.627***	5.229***	5.213***
	(2.803)	(2.807)	(3.948)	(3.952)	(2.334)	(2.342)	(0.976)	(0.978)
$SIGMA_t$	3.608***	3.385***	4.871***	4.554***	-0.724	-0.920	-0.410	-0.478*
	(0.939)	(0.931)	(1.331)	(1.316)	(0.763)	(0.753)	(0.274)	(0.272)
LEV_t	-0.158	-0.165	-0.211	-0.220	-0.153	-0.158*	-0.054	-0.056
	(0.101)	(0.101)	(0.135)	(0.135)	(0.094)	(0.095)	(0.034)	(0.034)
$SIZE$	-0.004	-0.004	-0.004	-0.004	0.054***	0.053***	0.023***	0.022***
	(0.012)	(0.013)	(0.017)	(0.017)	(0.010)	(0.010)	(0.004)	(0.004)
MB_t	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA_t	0.492***	0.478***	0.703***	0.682***	0.291**	0.277*	0.084	0.079
	(0.162)	(0.162)	(0.227)	(0.227)	(0.143)	(0.142)	(0.055)	(0.054)
$OPAQUE_t$	0.395**	0.412***	.403***	0.430***	0.081*	0.112**	0.032	0.052*
	(0.165)	(0.136)	(0.118)	(0.137)	(0.043)	(0.050)	(0.021)	(0.027)
$NCSKEW_t$	0.030*	0.031*	0.044*	0.046*				
	(0.017)	(0.017)	(0.024)	(0.024)				
$Dependent_t$					0.027*	0.028*	0.008	0.009
					(0.016)	(0.016)	(0.017)	(0.017)
$Dependent_{t-1}$					-0.008	-0.008	-0.014	-0.014
					(0.012)	(0.012)	(0.012)	(0.012)
$Dependent_{t-2}$					-0.003	-0.002	-0.004	-0.004
					(0.013)	(0.013)	(0.013)	(0.013)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
#Observations	10527	10527	10527	10527	7773	7773	7771	7771
Pseudo / Adjusted R2	0.0215	0.0212	0.0304	0.0299	0.0207	0.0198	0.0293	0.0285
#Firms	1484	1484	1484	1484	1384	1384	1384	1384

As observed, the coefficients for the poor governance dummy are positive and statistically significant only with nG-Index, consistent with our expectation that firms with good governance have a lower likelihood of future stock price crashes. To estimate the economic significance of this coefficient, we look at the marginal effect of our poor governance indicator, that is, the nG dummy on these crash risk variables by setting the remaining variables to their respective means. The marginal effect of bad governance is on an average approximately 11% of the unconditional stock price crash probability.

The OLS regression estimates for negative conditional skewness ($NCSKEW_t$) and down up volatility ($DUVOL_t$) are also positive only for the poor governance identified using nG-Index and show statistical significance at the 5% level. As in previous studies on crash risk, the variable $NCSKEW_t$ tends to show higher magnitudes for the explanatory variables than $DUVOL_t$ does by construction. Although increasing values of these two variables indicate a higher likelihood of stock price crashes, their economic interpretation is limited by their definitions. However, these coefficients do show that our main result that firms with good (bad) governance as classified using nG-Index have a lower (higher) likelihood of crash risk is not driven by the 10% lower limit specified for the other two crash risk variables. When it comes to the mG-Index, we find that the associated poor governance dummy cannot predict future price crashes across all the four crash risk proxies.

Overall, we find evidence that poor governance firms as identified only using the nG-Index are more likely to face future stock price crashes. This provides some credence to our proposition that governance index weights are important for investors to highlight the agency risks associated with poor governance stocks. This inference requires caution because we modeled and measured only one dimension of the possible future downside risk as an outcome of existing agency risk within the firms. When looking at a firm's total risk, there may be several other dimensions of idiosyncratic volatility and other variability measures to consider. Nevertheless, the marginal effect that we see in these results is economically significant and may indeed influence investment decisions.

3.5.4.2 Future Stock Returns and Corporate Governance

To assess if investors react positively to good governance signals (as depicted by nG-Index) in the period immediately following the availability of governance information, we run similar hedge portfolio regressions on the risk factors in Table 3.10 using the specification in Equation 3.9. However, instead of creating portfolios using one-year lagged nG-Index scores, we consider two- and three-year lags. We report the results from these regressions in Table 3.12. We observe a monotonic upward trend for both the abnormal returns and mean excess returns for the nG-Index based decile portfolios as the lag period increases from 1 year to 3 years. This trend exists for both the equal- and value-weighted portfolios.

Whether we consider a value- or equal-weighted hedge, we see that positive abnormal returns appear for a long good governance short poor governance hedge with both 2 and 3 year lags. However, the statistical significance disappears for the value-weighted hedge beyond the 1-year lag. Overall, there does seem to be evidence that investors do benefit from good governance signals in the long run, with the measures of abnormal returns and mean excess returns having economically significant magnitudes that tend to increase for governance hedges with increasing lags. Even considering the lack of statistical significance, reflecting zero abnormal returns beyond the first year for the value-weighted hedge indicates that investors start benefiting from good governance signals after first year. However, the lack of statistical significance for portfolios that use longer lags requires cautious interpretation. With in-

Table 3.12 Returns on 2- and 3-year lagged nG-Index-based hedge portfolios

This table provides the results for the five-factor regressions (i.e., the three factors from Fama and French (1993) along with the momentum factor and the Pástor and Stambaugh (2003) liquidity factor) for governance hedge portfolios, i.e., Democracy–Dictatorship (both value- and equal-weighted) using deciles created in accordance with 2-year and 3-year lagged nG-Index scores. These portfolios are reset at the beginning of each year when new data is available. The monthly portfolio returns for each hedge portfolio (buy Democracy-sell Dictatorship) are regressed over factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM), and liquidity (LIQ) with White (1980) standard errors. Part A in the table repeats the results in Table 3.10 for a comparison with the 1-year lagged results. Parts B and C show the abnormal returns and mean excess returns for each of the 2-year and 3-year lag-based hedge portfolios, respectively. For abnormal returns, the statistical significance at 10%, 5%, and 1% are shown by *, **, and ***, respectively.

	A: Using nG_{t-1}		**B: Using nG_{t-2}**		**C: Using nG_{t-3}**	
Hedge Portfolios	Alpha	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns
Value-weighted	-1.333**	-1.233	0.013	-0.318	0.165	-0.142
	(0.623)		(0.385)		(0.370)	
Equal-weighted	-0.316	-0.275	0.337	0.241	0.452	0.413
	(0.405)		(0.297)		(0.293)	

creasing lags, the available set of data declines, resulting in lower statistical power. This in turn affects interpretability, since with every additional lag year, we lose 12 observations from the time-series regressions we use to obtain abnormal returns. This is a significant loss considering that our sample period is only 9 years. When we run similar analysis using the mG-Index based portfolio deciles, the benefits of good governance are not clearly visible. Both the abnormal returns and mean excess returns remain statistically insignificant regardless of one-, two- or three-year lags. These results are untabulated for the sake of brevity.

3.6 Discussion

In this study, we set out to investigate the corporate governance–performance puzzle, and especially the disappearance of the governance–returns relation by examining recent ATP data. While doing so, we demonstrate the importance of accounting for the evolution of these provisions and how they contribute to measuring corporate governance. We make several contributions to this literature by exploring the benefits of using an unequally weighted index.

First, our primary contribution is methodological. It allowed us to introduce the "new Governance" (nG) index, an unequally weighted corporate governance measure. The design of this index applies a methodology that ensures that the weights of individual provisions consider both the timing of its introduction in a firm and its relative importance to other provisions. Prior studies explore only equally weighted methodology to operationalize governance indices. We apply an inclusion rule that guarantees that the index introduces only relevant factors, hence ensuring that the constructed index explains the maximum of governance variations amongst the sample firms. Moreover, the nG-Index is dynamic because the weights allotted to each provision are updated annually, as and when newer data on ATPs become available. All previous indices, in contrast, were static because they gave equal importance to each provision, regardless of the year in which the index was constructed.

Second, we highlight the importance of weights in aggregated indices by showing that only the unequally weighted nG-Index has a persistent and robust relation with firm value. Using the equal-weighted mG-Index for a governance measure would entail that no relationship exists between governance and firm value. Only with the nG-Index do we see that firms with poor governance structures (high nG scores) have significantly lower firm valuations than those with good governance structures across all model specifications in our sample period.

Third, we show that the relationship between corporate governance and several operating performance measures are explained better using the nG-Index than with the mG-Index. For the nG-Index, we find a consistently negative relationship between governance scores and operating performance, meaning that poorly governed firms underperform the well-governed ones. The mG-

Index, on the other hand, traces this relationship inconsistently, implying that the equal weights assumption may induce measurement errors in governance indices.

Fourth, using the nG-Index we show that corporate governance remains an important factor to consider in investment decisions. We can see the economic and financial significance of our findings from the fact that a dollar invested in good governance firms between 2007 and 2015 (using nG-sorted annual portfolios) would result in a good governance portfolio (Democracy) reduced to 0.40 dollars (i.e., on average, reduced by 95 basis points per month).[50] In contrast, the bad governance portfolio (Dictatorship) increases from one dollar at the beginning of the investment period to 1.44 dollars (increasing by about 38 basis points per month). This shows that investors who created a hedge portfolio by buying a bad governance portfolio and selling a good governance portfolio could have potentially earned 1.23% excess returns per month in this period. Our results are markedly different to those using governance-sorted portfolios in Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009) in the 1990s. While the prior literature suggests hedging by going long democracy and short dictatorship to beat the markets, we show a newer hedge position for the period of our study.

Fifth, we provide some preliminary insights into how investors can benefit from using unequal-weighted governance index. We show that firms' governance differences using nG-Index are indicative of poor governance firms being riskier than good governance ones as they are associated with higher stock price crash risks. On the other hand, mG-Index based classification of good and poor governance firms does not show any association with future stock crashes. We

[50] Using the mean excess returns in Table 3.9. We consider only the value-weighted portfolio over 8 years because it robustly shows statistically significant abnormal returns over this period.

also find that investors' long run benefits from good governance signals in the period following the availability of governance information is only tracked by the nG-Index, and not the mG-Index.

Finally, we contribute to the general understanding of the governance– performance relationship in recent years and provide a foundation for future research into other outcomes of superior corporate governance. With the nG-Index, researchers have an empirically testable governance measure that captures the overall essence of ISS governance provisions, while also retaining the comparative prominence of each individual provision. We show that certain provisions (such as unequal voting rights, limited ability to amend bylaws, etc.) have higher relative importance than others do in measuring governance quality. Moreover, with our dynamic index weights that capture all up-to-date information, the nG-Index is better able to withstand the test of time compared to the previously conceptualized indices. Thus, our indexing methodology can also lay the basis for practical implications in the governance ranking industry, as well as for regulatory authorities and policy decisions. We also open the doors for researchers to employ a similar unequal-weighted methodology for other firm-level aggregate measures that influence firms' returns.

3.7 Conclusion

The main purpose of this study is to examine if we can use recent data on firms' ATPs to construct an index that can differentiate well-governed firms from poorly governed ones. After reviewing previous index construction methodologies, such as those in Gompers, Ishii, and Metrick (2003), Cremers and Nair (2005), Brown and Caylor (2006), and Bebchuk, Cohen, and Ferrell (2009), we found that for recent years, equal-weighted indices may not be able to assess governance quality well due to measurement errors. As an alternative, we thus present the nG-Index, an unequal-weighted measure of corporate governance that captures the heterogeneity of its individual ATPs. Gompers, Ishii, and Metrick (2003) mention that using simple binary codes for provisions and then adding them "sacrifices precision for the simplicity necessary to build an index". We show that for a governance measure, such a simple addition of coded provisions is not enough to understand the economic and financial impact of governance. This, as our results show, is especially important with respect to investors.

Overall, the new unequal-weighted nG-Index tracks the governance– performance relationship more consistently than the alternative equal-weighted mG-Index does. Our results show that if we use the nG-Index as a measure of governance quality for our sample firms, we can judge its management in terms of the alignment of their interests with those of shareholders through superior firm values and operating performance. The same is not true when using an equal-weighted index.

Our analysis also reveals a newer governance-based hedge strategy to that shown in prior literature that can generate abnormal returns. Previous studies show that investors could make abnormal returns by investing in good governance stocks. However, we show that investors will lose money if they keep using the old long good governance–short poor governance strategy. An investor going long bad governance stocks (Dictatorship) and shorting good governance ones (Democracy) would have made approximately 16% abnormal returns in our sample period. This indicates that investors may be taking a longer time now to impound the performance benefits of good governance stocks than they did in previous years. We can also take this to indicate a preference for risk-seeking behaviour in recent years, especially if governance quality is measured well. Specifically, we show that in terms of stock returns in the short run, poor governance quality in firms benefits the investors more than the goodness of firm's governance quality.

While we thoroughly examine the governance–performance relationship by introducing a dynamic and more informative new governance index, there are several limitations that future research could address. For instance, we largely study the association between governance and performance, while only briefly exploring endogeneity and causality. Moreover, there is scope to assess the heterogeneity of these provisions in a multiple-country setting to draw international comparisons. Additionally, does the relative importance of ATPs have similar effects on other firm outcomes and decisions, such as innovation and/or takeovers? Our study opens the door for many such research questions.

3.8 References

Acharya, V. V., Myers, S. C., Rajan, R. G., 2011. The internal governance of firms. Journal of Finance 66 (3), 689–720.

Allayannis, G., Lel, U., Miller, D. P., 2012. The use of foreign currency derivatives, corporate governance, and firm value around the world. Journal of International Economics 87 (1), 65–79.

Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23 (4), 589–609.

Andreou, P. C., Antoniou, C., Horton, J., Louca, C., 2016. Corporate governance and firm-specific stock price crashes. European Financial Management 22 (5), 916–956.

Bebchuk, L., Coates IV, J. C., Subramanian, G., 2002. The powerful antitakeover force of staggered boards: Further findings and a reply to symposium participants. Stanford Law Review 54 (5), 885–917.

Bebchuk, L., Cohen, A., 2005. The costs of entrenched boards. Journal of Financial Economics 78 (2), 409–433.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22 (2), 783–827.

Bebchuk, L., Cohen, A., Wang, C. C., 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics 108 (2), 323–348.

Bebchuk, L., Cohen, A., Wang, C. C., 2014. Golden parachutes and the wealth of shareholders. Journal of Corporate Finance 25, 140–154.

Bebchuk, L., Stole, L. A., 1993. Do short-term objectives lead to under-or overinvestment in long-term projects? Journal of Finance 48 (2), 719–729.

Beiner, S., Drobetz, W., Schmid, M. M., Zimmermann, H., 2006. An integrated framework of corporate governance and firm valuation. European Financial Management 12 (2), 249–283.

Bekaert, G., Hodrick, R. J., Zhang, X., 2009. International stock return comovements. Journal of Finance 64 (6), 2591–2626.

Bhagat, S., Black, B., 2001. The non-correlation between board independence and long-term firm performance. Journal of Corporation Law 27, 231–274.

Bhagat, S., Bolton, B., 2008. Corporate governance and firm performance. Journal of Corporate Finance 14 (3), 257–273.

Bhagat, S., Bolton, B., 2009. Sarbanes-oxley, governance and performance. Unpublished working paper, http://ssrn.com/abstract=1361815.

Bhagat, S., Bolton, B., 2013. Director ownership, governance, and performance. Journal of Financial and Quantitative Analysis 48 (01), 105–135.

Bhagat, S., Bolton, B., Romano, R., 2008. The promise and peril of corporate governance indices. Columbia Law Review 108, 1803–1882.

Brennan, M. J., Chordia, T., Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. Journal of Financial Economics 49 (3), 345–373.

Brown, L. D., Caylor, M. L., 2006. Corporate governance and firm valuation. Journal of Accounting and Public Policy 25 (4), 409–434.

Brown, L. D., Caylor, M. L., 2009. Corporate governance and firm operating performance. Review of Quantitative Finance and Accounting 32 (2), 129–144.

Cain, M. D., McKeon, S. B., Solomon, S. D., 2017. Do takeover laws matter? evidence from five decades of hostile takeovers. Journal of Financial Economics 124 (3), 464–485.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52 (1), 57–82.

Carter, D. A., Simkins, B. J., Simpson, W. G., 2003. Corporate governance, board diversity, and firm value. Financial Review 38 (1), 33–53.

Chemmanur, T. J., Tian, X., 2017. Do anti-takeover provisions spur corporate innovation? A regression discontinuity analysis. Unpublished working paper, http://ssrn.com/abstract=1572219.

Chen, J., Hong, H., Stein, J. C., 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. Journal of Financial Economics 61 (3), 345–381.

Chen, K. C., Chen, Z., Wei, K. J., 2009. Legal protection of investors, corporate governance, and the cost of equity capital. Journal of Corporate Finance 15 (3), 273–289.

Chinco, A., Clark-Joseph, A. D., Ye, M., 2019. Sparse signals in the cross-section of returns. Journal of Finance 74 (1), 449–492.

Cho, M.-H., 1998. Ownership structure, investment, and the corporate value: An empirical analysis. Journal of Financial Economics 47 (1), 103–121.

Chung, K. H., Elder, J., Kim, J.-C., 2010. Corporate governance and liquidity. Journal of Financial and Quantitative Analysis 45 (2), 265–291.

Core, J. E., Guay, W. R., Rusticus, T. O., 2006. Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations. Journal of Finance 61 (2), 655–687.

Cremers, K., Nair, V. B., 2005. Governance mechanisms and equity prices. Journal of Finance 60 (6), 2859–2894.

Cremers, K. M., Nair, V. B., John, K., 2009. Takeovers and the cross-section of returns. Review of Financial Studies 22 (4), 1409–1445.

Cremers, M., Ferrell, A., 2014. Thirty years of shareholder rights and firm value. Journal of Finance 69 (3), 1167–1196.

Cuñat, V., Gine, M., Guadalupe, M., 2012. The vote is cast: The effect of corporate governance on shareholder value. Journal of Finance 67 (5), 1943–1977.

Cuñat, V., Gine, M., Guadalupe, M., 2016. Say pays! shareholder voice and firm performance. Review of Finance 20 (5), 1799–1834.

Daines, R. M., Gow, I. D., Larcker, D. F., 2010. Rating the ratings: How good are commercial governance ratings? Journal of Financial Economics 98 (3), 439–461.

DeAngelo, H., Rice, E. M., 1983. Antitakeover charter amendments and stockholder wealth. Journal of Financial Economics 11 (1-4), 329–359.

Dumitrescu, A., 2015. Corporate governance, disclosure and market liquidity. Unpublished working paper, Available at: http://ssrn.com/abstract=1356204.

Durnev, A., Kim, E., 2005. To steal or not to steal: Firm attributes, legal environment, and valuation. Journal of Finance 60 (3), 1461–1493.

Eisenberg, T., Sundgren, S., Wells, M. T., 1998. Larger board size and decreasing firm value in small firms. Journal of Financial Economics 48 (1), 35–54.

Erkens, D. H., Hung, M., Matos, P., 2012. Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. Journal of Corporate Finance 18 (2), 389–411.

Fama, E. F., 1980. Agency problems and the theory of the firm. Journal of Political Economy 88 (2), 288–307.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33 (1), 3–56.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics 43 (2), 153–193.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies 29 (1), 69–103.

Fama, E. F., Jensen, M. C., 1983. Separation of ownership and control. Journal of Law and Economics 26 (2), 301–325.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81 (3), 607–636.

Fiss, P. C., Kennedy, M. T., Davis, G. F., 2012. How golden parachutes unfolded: Diffusion and variation of a controversial practice. Organization Science 23 (4), 1077–1099.

Giamouridis, D., Paterlini, S., 2010. Regular(ized) hedge fund clones. Journal of Financial Research 33 (3), 223–247.

Giroud, X., Mueller, H. M., 2011. Corporate governance, product market competition, and equity prices. Journal of Finance 66 (2), 563–600.

Gompers, P. A., Ishii, J. L., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118 (1), 107–155.

Gu, L., Hackbarth, D., 2013. Governance and equity prices: Does transparency matter? Review of Finance 17 (6), 1989–2033.

Güner, A. B., Malmendier, U., Tate, G., 2008. Financial expertise of directors. Journal of Financial Economics 88 (2), 323–354.

Guo, R.-J., Kruse, T. A., Nohel, T., 2008. Undoing the powerful anti-takeover force of staggered boards. Journal of Corporate Finance 14 (3), 274–288.

Hermalin, B. E., Weisbach, M. S., 1991. The effects of board composition and direct incentives on firm performance. Financial Management, 101–112.

Heston, S. L., Rouwenhorst, K. G., 1994. Does industrial structure explain the benefits of international diversification? Journal of Financial Economics 36 (1), 3–27.

Hoerl, A. E., Kennard, R. W., 1970. Ridge regression: Biased estimation for nonorthogonal problems. Technometrics 12 (1), 55–67.

Hong, H., Stein, J. C., 2003. Differences of opinion, short-sales constraints, and market crashes. Review of Financial Studies 16 (2), 487–525.

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28 (3), 791–837.

Hutton, A. P., Marcus, A. J., Tehranian, H., 2009. Opaque financial reports, r 2, and crash risk. Journal of Financial Economics 94 (1), 67–86.

Jensen, M. C., 1986. Agency costs of free cash flow, corporate finance, and takeovers. American Economic Review 76 (2), 323–329.

Jensen, M. C., Meckling, W. H., 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics 3 (4), 305–360.

Jin, L., Myers, S., 2006. R2 around the world: New theory and new tests. Journal of Financial Economics 79 (2), 257–292.

Karpoff, J. M., Wittry, M. D., 2018. Institutional and legal context in natural experiments: The case of state antitakeover laws. Journal of Finance 73 (2), 657–714.

Kee, H. L., 2009. The coefficient of the whole is an average of the coefficients of its parts: A special case of restricted least squares. Economics Letters 104 (3), 136–139.

Kim, J.-B., Wang, Z., Zhang, L., 2016. CEO overconfidence and stock price crash risk. Contemporary Accounting Research 33 (4), 1720–1749.

Kim, J.-B., Zhang, L., 2016. Accounting conservatism and stock price crash risk: Firm-level evidence. Contemporary Accounting Research 33 (1), 412–441.

Klapper, L. F., Love, I., 2004. Corporate governance, investor protection, and performance in emerging markets. Journal of Corporate Finance 10 (5), 703–728.

Lombardo, D., Pagano, M., 2002. Law and equity markets: A simple model. In: McCahery, J., Moerland, P., Raaijmakers, T., Renneboog, L. (Eds.), Corporate governance regimes: Convergence and diversity. Oxford University Press, Oxford, pp. 343–362.

Maskara, P. K., Maskara, A., Aggarwal, R., 2013. Corporate governance: Known, unknown, and the wrongly known. Journal of Business and Economics 4 (2).

McCahery, J. A., Sautner, Z., Starks, L. T., 2016. Behind the scenes: The corporate governance preferences of institutional investors. Journal of Finance 71 (6), 2905–2932.

Mehran, H., 1995. Executive compensation structure, ownership, and firm performance. Journal of Financial Economics 38 (2), 163–184.

Morck, R., Yang, F., 2001. The mysterious growing value of s&p 500 membership. Tech. rep., National Bureau of Economic Research.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111 (3), 642–685.

Pukthuanthong, K., Roll, R., Subrahmanyam, A., 2018. A protocol for factor identification. Review of Financial Studies 32 (4), 1573–1607.

Rajan, R. G., Zingales, L., 1998. Power in a theory of the firm. Quarterly Journal of Economics 113 (2), 387–432.

Schnyder, G., 2012. Measuring corporate governance: Lessons from the 'bundles approach'. Unpublished working paper, http://ssrn.com/abstract=2220616.

Schultz, E. L., Tan, D. T., Walsh, K. D., 2010. Endogeneity and the corporate governance-performance relation. Australian Journal of Management 35 (2), 145–163.

Sharpe, W. F., 1992. Asset allocation: Management style and performance measurement. Journal of Portfolio Management 18 (2), 7–19.

Shleifer, A., Vishny, R. W., 1989. Management entrenchment: The case of manager-specific investments. Journal of Financial Economics 25 (1), 123–139.

Shleifer, A., Vishny, R. W., 1994. Politicians and firms. Quarterly Journal of Economics 109 (4), 995–1025.

Shleifer, A., Vishny, R. W., 1997. A survey of corporate governance. Journal of Finance 52 (2), 737–783.

Singh, H., Harianto, F., 1989. Management-board relationships, takeover risk, and the adoption of golden parachutes. Academy of Management Journal 32 (1), 7–24.

Stein, J. C., 1988. Takeover threats and managerial myopia. Journal of Political Economy 96 (1), 61–80.

Stein, J. C., 1989. Efficient capital markets, inefficient firms: A model of myopic corporate behavior. Quarterly Journal of Economics 104 (4), 655–669.

Tibshirani, R., 1996. Regression shrinkage and selection via the Lasso. Journal of the Royal Statistical Society. Series B (Methodological), 267–288.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 817–838.

Williamson, O. E., 1988. Corporate finance and corporate governance. Journal of Finance 43 (3), 567–591.

Williamson, O. E., 1998. Transaction cost economics: How it works; where it is headed. De Economist 146 (1), 23–58.

Wintoki, M. B., Linck, J. S., Netter, J. M., 2012. Endogeneity and the dynamics of internal corporate governance. Journal of Financial Economics 105 (3), 581–606.

3.A Appendices

3.A.1 ISS Corporate Governance Provisions (2007 onwards)

This appendix briefly explains all provisions listed in Table 3.1 and which we use as factors to construct the equal-weighted new Governance (nG) index and equal-weighted modified Governance (mG) Index. We provide these descriptions in alphabetical order; they are similar to descriptions provided in Gompers, Ishii, and Metrick (2003) for certain provisions that existed in the older ISS provisions dataset. We also provide a quick brief on each provision's impact on shareholder rights and the rationale for their categorizations in Table 3.1.

Blank Check preferred stock is a provision through which the company can create and issue new classes of preferred stocks without seeking shareholder approval to raise additional funds. Preferred stock is called "blank checks" because the board of directors has complete authority to determine voting, dividend, conversion, and other rights. It is most commonly applied to 'delay takeovers' by implementing poison pills or by placing such preferred stocks with friendly investors.

Bylaw and Charter amendment limitations limit shareholders' ability to amend the corporation's governing documents. This might take the form of a supermajority vote requirement for charter or bylaw amendments, total elimination of shareholders' ability to amend the bylaws, or the ability of directors (beyond the provisions of state law) to amend the bylaws without shareholder approval.

A Classified Board (or **staggered board)** is one in which directors are placed into different classes and serve overlapping terms. Since the firm can replace only a part of the board each year, an outsider who gains control of a corporation may have to wait a few years before being able to gain control of the board, causing a possible 'delay' in takeovers.

Cumulative Voting allows a shareholder to allocate his total votes in any manner desired, where the total number of votes is the product of the number of shares owned and the number of directors to be elected. By allowing them to concentrate their votes, this practice helps minority shareholders elect directors. Cumulative Voting and Secret Ballot (below) are the only two provisions whose presence is coded as an increase in shareholder rights, with an additional point to the nG or mG index if the provision is absent.

Fair-Price provisions limit the range of prices a bidder can pay in two-tier offers. They typically require a bidder to pay the highest price to all shareholders during a specified period before the commencement of a tender offer, and do not apply if the board of directors or a supermajority of the target's shareholders approve the deal. The goal of this provision is to prevent pressure on the target's shareholders to tender their shares at the front end of a two-tiered tender offer, and they make such an acquisition more expensive.

Golden Parachutes are severance agreements that provide a large payment or other financial compensation to company executives if they should be dismissed as a result of a merger or takeover. They do not require shareholder approval. While the net impact on managerial entrenchment and shareholder wealth is ambiguous, the more important effect is a clear decrease in shareholder rights. In this case, the "right" is the ability of a controlling shareholder to fire management without incurring an additional cost.

Limitations on action by Written Consent can take the form of establishing majority thresholds beyond the level of state law, requiring unanimous consent, or eliminating the right to take action by written consent. Such requirements add extra time to many proxy fights since bidders must wait until the regularly scheduled annual meeting to replace board members or dismantle takeover defenses. This delay is especially potent when combined with limitations for calling special meetings (above).

With **Limited Ability to call Special Meetings**, special meetings of shareholders may be called only by the board of directors or by other persons authorized by the company's certificate of incorporation or bylaws. If the company's certificate of incorporation does not contain any provisions on the calling of a special meeting, and shareholders' right to cause a special meeting to be called is only contained in the bylaws, the company's board of directors can act, without shareholder approval, to amend the bylaws to specifically deny shareholders the right to call a special meeting.

Poison Pills provide their holders with special rights in the case of a triggering event, such as a hostile takeover bid. If the board of directors approve a deal, the poison pill can be revoked, but if the deal is not approved and the bidder proceeds, the pill is triggered. Typical poison pills give the holders of the target's stock, besides the bidder, the right to purchase stock in the target or the bidder's company at a steep discount, making the target unattractive or diluting the acquirer's voting power. Poison pills may even be used as a "delay" strategy at the core of modern defensive tactics.

Under a **Secret Ballot** (also called **confidential voting**), either an independent third party or employees sworn to secrecy count proxy votes, and the management usually agrees not to look at individual proxy cards. This can help eliminate potential conflicts of interest for fiduciaries' voting shares on behalf of others, and can reduce management pressure on shareholder-employees or shareholder-partners.

Special Meeting limitations either increase the level of shareholder support required to call a special meeting beyond that specified by state law or eliminate the ability to call one entirely. Such provisions add extra time to proxy fights, since bidders must wait until the regularly scheduled annual meeting to replace board members or dismantle takeover defenses. This delay is especially potent when combined with limitations on actions by written consent (below).

The **State Laws** provision summarizes antitakeover laws (i.e., Business Combination laws, control share acquisition laws, cash-out laws, etc.) in a single measure representing the presence of any of these state legislations within the jurisdiction in which the company is located.

Supermajority requirements to approve mergers are charter provisions that establish voting requirements for mergers or other business combinations above the threshold requirements of state law. They limit is typically over 1/3rd and may often exceed attendance at the annual meeting. We consider a more conservative 2/3rd requirement.

Supermajority for Written Consent/ Special Meeting/ Amending Bylaws/ Amending Charter are supermajority provisions similar to Supermajority requirements to approve mergers in terms of a minimum requirement (we define them as over 2/3rds) to vote for either passing a written consent, call for a special meeting, or to amend bylaws. These provisions require a majority of disinterested shareholders to vote on such changes and are treated as a structural defense against shareholder activism.

Unequal Voting rights limit the voting rights of some shareholders and expand those of others. Under time-phased voting, shareholders who held the stock for a given period of time are given more votes per share than recent purchasers.

3.A.2 Variables and Controls Used in the Tobin's Q and Operating Performance Regressions

Tobin's Q: Measure created following Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009). Q is the ratio of the market value of assets to the book value of assets (Compustat data item 6) with the numerator calculated as: (book value of assets + market value of common stock) – (book value of common stock + deferred taxes). All inputs for the Q measure were taken from corresponding headers in the COMPUSTAT data.

ROA: As a measure of operating performance, Return on Assets (ROA) is calculated as the operating income divided by end of year total assets (Compustat data item 6). We applied operating income before depreciation (Compustat data item 13) as Bhagat and Bolton (2008) suggest.

Size: Log transformation of Total Assets (Compustat data item 6).

Age: Log transformation of firm age measured in months at the end of each calendar year.

Altman's Z Score: Unlike Bhagat and Bolton (2008), who employ the modified Altman's Z-score, we use the conceptualization of Z-score as Altman (1968) suggests, but not including leverage as a factor (since we take leverage as a separate control variable). The component factors, such as Working Capital to Total Assets, Retained Earnings to Total Assets, Sales to Total Assets, and EBIT to Total Assets were calculated from corresponding headers in the COMPUSTAT data.

Leverage: Following Bhagat and Bolton (2008) and Bebchuk, Cohen, and Ferrell (2009): Long term debt (Compustat data item 9) / Total Assets (Compustat data item 6). An alternative measure of leverage, the Debt/Equity ratio, was also used as a robustness check.

CAPEXTA: is the log transformation of the ratio of Capital Expenditures to Total Assets.

Delaware Dummy: Dummy variable indicating whether a firm is incorporated in Delaware or not (coded 1 and 0, respectively) as first used in Gompers, Ishii, and Metrick (2003).

S&P500: Dummy variable indicating whether a firm is included in the S&P500 in the corresponding calendar year.

Book-to-Market: The ratio of the book value of common equity to the market value of common equity. The book value of common equity is the sum of the book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

NPM: Net income divided by sales (Compustat item 12).

ROE: Net income divided by the book value of common stock, i.e., the sum of the book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

3.A.3 Variables and Controls Used to Extract Factor Weights

Price: Monthly Closing Price for time t–2 (in logs).

Size: Market capitalization observed at the end of month t–2 (in logs).

Volume: Dollar volume of trading recorded at the end of month t–2 (in logs).

S&P500: Dummy variable indicating whether a firm is included in the S&P500 for month t.

Yield: Computed as one-year lagged dividends (Compustat item 21) divided by market capitalization measured at calendar year-end.

2-Year Return: The compounded return from month t–1 to month t–25 (in logs).

Value: Tobin's Q computed as the ratio of the market value of assets to the book value of assets (Compustat data item 6) with the numerator calculated as: (book value of assets + market value of common stock) – (book value of common stock + deferred taxes), item 74). (Industry-adjusted using median Q values for each industry).

Past 2-Month Returns: Compounded gross returns for months t–3 and t–2 (in logs).

Past Quarterly Returns: Compounded gross returns for months t–6 to t–4 (in logs).

Past Semi-Annual Returns: Compounded gross returns for months t–12 to t–7 (in logs).

SE Code: A dummy variable representing the specific stock exchange on which the firm's stock is listed in that month.

3.A.4 Variables and Controls Used in Crash Risk Regressions

CRASH: A dummy variable that takes the value 1 when in a given year, the firm experiences one or more crash weeks. A crash week is when the firm-specific weekly return (FSWR) falls 2.98 standard deviations below the annual average FSWR. The number of standard deviations here represents the lower 10% level of the FSWR distribution for that firm-year.

CRASHNUM: An indicator that counts the number of crash weeks a firm experienced in a given year. Crash weeks are measured as above for the variable CRASH.

NCSKEW: The negative conditional skewness of FSWR over a given year.

DUVOL: Down-to-up volatility is measured as the logarithmic transformation of the ratio of the standard deviation of FSWR for down weeks (below average) to that for the up weeks (above average) for each firm-year.

DIFTURN: The difference in mean monthly share turnover for current year t and the mean monthly share turnover of prior year $t-1$. For each firm-month, the monthly share turnover is the ratio of corresponding trading volume to the total shares outstanding.

AVG: The average FSWR for a given firm over that year.

SIGMA: Volatility or standard deviation of FSWR for a given firm over that year.

SIZE: The market value of equity (in logs).

MB: The market-to-book ratio taken as the market value of equity divided by the book value. Book value is the sum of the book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

LEV: Same as 'Leverage' in Appendix 3.A.2.

ROA: As defined in Appendix 3.A.2.

OPAQUE: Discretionary accruals that indicate opacity measured by Hutton, Marcus, and Tehranian (2009) using a three-year moving sum of the absolute value of discretionary accruals calculated with a modified Jones model.

3.A.5 Additional Details for Section 3.4.2.1

For example, if we consider a simple unconstrained estimation of stock returns Ret on three ATPs X_1, X_2 and X_3:

$$Ret = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{3.13}$$

For the unconstrained model to be unbiased, we assume all of the provisions are independent of each other (orthogonal), which is not the case for governance provisions as is seen by their high correlations. Thus, applying a constraint $\beta_1 + \beta_2 + \beta_3 = -1$ would imply a constrained regression of the form:

$$Ret = \beta_1 X_1 - (1 + \beta_1 + \beta_3) X_2 - (1 + \beta_1 + \beta_2) X_3 \tag{3.14}$$

We see that the use of constraint ensures that the estimation procedure, which extracts the coefficients of factors for each year in the sample, represents the contribution of each factor towards returns by accounting for the variation in each of the remaining factors. Such localization procedures have widely been used to replicate interdependence amongst the otherwise independent variables in many studies (e.g., Heston and Rouwenhorst, 1994). In other words, all the covariances between each of the ATPs or factors (i.e. the focal factor and rest of the factors) are corrected for in the solution, making the estimates less biased. In our case, this is done by assuming that all of the available ATPs have a peculiar linear dependence. To elaborate this further, consider a system of related regressions that estimate each factor's contribution to returns separately while controlling for other factors:

$$Ret = \gamma_1 X_1 + \gamma_2 (X_2 + X_3) \tag{3.15a}$$

$$Ret = \theta_1 X_2 + \theta_2 (X_1 + X_3) \tag{3.15b}$$

$$Ret = \eta_1 X_3 + \eta_2 (X_1 + X_2) \tag{3.15c}$$

By subtracting equations 3.15b and 3.15c, we obtain a linear equation $(\theta_2 - \eta_2)X_1 + (\theta_1 - \eta_2)X_2 + (\theta_2 - \eta_1)X_3 = 0$ that can be treated as a constraint for estimating equation 3.15a (given that the coefficient γ_2 for the sum of two correlated variables is the weighted average of individual marginal effects, see Kee, 2009) to get a unique solution for this system. This is the underlying rationale behind applying constrained regression for the ATPs and returns.

In recent years, asset allocation literature has extended the application of Sharpe (1992) methodology by introducing regularization and optimization procedures (see, for e.g., Giamouridis and Paterlini, 2010) that employ LASSO regression (Tibshirani, 1996) or ridge regression (Hoerl and Kennard, 1970). However, these methods are ideal for factor selection when facing non-orthogonality, whereas our objective is to capture factor relativity. Additional problems arise out of the binary nature of ATP variables that restricts the ability of these penalized regressions. Nevertheless, we do assess LASSO estimation procedure for ATP selection in the Section 3.4.2.2.

3.A.6 Supplementary Results

Table 3.13 Correlations between the nG-Index and the G and E indices

This table shows the correlations and corresponding significance levels for the new unequally weighted nG-Index with two existing indices. While the nG-Index and mG-Index (used as a proxy for the G-Index) are computed using 19 provisions as in Table 3.1, the E-Index is created using a subset of these 19 provisions as in Bebchuk, Cohen, and Ferrell (2009). The statistical significance at 10%, 5%, and 1% are shown by *, **, and ***, respectively.

	nG-Index	**mG-Index**	**E-Index**
nG-Index	1.0000		
mG-Index	0.3659***	1.0000	
	(0.0000)		
E-Index	0.1237***	0.7155***	1.0000
	(0.0000)	(0.0000)	

Table 3.14 OLS, panel, dynamic OLS and system GMM regressions for Tobin's Q on governance (in-sample test)

These results extend those in Table 3.7 by using an nG-Index with in-sample period weights assigned (i.e., the factor weights obtained by including current year's returns and ATPs in constrained regressions). By construction, the results for the mG-Index remain the same as reported earlier. All controls and models are exactly the same as in Table 3.7. Model 1 considers Tobin's Q with the two indices without any controls. Models 2 and 3 improve on model 1 by including the additional controls and firm fixed effects respectively. Models 4 and 5 improves on the static OLS models by introducing past firm values for two and four years respectively, along with the industry fixed effects. Model 6 gives the estimates for system GMM. Significance levels are represented by *, **, and *** for 10%, 5%, and 1%.

	Static OLS		Panel FE	Dynamic OLS		System GMM	Static OLS		Panel FE	Dynamic OLS		System GMM
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
nG (–)	**-0.8893*** **	**-0.8086*** **	**-0.4321** **	**-0.1764** **	**-0.1947** **	**-4.3010* **						
	(0.148)	**(0.144)**	**(0.151)**	**(0.085)**	**(0.091)**	**(2.456)**						
mG (–)							**-0.0297*** **	**-0.0183** **	**0.0107**	**-0.0065** **	**-0.0063* **	**-0.0098**
							(0.005)	**(0.006)**	**(0.007)**	**(0.003)**	**(0.003)**	**(0.027)**
ROA		4.6332***	1.3617***	1.1046***	0.9954***	1.6116		4.6239***	1.3624***	1.1001***	0.9917***	1.7226
		(0.568)	(0.121)	(0.260)	(0.256)	(1.160)		(0.570)	(0.121)	(0.261)	(0.256)	(1.250)
Size		-0.2041***	-0.3562***	-0.0650***	-0.0635***	0.0927		-0.2054***	-0.3567***	-0.0662***	-0.0648***	-0.0436
		(0.014)	(0.027)	(0.007)	(0.007)	(0.113)		(0.015)	(0.027)	(0.008)	(0.008)	(0.089)
Age		-0.0911***	-0.2422***	0.0266***	0.0298***	-0.0600		-0.0935***	-0.2359***	0.0252***	0.0283***	-0.0110
		(0.015)	(0.045)	(0.010)	(0.010)	(0.054)		(0.015)	(0.045)	(0.010)	(0.010)	(0.045)
Altman's Z		-0.0368**	0.0753***	-0.0020	-0.0021	0.0138		-0.0373**	0.0758***	-0.0019	-0.0020	-0.0422
		(0.016)	(0.016)	(0.009)	(0.009)	(0.129)		(0.016)	(0.016)	(0.009)	(0.009)	(0.124)
Leverage		-0.9570***	-0.9567***	-0.3119***	-0.2430***	-0.2914		-0.9635***	-0.9584***	-0.3123***	-0.2435***	-0.3140
		(0.128)	(0.081)	(0.075)	(0.075)	(0.335)		(0.128)	(0.081)	(0.076)	(0.076)	(0.352)
CAPEX / Assets		-0.0561***	0.0791***	-0.0075	-0.0095	-0.0644		-0.0564***	0.0797***	-0.0077	-0.0095	-0.0179
		(0.014)	(0.014)	(0.010)	(0.011)	(0.066)		(0.014)	(0.014)	(0.010)	(0.011)	(0.059)
S&P500		0.5259***	0.3686***	0.1441***	0.1342***	-0.2121		0.5178***	0.3679***	0.1425***	0.1330***	-0.1083
		(0.042)	(0.048)	(0.020)	(0.020)	(0.249)		(0.041)	(0.048)	(0.020)	(0.020)	(0.181)
Delaware Dummy		0.0078	-0.0598**	0.0038	-0.0054	0.0058		0.0073	-0.0550**	0.0023	-0.0070	0.0365
		(0.022)	(0.026)	(0.014)	(0.014)	(0.062)		(0.022)	(0.027)	(0.014)	(0.015)	(0.063)
Tobin's Q (t–1)				0.7457***	0.7503***	0.4270**				0.7457***	0.7505***	0.4932**
				(0.035)	(0.040)	(0.183)				(0.035)	(0.040)	(0.185)
Tobin's Q (t–2)				0.0103	-0.0492	0.1161				0.0100	-0.0494	0.0856
				(0.024)	(0.035)	(0.104)				(0.024)	(0.035)	(0.100)
Tobin's Q (t–3)					0.1157***						0.1157***	
					(0.030)						(0.030)	
Tobin's Q (t–4)					-0.0285						-0.0286	
					(0.021)						(0.021)	
Year Effects	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm/Industry Fixed Effects	No	No	Firm	Industry	Industry	Firm	No	No	Firm	Industry	Industry	Firm
Number of observations	10190	9388	9388	9276	8132	9276	10190	9388	9388	9276	8132	9276
R-Squared	0.003	0.322	0.189	0.748	0.758		0.003	0.321	0.185	0.748	0.758	
Number of Groups			1472			1453			1472			1453
Number of Instruments						37						37
AR(1) / AR(2) Test (p-value)						0.075 / 0.036						0.061 / 0.052
Hansen J Test (p-value)						0.000						0.000

Table 3.15 Robustness check for Tobin's Q on governance (controlling for entrenchment and active ownership)

This table replicates the panel fixed effects (FE) model in Table 3.7, but introduces additional controls for the entrenchment index (E-Index) and active ownership (AO). We use three proxies for AO, shown separately within the table. The Blockholder dummy indicates the presence of one or more blockholders (with at least 5% ownership). Number of blockholders accounts for the dispersion of these blockholders. Institutional ownership is the % of shares owned by institutional investors. All regressions use industry-adjusted Tobin's Q calculated as Tobin's Q minus the median Tobin's Q for that industry using the Fama and French (1997) 48 industry classification. All other controls remain the same. Models 1, 2, and 3 consider the nG-Index, E-Index, and AO, respectively, as the main regressor. Model 4 includes all three governance aspects in a horse race regression. The coefficients for constant and year dummies are not reported. Robust standard errors are given in parenthesis. Significance levels at 10%, 5%, and 1% are shown by *, **, and ***, respectively.

			AO = Blockholder Dummy		AO = # of Blockholders		AO = Institutional Ownership	
	(1)	(2)	(3)	(4)	(3)	(4)	(3)	(4)
nG	**-0.4320****			**-0.5249****		**-0.5117****		**-0.5230****
	(0.208)			**(0.211)**		**(0.206)**		**(0.212)**
E-Index		**0.0305****		**0.0367****		**0.0378****		**0.0384****
		(0.014)		**(0.014)**		**(0.014)**		**(0.014)**
Active Ownership (AO)			**-0.0354**	**-0.0356**	**-0.0333*****	**-0.0328*****	**-0.0475**	**-0.0407**
			(0.027)	**(0.027)**	**(0.010)**	**(0.010)**	**(0.118)**	**(0.118)**
ROA	1.3615**	1.3544**	1.3653**	1.3449**	1.3049**	1.2856**	1.3482**	1.3285**
	(0.510)	(0.510)	(0.512)	(0.508)	(0.565)	(0.561)	(0.572)	(0.568)
Size	-0.3564***	-0.3575***	-0.3567***	-0.3582***	-0.3618***	-0.3635***	-0.3561***	-0.3582***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.049)	(0.049)	(0.049)	(0.049)
Age	-0.2420**	-0.2417**	-0.2379**	-0.2507**	-0.3106***	-0.3240***	-0.3089***	-0.3228***
	(0.081)	(0.081)	(0.081)	(0.081)	(0.085)	(0.084)	(0.086)	(0.085)
Altman's Z	0.0754**	0.0767**	0.0757**	0.0769**	0.0671	0.0682	0.0675	0.0684
	(0.038)	(0.038)	(0.038)	(0.038)	(0.059)	(0.059)	(0.059)	(0.059)
Leverage	-0.9568***	-0.9630***	-0.9593***	-0.9604***	-0.9618***	-0.9632***	-0.9701***	-0.9712***
	(0.242)	(0.242)	(0.242)	(0.242)	(0.263)	(0.264)	(0.265)	(0.266)
CAPEX / Assets	0.0792***	0.0803***	0.0792***	0.0799***	0.0786***	0.0792***	0.0797***	0.0803***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
S&P500	0.3687***	0.3660***	0.3686***	0.3658***	0.3750***	0.3728***	0.3822***	0.3801***
	(0.102)	(0.103)	(0.102)	(0.103)	(0.109)	(0.109)	(0.108)	(0.108)
Delaware Dummy	-0.0598**	-0.0514*	-0.0579**	-0.0529*	-0.0521*	-0.0466	-0.0522*	-0.0465
	(0.028)	(0.028)	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	9387	9387	9387	9387	9037	9037	9037	9037
R-squared	0.128	0.128	0.127	0.129	0.130	0.133	0.127	0.130
Number of Groups	1472	1472	1472	1472	1421	1421	1421	1421

Table 3.16 Additional robustness check for Tobin's Q on governance (controlling for entrenchment and active ownership)

This table replicates the OLS and dynamic OLS models of Table 3.7, but introduces additional controls for the entrenchment index (E-Index) and active ownership (AO). We use three proxies for AO, shown separately within the table. The Blockholder dummy represents the presence of one or more blockholders (having 5% ownership or more in the firm). Number of blockholders accounts for the dispersion of blockholders. Institutional ownership is the % of shares owned by institutional investors. All regressions use industry-adjusted Tobin's Q calculated as Tobin's Q minus the median Tobin's Q for that industry using the Fama and French (1997) 48 industry classification. All other controls remain the same. Models 1, 2, and 3 consider the nG-Index, E-Index, and AO, respectively, as the main regressor. Model 4 includes all three governance aspects in a horse race regression. Model 5 improves on model 4 by controlling for the lagged dependent variable (DV). The coefficients for constant, year dummies, and industry dummies are excluded for brevity. Robust standard errors are in parenthesis. Significance levels are shown by *, **, and *** for 10%, 5%, and 1%, respectively.

			AO = Blockholder Dummy			AO = # of Blockholders			AO = Institutional Ownership		
	(1)	(2)	(3)	(4)	(5)	(3)	(4)	(5)	(3)	(4)	(5)
nG	**-0.7947*** (0.135)**			**-0.6656*** (0.132)**	**-0.2023** (0.086)**		**-0.6846*** (0.131)**	**-0.2164** (0.087)**		**-0.6774*** (0.134)**	**-0.2110** (0.087)**
E-Index		**-0.0397*** (0.010)**		**-0.0287** (0.010)**	**-0.0014 (0.006)**		**-0.0289** (0.010)**	**-0.0006 (0.006)**		**-0.0334*** (0.010)**	**-0.0015 (0.006)**
Active Ownership (AO)			**-0.2492*** (0.044)**	**-0.2400*** (0.043)**	**-0.0134 (0.024)**	**-0.0582*** (0.010)**	**-0.0571*** (0.009)**	**-0.0059 (0.005)**	**0.1305** (0.066)**	**0.1457** (0.066)**	**0.0491 (0.044)**
ROA	4.5455*** (0.601)	4.5448*** (0.602)	4.5517*** (0.602)	4.5164*** (0.599)	0.9695*** (0.268)	4.2915*** (0.635)	4.2558*** (0.631)	0.9020*** (0.268)	4.4165*** (0.640)	4.3762*** (0.636)	0.9097*** (0.269)
Size	-0.3054*** (0.015)	-0.3056*** (0.015)	-0.3120*** (0.015)	-0.3143*** (0.015)	-0.0596*** (0.008)	-0.3282*** (0.016)	-0.3302*** (0.016)	-0.0634*** (0.008)	-0.3048*** (0.015)	-0.3073*** (0.015)	-0.0607*** (0.008)
Age	-0.0662*** (0.014)	-0.0657*** (0.015)	-0.0681*** (0.014)	-0.0673*** (0.014)	0.0170 (0.011)	-0.0704*** (0.015)	-0.0696*** (0.015)	0.0181* (0.011)	-0.0638*** (0.015)	-0.0626*** (0.015)	0.0206* (0.011)
Altman's Z	0.0082 (0.016)	0.0075 (0.016)	0.0071 (0.016)	0.0083 (0.016)	0.0032 (0.008)	0.0041 (0.025)	0.0056 (0.025)	0.0034 (0.011)	0.0004 (0.026)	0.0018 (0.025)	0.0030 (0.011)
Leverage	-0.7738*** (0.139)	-0.7753*** (0.139)	-0.7621*** (0.139)	-0.7500*** (0.139)	-0.2930*** (0.068)	-0.6875*** (0.151)	-0.6740*** (0.151)	-0.2827*** (0.071)	-0.7773*** (0.153)	-0.7638*** (0.153)	-0.2960*** (0.072)
CAPEX / Assets	0.0300 (0.020)	0.0319 (0.020)	0.0303 (0.020)	0.0294 (0.020)	-0.0018 (0.011)	0.0233 (0.020)	0.0225 (0.020)	-0.0041 (0.011)	0.0259 (0.020)	0.0250 (0.020)	-0.0038 (0.011)
S&P500	0.7457*** (0.041)	0.7406*** (0.040)	0.7505*** (0.041)	0.7438*** (0.040)	0.1395*** (0.022)	0.7361*** (0.040)	0.7291*** (0.040)	0.1476*** (0.022)	0.7606*** (0.041)	0.7529*** (0.041)	0.1502*** (0.022)
Delaware Dummy	0.0756*** (0.023)	0.0869*** (0.022)	0.0864*** (0.022)	0.0769*** (0.023)	-0.0039 (0.015)	0.0842*** (0.023)	0.0743** (0.023)	-0.0052 (0.015)	0.0737** (0.023)	0.0635** (0.024)	-0.0071 (0.015)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged DV					Yes			Yes			Yes
Number of Observations	9387	9387	9387	9387	7873	9037	9037	7660	9037	9037	7660
R-squared	0.374	0.374	0.374	0.376	0.767	0.365	0.367	0.760	0.360	0.363	0.760

Table 3.17 Regression for operating performance on governance (in-sample test)

This table summarizes results obtained by running several variations of median the (minimum absolute deviation) regressions that specify operating performance as dependent on the nG and mG indices for the entire sample. The results here extend those in Table 3.9 by using the nG-Index with in-sample period weights (i.e., the factor weights obtained inclusive of current year's returns). All other variable definitions, controls, and models are exactly the same as in Table 3.9. By construction, the results for the mG-Index remain the same as reported earlier. Significance levels are represented by *, **, and *** for 10%, 5%, and 1%, respectively.

Panel A: ROA as the performance measure

	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
nG (−)	-0.0145**	-0.0149**	-0.0214**			
	(0.005)	(0.006)	(0.009)			
mG (−)				-0.0011***	-0.0019***	-0.0020***
				(0.000)	(0.000)	(0.000)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	10190	8276	8276	10190	8276	8276

Panel B: ROE as the performance measure

	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
nG (−)	-0.7779*	-3.7329***	-3.8053***			
	(0.406)	(1.005)	(1.146)			
mG (−)				-0.0272***	0.1564***	0.1148**
				(0.007)	(0.048)	(0.054)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	7615	7442	7442	7615	7442	7442

Panel C: NPM as the performance measure

	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
nG (−)	-0.0345**	-0.0313**	-0.0410**			
	(0.016)	(0.013)	(0.014)			
mG (−)				-0.0021***	-0.0015***	-0.0017***
				(0.000)	(0.000)	(0.000)
Controls		Yes	Yes		Yes	Yes
Year Fixed Effects			Yes			Yes
Number of Observations	9156	7805	7805	9156	7805	7805

Table 3.18 Do changes in nG-Index cause changes in operating performance?

This table reports the Diff-in-Diff-in-Diff (DDD) estimation results for all main and interaction effects for the impact of changes in nG-Index on operating performance (i.e. ROA, ROE or NPM as indicated). All models are estimated using Equation 3.7, but taking the operating performance measures in place of Tobin's Q and controlling for the same firm characteristics as those introduced in Table 3.9. Robust standard errors are shown in parenthesis. ΔnG represents the annual change in nG-Index values for a firm. $Post$ indicates years after Revlon ruling is passed in Maryland (i.e. beginning 2010) and $Treat$ is a dummy representing Maryland-based firms, where Delaware-based firms are taken as control group. Baseline DDD estimation in Panel A considers the Maryland and Delaware firms as is. Propensity score (PS) matched DDD estimation considers a comparable Delaware firm matched on log of assets, log of book-to-market and S&P500 membership, for every Maryland firm in a given year (using nearest-neighbor match with a 0.001 calliper). Panel B validates the results of Panel A by running placebo treatments. First placebo test assumes placebo treatment group for firms based in the state of Ohio, and the second test modifies the baseline DDD estimation by considering placebo $Post$ (beginning 2012). All models include industry and year fixed effects. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: Baseline and Propensity Score (PS) Matched DDD estimations

	Baseline DDD			PS Matched DDD		
	ΔROA	ΔROE	ΔNPM	ΔROA	ΔROE	ΔNPM
ΔnG	0.0444	-1.2884	-0.0304	0.0854	-16.6061**	1.8660
	(0.051)	(0.797)	(0.321)	(0.246)	(6.479)	(2.069)
$Post$	0.0062*	0.0225	0.0325	-0.0039	-0.2649	-0.0266
	(0.003)	(0.035)	(0.034)	(0.010)	(0.215)	(0.118)
$Treat$	-0.0013	-0.1081	-0.0225	0.0016	-0.1245	-0.0279
	(0.006)	(0.086)	(0.048)	(0.012)	(0.203)	(0.069)
$\Delta nG * Post$	0.0204	1.1760	0.1194	-0.4114	11.1440	-1.5616
	(0.063)	(0.807)	(0.320)	(0.293)	(7.357)	(2.210)
$\Delta nG * Treat$	-0.2254*	0.1616	-2.1223	-0.4385*	15.0925**	-2.4990
	(0.135)	(2.866)	(1.352)	(0.228)	(6.473)	(1.863)
$Post * Treat$	0.0030	0.1672*	-0.0166	0.0050	0.4266*	0.0625
	(0.006)	(0.099)	(0.050)	(0.010)	(0.227)	(0.072)
$\Delta nG * Post * Treat$	**0.3251****	**2.7674**	**2.4477***	**0.7799*****	**-5.4865**	**3.1057***
	(0.164)	**(3.456)**	**(1.485)**	**(0.272)**	**(7.121)**	**(1.792)**
Observations	4189	3442	3884	626	440	428
R-squared	0.011	0.028	0.019	0.140	0.219	0.200

Panel B: Placebo DDD tests

	Placebo Treated State (Ohio)			Placebo Post-Treatment (2012)		
	ΔROA	ΔROE	ΔNPM	ΔROA	ΔROE	ΔNPM
ΔnG	0.0352	-1.2788*	0.0317	0.0067	-0.6648*	0.0149
	(0.052)	(0.770)	(0.271)	(0.036)	(0.357)	(0.165)
$Post$	0.0136***	0.0035	0.0323	-0.0024	0.0271	-0.0444*
	(0.004)	(0.040)	(0.032)	(0.004)	(0.031)	(0.027)
$Treat$	0.0033	0.0193	0.0333	0.0049	0.0040	-0.0264
	(0.009)	(0.034)	(0.027)	(0.003)	(0.050)	(0.029)
$\Delta nG * Post$	0.0274	1.1648	0.0410	0.0952*	0.5844	0.0908
	(0.063)	(0.779)	(0.284)	(0.057)	(0.384)	(0.213)
$\Delta nG * Treat$	0.0680	1.4890*	0.2429	-0.0987	0.8152	-0.9423
	(0.084)	(0.782)	(0.343)	(0.095)	(1.849)	(0.843)
$Post * Treat$	-0.0194	0.0202	-0.0618*	-0.0167***	0.1884	-0.0872*
	(0.019)	(0.039)	(0.033)	(0.006)	(0.176)	(0.052)
$\Delta nG * Post * Treat$	**-0.0616**	**-1.5255***	**-0.2550**	**-0.1281**	**7.9574**	**-1.1119**
	(0.102)	**(0.795)**	**(0.402)**	**(0.192)**	**(5.732)**	**(1.485)**
Observations	4061	3404	3961	4189	3442	3884
R-squared	0.019	0.025	0.019	0.012	0.027	0.019

Table 3.19 Robustness check for nG-based trading strategy: Alternative governance-hedge portfolios.

This table reports the result for a five-factor regression (i.e., three factors of Fama and French (1993) along with the momentum factor and the Pástor and Stambaugh (2003) liquidity factor) for alternative decile portfolios created using the nG-Index (both value- and equal-weighted portfolios). These portfolios are reset at the beginning of each year when new data is available. The monthly portfolio returns for each hedge portfolio (buy Democracy–sell Dictatorship) are regressed over factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM), and liquidity (LIQ) with White (1980) standard errors. Row (1) replicates the results in Table 9 for a comparison to the alternative portfolio constructions shown in the remaining rows. Rows (2) to (4) use different criteria, either by allowing for (a) changing cutoffs with years, (b) using new 2%-98% cutoffs, or (c) strict quantile division. Row (5) presents the hedge on industry-adjusted portfolios using the Fama-French Fama and French (1997)48 industry classification taking the median industry monthly returns. Rows (6) and (7) break the sample period into two halves (48 months each). Portfolios in rows (5) to (7) were drawn following Gompers, Ishii, and Metrick (2003). Rows (8) and (9) take the same criteria as in row (1), but combine either the top 2 deciles and bottom 2 deciles or top 3 and bottom 3 deciles as the Democracy and Dictatorship portfolios. For these compositions, we follow Bebchuk, Cohen, and Ferrell (2009). The last row considers the same 5%-95% criteria as for the main results (same as Row (1)), but uses the equal-weighted mG-Index in place of the nG-Index. Heptiles were used for last row with extreme portfolios to create a hedged position because a decile distribution was not possible using mG-Index values. Significance at 10%, 5%, and 1% are shown by *, **, and ***, respectively.

Portfolios	**Value-weighted**		**Equal-weighted**	
	Alpha	Excess Returns	Alpha	Excess Returns
Democracy – Dictatorship	-1.333**	-1.233	-0.316	-0.275
(1)	(0.623)		(0.405)	
Rolling 5%-95% criteria (a)	-0.324*	-0.412	-0.266	-0.273
(2)	(0.196)		(0.204)	
Single 2%-98% criteria (b)	-0.605	-0.525	-0.025	-0.051
(3)	(0.614)		(0.473)	
Strictly quantile criteria (c)	-0.001	-0.001	-0.002	-0.001
(4)	(0.002)		(0.159)	
Industry-adjusted	-0.869*	-0.764	-0.309	-0.291
(5)	(0.517)		(0.366)	
First-half sample period	-0.131	-0.298	+0.125	+0.365
(6)	(0.687)		(0.099)	
Second-half sample period	-2.452**	-2.168	-0.734	-0.915
(7)	(1.122)		(0.697)	
Double deciles (1,2 – 9,10)	-1.128**	-1.085	-0.608**	-0.549
(8)	(0.515)		(0.302)	
Triple deciles (1,2,3 – 8,9,10)	-1.081***	-1.088	-0.564**	-0.514
(9)	(0.389)		(0.255)	
mG-Index based portfolios	-0.001	0.002	-0.002	-0.001
(10)	(0.002)		(0.002)	

Table 3.20 Robustness check for nG-based trading strategy: Alternative factor models

This table summarizes the results for the abnormal returns on the governance hedge, i.e., Democracy–Dictatorship portfolios (both value- and equal-weighted) when using alternative asset pricing models. The first row shows the result for the baseline model using raw returns as reported in Table 3.10 along with the industry-adjusted returns as in Table 3.19. The second row considers a market risk model (i.e., the capital asset pricing model). The third shows abnormal returns with the Fama-French (FF) three-factor model. In the fourth row, we augment the previous model by adding the Pástor and Stambaugh (2003) liquidity factor. The next row reports the alpha from the FF four-factor model. Last, we also assess the FF five-factor model Fama and French (2016) and the same FF five-factor model with the liquidity factor. The robust standard errors are reported in parentheses for each alpha. Significance at 10%, 5%, and 1% are denoted using *, **, and ***, respectively.

Asset Pricing Model	**Value-weighted**		**Equal-weighted**	
	Raw	**Industry-Adjusted**	**Raw**	**Industry-Adjusted**
FF four factors + liquidity factor	-1.333**	-0.869*	-0.316	-0.309
(1)	(0.623)	(0.517)	(0.405)	(0.366)
CAPM	-1.314**	-0.798	-0.32	-0.343
(2)	(0.631)	(0.546)	(0.422)	(0.390)
FF three factors	-1.351**	-0.803	-0.343	-0.335
(3)	(0.622)	(0.548)	(0.425)	(0.394)
FF three factors + liquidity factor	-1.338**	-0.810	-0.325	-0.319
(4)	(0.623)	(0.545)	(0.423)	(0.393)
FF four factors	-1.347**	-0.802	-0.336	-0.327
(5)	(0.622)	(0.551)	(0.407)	(0.368)
FF five factors	-1.493**	-0.966*	-0.34	-0.364
(6)	(0.638)	(0.540)	(0.450)	(0.409)
FF five factors + liquidity factor	-1.482**	-0.971*	-0.327	-0.353
(7)	(0.639)	(0.539)	(0.448)	(0.407)

CHAPTER 4

Sustain and Deliver: Capturing the Valuation Effects of Corporate Sustainability

4.1 Abstract

This study identifies a select few indicators from a large set of environmental, social and governance (ESG) factors; and introduces a corporate sustainability measure. Sustainable part of corporate social performance completely explains its positive relation with firm value. In parallel, those ESG initiatives that are irrelevant to sustainability do not affect firm value. These findings remain robust after controlling for potential endogeneity issues. Moreover,

sustainability-based hedge portfolios would have generated abnormal returns of over 4% per year in the sample period. Together, these results imply that *only* the sustainable aspects of ESG are associated with superior financial performance in terms of both accounting- and market-based value.

4.2 Introduction

> "Sustainable investing is simply smart investing. Sustainable investing seeks to drive positive social or environmental impact alongside financial results, allowing investors to accomplish more with their money."
>
> [*BlackRock, Inc.*]

Investors, and especially large institutional investors such as BlackRock, are increasingly employing screening processes to identify firms with better environmental, social and governance (ESG henceforth) practices. Do these social responsibility screens benefit investors? While this question has drawn a lot of attention in the literature over the last 10 years, the jury is still out due to mixed empirical evidence on the relationship between corporate social responsibility/ performance (CSR/CSP) and financial performance (CFP).[51] While some studies indicate that ESG screens work for investors (e.g., Kempf and Osthoff, 2007), others show no significant benefits from such investments (e.g., Humphrey, Lee, and Shen, 2012).[52] Put alternatively, the valuation benefits accompanying ESG activities are yet to be firmly established.

In this study, thus, I contribute to this literature by highlighting those finer yet vital aspects of ESG initiatives that may affect the way firms and their man-

[51] In different streams of literature, ESG-based measures are known by different names such as stakeholder welfare (Jiao, 2010), stakeholder-relations index (Borgers et al., 2013), or more popularly CSR/CSP (Humphrey, Lee, and Shen, 2012; Becchetti, Ciciretti, and Giovannelli, 2013; Becchetti, Ciciretti, and Hasan, 2015; Lins, Servaes, and Tamayo, 2017; Buchanan, Cao, and Chen, 2018).

[52] See Van Beurden and Gössling (2008) and Fulton, Kahn, and Sharples (2012) for detailed reviews.

agers respond to these. To begin with, using theoretical insights from Fatemi, Fooladi, and Tehranian (2015), I identify a select few ESG indicators that are significant predictors of firms' survival. Further assessment of these indicators using inputs from sustainability and CSR literature, along with the United Nations' sustainability-specific guidelines, confirm that the selected indicators importantly converge towards the concept of corporate sustainability. Subsequently, I run empirical tests with these sustainability-relevant CSR initiatives to show a monotonic ESG–valuation relationship. In addition, I examine the practical significance of corporate sustainability by assessing if sustainability-based hedge portfolios could have generated abnormal returns for investors.

Do each of the ESG indicators necessarily warrant a presence in the ESG-based ratings? Which of the ESG subcomponents (both strengths and concerns) largely contribute towards the CSR and CFP relationship? These questions are central to the research objectives of this study. Further motivation comes from the fact that most ESG rating agencies, as well as prior research, combines a heterogeneous set of ESG strengths and concerns using a "kitchen sink" or "all-in" approach to either measure individual ESG dimensions (i.e., environmental, social or governance aspects separately) or a composite ESG score that represents CSP.[53] However, there is no theoretical argument for assuming that all of the available ESG indicators are essential as contributors towards better CSR firms outperforming their poor CSR counterparts. In fact, Fatemi, Fooladi, and Tehranian (2015) firm valuation model –that captures the net benefits of ESG initiatives– shows that "the nature of CSR [or ESG] activities .. undertaken" does have value implications. Essentially, different ESG

[53]Note that some ESG-rating agencies such as MSCI have started assessing only a set of key industry-specific indicators in recent years following the works on industry-relevance or *materiality* in Khan, Serafeim, and Yoon (2016). But despite the introduction of industry relevance, broad kitchen-sink/all-in approach prevails since there is no industry-neutral selection applied.

activities can have different effects on the firms' cash flows, their probability of survival, and their capitalization rates. Hence, those CSR activities that are central to firms' long-term survival should show superior valuation effects. Moreover, if indeed such survival is a consequence of corporate sustainability, these indicators should also represent the firms' sustainability focus.

In recent years, empirical research exploring the relationship between accounting-based CFP measures and CSP has largely revealed unidirectional results, i.e., firms with high CSR ratings have better firm value than their low CSR counterparts. The same cannot be said, however, when market-based performance or stock returns are used (Derwall, Koedijk, and Ter Horst, 2011; Fulton, Kahn, and Sharples, 2012).[54] I argue that the positive correlation between CSR and accounting CFP may be driven by some dominant ESG indicators whence possibly others diminish the value or are irrelevant. Managers' need to balance amongst stakeholders' demands may, additionally, suppress the influence of certain important ESG components or indicators (Bouslah, Kryzanowski, and M'Zali, 2013). When it comes to stock returns, however, Krüger (2015) shows that markets react differently to different CSR news. Hence, while the net effect of CSP on accounting CFP remains consistent, its impact on stock returns may be directed solely through the survival-relevant CSR initiatives.

ESG data, using *all-in* approach, has been extensively used to measure proxies for several concepts such as the social capital (Jha and Cox, 2015; Lins, Servaes, and Tamayo, 2017), stakeholder relations (Borgers et al., 2013) and CSP/ CSR (Humphrey, Lee, and Shen, 2012; Kim, Li, and Li, 2014; Dyck et al., 2018). But, as far as I know, this is the first time a *selective* approach is being used to identify a few ESG indicators from all the ESG dimensions

[54]Much of this literature employs aggregate CSP measures or broad commercial CSR ratings. However, results mostly remain the same even when ESG sub-dimensions i.e., the environmental, social and governance sub-ratings are separately considered (e.g., Galema, Plantinga, and Scholtens, 2008; Ng and Rezaee, 2015).

to construct a more latent corporate sustainability measure.[55] I employ an empirical identification that instruments firm survival as an outcome of sustainability in a partial least square (PLS) framework to select a subset of available ESG strengths and concerns, before confirming with a review of the MSCI ESG indicator definitions that these indicators conceptually converge towards corporate sustainability. Sustainability, in this context, is defined as the firm's ability to meet current goals, i.e., shareholders wealth maximization, without comprising the societal goals and the needs of future generations or other stakeholders (WCED, 1987; Van Marrewijk, 2003).[56] Or, in other words, it is the ability to balance the triple bottom line comprising of profit, people and planet (Kaptein and Wempe, 2002).[57] Essentially, sustainability captures a firm's moral obligation towards future generations (Solow, 1993) and therein lies the big bone of contention, whether these so-called moral obligations do create value for the firm and its shareholders, or merely cause value diminution.

My initial hypothesis is that, out of about 140 available MSCI ESG indicators, only the ESG strengths and concerns that matter for firm survival are most influential in contributing towards the well-documented CSP–firm value correlation. Using inputs from Kelly and Pruitt (2015), I employ a partial three-pass regression filter (i.e., PLS) to identify those ESG indicators that

[55]Khan, Serafeim, and Yoon (2016) use a selective approach as well, but focus on "material sustainability", which is the subset of ESG factors that are materially relevant for each of the 45 industries as classified by the Sustainability Accounting Standards Board (SASB). However, I focus on a more generic corporate sustainability measure that is industry-neutral.

[56]In certain streams of management literature, corporate sustainability is aimed at minimizing risks for long-term survival by ensuring the firms' future financial growth. However, note that I apply corporate sustainability from stakeholder perspective as defined by United Nations Global Compact Guide to Corporate Sustainability, 2015. Thus, within this conceptual framework, the long-term survival and financial growth are possible consequences of corporate sustainability, and not necessarily corporate sustainability itself.

[57]The term triple bottom line is widely used to represent a win–win–win objective focused on the "company, its customers, and the environment" as first explored in Elkington (1994). In recent years, these objectives are largely represented by the 3Ps i.e., profit, people and planet.

managers should ideally be most attentive towards since they can predict future financial distress, and hence, the likelihood of firms' survival. I further find that this subset of ESG indicators is also significantly different as it is reflective of corporate sustainability as recognized by the CSR literature, as well as the United Nations (UN) sponsored programs and initiatives. My analysis reveals that only 30 strengths and 21 concerns (out of the 140 ESG indicators) are relevant to firms' survival. Since more than 80% of these indicators are also representative of corporate sustainability, the composite score of this identified subset of ESG indicators is called the sustainability index (SUS-Index or simply, SUS). Each firm in the MSCI ESG database is assigned SUS scores using their ESG strengths (+) and concerns (–) reflected by these 51 select-few sustainability indicators. Bebchuk, Cohen, and Ferrell (2009) follow a similar identification strategy to show that only 6 entrenchment variables out of the total 24 used in Gompers, Ishii, and Metrick (2003) Governance Index (G-Index) capture most of the variations seen in the aggregated all-in G-Index.

Next, I assess if the identified indicators are significantly associated with firm value's proxy Tobin's Q. The results using both aggregated measure (SUS) and its subcomponent strengths (SUSstr) and concerns (SUScon) show significant correlations with firm value even after controlling for important firm characteristics and the remaining ESG indicators. The sustainability index has a monotonic and significantly positive association with Tobin's Q, while the aggregate remnant ESG score does not show a significant relationship with the same. Even when it comes to strength and concern subcomponents, as expected, the SUSstr has a positive association with firm value and SUScon is negatively related to it. On comparing these results with those of corresponding all-in approach based CSP measure, I find that SUS-Index and its subcomponents capture much of the CSP–firm value relationship across the sample period. These findings remain robust even with dynamic models that control for simultaneity, or with firm fixed effects and cross-sectional panel estimations.

I further employ a cleaner identification strategy to get causal estimates using a quasi-experimental setting that exploits the application of industry-based indicator assessment by MSCI. Before 2010, all the ESG indicators were assessed for each of the firms covered by MSCI. However beginning 2010, MSCI initiated a new data collection criteria that limited the assessment to a smaller set of *industry-relevant* indicators for each firm. The results from this exogenous shock to the ESG-based measures show that only the changes in SUS-Index do cause changes in Tobin's Q for the treatment firms across the change in assessment methodology. To corroborate my findings, I run a robustness check using the instrumental variables (IV) approach. My results from the IV estimations, once again, support the existence of a causal relationship between all the sustainability measures (SUS, SUSstr, and SUScon) and the firm value.

Better sustainability scores resulting in superior firm value need not necessarily imply that an investment strategy using sustainability index should generate abnormal stock returns, as we expect market participants to understand the differences between the more and less sustainable firms so that the market prices correct for them. However, I find that there is a monotonic and increasing relationship between sustainability and abnormal returns in my sample period. As mentioned earlier, much of the empirical evidence on the relation between ESG-based measures and abnormal returns are mixed. Hence, a positive significant relationship using the selective sustainability index may be indicative of drawbacks accompanying the use of composite indices or scores applying the kitchen sink approach whence investors do not ascertain the importance of individual components within these composites.[58]

The premium associated with sustainable CSR activities is difficult for both the investors and markets to understand because much of their future long-term valuation benefits are driven by external sources such as better reputation, more customer loyalty, superior talent acquisition, etc. Long high sustainability / short low sustainability hedge using the SUS-Index, thus, could generate economically and statistically significant abnormal returns of about 4.3% per annum. The fact that a similar investment hedge using the rest of ESG components does not show any significant correlations with abnormal returns in the analyzed sample period, signifies the importance of sustainability index. Note that the existence of abnormal returns in my findings does not necessarily indicate considerable market inefficiency nor guarantees that a similar trend can be expected in the coming years. However, by comparing the hedging strategies that use the sustainability index and the other components index, I show that the outcome of investment strategies that focus on relevant parts of a composite index can be much different from that of the one that applies a pooled index. This may just be because the sustainability index is less noisy than a comparable ESG-composite CSP/ CSR score.

The rest of this study is organized as follows. Section 4.3 provides a background for measuring sustainability. Section 4.4 presents the data and SUS-Index along with some preliminary analysis. Next, Section 4.5 explains the empirical models and corresponding results for the relationship between firm value and sustainability, including additional tests to draw causal inferences. Section 4.6 assesses sustainability-based investment portfolios and their abnormal returns. Finally, Section 4.7 discusses the main findings and concludes.

[58]Using the three sub-dimensions within ESG (i.e., environmental, social and governance dimensions), some papers have highlighted the same (Kempf and Osthoff, 2007; Galema, Plantinga, and Scholtens, 2008). However, this is the first study that disentangles the relevance of individual ESG factors instead of disaggregating the broader three dimensions.

4.3 ESG and Sustainability

4.3.1 Background: The CSR View

Just like individuals, firms do not exist in isolation. As legal entities, they are a part of the society and ecology to which they belong. Does this mean that they have additional social responsibilities along with their fiduciary responsibility towards shareholders? This is the central question in the CSR literature. In economics and finance, the attention towards CSR view has grown in recent years with an increasing emphasis on social accounting and sustainability reports by large corporations. The Volkswagen scandal and its fallout highlights the relevance of ESG accountability and codes for both the firms and their investors. Sustainability and the triple bottom line have become the new buzz words.

In economics and finance, there are two broad contrasting views concerning corporate social expenditures. While one stream of literature treats stakeholder and social welfare maximization complementary to shareholder wealth maximization (e.g., Edmans, 2011), the other stream builds on Friedman (1970) argument that CSR is an avoidable cost for firms that comes at the expense of shareholders. This debate is ongoing with recent evidence supporting both views. I contribute to this debate by focusing on investment strategies employing ESG data to assess if the corporate social response and sum of sustainability initiatives are value-enhancing for shareholders. Taking the investors perspective also allows us to understand the real outcomes of CSP and the economic impact it has in terms of shareholder wealth generation.

Using either of the two contrasting views stated above, in theory, the association between firm valuation and sustainability or CSP could be accordingly positive or negative. The firm's CSR objectives may be in sync with its wealth maximization objective, or it may have additional costs that contradict the said objective (Ferrell, Liang, and Renneboog, 2016). Empirical evidence is seen to support either of these views depending on the type of CSR-related costs and corresponding firm outcomes studied. Hillman and Keim (2001), for example, show that while CSP and stakeholder management focusing on primary stakeholders can increase shareholder value, strict social screens that exclude alcohol, tobacco or other controversial industries may be detrimental to the shareholders. Since my analysis focuses on qualitative indicators affecting primary stakeholders and does not include exclusionary screens, I hypothesize that shareholders will reap benefits from CSP, and more so from sustainability. By further exploring the sustainability strengths and concerns separately, I seek to identify how each of these drives the shareholders' value.

4.3.2 Measuring Sustainability

The MSCI ESG data (previously the Kinder, Lydenberg, and Domini Research & Analytics, Inc. or RiskMetrics-KLD) has about 140 ESG related strengths and concerns categorized under eight different dimensions: community, controversial business, governance, diversity, employee relations, environment, human rights, and product-related aspects. Over the years, some indicators get added to each dimension while others are dropped as and when they seem to influence or become irrelevant to each of these dimensions. There are also instances when some of the ESG components were moved from one dimension to another (e.g., indigenous people relations was moved in 2002 from the community to human rights). This lays credence to my argument that the ESG landscape is evolving with time and not all components in the ESG database are value-enhancing or value-diminishing. However, since the aim of this study is to measure sustainability, which is a long-term focused measure, all components that affect the firms' sustainability should necessarily be expected to have a long-lasting impact and have value-enhancing relevance.

In empirical terms, following the theoretical prediction of Fatemi, Fooladi, and Tehranian (2015), I start with the hypothesis that only those ESG indicators that are relevant to firm survival should be important for the firms, and hence should impact their valuations. Note that this identification assumes that firm survival is an outcome of corporate sustainability to isolate the underlying latent factor from ESG data that can predict future firm survival. Then, I run a conceptual assessment of whether these indicators also matter towards stakeholders' interest alignment in the long-run by contributing to the firm's sustainability or not. In other words, the purpose of this conceptual identification is to assess if my assumption that survival-predicting ESG indicators converge to corporate sustainability is indeed true or not.

In theory, sustainability indicators should be the ones that firms' decision makers largely consider when balancing between various stakeholders to maximize their triple bottom line. It is important to note that, in my definition of stakeholders, I also include shareholders although the ESG database only covers a small part of shareholders' and management's interest-aligning governance mechanisms.[59] The broad-based governance attributes rated by MSCI such as corruption, public policy, and business ethics are not strictly concerned with corporate governance per se as they have wider societal implications affecting other stakeholders. Therefore, following Bereskin et al. (2018), and to avoid category omission bias as forewarned in Ferrell, Liang, and Renneboog (2016), I initially include governance indicators, and later omit it for robustness checks.[60] Balancing between different stakeholders while ensuring shareholder wealth maximization may be beneficial for the managers themselves (Cheng,

[59]For this reason, in my analysis, I further explore other dimensions of corporate governance (i.e., managerial entrenchment, institutional ownership, and blockholding patterns) as additional control variables to assess if agency problems substitute or contribute to the valuation benefits from corporate sustainability.

[60]The exclusion of MSCI corporate governance indicators from the ESG measures does not affect any of my results. For example, see Appendix Table 4.13.

Ioannou, and Serafeim, 2014). Nonetheless, assuming that market forces and firms' internal corporate governance mechanisms function well, such adverse effects may be minimized to eventually benefit the firm and increase its valuation (Ferrell, Liang, and Renneboog, 2016).

Why should sustainability matter? Sustainability and the balancing of the triple bottom line (i.e., profits, people, and planet) can not only align the interests of shareholders with other stakeholders but can also benefit the firm through positive externalities that indirectly influence its reputation, goodwill and in turn, its value (Gregory, Whittaker, and Yan, 2016; Gong and Grundy, 2017). With the sustainability viewed through a long-term lens, stakeholders can also benefit by reducing the threat of short-termism and consequential managerial myopia (Louche, 2009). These arguments have been used in the literature to hypothesize the benefits of corporate sustainability in terms of higher valuations. However, alternatively, the Friedman (1970) view that sustainability is merely a cost cannot be ignored in theory. When the managers pay attention to other stakeholders' needs, shareholders may be negatively affected as there will be some decisions undertaken that are detrimental to shareholder wealth maximization, especially in the short-run. Nevertheless, as we define sustainability and identify its indicators through a long-term lens, all stakeholders including the shareholders should reap the benefits of superior sustainability in comparison to other firms.

In light of the aforementioned argument highlighting the benefits of sustainability, I next identify the ESG components that should contribute to firms survival positively (i.e., the strengths) or negatively (i.e., the concerns), confirm that these represent corporate sustainability, and then run empirical tests to assess if these hypothesized components drive the valuation outcomes documented in the literature for CSR performance.

4.3.3 Identification of the ESG Factors Relevant to Firm Survival

To empirically identify the sustainability-relevant indicators, I assume that corporate sustainability directly influences firms' survival by affecting its distress risk. To this end, the expected survival measures are assumed to be linearly related to sustainability indicators in the following manner:

$$E(Survival_{t+1}) = A_0 + A_1 * SUS_t \tag{4.1}$$

where SUS_t are those ESG indicators that are truly a formative part of corporate sustainability and, hence, matter for firms' survival. The actual firm survival measures are then a combination of their conditional expectations and any unexpected variations.

$$Survival_{t+1} = E(Survival_{t+1}) + \varepsilon_{t+1} \tag{4.2}$$

or,

$$Survival_{t+1} = A_0 + A_1 * SUS_t + \varepsilon_{t+1} \tag{4.3}$$

where ε_t is sustainability-irrelevant part of the firm survival measurement, which is clearly independent of SUS_tâĄă.

Let $F_t = \left(F_{1,t}, F_{2,t}, , F_{n,t}\right)$ represent the n ESG indicators set. The underlying assumption is that the factor structure for each of the indicators $F_{i,t}$ can be modeled as:

$$F_{i,t} = B_{i0} + B_{i1} * SUS_t + B_{i2} * remCSP_t + e_{i,t} \tag{4.4}$$

where SUS_t captures the sustainability component, $remCSP_t$ accounts for the additional component within each factor that controls for all non-sustainability (remnant) characteristics, and $e_{i,t}$ is the error component of each factor $F_{i,t}$. Thus, the key objective of the identification strategy here is to isolate the loading B_{i1} (the sensitivity of each ESG criteria to the sustainability construct) and test if it is statistically different from zero. However, this cannot be achieved for the aforesaid factor structure without employing estimation techniques that can effectively curtail both the non-sustainability component $remCSP_t$ and the error term $e_{i,t}$. Several econometric tools such as the principal component analysis (PCA) are available to separate SUS_t from $e_{i,t}$ (Girerd-Potin, Jimenez-Garcès, and Louvet, 2014). Importantly though, techniques like PCA are unable to completely isolate SUS_t, as the $remCSP_{i,t}$ remains an influential part of any of the identified orthogonal components (for a detailed discussion on the limitations of PCA, see Huang et al., 2015). Conversely, when non-sustainability characteristics form a large part of ESG indicators, PCA might mostly capture variations in $remCSP_{i,t}$ making the identification of corporate sustainability impractical. Moreover, applying PCA on ESG data is problematic since the number of indicators vary with time as and when MSCI updates its reporting methodology. With factor methods like PCA employing estimation based on the ESG indicators' covariances/ correlations, they are ineffective in the presence of missing data whence an indicator is dropped or isn't reported for a firm.

In the light of these arguments, there is a need to use an alternative econometric tool that can ensure isolation of SUS_t component by introducing a measurable outcome of corporate sustainability (in our case, the firm survival proxy) as an instrument within the estimation process. To do so, using the methodology from Kelly and Pruitt (2013, 2015), I run the PLS estimation to eliminate the sustainability-irrelevant component. Combining the factor structure in Equation 4.4 with the assumed relation in Equation 4.3, I seek to identify the sustainability indicators as those ESG factors that have an impact on firms' future survival. Instead of extracting components based on with-in covariations (as in PCA), PLS allows for the identification of sustainability indicators by examining the covariation of ESG indicators with the firm survival proxies. Following Huang et al. (2015), I implement the PLS technique using the first two passes of the three-pass regression filter introduced in Kelly and Pruitt (2015).

In the first pass, I estimate n time-series regressions, i.e., one for each ESG indicator, with the firm survival proxy as the independent variable.

$$F_{i,t} = \eta_{i0} + \eta_{i1} Survival_{t+1} + \mu_{i,t} \tag{4.5}$$

Here, the coefficient η_{i1} measures the sensitivity of each ESG factor $F_{i,t}$ to the true corporate sustainability component that is instrumented using the firm survival proxy. Kelly and Pruitt (2015) show that there is no strict requirement that the survival proxy itself is noise-free. The two-pass process ensures that the impact of such noise is minimized. Since the expected true survival measure is affected only by SUS_t (Equation 4.1), only the sustainability-relevant ESG indicators are allowed to influence expected firm survival while being independent of unexpected variations (from Equations 4.3 and 4.4). From these first pass time-series regressions (Equation 4.5), hence, η_{i1} estimates the relation between each ESG indicator i and the true corporate sustainability component.

Next, in the second step, I run the cross-sectional regressions for each time period t using the estimated coefficients η_{i1} from the first step to obtain the PLS coefficient estimates for each ESG indicator using the following:

$$F_{i,t} = \zeta_{t0} + SUS_t^{PLS} \widehat{\eta_{i1}} + \nu_{i,t} \tag{4.6}$$

where the coefficient SUS_t^{PLS} is the estimated PLS for each of the ESG indicators in a given time t. As shown in Equation 4.6, the second pass introduces the first-stage coefficient estimates from Equation 4.5 as independent variables while retaining the same dependent variables $F_{i,t}$. Since the PLS estimation is done separately for each of the ESG indicators, missing values for one indicator do not have a bearing on the rest (unlike in PCA). The Equations 4.3 and 4.4 are combined together within this PLS framework to obtain the SUS_t^{PLS} coefficient, hence, allowing us to assess the relevance of each ESG indicator towards corporate sustainability (using firm survival proxy). Since the true relationship between each ESG indicator and the survival proxy is unknown, the first pass gives a biased coefficient estimate that includes noisy element $remCSP_t$; although the other error component $e_{i,t}$ is discarded. Eventually, the second pass eliminates all the sustainability-irrelevant components to identify the true relationships.

Finally, I classify each ESG factor as either sustainability or remnant CSP indicator by running univariate t-tests for the time-series of estimated coefficients SUS_t^{PLS}, and checking whether they are statistically different from zero. The aim is to segregate corporate sustainability from within the ESG indicators by only considering those factors that persistently impact firms' survival. I employ two measures of distress risk to proxy for firm survival, Altman (1968) Z-score (for main analysis) and Bharath and Shumway (2008) distance to default (for robustness check).[61]

4.3.3.1 Do the Identified Indicators Reflect Corporate Sustainability?

To confirm that the empirically identified indicators correspond to corporate sustainability concept, I follow an independent secondary identification using four step filtration process. While the identification in Section 4.3.3 is data-

[61] Despite its limitations, Altman's Z-score is preferred in the main analysis because it can be computed easily from accounting data, unlike other measures of distress risk such as the distance to default (DD). This allows me to identify sustainability indicators without any significant loss of observations. Note that when DD is used as survival proxy, many of the identified indicators remain robust. However, the identification is less powerful as fewer indicators are found to be related to future DD.

driven and assumes that firm survival is an outcome of corporate sustainability, the purpose of conceptual identification in this section is to confirm that this assumption is indeed true. In other words, I check if the indicators obtained empirically (assuming that firm survival instruments corporate sustainability) are similar to the ones identified using sustainability-focused theoretical and conceptual lens.

In the first step, since my definition of sustainability focuses on long term benefits, I examine each of the available 140 ESG components to trace the number of years for which their data was gathered. This provided me with possible indicators that have lost relevance with time or were short-lived ESG indicators that do not matter in the long-run and may not represent sustainability and triple bottom line objective.

In the second step, I reviewed the sustainability literature across the economics, finance and management perspectives to assess which components from the identified subset of long-lasting indicators should be theoretically relevant. Using over 1800 indicators from 20 different ESG datasets, Rahdari and Rostamy (2015) extract 30 common sustainability constructs. I examined each of the 140 MSCI ESG components and their definitions to check if it is directly associated with any of these identified constructs.

In step three, I further assessed the theoretically relevant indicators in terms of how well they fit in 2015 United Nations (UN) Global Compact Guide to Corporate Sustainability. This benchmark was selected for three reasons. Firstly, the very definition of corporate sustainability by UN Global Compact (UNGC) initiative in terms of "well-being of workers, communities and planets .. [along with] .. health of the business" is in sync with the way I want to measure it. This is especially important because Rahdari and Rostamy (2015) do not provide a clear definition of corporate sustainability. Secondly, this initiative is worlds largest sustainability project with almost 12000 for-profit and non-profit participants worldwide.[62] This shows the wide acceptance of the UNGC guide across the globe and allows me to use a set of sustainability constructs that have industry-wide relevance. Thirdly, being a UN initiative, assuming a well-researched plan, the identified constructs can be expected to be the most powerful indicators of sustainability. In this UNGC guide, the UN expands ten principles related to human rights, labor, environment and anti-corruption that are fundamental to corporate sustainability. The ESG components shortlisted from step two were cross-verified and further filtered using these principles. Additionally, to check the robustness of the identified ESG components, the United Nations Principles for Responsible Investment (UN-PRI) and United Nations Conference on Trade and Development's (UNCTAD) 2011 Investor and Enterprise Responsibility Review and the 2015 Investment Policy Framework for Sustainable Development were referred to reaffirm the filtered indicators.[63]

Lastly, in step four, I run confirmatory test to check the relevance of these identified sustainability indicators in terms of the way they have recently reflected in media articles and Google Trends in comparison to rest of the ESG indicators. The idea here is to ascertain that the relevant sustainability indicators are those that have commonly impacted firms across businesses, industries and countries through their "popularity". This test confirms the degree to which issues relating to these indicators draw significant attention in comparison to other less relevant or irrelevant indicators.

[62]The UNGC initiative is followed across companies and other participants spread over 160 countries.

[63]Other initiatives were also considered but eventually left out since they were not suitable for identifying *corporate sustainability*. Some of these were broad-based criteria such as the Global Reporting Initiative (as it focuses on CSR in entirety and not only on corporate sustainability), while others were too narrow-focused such as the carbon footprint maps and Commission on Sustainable Development initiatives (as they are largely environment-oriented).

Table 4.1 List of sustainability indicators identified from MSCI ESG data

This is a summary list of all indicators included in the sustainability index (SUS) and its corresponding strengths (SUSstr) and concerns (SUScon) subcomponents. The sustainability indicators that overlap with the independent conceptual identification in Section 4.3.3.1 are shown in bold. For a complete list of all the MSCI ESG indicators, see Appendix 4.A.1. The selection criteria that were met for each of these indicators are accordingly shown by †, ‡ and ⋇ for Rahdari and Rostamy (2015) 30 sustainability constructs, UNGC Guide to Corporate Sustainability and UNCTAD's 2015 Framework for Sustainable Development respectively.

Community	
Strengths:	*Concerns:*
Support for Housing†‡	**Tax Disputes†‡**
Support for Education†‡	Negative Economic/ Community Impact†‡
Non-US Charitable Giving†‡	**Other Community Concerns†‡**
Community Engagement†‡	
Diversity	
Strengths:	*Concerns:*
CEO Diversity‡	Non-Representation †
Board of Directors - Gender Diversity†‡	Other Diversity Concerns†‡
Work-Life Balance/ Family Benefits†‡	
Employment of the Disabled†‡	
Other Diversity Strengths†‡	
Employees	
Strengths:	*Concerns:*
Employee Involvement† ‡ ⋇	**Workforce Reductions†**
Strong Retirement Benefits†	Supply Chain Controversies†
Employee Health & Safety† ‡ ⋇	**Child Labor† ‡ ⋇**
Compensation & Benefits†‡	
Human Capital - Other Strengths† ‡ ⋇	
Environment	
Strengths:	*Concerns:*
Beneficial Products & Services/ Env. Opportunities†	**Hazardous Waste† ‡ ⋇**
Pollution Prevention/ Waste Management† ‡ ⋇	**Ozone Depleting Chemicals† ‡ ⋇**
Climate Change/ Alternative Fuels/ Clean Energy† ‡ ⋇	**Toxic Spills & Releases/ Substantial Emissions† ‡ ⋇**
Environmental Management Systems† ‡ ⋇	**Agricultural Chemicals† ‡ ⋇**
Raw Material Sourcing	Climate Change† ‡ ⋇
Natural Resource Use‡⋇	Other Environment Concerns†‡
Governance	
Strengths:	*Concerns:*
Limited Compensation†⋇	**Accounting Concern† ‡ ⋇**
Ownership Strength† ‡ ⋇	**Reporting Quality/ Transparency Concern † ‡ ⋇**
Transparency/ Reporting Quality Strength† ‡ ⋇	**Other Governance Concerns†⋇**
Political Accountability Strength†‡	
Human Rights	
Strengths:	*Concerns:*
Labor Rights Strength† ‡ ⋇	**Support for Controversial Regimes⋇**
	International Labor Rights Concern† ‡ ⋇
	Indigenous Peoples Relations
Product	
Strengths:	*Concerns:*
Product Safety & Quality†‡	**Antitrust & Anticompetitive Practices†‡**
R & D/ Innovation†‡	
Social Opportunities - Access to Communications†‡	
Social Opportunities - Nutrition and Health†‡	
Other Product Strengths	

4.3.3.2 An Overview of the Sustainability Indicators

Using the PLS estimation from Section 4.3.3 and the aforementioned filtering steps, I identify the ESG strengths and concerns that essentially matter for firm survival. By using a two-pronged identification, I am able to select the sustainability indicators which are theory driven, empirically tested, and conceptually robust. Thus, in addition to being the predictors of future firm survival, these indicators reflect the preference and importance that ESG rating agencies, the United Nations and media assign to these over the rest of the ESG indicators. Put differently, my hypothesis that these indicators are the ones that matter, comes from an objective assessment of what shapes managerial response to the investors' and other stakeholders' demands regarding ESG factors.

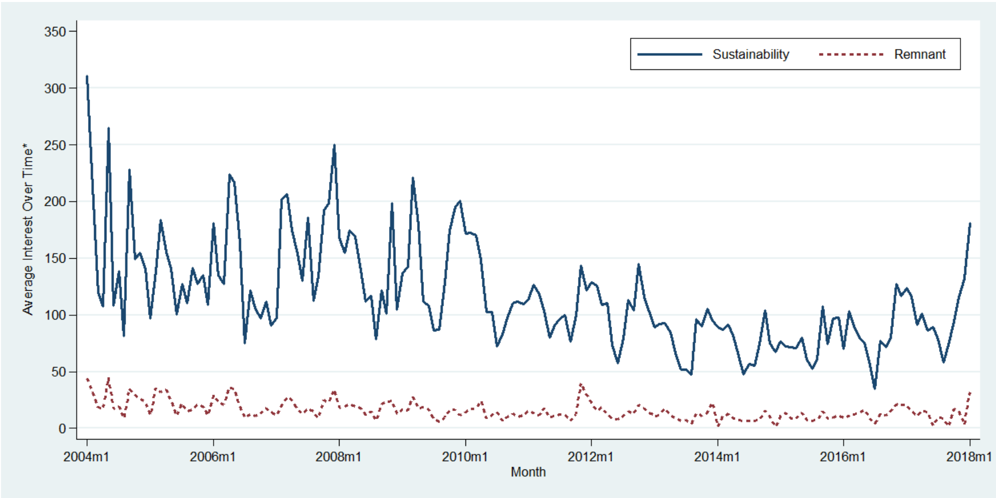
For a complete list of available MSCI ESG indicators, refer to Appendix 4.A.1.[64] The list of identified sustainability indicators from ESG dataset using PLS estimation with the Altman's Z-score as the firm survival proxy is provided in Table 4.1. The conceptual relevance of these indicators is confirmed by the fact that corporate sustainability indicators identified using Section 4.3.3.1 (see Appendix Table 4.11) overlap with over 80% of the indicators in Table 4.1 (as shown in bold).[65] Furthermore, over 80% of the empirically identified sustainability indicators using PLS fit in at least two of the three main objective references employed in the secondary conceptual identification i.e., a) Rahdari and Rostamy (2015) 30 broad constructs list (indicated by † in Table

[64]For definitions of each of these ESG indicators, see MSCI ESG KLD STATS: 1991-2014 Data Sets Methodology guide, version: June 2015.

[65]A detailed discussion on some of these sustainability and remnant ESG indicators, and the reasons for their inclusion/exclusion as per Section 4.3.3.1 is presented in Appendix 4.A.2. For example, some of the more recently introduced ESG indicators such as freedom of expression, privacy and data security, biodiversity and different dimensions of climate change such as carbon footprint, energy efficiency etc. were found to be relevant for SUS in the filtering process. However, since all these new indicators were only introduced after 2012 and had too many missing values they were dropped from the final list.

Figure 4.1 Google Trends' interest scores for sustainability and remnant ESG indicators

This figure shows the plots of average Google Trends' *interest over time* measures for each month from January 2004 to December 2017. All searches are normalized with respect to the keyword "Charitable Giving" that represents one of the sustainability indicators. For the complete list of keywords used for each of the ESG indicators, see Appendix 4.A.5. The indicators whose respective keywords do not appear in Google Trends are omitted from these averages.



* relative to the 'Charitable Giving' keyword.

4.1), b) UNGC Guide to corporate sustainability (‡), and c) UNCTAD's 2015 Framework for Sustainable Development (⋇).

4.3.3.3 Sustainability Versus Remnant ESG Indicators: The Trend

While the criteria employed to demarcate sustainability indicators from the remnant ESG components are chosen to ensure that the selection remains objective, there may be questions on its effectiveness. To mitigate these concerns, I next evaluate the two sets of indicators in terms of their popularity shown in Google search. Ideally, the sustainability-related issues should draw relatively more attention –not only amongst the media but also people at large– than the other ESG parameters, hence, increasing their relevance to the firms.

The time series of average interest scores of all sustainability indicators is shown against the remnant ESG indicators in Figure I. While 75% of all sustainability indicators had their respective keywords covered by Google Trends, only about 25% of the remnant ESG ones appeared in the same (see Appendix 4.A.5 for details). As seen in the figure, sustainability issues remained almost ten times more popular than other CSR issues across the years on an average. In fact, if the non-appearing indicators (i.e., those whose keywords do not show on the Google Trends) are set to zero, the sustainability interest scores become 25 times that of remnant ESG averages. This lays credence to my argument that relevance of sustainability issues within the ESG dataset cannot be ignored.

4.3.4 Relationship with Stock Returns

The multidimensionality of ESG-based measures, along with underlying country-factors and cultural influences, makes it difficult to capture abnormal returns using investment strategies based on CSP measures. In terms of country-based influence, for example, a firm's CSR ranking is seen to be associated with its home country's legal origins (Liang and Renneboog, 2017). In terms of CSP multidimensionality, each of the dimensions within ESG composite measure may have contradictory effects on returns leading to confounding results (Galema, Plantinga, and Scholtens, 2008). While this does explain the mixed evidence seen in the literature, there is no explanation available yet as to why investors continue to be attracted to the firm's CSR ratings. Furthermore, CSR in firms is related to future stock price crash risk (Kim, Li, and Li, 2014) and also book-to-market ratios that can increase resultant portfolio sensitivities to the Fama-French HML risk-factor (Galema, Plantinga, and Scholtens, 2008). This would accentuate difficulties encountered in capturing the stock returns–sustainability association as the sustainability itself is measured as a subcomponent of CSR/CSP.

Despite the challenges mentioned above, the market for commercial ESG-based ratings is booming with institutional investors being their main target customers. So, numerous studies have tried to assess whether there are real benefits for investors arising out of socially responsible investments or SRIs (Galema, Plantinga, and Scholtens, 2008; Derwall, Koedijk, and Ter Horst, 2011). It has been shown that there is a considerable effect of CSP on returns when markets are undergoing a crisis and investor trust is running low (Lins, Servaes, and Tamayo, 2017). But, what should investors expect during otherwise stable market conditions? I hypothesize that when sustainable aspects of CSP are considered, markets do not completely correct for the differences in corporate sustainability. The long-term perspective of sustainability makes it difficult for the investors and markets to completely understand the benefits of sustainability for the stock prices to immediately adjust accordingly. Alternatively, nonexistence of abnormal returns for sustainability-based investment hedges would suggest that markets have already learnt to correct for corporate sustainability so as to override any possible mispricing (Borgers et al., 2013).

4.4 Methodology and Data

4.4.1 Empirical Approach

The empirical strategy applied in this study is as follows. In the first stage, I identify a robust measure of sustainability using ESG data. This is done using the two-step methodology proposed in Bebchuk, Cohen, and Ferrell (2009). First identifying those indicators which are relevant to sustainability from within the available ESG factors in MSCI dataset (as shown in previous section), and then assessing if the sustainability measure SUS-Index itself is relatively more important subcomponent within the all-in CSP measure. Although there is a considerable amount of literature which has disaggregated broad CSP measures based on ESG dimensions and its underlying strengths and concerns (e.g., Bouslah, Kryzanowski, and M'Zali, 2013), the idea of selecting a subset of indicators from the whole lot of available ESG data is unexplored in the literature. While the influence of sustainability itself is subject to reverse causality, simultaneity and endogeneity, my objective in the first part of analysis is to capture the variability in correlations before drawing inferences on causality. Subsequently, in the second stage, I establish causal relationship between sustainability and firm value using multiple identification strategies that collectively alleviate any possible endogeneity concerns. Finally, in the last stage, I evaluate investment strategies using the proposed sustainability measure SUS-Index to capture risk-adjusted returns. Several alternative portfolios and asset pricing models are considered to test the robustness of my findings.

4.4.2 ESG Data

The sustainability measure and other aspects of corporate social performance are obtained using MSCI (formerly KLD) ESG data. My entire sample consists of firm-level data spanning from 1991 to 2015. The sample size covered by MSCI-KLD for the ESG data has expanded from about 650 U.S. companies in 1991 to about 3000 companies in the year 2015. MSCI evaluates these companies on multiple indicators covered under several categories: community, diversity, employees, environment, human rights, governance and product. For each of these categories, a number of characteristics (i.e., indicators) reflecting the strengths or concerns under each category are represented for their presence (1) or absence (0).[66]

Almost all prior ESG-based studies, measure the total number of strengths

[66]Only the qualitative indicators were used to construct ESG measures. The exclusionary screens that identify controversial business areas such as alcohol, gambling, firearms, military, nuclear power and tobacco are excluded as they are mainly concerns which conceptually do not contribute to CSP or sustainability (Hillman and Keim, 2001).

minus total number of concerns as the CSP measure. I use the same CSP measure as a benchmark to compare the sustainability measure SUS. Some recent papers in ESG literature (e.g., Ng and Rezaee, 2015), measure specific ESG dimensions i.e., environmental, social and governance, by taking only their respective strengths and concerns to compute individual difference scores for each. However, such sub-division is not preferred here as my objective is not to explore specific ESG dimensions, but instead to identify sustainability measure as a significant component of the all-in CSP measure. My final sample consists of over 36,000 firm year observations of the CSP and other ESG-based measures.

4.4.3 The Sustainability Index and the Remnant ESG Components Index

To compute the sustainability index SUS for each year, I use an approach similar to that used in prior literature employing MSCI ESG data (e.g., Jiao, 2010; Borgers et al., 2013) i.e., taking an aggregate of all the strengths (+) and concerns (–), but using only the sustainability indicators identified in Section 4.3.3. Additional subcomponents for this index are captured by summing up only the strengths ($SUSstr$) or the concerns ($SUScon$). In other words, the SUS-Index score is the difference between $SUSstr$ and $SUScon$. This measure captures the net sustainability improvement (if $SUS > 0$) or deterioration ($SUS < 0$) experienced by a firm in a given year in terms of how it balances all important stakeholders' needs to achieve its triple bottom line objective. For the comparable CSP measure as well, respective strength and concern subcomponents (i.e., $CSPstr$ and $CSPcon$) are calculated by following an all-in approach and including all the ESG indicators.

Since SUS-Index is constructed using a subset of indicators from those used in constructing the CSP measure, I additionally include all the leftover indicators (i.e., those that do not contribute to sustainability) using similar aggregation procedure as before, to create the remnant CSP score ($remCSP$). Essentially $remCSP$ is the difference between the net CSP score and the SUS score. If variations in SUS measure captures much of the variation in CSP, the corresponding coefficient for $remCSP$ in my analysis should predominantly remain statistically insignificant. This focal criteria forms the base for empirical tests that I run subsequently. Key attributes of the sustainability measures, CSP measures and the remnant CSP are all summarized in Table 4.2 Panel A.

I further create a pseudo-sustainability measure by randomly dropping some of the ESG indicators. This may be considered as a placebo experiment to check that my results are not chance-driven, and to test the validity of "corporate sustainability" measure itself.[67] To allow for the replicability of this experiment, a systematic sample of indicators was chosen by selecting every third strength indicator, and every second concern indicator from each of the 8 categories reported by MSCI, to combine them into a pseudo-sustainability score using exactly the same number of indicators as in the actual SUS-Index. Subsequently, all those indicators that did not form the part of this measure were combined into the pseudo-remnant CSP score.

4.4.4 Performance, Returns and Other Data

The performance variables and firm-level controls are taken from COMPUSTAT annual data, and the monthly stock prices and corresponding returns are provided by Center for Research in Security Prices (CRSP) as available on WRDS. Additional governance data, mainly the Bebchuk, Cohen, and Ferrell (2009) entrenchment index (E-Index) and institutional ownership/ blockholder distribution, was taken from ISS-Riskmetrics and Thomson Reuters Institutional Holdings data respectively, while the Fama-French four factors, five

[67] I am grateful to an anonymous referee for suggesting this test.

Table 4.2 Descriptive statistics for firm-specific variables, ESG-based measures, and instruments

This table presents the mean, median, standard deviation (SD), extreme values and the total number of observations (N) for all variables used in firm value on ESG regressions. Panel A covers all ESG-based measures. Panel B summarizes key aspects of independent variables and main controls, whereas Panels C and D show summary statistics for additional controls and instruments. These variables are computed from MSCI ESG, ISS Governance and COMPUSTAT data. For details on the composition of these variables, see Appendices C and D. All regressions applying ratios such as Tobin's Q, Sales Growth and ROA use these values winsorized at the 5th and 95th percentiles in the presence of extreme outliers.

Panel A: ESG based measures and dimensions						
Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
SUS	0.133	1.481	-6.00	0.00	13.00	36040
SUSstr	0.803	1.352	0.00	0.00	15.00	36040
SUScon	0.669	0.929	0.00	0.00	9.00	36040
CSP	-0.122	2.407	-11.00	0.00	19.00	36040
CSPstr	1.482	2.307	0.00	1.00	22.00	36040
CSPcon	1.604	1.801	0.00	1.00	18.00	36040
remCSP	-0.255	1.440	-10.00	0.00	10.00	36040
Environment	0.061	0.801	-5.00	0.00	6.00	36040
Social	0.000	1.913	-9.00	0.00	14.00	36040
1. Community	0.085	0.501	-2.00	0.00	4.00	36040
2. Diversity	-0.005	1.235	-3.00	0.00	7.00	36040
3. Employee	0.050	0.953	-4.00	0.00	8.00	36040
4. Human Rights	-0.023	0.272	-3.00	0.00	2.00	35021
5. Product	-0.106	0.587	-4.00	0.00	3.00	36040
Governance	-0.180	0.666	-4.00	0.00	3.00	36040
Panel B: Main Regressors						
Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
Tobin's Q	2.407	4.279	-23.25	1.89	690.82	35915
SIC Industry Adjusted Tobin's Q	0.429	4.206	-25.81	0.02	688.26	35915
FF48 Industry Adjusted Tobin's Q	0.432	4.194	-26.37	0.02	687.93	35915
ROA	0.100	1.769	-120.96	0.11	226.31	36074
Size (Log of Total Assets)	7.512	1.802	-3.82	7.45	14.76	35971
Leverage	0.194	0.210	0.00	0.14	3.68	36074
Volume	18.470	1.616	8.97	18.48	25.67	36061
CAPEX/Total Assets	-3.739	1.454	-12.75	-3.47	-0.19	33129
R&D Expense/Total Sales	-1.170	1.826	-11.42	0.00	10.15	36074
Sales Growth (2 Years)	1.983	44.889	-34.95	1.16	7344.91	35485
Log of Age	5.033	1.039	0.00	5.23	6.48	35870
Delaware Dummy	0.585	0.493	0.00	1.00	1.00	36040
Panel C: Additional Controls						
Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
E-Index	3.093	1.446	0.00	3.00	6.00	19698
Institutional Ownership (%)	0.734	0.201	0.01	0.768	1.00	19861
Blockholders (#)	2.561	1.607	0.00	2.50	14.25	20261
Panel D: Instruments						
Variables	**Mean**	**SD**	**Minimum**	**Median**	**Maximum**	**N**
PVD	0.546	0.064	0.25	0.55	0.93	34383
CDD	0.631	0.268	0.00	0.50	1.00	34370
SGD	0.727	0.313	0.00	0.75	1.00	34370

factors (Fama and French, 2016) and Pástor and Stambaugh (2003) liquidity factor were included for analyses concerning abnormal returns.

For first part of the analysis, the MSCI ESG and COMPUSTAT data were merged together to pool them into an unbalanced master yearly panel. In subsequent analysis, the E-Index and the institutional ownership details were also added from the ISS governance and Thomson Reuters Institutional Holdings data respectively. For computing monthly portfolio returns and to assess corresponding abnormal returns, the CRSP data was appended to this master panel such that the ESG and performance data remained same in each fiscal year for any given firm.

For political leanings as instrumental variables (Di Giuli and Kostovetsky, 2014), I gather data for states in which MSCI sample firms are headquartered. The data for state-level Presidential voting percentages is obtained from Dave LeipâĂŹs Atlas of U.S. Presidential elections, and the data on composition of the House of Representatives, the Senate, and the state governments are obtained from various online sources. Table 4.2 Panels B, C and D summarize all the main variables, additional control variables and the instruments respectively. The correlations between all the main variables are reported in Appendix Table 4.12.

4.5 Sustainability and Firm Value

Numerous studies have demonstrated that ESG-based measures are associated with firm performance measures (e.g., Gregory, Whittaker, and Yan, 2016). What I aim to show in this section is that sustainability or SUS explains much of the cross-sectional relationship between firm value and broader measures of corporate social performance such as CSP. Starting with McGuire, Sundgren, and Schneeweis (1988), many studies have examined the CSP–CFP nexus. In recent years, firm value proxy Tobin's Q (Jiao, 2010) and operating performance measures such as return on assets (ROA) and return on equity (Eccles, Ioannou, and Serafeim, 2014) are commonly used to represent financial performance.

I use Tobin's Q as the accounting-based CFP proxy. Thus, all regression models in this section use Tobin's Q (adjusted for the median 2-digit SIC or Standard Industry Classification Tobin's Q values) as the dependent variable.[68] The main empirical models are either of the following specifications:

$$Q_{j,t} = a_1 + b_1 * CSP_{j,t} + z_1 * X_{j,t} + \epsilon_{j,t} \tag{4.7}$$

or

$$Q_{j,t} = a_2 + b_2 * SUS_{j,t} + c_2 * remCSP_{j,t} + z_2 * X_{j,t} + \epsilon_{j,t} \tag{4.8}$$

where $Q_{j,t}$ is the firm j's Tobin's Q value in year t and $X_{j,t}$ are all firm-specific control variables. $CSP_{i,t}$ is the broader kitchen-sink all-inclusive corporate social performance measure that sums up all the ESG strengths (+) and concerns (–) and $SUS_{i,t}$ is the firm j's sustainability index measure constructed by only adding the sustainability-specific strengths (+) and concerns (–) as identified in Section 4.3.3. When sustainability measures are used, the leftover ESG strengths and concerns form the remnant CSP score or $remCSP_{j,t}$. In other words, Equation 4.8 separates the sustainability component from the overall CSP score used in Equation 4.7, while also controlling for the remaining ESG indicators in $remCSP_{j,t}$. Certain variations of these models break down the $CSP_{i,t}$ and $SUS_{i,t}$ into its constituent strengths (i.e., $SUSstr_{i,t}$ and $CSPstr_{i,t}$) and concerns (i.e., $SUScon_{i,t}$ and $CSPcon_{i,t}$) to provide additional insights.

Tobin's Q is defined as in Gompers, Ishii, and Metrick (2003), Bebchuk, Cohen, and Ferrell (2009) and Jiao (2010) among others. The definitions and oper-

[68]In addition, I run Fama and French (1997) 48 industry adjusted Tobin's Q and do not find any standout differences in any of the results. For example, see Appendix Table 4.15

ationalizations of this and other variables are provided in Appendix 4.A.3. Using empirical evidence and theoretical arguments from prior literature (Bebchuk and Cohen, 2005; Jiao, 2010), the control variables $X_{j,t}$ include operating performance (using ROA as proxy), firm size (proxied by log of firm's total assets), leverage, liquidity (volume of shares traded), log of capital expenditures/total assets ratio (CAPEXTA), research and development expense ratio (R&D/total sales), log of firm age (in months), 2 year sales growth and Delaware incorporation dummy. One more control variable, insider ownership level and its square (Morck, Shleifer, and Vishny, 1988) was also considered but left out from the main results as the Execucomp data on executive ownership has gaps and leads to considerable loss of sample size. However, note that the use of insider ownership produces similar results, albeit much smaller number of observations.

4.5.1 Corporate Social Performance Versus Sustainability

Is much of the association between corporate social performance (CSP) and firm value explained by the sustainability component of the CSP? This is the main question of focus in this part of analysis. Multiple variations of Equations 4.7 and 4.8 are used in CSR and sustainability literature to reflect the cross-sectional variations in Tobin's Q of good ESG score firms versus the poor ESG ones. I apply ordinary least squares (OLS) and the dynamic OLS as the preliminary models and then two additional variants of the OLS estimation. Firstly, as suggested in Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009), I run annual cross-sectional regressions and then show time-series averages using Fama and MacBeth (1973) method. This reflects the way cross-sectional valuations vary with sustainability and aggregate CSP over time. Secondly, I run panel regressions to examine how the CSP and SUS-Index truly have an impact on Tobin's Q cross-sectionally (using between-effects estimation) and within firms' across time (using fixed-effects estimation). Gormley and Matsa (2014) show that fixed effects model is more consistent when "controlling for unobserved [firm] heterogeneity" than the industry-adjusted models.

The OLS and dynamic OLS estimations for Tobin's Q on ESG aggregate scores, along with their segregated strengths and concerns components, are shown in Table 4.3. With a static model (1) that includes industry and year fixed effects, a significant association is seen with Tobin's Q for both the all-in CSP measure and the newly introduced sustainability score. The sign and magnitude of CSP coefficients are similar to those reported in Jiao (2010) for a smaller sample period between 1992 and 2003. As expected, CSP is seen to have a positive and significant influence on firm value. However, sustainability index seems to be the main driver of this result when CSP is divided into SUS-Index and remnant CSP components, as the coefficient for SUS is almost twice in magnitude when compared to the CSP coefficient. Remnant CSP score (constituting indicators that are leftover after sustainability indicators are identified) in this specification, shows no significant contribution towards Tobin's Q. Almost all the control variables show expected signs and statistical significance with the dependent variable.

Firm performance proxies are known to be sticky, with past performances associated with current and subsequent performance (Wintoki, Linck, and Netter, 2012). To counter this, I introduce a dynamic OLS model (2) with past two years Tobin's Q values included as controls. Interestingly, the introduction of dynamism in the OLS estimation has no effect on the statistical insignificance seen previously for remnant CSP score. Only the sustainability component is found to contribute significantly to Tobin's Q amongst the ESG sample firms. Additionally, the magnitude of selective SUS-Index remains almost double that of the all-in CSP score as seen in the static model.

Next, I assess how the segregated ESG strengths and concerns within these two

Table 4.3 OLS and dynamic OLS regressions for Tobin's Q on ESG measures

This table shows the results of two variations of OLS estimation for Tobin's Q on the CSP and sustainability scores (SUS-Index), as well as their subcomponent strengths and concerns. When SUS-Index is used as the regressor, additional control for remaining CSP indicators ($remCSP$) is included. For definitions of the variables see Appendix 4.A.3. Model 1 shows Tobin's Q with the two ESG measures, and all the main controls included along with year and industry fixed effects. Model 2 improves Model 1 by controlling for past two years' Tobin's Q in a dynamic OLS. Dependent variable is the industry-adjusted Tobin's Q taken as Tobin's Q minus the median Tobin's Q for that industry using SIC 2-digit classification. Coefficients for the constant, year dummies and industry dummies are omitted. Significance levels are represented by *, **, and *** for 10%, 5%, and 1% respectively.

	ESG Aggregate Measures				ESG Subcomponents			
	Model (1)		Model (2)		Model (1)		Model (2)	
CSP	0.0333***		0.0137***					
	(0.004)		(0.003)					
SUS		0.0757***		0.0297***				
		(0.007)		(0.005)				
CSPstr (+)					0.0555***		0.0236***	
					(0.005)		(0.003)	
CSPcon (−)					0.0093		0.0052	
					(0.006)		(0.004)	
SUSstr (+)						0.0971***		0.0399***
						(0.008)		(0.006)
SUScon (−)						-0.0205**		-0.0036
						(0.010)		(0.007)
remCSP		-0.0071		-0.0015		-0.0056		-0.0009
		(0.005)		(0.004)		(0.005)		(0.004)
ROA	-0.0162	-0.0186	-0.6495	-0.6501	0.0091	-0.0047	-0.6373	-0.6428
	(1.017)	(1.016)	(0.769)	(0.769)	(1.018)	(1.017)	(0.771)	(0.770)
Size	-0.4712***	-0.4817***	-0.1376***	-0.1420***	-0.5035***	-0.4951***	-0.1528***	-0.1488***
	(0.014)	(0.014)	(0.026)	(0.026)	(0.016)	(0.015)	(0.028)	(0.027)
Leverage	-0.9828***	-0.9708***	-0.3125**	-0.3088**	-0.9396***	-0.9494***	-0.2941**	-0.2987**
	(0.146)	(0.146)	(0.149)	(0.149)	(0.147)	(0.147)	(0.149)	(0.149)
Volume	0.3984***	0.3986***	0.0974***	0.0979***	0.3897***	0.3948***	0.0941***	0.0964***
	(0.013)	(0.013)	(0.023)	(0.023)	(0.012)	(0.013)	(0.023)	(0.023)
CAPEX / Assets	0.1183***	0.1160***	0.0484**	0.0476**	0.1148***	0.1150***	0.0470**	0.0472**
	(0.029)	(0.029)	(0.020)	(0.020)	(0.029)	(0.029)	(0.020)	(0.020)
R & D / Sales	-0.0050	-0.0039	-0.0077	-0.0073	-0.0014	-0.0019	-0.0061	-0.0063
	(0.016)	(0.016)	(0.012)	(0.012)	(0.017)	(0.016)	(0.012)	(0.012)
Sales Growth	0.0003*	0.0003*	0.0001*	0.0001**	0.0003*	0.0003*	0.0001**	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.0845***	-0.0871***	0.0383***	0.0373***	-0.0901***	-0.0894***	0.0353***	0.0359***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
Delaware Dummy	0.0237	0.0247	0.0223	0.0227	0.0219	0.0249	0.0215	0.0228
	(0.024)	(0.023)	(0.019)	(0.019)	(0.024)	(0.023)	(0.019)	(0.019)
Lag 1 Tobin's Q			0.5822***	0.5817***			0.5812***	0.5812***
			(0.070)	(0.070)			(0.070)	(0.070)
Lag 2 Tobin's Q			0.0606**	0.0604**			0.0606**	0.0604**
			(0.028)	(0.028)			(0.028)	(0.028)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	32546	32546	30991	30991	32546	32546	30991	30991
R-Squared	0.209	0.211	0.550	0.551	0.212	0.212	0.551	0.551

ESG-based measures get influenced when sustainability indicators are identified. As shown before, intuitively and expectedly, ESG-based strengths should positively influence the firm value whereas the ESG concerns must have a negative impact on the same (as indicated alongside each subcomponent in the table). Using the same two estimation models (i.e., static and dynamic OLS), the coefficients and standard errors for the strengths and concerns subcomponents are also reported in Table 4.3. In the static model (1), when only time and industry heterogeneity is controlled for, the CSP concerns variable shows a statistically insignificant positive coefficient. In contrast, both the SUS-Index subcomponents are shown to reflect statistically significant contributions to Tobin's Q, and with expected signs. In my full model (2), which allows for dynamism, the sustainability concerns subcomponent loses its statistical significance but retains its sign. Also, once again, both the static and dynamic OLS models for the ESG subcomponents indicate that the remnant CSP indicators are not related to Tobin's Q.

4.5.1.1 Additional Controls

Since antitakeover provisions based corporate governance measures such as the Bebchuk, Cohen, and Ferrell (2009) E-Index that is indicative of managerial entrenchment are not covered in the ESG data used for CSP measures, I subsequently ran robustness tests by including the E-Index as an extra control variable. Furthermore, other governance mechanisms such as monitoring through institutional ownership (Buchanan, Cao, and Chen, 2018; Dyck et al., 2018) and blockholders (Konijn, Kräussl, and Lucas, 2011) have been shown to influence firm value. Matching firms with their E-Index scores, % institutional ownership and the number of blockholders further reduced my sample size, but the results remain robust for all the ESG-based measures (shown in Appendix Table 4.14). This shows that the importance of sustainability indicators over the other remnant CSP indicators persists even when other governance characteristics are controlled for.

4.5.1.2 Annual Regressions

I run cross-sectional regressions to compare the consistency of the relationships between each of the two ESG-based measures and firm value over time. The summary of coefficients obtained using Equations 4.7 (CSP) and 4.8 (SUS and $remCSP$) for each year are given in Table 4.4 for Tobin's Q on ESG aggregate scores and their respective strengths ($CSPstr$, $SUSstr$) and concerns ($CSPcon$, $SUScon$) subcomponents. For each measure, their corresponding Fama and MacBeth (1973) time-series averages are also reported. In Table 4.4, though the time-series averages are statistically significant for both the all-in CSP aggregate score and the selective SUS-Index, the magnitude for sustainability score is roughly twice that of the CSP score, and the coefficient for remnant CSP indicators reflects no significant relation with Tobin's Q. This result is essentially similar to that seen in static and dynamic OLS regressions. An inspection of yearly cross-sectional coefficients shows that the lack of statistical significance for the remnant CSP indicators' aggregate is primarily due to the fact that it has both positive and negative relationship with Tobin's Q in the sample period. Also, while the aggregate CSP score is significantly related to Tobin's Q only in the second half of the sample years, the sustainability score shows a widespread significant association with Tobin's Q across time.

For the ESG strengths and concerns subcomponents in Table 4.4, the Fama-Macbeth average coefficients for both the strengths and concerns using sustainability indicators are significantly associated with Tobin's Q. The all-in CSP based subcomponents, meanwhile, shows statistical significance only for the strengths, similar to the OLS results. Moreover, the signs for strengths (+) and concerns (–) are as expected when it comes to sustainability indica-

Table 4.4 Annual regressions and time-series averages for Tobin's Q on ESG measures

This table summarizes yearly and time-series average regressions for Tobin's Q on the CSP score and sustainability score (SUS-Index). When SUS-Index is used as the regressor (Model 2 based on Equation 4.8), additional control for remaining CSP indicators ($remCSP$) is shown. All other control variables are the same as those used in Table 4.3. Both the aggregate ESG measures and their respective strengths and concerns subcomponents are reported. All estimations use SIC 2-Digit industry classification to obtain industry-adjusted Tobin's Q calculated as Tobin's Q minus the median Tobin's Q for that industry. For each year, only the main regressors coefficients and robust standard errors are shown. Time-series average coefficients and standard errors (using Fama and MacBeth, 1973 methodology) are given at the bottom. *, **, and *** are significance levels for 10%, 5%, and 1% respectively.

Year	# Observations	ESG Aggregate Measures			ESG Subcomponents				
		Model (1)	Model (2)		Model (1)		Model (2)		
		CSP	SUS	remCSP	CSPstr	CSPcon	SUSstr	SUScon	remCSP
1991	260	0.0320	0.1147**	-0.0343	-0.0252	-0.1024**	0.0357	-0.2622***	-0.0444
		(0.027)	(0.039)	(0.053)	(0.042)	(0.048)	(0.065)	(0.073)	(0.040)
1992	267	-0.0028	0.0341	-0.0358	-0.0379	-0.0456	-0.0541	-0.2081***	-0.0499
		(0.021)	(0.035)	(0.042)	(0.029)	(0.038)	(0.049)	(0.067)	(0.034)
1993	274	-0.0176	-0.0194	-0.0159	-0.0095	0.0292	-0.0368	-0.0071	-0.0178
		(0.019)	(0.032)	(0.035)	(0.035)	(0.044)	(0.058)	(0.058)	(0.032)
1994	281	-0.0015	0.0236	-0.0286	0.0187	0.0388	0.0367	0.0028	-0.0283
		(0.015)	(0.027)	(0.021)	(0.020)	(0.030)	(0.031)	(0.043)	(0.027)
1995	289	0.0156	0.0335*	-0.0029	0.0323	0.0185	0.0523	0.0251	-0.0024
		(0.020)	(0.021)	(0.030)	(0.027)	(0.044)	(0.039)	(0.080)	(0.031)
1996	301	0.0150	0.0228	0.0068	0.0170	-0.0104	0.0239	-0.0191	0.0070
		(0.024)	(0.034)	(0.035)	(0.029)	(0.038)	(0.041)	(0.062)	(0.033)
1997	319	0.0446*	0.0488**	0.0404	0.0548	-0.0269	0.0554*	-0.0275	0.0422
		(0.025)	(0.023)	(0.037)	(0.034)	(0.030)	(0.032)	(0.061)	(0.043)
1998	326	0.0188	0.0128	0.0250	0.0040	-0.0418	-0.0097	-0.0875	0.0174
		(0.025)	(0.047)	(0.047)	(0.032)	(0.032)	(0.052)	(0.072)	(0.047)
1999	349	-0.0063	0.0340	-0.0530	-0.0041	0.0093	0.0317	-0.0384	-0.0532
		(0.038)	(0.090)	(0.060)	(0.047)	(0.061)	(0.075)	(0.077)	(0.090)
2000	377	0.0184	0.0327	0.0003	-0.0158	-0.0618*	-0.021	-0.1212**	-0.0049
		(0.027)	(0.053)	(0.044)	(0.039)	(0.034)	(0.058)	(0.057)	(0.053)
2001	673	0.0155	0.0751***	-0.0633**	0.0289	0.0026	0.0859**	-0.0543	-0.0613**
		(0.017)	(0.030)	(0.027)	(0.023)	(0.023)	(0.035)	(0.036)	(0.030)
2002	704	0.0055	0.0413**	-0.0412**	0.0115	0.0033	0.0465**	-0.0302	-0.0402**
		(0.011)	(0.020)	(0.016)	(0.013)	(0.014)	(0.020)	(0.023)	(0.020)
2003	1722	0.0292*	0.1198***	-0.0900***	0.0949***	0.0345*	0.1764***	-0.0344	-0.0707**
		(0.015)	(0.028)	(0.026)	(0.021)	(0.020)	(0.032)	(0.031)	(0.028)
2004	2071	0.0616***	0.1600***	-0.0630**	0.1053***	-0.0129	0.1765***	-0.1356***	-0.0609**
		(0.018)	(0.025)	(0.031)	(0.027)	(0.018)	(0.040)	(0.030)	(0.025)
2005	2085	0.0494***	0.0817***	0.0121	0.0740***	-0.0160	0.1052***	-0.0393	0.0146
		(0.013)	(0.020)	(0.021)	(0.016)	(0.017)	(0.025)	(0.027)	(0.020)
2006	2123	0.0630***	0.1022***	0.0169	0.0916***	-0.0232	0.1275***	-0.0411	0.0213
		(0.012)	(0.020)	(0.022)	(0.016)	(0.015)	(0.025)	(0.027)	(0.020)
2007	2145	0.0524***	0.0798***	0.0223	0.0742***	-0.0234	0.1094***	-0.0126	0.0238
		(0.011)	(0.020)	(0.017)	(0.012)	(0.017)	(0.020)	(0.027)	(0.020)
2008	2263	0.0352***	0.0514***	0.0161	0.0403***	-0.0287**	0.0484***	-0.0583**	0.0157
		(0.009)	(0.016)	(0.015)	(0.011)	(0.013)	(0.017)	(0.027)	(0.016)
2009	2304	0.0367***	0.0447***	0.0278**	0.0449***	-0.0266**	0.0550***	-0.0217	0.0292**
		(0.008)	(0.014)	(0.012)	(0.010)	(0.010)	(0.014)	(0.019)	(0.014)
2010	2383	0.0233**	0.0503***	-0.0026	0.0392***	0.0157	0.0475***	0.0773***	0.0329*
		(0.008)	(0.016)	(0.015)	(0.009)	(0.013)	(0.015)	(0.029)	(0.018)
2011	2288	0.0299***	0.0627***	0.0019	0.0405***	0.0031	0.0635***	0.0656**	0.0289
		(0.007)	(0.015)	(0.018)	(0.009)	(0.015)	(0.018)	(0.028)	(0.018)
2012	2333	0.0589***	0.0767***	0.0498**	0.0734***	0.0150	0.1061***	0.1008**	0.0408*
		(0.014)	(0.022)	(0.025)	(0.014)	(0.031)	(0.027)	(0.049)	(0.022)
2013	2133	0.0278**	-0.002	0.0438**	0.0400***	0.0356	0.0146	0.1188*	0.0370*
		(0.012)	(0.020)	(0.028)	(0.013)	(0.027)	(0.030)	(0.063)	(0.020)
2014	2213	0.0667**	0.1093***	0.0206	0.0838***	-0.0091	0.1251***	0.0254	0.0222
		(0.023)	(0.032)	(0.032)	(0.025)	(0.032)	(0.033)	(0.072)	(0.032)
2015	2086	0.1154***	0.1392***	0.0933***	0.1342***	-0.0342	0.1535***	0.0124	0.0924***
		(0.020)	(0.031)	(0.032)	(0.022)	(0.031)	(0.033)	(0.053)	(0.031)
Fama-MacBeth	32546	0.0317***	0.0566***	0.0024	0.0404***	-0.0103	0.0602***	-0.0308*	0.0016
		(0.006)	(0.009)	(0.009)	(0.009)	(0.007)	(0.012)	(0.017)	(0.009)

tors based subcomponents ($SUSstr$ and $SUScon$), as they have more years showing significant and monotonic relationship with firm value than the all-in ESG indicators based CSP subcomponents.

Overall, the results for OLS, dynamic OLS and annual regressions show that most of the variations in all-in CSP scores that drives its relationship with firm value is powered by the sustainability indicators. Even after controlling for time trends, unobserved industry characteristics and past performances, only the sustainability indicators through SUS-Index shows significant and monotonic positive association with Tobin's Q. The leftover indicators' $remCSP$ score is unrelated to firm value. These preliminary tests provide credence against the use of all-in approaches for CSP that sum up all available ESG indicators. The selected sustainability indicators are seen to better reflect the variations in ESG data when studying firm-level outcomes such as the Tobin's Q.

4.5.1.3 Between and Within Panel Estimations

I further test the robustness of previous results by employing panel regressions. Table 4.5 summarizes the results from both between-firm and within-firm estimations using the aggregated ESG scores i.e., all-in CSP score and the selective SUS-Index, and their segregated strengths and concerns subcomponents. ESG-based aggregated measures exhibit little time series (within firm) variations and thus have relatively lower power to detect a statistically significant relationship using fixed effects estimations. Hence, to robustly capture the variations for ESG measures in fixed effects models, I additionally employ above- versus below-median ESG measures (Panel B) along with the true ESG-based scores (Panel A).[69] In all panel regressions, year and industry dum-

[69]In additional unreported analysis, I use quartile classification of ESG measures in place of median-based division as a robustness check. All the main results remain the same.

mies are included when required to control for the time trends and industry characteristics.

The between effects panel regression coefficients show the effect of independent variables as they change between the sample firms, while the fixed effects coefficients reflects the changes on outcome variable when the independent variable changes within the firm. On comparing Tables 4.5 and 4.3 for the coefficients of ESG aggregated measures, i.e., CSP and SUS-Index, the panel estimates are expectedly much larger than the simple OLS estimates when they employ a broad-based dichotomous ESG dummies in Panel B. The results are identical for each of the two strengths and concerns subcomponents as well. In Panel A, while CSP and its subcomponents are all insignificant in fixed effects estimations (Model 2), most sustainability measures are statistically significant (only strengths dimension does not pick any significant effect on Tobin's Q). In Panel B, it is seen that with firm-specific heterogeneous characteristics controlled for, the overall SUS-Index as well as its two subcomponents i.e., strengths and concerns can significantly influence an average firm's value over time. The all-in ESG measures (i.e., CSP and its subcomponents), meanwhile, show similar statistical insignificance as previously seen in Panel A.

4.5.1.4 Pseudo-Sustainability Placebo

I repeated all of the above analyses using the pseudo-sustainability and remnant scores. The results for OLS, dynamic OLS and Fama-Macbeth regressions using the pseudo scores, instead of SUS and $remCSP$, are shown in the Appendix Table 4.16. Other results are omitted for brevity. The randomly identified placebo measure (consisting of 30 strengths and 21 concerns), in contrast to SUS-Index, fails to completely capture the CSP–firm value relation. The remnant CSP indicators for the placebo measure consistently shows positive association with firm value. While in some instances the pseudo-

Table 4.5 Panel regressions for Tobin's Q on ESG measures

This table shows the coefficients for between effects (cross-sectional) and fixed effects (within-firm) estimations of Equations 4.7 and 4.8 by first considering the aggregated measures CSP and SUS-Index, and then its respective strengths and concerns subcomponents. Expected signs for the ESG subcomponent variables are shown in parenthesis alongside. Panel A reports the results with true ESG scores. Panel B has ESG measures indicated by a dummy taking the value of 1 for above median values in each year. All controls are the same as those used in Tables 4.3 and 4.4. With SUS-Index as the regressor, additional control representing leftover CSP indicators is included. Each column with between- and fixed-effects models are denoted by Models 1 and 2 accordingly. All regressions use industry-adjusted Tobin's Q calculated as Tobin's Q minus the median Tobin's Q for that SIC 2-digit industry. The coefficients for controls variables, constants, year dummies and industry dummies are omitted. Significance levels at *, **, and *** are indicative of 10%, 5%, and 1% respectively.

Panel A: True ESG Scores

	ESG Aggregate Measures				ESG Subcomponents			
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
CSP	0.0671***	-0.0038						
	(0.016)	(0.005)						
SUS			**0.1622*** **	**0.0177** **				
			(0.030)	**(0.008)**				
CSPstr (+)					0.1106***	-0.0091		
					(0.019)	(0.007)		
CSPcon (−)					0.0175	-0.0048		
					(0.025)	(0.008)		
SUSstr (+)							**0.1952*** **	**0.0062**
							(0.033)	**(0.011)**
SUScon (−)							**-0.0823***	**-0.0446*** **
							(0.047)	**(0.013)**
remCSP			-0.0286	-0.0217***			-0.0263	-0.0167**
			(0.030)	(0.006)			(0.030)	(0.006)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
# Observations	32546	32546	32546	32546	32546	32546	32546	32672
R-Squared	0.264	0.110	0.267	0.111	0.268	0.111	0.268	0.105
Number of Groups	4069	4069	4069	4069	4069	4069	4069	4095

Panel B: ESG Dummies

	ESG Aggregate Measures				ESG Subcomponents			
	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)	Model (1)	Model (2)
CSP	0.1340**	0.0200						
	(0.067)	(0.018)						
SUS			**0.3815*** **	**0.0733*** **				
			(0.076)	**(0.020)**				
CSPstr (+)					0.3512***	0.0435*		
					(0.082)	(0.024)		
CSPcon (−)					0.1546**	-0.0298		
					(0.077)	(0.023)		
SUSstr (+)							**0.3341*** **	**0.0644*** **
							(0.070)	**(0.021)**
SUScon (−)							**-0.1939** **	**-0.0660*** **
							(0.076)	**(0.022)**
remCSP			-0.1521**	-0.0287			-0.1539**	-0.0130
			(0.074)	(0.017)			(0.074)	(0.017)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Number of observations	32546	32546	32546	32546	32546	32546	32546	32672
R-Squared	0.277	0.111	0.281	0.112	0.280	0.112	0.281	0.106
Number of Groups	4069	4069	4069	4069	4069	4069	4069	4095

sustainability measure does have higher coefficients than the actual SUS-Index, the pseudo-remnant measure consistently shows statistically significant coefficients across all the models (unlike the lack of statistical significance for the actual $remCSP$). This shows that only the identified set of sustainability indicators, and not some randomly picked set, can completely explain the CSR's relationship with firm value.

4.5.2 Exploring Causality

While the previous inferences do indicate that sustainability and its subcomponents are more powerful part of CSP when it comes to explaining the CSP–firm value relationship, all of the findings reported so far are hounded by severe endogeneity problems. To overcome these concerns and draw causal inferences, in this section, I run additional analysis first using a quasi-natural experiment exploiting an exogenous shock to ESG measures themselves, and then running confirmatory check with instrumental variables approach.

4.5.2.1 Quasi-Natural Experiment

The baseline causal estimates are found across the year 2010 when MSCI changed its indicator assessment strategy as part of its new data collection methodology that ensures only industry-relevant indicators get rated. In other words, beyond 2010, the set of ESG indicators assessed for each of the sample firms is restricted to a subset of key industry-specific indicators that are unique to the industry to which the focal firm belongs.

Accordingly, I identify the treatment firms as the ones whose ESG measures (either CSP or SUS) change from 2009 to 2010.[70] Alternatively, the control firms' ESG measures remain constant across this exogenous shock. The

[70]Note that this identification assumes that the ESG indicator ratings are sticky and undergo very few changes across the years. This characteristic of ESG factors is elaborated in panel estimations earlier.

rationale behind this identification of treatment and control firms is further illustrated as follows. If a firm had 20 ESG strengths and 10 concerns in 2009, its overall CSP score is +10. But, supposing that only 15 of these strengths are industry-relevant, the subsequent CSP score in 2010 is +5. Given that these indicators do not considerably change within a firm over the years, it can be safely assumed that the change of ESG measures across this year is hence an exogenous treatment. Similarly, a lack of such a treatment or change implies that the firm falls in the control group. I estimate the overall treatment effect on Tobin's Q using triple difference (DDD or diff-in-diff-in-diff) analysis. Even though I control for possible confounds and alternative explanations in two of the differences within DDD i.e., treatment vs. control group and pre- vs. post-treatment periods, further inclusion of firm fixed effects ensures that all other firm-specific characteristics are also controlled for.

The change in indicator assessment rule by MSCI is an exogenous shock to its sample firms. However, since the new rule applies assessment of only the key industry indicators, it can be argued that the firms and their managers may have been aware of the important ESG indicators for each of their industries, hence marginalizing the impact of the shock itself. I run placebo tests to assess if such anticipation indeed occurs. Furthermore, I run propensity score matching to account for any selection and sampling biases borne out of the differences in the size of control and treatment groups.

Model: This quasi-natural experiment is modeled for analysis using DDD estimation. I introduce firm fixed effects to control for firm heterogeneity as shown in Section 4.5.1.3. Additional dummy variables $Post_{j,t}$ and $Treated_{j,t}$ represent the post-treatment period (2010 onwards) and the treatment firms respectively. Either of the following specifications are employed depending on whether the all-in CSP or the selective SUS is used:

$$\begin{aligned}Q_{j,t} = a_3 + b_{3,1} * CSP_{j,t} + b_{3,2} * Post_{j,t} + b_{3,3} * Treated_{j,t} + b_{3,4} * CSP_{j,t} * Post_{j,t} \\ + b_{3,5} * CSP_{j,t} * Treated_{j,t} + b_{3,6} * Post_{j,t} * Treated_{j,t} \\ + b_{3,7} * CSP_{j,t} * Post_{j,t} * Treated_{j,t} + z_3 * X_{j,t} + a_{3_j} + \epsilon_{j,t}\end{aligned} \tag{4.9}$$

$$\begin{aligned}Q_{j,t} = a_4 + b_{4,1} * SUS_{j,t} + b_{4,2} * Post_{j,t} + b_{4,3} * Treated_{j,t} + b_{4,4} * SUS_{j,t} * Post_{j,t} \\ + b_{4,5} * SUS_{j,t} * Treated_{j,t} + b_{4,6} * Post_{j,t} * Treated_{j,t} \\ + b_{4,7} * SUS_{j,t} * Post_{j,t} * Treated_{j,t} + c_4 * remCSP_{j,t} \\ + z_4 * X_{j,t} + a_{4_j} + \epsilon_{j,t}\end{aligned} \tag{4.10}$$

I seek to identify the impact on Tobin's Q when there is an increase (decrease) of ESG measures from below (above) average levels for treatment firms after the adoption of new industry-relevant indicators assessment. So the coefficients of interactions for each of the CSP and SUS with $Post$ and $Treated$ given by $b_{3,7}$ and $b_{4,7}$ respectively, are the ones that capture the DDD terms.[71] Treatment firms are those with a change in their ESG measures from year 2009 to 2010, i.e., either with change in their true CSP (with 420 control firms having unchanged scores) or SUS-Index (with 658 in control group). The firm fixed effects a as well as the controls $X_{j,t}$ (from Equations 4.7 and 4.8) are included accordingly for each of the ESG-based measures.

Results: Table 4.6 shows the results for all the DDD estimations. Baseline result in panel A shows that an improvement in sustainability rating due to the sudden application of industry-specific assessment has a negative effect

[71] In these models, the focus is on assessing the net impact on firm value whenever there is a change (regardless of the sign) in ESG scores after the MSCI methodology update in 2010. Hence, both the treatment firms with increased and decreased ESG values are included together in one model specification.

Table 4.6 Do changes in SUS-Index cause changes in Tobin's Q?

This table reports the results of multiple triple difference (DDD) estimations for the impact of changes in ESG measures on Tobin's Q. All regressions in Panels A and B are estimated using Equations 4.9 and 4.10 depending on whether the all-in CSP or selective SUS is applied. Firm controls are the same as those introduced in OLS and panel estimations (except the Delaware dummy, which becomes redundant with firm fixed effects). Standard errors are shown in parenthesis. Panel A gives the results when aggregated ESG measures are used, and Panel B shows the results with each of the ESG strengths and concerns subcomponents disaggregated. $Post$ indicates years after the MSCI indicator assessment change (i.e., 2010 onwards) for baseline and propensity score (PS) matched estimations. $Treated$ is a dummy representing firms that experienced a change in their ESG scores from 2009 to 2010 (with the unchanged scores belonging to the control firms). Baseline DDD estimations reflect the control and treatment firms as is. PS matched DDD estimation randomly identifies a comparable control firm observation matched on log of assets, return on assets and leverage, for every treatment observation. First placebo test assumes placebo treatment in 2003, and the second test applies placebo $Post$ in 2007. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: ESG Aggregate Measures

	Baseline DDD		PS Matched DDD		Placebo Year 2003		Placebo Year 2007	
	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS
ESG	0.0760***	0.0228	0.0681***	-0.0274	0.0236*	0.0744***	0.0458***	0.0624***
	(0.014)	(0.017)	(0.013)	(0.030)	(0.013)	(0.022)	(0.006)	(0.016)
$Post$	0.0924***	0.1184***	0.0890***	0.1603***	-0.2647***	-0.2946***	-0.0762**	-0.0356
	(0.031)	(0.024)	(0.034)	(0.038)	(0.034)	(0.028)	(0.033)	(0.026)
$ESG * Post$	-0.0434***	0.0043	-0.0397***	0.0485**	-0.0248*	-0.0213**	-0.0208*	-0.0218*
	(0.015)	(0.013)	(0.015)	(0.024)	(0.013)	(0.009)	(0.011)	(0.013)
$ESG * Treated$	-0.0574***	0.0454***	-0.0365*	0.0817***	-0.0126	0.0002	-0.0162***	0.0168**
	(0.015)	(0.008)	(0.019)	(0.017)	(0.015)	(0.015)	(0.006)	(0.008)
$Post * Treated$	0.0077	0.0065	0.0319	-0.0309	0.0039	0.0733**	0.0331	0.0117
	(0.032)	(0.026)	(0.043)	(0.043)	(0.037)	(0.037)	(0.034)	(0.028)
$\boldsymbol{ESG * Post * Treated}$	**0.0219**	**-0.0430*** **	**0.0269**	**-0.0844*** **	**0.0054**	**0.0023**	**-0.0158**	**-0.0038**
	(0.016)	**(0.015)**	**(0.021)**	**(0.030)**	**(0.015)**	**(0.017)**	**(0.011)**	**(0.014)**
$remCSP$		-0.0041		0.0125		-0.0059		0.0058
		(0.005)		(0.010)		(0.005)		(0.005)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26085	26085	8840	8840	12069	12069	22599	22599
R-squared	0.154	0.153	0.191	0.191	0.234	0.235	0.165	0.164

Panel B: ESG Subcomponents

	Baseline DDD		PS Matched DDD		Placebo Treatment 2003		Placebo Treatment 2007	
	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS	ESG=CSP	ESG=SUS
$ESGstr$	0.0789***	0.0005	0.0759***	0.0563	0.0420**	0.0470***	0.1053***	-0.0456**
	(0.019)	(0.017)	(0.019)	(0.035)	(0.017)	(0.017)	(0.022)	(0.020)
$ESGcon$	-0.0700***	-0.0535**	-0.0566***	-0.0641	-0.0225	-0.0862***	-0.0820***	-0.0593*
	(0.018)	(0.023)	(0.018)	(0.041)	(0.016)	(0.023)	(0.021)	(0.031)
$Post$	0.2325***	0.1565***	0.2360***	0.1931***	-0.1421***	-0.2359***	0.0410	0.0317
	(0.046)	(0.032)	(0.049)	(0.052)	(0.047)	(0.035)	(0.026)	(0.024)
$Post * Treated$	-0.0672	0.0207	-0.0320	0.0083	-0.0189	0.0519	-0.0687*	-0.0828**
	(0.047)	(0.035)	(0.063)	(0.060)	(0.055)	(0.051)	(0.036)	(0.034)
$ESGstr * Post$	-0.0913***	-0.0311*	-0.0862***	-0.0613	-0.0557***	-0.0704***	-0.0360***	-0.0459***
	(0.019)	(0.019)	(0.018)	(0.043)	(0.017)	(0.017)	(0.009)	(0.014)
$ESGstr * Treated$	-0.0733***	0.0274	-0.0529**	-0.0005	-0.0356*	-0.0472**	-0.0140	-0.0002
	(0.020)	(0.019)	(0.025)	(0.040)	(0.019)	(0.023)	(0.013)	(0.018)
$\boldsymbol{ESGstr * Post * Treated}$	**0.0627*** **	**-0.0259** **	**0.0592** **	**-0.0154** **	**0.0267**	**0.0480**	**-0.0054**	**-0.0141**
	(0.020)	**(0.012**	**(0.025)**	**(0.008)**	**(0.019)**	**(0.043)**	**(0.012)**	**(0.018)**
$ESGcon * Post$	-0.0207	-0.0309	-0.0250	-0.0426	-0.0015	0.0419*	0.0050	0.0136
	(0.022)	(0.027)	(0.021)	(0.048)	(0.015)	(0.023)	(0.010)	(0.018)
$ESGcon * Treated$	0.0344*	-0.0306	0.0157	-0.0313	0.0020	0.0372	-0.0066	-0.0210
	(0.019)	(0.026)	(0.024)	(0.048)	(0.019)	(0.031)	(0.012)	(0.022)
$\boldsymbol{ESGcon * Post * Treated}$	**0.0163**	**0.0290**	**0.0059**	**0.0178**	**0.0012**	**-0.0326**	**0.0184**	**0.0398**
	(0.023)	**(0.031)**	**(0.029)**	**(0.057)**	**(0.018)**	**(0.032)**	**(0.013)**	**(0.025)**
$remCSP$		-0.0036		0.0140		-0.0087*		-0.0046
		(0.005)		(0.010)		(0.005)		(0.005)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26085	26085	8840	8840	12069	12069	24167	24167
R-squared	0.158	0.157	0.196	0.195	0.238	0.237	0.170	0.169

on Tobin's Q. Most importantly, the coefficient for $remCSP$ corroborates our previous inferences from OLS and time-series regressions that the remaining CSP indicators do not have a significant impact on Tobin's Q. Moreover, interestingly, the result for the all-in CSP measure does not support any causal link with Tobin's Q having the DDD term statistically indistinguishable from zero. Note that although both the strengths and concerns indicators' assessment was made industry-specific from 2010 onwards, the assessment regarding concerns was reverted to being all-inclusive (and not industry-specific) from 2012. Thus, with disaggregated strengths and concerns subcomponents I find support for the reliability of the identified treatment, as only the strengths for both SUS and CSP show a statistically significant DDD term.[72]

Validity Tests: To address the threats to internal validity of my inferences from this quasi-natural experiment in terms of the selection biases and counterfactuals, I employ propensity score-matching for treatment firms and additional placebo tests. These additional results are accordingly shown in Table 4.6 next to the baseline results.

Despite controlling for firm characteristics $X_{j,t}$ and the additional firm fixed effects, there remains concerns regarding the nonequivalence of the treatment and control groups both with respect to their sizes and characteristics. For this reason, I apply one-to-one nearest neighbor propensity score matching on size, profitability and leverage dimensions using a 0.001 calliper.[73] This way I randomly identify a comparable treatment firm observation for every control firm one. The main results shown in Panel A remain robust for this matched

[72]A subsample analysis restricting the observations to the year 2011 confirms this treatment reliability, as both the strengths and concerns subcomponents show significant impact on firm value in this sample period.

[73]These three characteristics are proxied using log of total assets, return on assets (ROA) and long-term debt to total asset ratio respectively. I find that the two groups have statistically different profitability and leverage.

sample with the sustainability DDD term indicating causal link between SUS and Tobin's Q.

I run two placebo tests, one to assess if pre-shock managerial anticipation occurs within the treatment firms ($Post = 1$ for 2007 onwards) and another to check if there is generic trend in the second-half of MSCI ESG data sample period ($Post = 1$ for 2003 onwards) as the managers grow wise with time to pay attention to only the most relevant indicators. Both these placebo estimations have the DDD term statistically insignificant, as expected, indicating that the treatment was relatively exogenous.

4.5.2.2 Instrumental Variables

While the quasi-natural experiment and its results provide support for the causal link between SUS-Index and Tobin's Q, its identification strategy exploits the introduction of a newer data collection methodology by MSCI that prioritized industry-relevance. This may have indirectly had a value-enhancing effect on the triple difference estimator if the previous all-inclusive methodology was more noisier than the new one for measuring CSR and sustainability. Thus, next I check the robustness of the DDD results by examining the causal impact of changes in the SUS scores using instrumental variables that are solely related to CSR/sustainability measures and are largely exogenous to firm value. Some studies in CSR literature employ variables such as the firm age as an instrument for ESG-based measures (Jo and Harjoto, 2011). However, it has been shown that growth opportunities and firm value decline as firms grow older (Loderer and Waelchli, 2010), and the same is observed with firm age included as control variable in previous results. Alternatively, many studies employ the industry average ESG scores as an instrument (El-Ghoul et al., 2011; Cheng, Ioannou, and Serafeim, 2014; Jha and Cox, 2015; Ferrell, Liang, and Renneboog, 2016), while some such as Jiao (2010) additionally introduce past negative earnings as a possible instrument. However, exogeneity of these instruments can still be questioned by the fact that firm value do get affected by industry-wide shocks, and that negative earnings can be restrictive to future firm value.[74]

Di Giuli and Kostovetsky (2014) show that there are systematic differences in the CSR preferences of Democrats and Republicans, and hence, the state-level political leanings can be an effective instrument for ESG scores.[75] Accordingly, I employ the state-level voting shares for Democratic presidential candidate, along with the state-wise congressional and the local governmental Democratic distribution as the three instrumental variables (see Appendix 4.A.4 for their definitions). The relevance and exogeneity for these instruments can be established by the fact that while the firm's CSR initiatives are influenced by local political leanings, there is no reason to suspect that they directly influence individual firm's value.

As shown in Table 4.7 the F-stats for first-stage of two-stage least squares (2SLS) estimation are much greater than the Stock and Yogo (2005) recommended cutoff (except for the $SUSstr$, which is only marginally greater than the cutoff) indicating that the instruments are not weak. For both SUS-Index and its strengths and concerns subcomponents, the hypothesis for joint validity of the used instruments (i.e., Hansen-Sargan test) is not rejected and all the reported Cragg-Donald F-test stats are well greater than the critical values supporting the IVs' relevance. All inferences from IV estimations support the results seen from the quasi-natural experiment. The corresponding signs for strengths (+) and concerns (–) are also as expected. Additionally, the causal estimates from 2SLS, once again, show that the remaining CSP indicators

[74]Nevertheless, in unreported analysis, I apply these instruments for robustness check and find support for a causal relationship between all the sustainability measures and Tobin's Q.

[75]I appreciate the comments from an anonymous referee, who suggested this IV.

Table 4.7 Instrumental variables regressions for Tobin's Q on sustainability measures

This table gives the results for two-stage least-squares (2SLS) IV regressions using state-level political leanings as instruments for the ESG-based measures. Voting % for Democrat Presidential candidate (PVD), proportion of Democrat Congressional members (CDD) and the proportion of Democrats in state legislative chambers (SGD) are the three variables used to proxy for the political leanings (Di Giuli and Kostovetsky, 2014). The IV estimations first consider the aggregated measure SUS and then its respective strengths and concerns subcomponents as indicated in the table. Expected signs for the ESG subcomponent variables are shown in parenthesis alongside. All controls are included along with a variable representing remnant CSP indicators. Dependent variables are shown on top to indicate first/second stage of the 2SLS estimations. Tobin's Q is industry adjusted as Tobin's Q minus the median Tobin's Q for that SIC 2-digit industry. Standard errors reported in parenthesis are clustered by firms. The coefficients for constants are omitted. Additional test statistics for IV estimation is given at the bottom of the table. Significance levels at *, **, and *** are indicative of 10%, 5%, and 1% respectively.

	Sustainability Aggregate			Sustainability Subcomponents		
	DV=SUS	DV=remCSP	DV=Tobin's Q	DV=SUSstr	DV=SUScon	DV=Tobin's Q
SUS			**0.8468*** (0.282)**			
SUSstr (+)						**0.6800* (0.407)**
SUScon (−)						**-0.8754*** (0.246)**
PVD	-2.0727*** (0.394)	-1.0134*** (0.368)		0.0643 (0.351)	1.7785*** (0.204)	
CDD	0.5890*** (0.075)	1.0229*** (0.069)		-0.3357*** (0.068)	-0.5629*** (0.042)	
SGD	-0.0013 (0.083)	-0.2251*** (0.070)		0.1159 (0.072)	0.0376 (0.042)	
Remnant CSP			-0.1839 (0.167)	0.1965*** (0.018)	-0.1573*** (0.011)	-0.2233* (0.133)
ROA	0.2265** (0.097)	0.2539*** (0.093)	-0.2295 (0.974)	-0.1888*** (0.064)	-0.3255*** (0.063)	-0.2533 (0.972)
Size	0.1691*** (0.018)	0.0154 (0.016)	-0.4862*** (0.055)	0.2654*** (0.017)	0.1018*** (0.013)	-0.4380*** (0.092)
Leverage	-0.5763*** (0.088)	-0.4235*** (0.079)	-0.6440*** (0.216)	-0.5845*** (0.077)	-0.1580*** (0.046)	-0.7747*** (0.291)
Volume	0.0918*** (0.017)	0.0306** (0.014)	0.2467*** (0.027)	0.1272*** (0.014)	0.0462*** (0.007)	0.2714*** (0.045)
CAPEX / Assets	0.0140 (0.013)	-0.0298*** (0.011)	-0.0069 (0.027)	0.0820*** (0.011)	0.0575*** (0.008)	0.0065 (0.032)
R & D / Sales	-0.0356*** (0.012)	0.0385*** (0.011)	0.0863*** (0.021)	-0.0749*** (0.010)	-0.0257*** (0.008)	0.0757*** (0.027)
Sales Growth	0.0001 (0.000)	0.0001** (0.000)	0.0003** (0.000)	-0.0001 (0.000)	-0.0001*** (0.000)	0.0003* (0.000)
Age	0.0824*** (0.017)	0.0255* (0.015)	-0.1780*** (0.028)	0.1089*** (0.014)	0.0356*** (0.010)	-0.1572*** (0.040)
\# Observations	31259	31259	31259	31259	31259	31259
R-Squared	0.094	0.031	0.248	0.277	0.143	0.154
First stage F-stat	26.48	78.31		10.01	72.32	
Cragg-Donald Wald F-statistic			27.43			16.62
Sargan-Hansen test (p-value)			0.255			0.626

($remCSP$) do not contribute to the firm value.

4.5.3 Individual ESG Components: The Sustainability Indicators

While the overall sustainability score is seen to significantly influence firm value, each of the sustainability indicators by themselves may not necessarily be contributing to this relationship. To explore this, I run additional regressions to study the association between each of the 51 sustainability indicators and Tobin's Q.[76] My focus is on ensuring that each sustainability indicator is not considered in isolation, so as to see whether it impacts firm value even after controlling for other ESG indicators. The regression model employed here is a simple alteration of Equation 4.8, with each sustainability indicator replacing SUS variable and the remaining CSP composite score (excluding that focal indicator) replacing the $remCSP$ variable. All the control variables X remain the same, with additional year fixed effects included to isolate any time-trends.

Table 4.8 summarizes the relationship between each of the 51 sustainability indicators and Tobin's Q. Panel A covers all the 30 sustainability strengths, which ideally should have a positive effect on Tobin's Q as they represent the sustainability-related initiatives undertaken in the sample firms. Panel B, on other hand, has all 21 sustainability concerns that are expected to have negative association with firm value. Out of the 51 sustainability indicators, it is seen that only 7 indicators have no statistically significant relationship with Tobin's Q at 10% level. Of these, three are strengths and the remaining four concerns. This result is important because it shows that management cannot take for granted that all sustainability initiatives or controversies may be value-impacting. While, the overall sustainability performance (SUS) itself and its two strength and concern components do influence the firm value, there

[76] These regressions follow the approach shown in Bebchuk, Cohen, and Ferrell (2009) where the contributions of individual entrenchment provisions were isolated after controlling for other antitakeover provisions.

Table 4.8 Sustainability indicators and Tobin's Q

This table summarizes coefficients and corresponding robust standard errors (given in parenthesis) when each of the individual sustainability indicators are regressed on Tobin's Q. All standard controls are retained. Additionally, the sum total of remaining strengths (+) and concerns (–) is included to control for remaining ESG characteristics. Tobin's Q is industry adjusted as Tobin's Q minus the median Tobin's Q for that SIC 2-digit industry. Year fixed effects were included to control for time-trends. For each indicator, whence the coefficients have expected signs i.e., (+) strengths and (–) concerns, they are highlighted in bold. Significance levels 10%, 5%, and 1% are indicated by *, **, and *** respectively.

Panel A: Sustainability Strength Indicators							
Community	Support for Housing	Support for Education	Non-US Charitable Giving	Community Engagement			
	0.2974* **	**0.2609*** **	**0.2395*** **	**0.1117* **			
	(0.051)	**(0.065)**	**(0.087)**	**(0.071)**			
Diversity	CEO Diversity	Board of Directors - Gender Diversity	Work-Life/ Family Benefits	Employment of the Disabled	Other Diversity Strengths		
	-0.1503***	**0.0752* **	**0.0976** **	**0.1398* **	-0.1116*		
	(0.051)	**(0.041)**	**(0.046)**	**(0.085)**	(0.061)		
Employees	Employee Involvement	Strong Retirement Benefits	Employee Health & Safety	Compensation & Benefits	Other Employees Strength		
	0.1376* **	**0.0553* **	-0.0874***	**0.1711** **	**0.0986** **		
	(0.035)	**(0.032)**	(0.029)	**(0.069)**	**(0.043)**		
Environment	Beneficial Products & Services	Pollution Prevention/ Waste Management	Climate Change/ Alternative Fuels/ Clean Energy	Environmental Management Systems	Raw Material Sourcing	Natural Resource Use	
	-0.1428***	-0.17966***	**0.0407* **	-0.2417***	**0.0871**	**0.5732** **	
	(0.040)	(0.035)	**(0.029)**	(0.033)	**(0.082)**	**(0.291)**	
Governance / Human Rights	Limited Compensation	Ownership Strength	Transparency/ Reporting Quality Strength	Political Accountability Strength			Labor Rights Strength
	0.1912* **	**0.4690*** **	-0.0706*	**0..2447*** **			-0.5351***
	(0.033)	**(0.247)**	(0.040)	**(0.117)**			(0.126)
Product	Product Quality & Safety	R&D / Innovation	Social Opp. Access to Communications	Social Opp. Nutrition & Health	Other Products Strength		
	0.0761 **	**0.4241*** **	**1.0071*** **	**0.0009**	-0.0035		
	(0.037)	**(0.090)**	**(0.356)**	**(0.229)**	(0.076)		
Panel B: Sustainability Concern Indicators							
Community	Tax Disputes	Negative Community Impact	Other Community Concerns				
	0.1230**	**-0.0104**	0.3065***				
	(0.051)	**(0.029)**	(0.064)				
Governance / Diversity	Accounting Concern	Reporting Quality/ Transparency Concern	Other Governance Concerns			Non-Representation	Other Diversity Concerns
	-0.1819* **	0.0074	**-0.1235*** **			**-0.0313* **	0.1440**
	(0.047)	(0.050)	**(0.032)**			**(0.018)**	(0.070)
Employees	Workforce Reductions	Supply Chain Controversies	Child Labor				
	-0.6513* **	0.1309	0.5987***				
	(0.097)	(0.097)	(0.243)				
Environment	Hazardous Waste	Ozone Depleting Chemicals	Toxic Spills Emissions	Agricultural Chemicals	Climate Change	Other Environmental Concerns	
	-0.2203* **	**-0.7861*** **	**-0.0755*** **	**-0.4768*** **	**-0.0337**	0.3153***	
	(0.056)	**(0.104)**	**(0.031)**	**(0.085)**	**(0.032)**	(0.061)	
Human Rights	Support for Controversial Regimes	International Labor Rights Concern	Indigenous People Concern				
	0.4998***	**-0.1316** **	0.0917*				
	(0.095)	**(0.056)**	(0.053)				
Product	Antitrust & Anticompetitive Practices						
	0.1348***						
	(0.035)						

are some indicators that have no value enhancing or diminishing effect.

Furthermore, while more than 70% of the strength indicators have positive influence on firm value, only 52% of the concerns seem to be negatively associated with the same. This finding, however, has to be interpreted with caution. Although, in general, sustainability strengths and concerns are expected to have positive and negative associations respectively with firm value, the presence of opposite association may still be influential. For example, if most of the sustainability strengths as well as concerns under community category were negative, there would still be a net positive influence of the community dimension of sustainability on the firm value, as long as the negative impact of concerns is lower than that of the strengths (so that the differential effect remains).

4.6 Sustainability and Stock Returns

Despite the superior explanatory power for sustainability component over the all-in CSP measure captured from the ESG data, the big question remains: can investors benefit from such sustainability measures? Could sustainable firms create superior abnormal returns for socially responsible investors? This potential would essentially exist if market participants fail to learn the difference between the more sustainable firms and the less sustainable ones (Galema, Plantinga, and Scholtens, 2008; Borgers et al., 2013). Similar reasoning is echoed for portfolios that bet on the differences in firm's corporate governance as well (Bebchuk, Cohen, and Wang, 2013).

Several studies exploring the relationship between abnormal returns and ESG-based measures have used the Carhart (1997) four-factor model to compute risk-adjusted returns (Galema, Plantinga, and Scholtens, 2008; Humphrey, Lee, and Shen, 2012; Borgers et al., 2013). I use the same four factors, but replace the Carhart (1997) momentum factor by the Fama-French momentum factor. The ESG-based measures are known to be related to corporate governance mechanisms (Jo and Harjoto, 2012). Governance, meanwhile, has been shown to impact stock market liquidity (e.g., Chung, Elder, and Kim, 2010). For this reason, I additionally include Pástor and Stambaugh (2003) liquidity factor in the asset pricing model specification to compute risk-adjusted returns:

$$R_t = \alpha + \beta_1 * RMRF_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * LIQ_t + \varepsilon_t \tag{4.11}$$

where α measures the abnormal returns or risk-adjusted returns. The excess returns over risk-free rate for each portfolio in month t is given by R_t. $RMRF_t$, SMB_t, HML_t along with MOM_t represents the three standard Fama and French (1993) factors measuring excess market returns, size, book-to-market, and the additional momentum factor respectively for each month t. LIQ_t is the Pástor and Stambaugh (2003) value-weighted traded liquidity factor.[77]

Borgers et al. (2013) show using an all-in ESG measure called *stakeholder index* that the positive risk-adjusted returns from this index-based hedge existed only from 1992 to 2004, with the subsequent years showing that the abnormal or risk-adjusted returns have disappeared.[78] Nevertheless, the ESG criteria and ESG-based screens have been increasingly employed by institutional investors even in recent years. These investors largely rely on third party ESG composite ratings or specific social, environmental or other indicative ratings. I aim to show that investors can benefit by using more focused and conceptually rich measures derived from ESG than the commonly used ESG aggregate measures such as CSP shown before. Having indicators that matter for firm

[77] The recent Fama and French (2016) five-factor model with investment and profitability factors was not applied in the main results because, the use of these additional factors merely makes the book-to-market factor HML_t redundant.

[78] Borgers et al. (2013) show the disappearing abnormal returns only for the subsequent 4 years after 2004.

survival, and that were even promoted in UN introduced sustainable investment programs (through UNPRI, UNCTAD and other related agencies), the SUS-Index may identify profitable investment opportunities that are otherwise neglected.

4.6.1 Sustainability Portfolios

To test if investment strategies could be made using sustainability measure, I created portfolios using the extreme SUS-Index scores. This was done by first dividing the sample each year in unequal-sized pentiles based on their sustainability scores. Similar portfolio construction has been used in prior literature for measuring abnormal returns on hypothetical hedge portfolios for various CSR based measures (Galema, Plantinga, and Scholtens, 2008; Humphrey, Lee, and Shen, 2012; Borgers et al., 2013) as well as for corporate governance based ones (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009; Giroud and Mueller, 2011). Using the nomenclature shown in Bouslah, Kryzanowski, and M'Zali (2013) and Fernando, Sharfman, and Uysal (2017), I name the first 'Pentile 1' portfolio as "Toxic" portfolio made up of unsustainable firms and last 'Pentile 5' as "Green" portfolio that includes all highly sustainable firms as indicated by high SUS-Index scores.

To understand how such portfolios work, similar investment strategy may have been replicated by investors during my sample period as follows. Each year, MSCI collects the ESG data for all the sample firms, and releases it in the beginning of next year. Based on this data, using the sustainability indicators, investors identify the SUS-Index scores for each firm in the previous year. Accordingly, the stocks of these firms are ranked as per their sustainability performance. Investors will then go long on the high sustainability firms and short sell the stocks of low sustainability ones. Holding period is thus assumed to be one year. When MSCI releases new ESG data the following year, the same is then used to generate new SUS-Index scores and accordingly re-balance the hedge portfolio. In other words, I use the calendar-time event hedge portfolios to compute the investors' abnormal returns.

After sorting the firms according to their SUS-Index scores for each year, the Toxic firms were grouped as those which have SUS-Index scores less than or equal to -2. On the other hand, firms with SUS-Index scores more than or equal to +2 were classified as Green firms. Firms corresponding to the scores of -1, 0 and +1 formed the remaining three pentiles. While the cross-sectional distribution of the sustainability scores does vary over time, the extreme portfolios criteria is largely seen to be consistent. For this reason, the cutoffs are held constant throughout the sample period.

4.6.2 Alternative Portfolios

As a means of robustness test, I use portfolio selection criteria used in Galema, Plantinga, and Scholtens (2008) where strength screening is taken as a separate group from the concern screened stocks. This is done by creating three unequal-sized portfolio terciles that represent a) Green stocks that have more sustainability strengths than concerns (SUS-Index $\geq +1$), b) Toxic stocks that have more sustainability concerns than strengths (SUS-Index $\leq$ -1), and c) Neutral stocks (SUS-Index = 0).

4.6.3 Results

Table 4.9 shows the outcomes when the asset pricing model given in Equation 4.11 is run for the two extreme portfolios' and the long Green - short Toxic hedge portfolio's monthly excess returns. Panel A applies the pentile portfolio classification while Panel B uses terciles. As seen in the table, equal-weighted portfolios for both these portfolio classifications allowed for sustainability based risk-neutral hedge. With equal-weighted monthly portfolio returns, Green stocks consistently outperformed the markets (positive and significant α) represented using the five factors, whereas the Toxic stock portfolios did not beat the market as their abnormal returns are not statistically significant or different from zero. In contrast, the value-weighted portfolios using both pentiles and terciles did not show possible risk-neutral hedge as both the Green and Toxic portfolios consistently outperformed the markets. Much of the recent literature that applies value-weighted portfolios has shown similar results with no difference in abnormal returns between the extreme portfolios (Galema, Plantinga, and Scholtens, 2008; Humphrey, Lee, and Shen, 2012). However, all the abnormal returns αs and the coefficients for book-to-market factor HML for value-weighted portfolios do confirm the findings in Galema, Plantinga, and Scholtens (2008) that CSR based hedges "impact ... stock returns by lowering the book-to-market ratio and not by generating positive alphas".[79]

For the equal-weighted hedge, it is seen that much of the outperformance of Green portfolio over the Toxic one is driven by positive abnormal returns for the Green stocks. I further find that as the sustainability scores decline from Green to Toxic portfolios, there is a monotonic decrease in both the abnormal returns and mean excess returns. This is summarized in Table 4.10 for both pentile and tercile portfolio constructions.

For the sustainability hedge portfolio, α is roughly 4.3% per annum (or 0.36% per month) when pentile portfolios are constructed and about 2.5% per annum (21 basis points per month) using tercile portfolio classification. These hedged positions are statistically significant at 5% level and have considerable economic significance considering that the MSCI ESG sample firms include most of the large cap stocks along with a large number of mid-cap firms. This result extends the findings in Borgers et al. (2013), Flammer (2015) and

[79] Galema, Plantinga, and Scholtens (2008) report this finding only for the value-weighted socially responsible investments.

Table 4.9 Abnormal returns using extreme sustainability portfolios

The results for a five-factor regression using Fama and French (1993) factors capturing market ($RMRF$), size (SMB) and book-to-market (HML) along with the Fama-French momentum factor (MOM) and Pástor and Stambaugh (2003) liquidity factor (LIQ) are shown in this table. Panel A uses pentile portfolio classification with $SUS-Index \leq -2$ (Toxic) and $SUS-Index \geq +2$ (Green) forming the two extreme portfolios. Tercile portfolios use $SUS-Index \leq -1$ (Toxic) and $SUS-Index \geq +1$ (Green) as cutoffs. The alphas and other factor coefficients are shown for both equal-weighted and value-weighted portfolios. Portfolios are rebalanced in the beginning of each year. White (1980) robust standard errors are shown in parenthesis. For each set of extreme portfolios, the corresponding differential hedge portfolio (long Green – short Toxic) is also shown. Significance at 10%, 5%, and 1% are indicated by *, ** and *** respectively.

Panel A: Pentile Portfolios

Portfolios	α	$RMRF_t$	SMB_t	HML_t	MOM_t	LIQ_t	R^2
Equal-weighted							
Green	0.0029***	0.9415***	0.1481***	0.3585***	-0.1491***	-0.0076	0.919
	(0.001)	(0.022)	(0.036)	(0.031)	(0.024)	(0.019)	
Toxic	-0.0007	1.0781***	0.1668**	0.5920***	-0.1591**	0.1446***	0.753
	(0.002)	(0.048)	(0.081)	(0.077)	(0.063)	(0.048)	
Green – Toxic Hedge	**0.0036****	-0.1366***	-0.0187	-0.2335***	0.0100	-0.1522***	0.095
	(0.002)	(0.046)	(0.067)	(0.069)	(0.053)	(0.044)	
Value-weighted							
Green	0.0069***	0.9317***	-0.2479***	-0.0973**	-0.0796**	-0.0358	0.881
	(0.001)	(0.026)	(0.031)	(0.047)	(0.032)	(0.026)	
Toxic	0.0053***	0.9513***	-0.2299**	0.1426*	0.0430	0.1798***	0.606
	(0.002)	(0.055)	(0.094)	(0.076)	(0.048)	(0.050)	
Green – Toxic Hedge	0.0016	-0.0195	-0.0180	-0.2399***	-0.1226**	-0.2156***	0.069
	(0.002)	(0.062)	(0.108)	(0.090)	(0.061)	(0.061)	

Panel B: Alternative Tercile Portfolios

Portfolios	α	$RMRF_t$	SMB_t	HML_t	MOM_t	LIQ_t	R^2
Equal-weighted							
Green	0.0021**	0.9834***	0.1917***	0.4195***	-0.1542***	0.0100	0.929
	(0.001)	(0.021)	(0.041)	(0.030)	(0.028)	(0.018)	
Toxic	-0.0000	1.0581***	0.2833***	0.5782***	-0.1976***	0.0894**	0.853
	(0.001)	(0.034)	(0.058)	(0.060)	(0.049)	(0.036)	
Green – Toxic Hedge	**0.0021****	-0.0747**	-0.0916**	-0.1587***	0.0433	-0.0794**	0.100
	(0.001)	(0.030)	(0.043)	(0.050)	(0.034)	(0.033)	
Value-weighted							
Green	0.0069***	0.9666***	-0.2073***	-0.0679**	-0.0512**	-0.0338*	0.924
	(0.001)	(0.021)	(0.033)	(0.033)	(0.022)	(0.019)	
Toxic	0.0057***	0.9404***	-0.0902**	0.1637***	0.0437	0.0858***	0.819
	(0.001)	(0.032)	(0.038)	(0.047)	(0.028)	(0.030)	
Green – Toxic Hedge	0.0012	0.0263	-0.1172**	-0.2316***	-0.0949**	-0.1195***	0.124
	(0.001)	(0.036)	(0.054)	(0.057)	(0.037)	(0.040)	

Table 4.10 Monotonic relationship between sustainability and returns

The alphas and mean excess returns are shown for equal-weighted pentile and tercile portfolios in this table. The portfolios get rebalanced with new data availability in the beginning of each year. Monthly portfolio returns are loaded on five factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM) and liquidity (LIQ). All estimations use White (1980) robust standard errors which are given for alphas in the parenthesis. Pentile portfolios have $SUS - Index \leq -2$ (Toxic) and $SUS - Index \geq +2$ (Green) as the two extreme portfolios along with additional three mid portfolios having $SUS - Index$ scores of -1, 0 and 1 respectively. Tercile portfolios use $SUS - Index \leq -1$ (Toxic) and $SUS - Index \geq +1$ (Green) as cutoffs with the mid portfolio having a neutral (0) $SUS - Index$ value. The factor loadings are omitted and significance levels for alphas are reported at 10%, 5%, and 1% using *, ** and *** respectively.

Pentile Portfolios			**Tercile Portfolios**		
Portfolios	Alpha	Excess Returns	Portfolios	Alpha	Excess Returns
Green – Toxic Hedge	0.0036** (0.002)	0.00125	Green – Toxic Hedge	0.0021** (0.001)	0.00022
Pentile 1 (Green)	0.0029*** (0.001)	0.0092	Tercile 1 (Green)	0.0021** (0.001)	0.0091
Pentile 2	0.0013* (0.001)	0.0089			
Pentile 3 (Neutral)	0.0009 (0.001)	0.0089	Tercile 2 (Neutral)	0.0009 (0.001)	0.0089
Pentile 4	0.0002 (0.001)	0.0090			
Pentile 5 (Toxic)	-0.0007 (0.002)	0.0079	Tercile 3 (Toxic)	-0.0000 (0.001)	0.0089

Krüger (2015) by showing that using a subcomponent of ESG characteristics that measures sustainability, investors could have potentially made risk-neutral returns. The disappearance of stock returns to ESG-based measures (Borgers et al., 2013) is seen to be restricted to only value-weighted portfolios. While ESG engagements and proposals do create value for shareholder in the short-run (Flammer, 2015; Krüger, 2015), I show that a sum total of sustainability-based initiatives could significantly explain the cross-sectional differences in shareholder value creating abilities of sustainable stocks vis-á-vis less sustainable firms even for longer holding periods of one year.

4.6.4 Robustness Checks

With the equal-weighted hedge portfolios showing positive risk-adjusted returns, I ran further tests to examine if the results are driven by industry-membership of sustainability firms, any time-specific trends, or by the five-factor model selected for generating abnormal returns (see Appendix Table 4.17). Consistently significant or insignificant alphas across all the alternate factor models shows that results are not biased by the chosen asset pricing model.

When industry adjusted monthly returns are used for each portfolio instead of unadjusted returns, the magnitudes of alpha reduce affecting the economic significance of the risk-adjusted returns from hedge portfolios (especially equal-weighted) but statistical significance remains.[80]

With the subsample periods considered, some of the evidence seem to weakly support the conclusions drawn in Borgers et al. (2013) that, over the years, attention towards ESG issues has diminished the chances of ESG-centric mispricing. However, interestingly, when it comes to equal-weighted hedge portfolios, the observed mispricing seems to have reappeared in recent years, especially when the sample period is broken down into three parts. This essentially extends the findings in Borgers et al. (2013) as the recent 8 years (from 2008 to 2015) were largely not included in that sample. The magnitude of alphas are largely similar to those reported in prior literature, which uses all-in CSP measures for portfolio construction. However, consistent positive alphas for sustainability hedge does indicate the importance of selecting conceptually grounded indicators of ESG instead of summing up all the available indicators. Could similar hedge portfolios using the other ESG indicators (or $remCSP$

[80]Monthly returns for each firm were adjusted by deducting the industry median returns using Fama and French (1997) 48 industry classification.

scores) have generated abnormal returns as well? I test this by constructing similar extreme portfolios using the remnant CSP score and then forming a long – short hedge (last row in Table 4.17 Panel A). Neither equal-weighted nor value-weighted portfolios show abnormal returns, confirming the benefits of measuring sustainability.

With respect to alternative factor models (Table 4.17 Panel B), the alpha values with the chosen five factor model (Equation 4.11) does not seem to be influenced considerably by the selected factors. For robustness testing, I include the Fama and French (1993) three-factor model, the Fama and French (2016) five-factor model and the variations of these Fama-French (FF) models with the Pástor and Stambaugh (2003) liquidity factor added. For the equal-weighted hedge portfolio, the risk-neutral returns vary from 44 basis points (bps) a month to 26bps a month for the pentile portfolios, and 29 bps to 21 bps monthly for tercile based hedge portfolios (statistically significant in most cases). The FF four factors + liquidity factor alphas seem to lie in the middle of alphas' range seen across various asset pricing models. With value-weighted hedge, as before, all alphas remain statistically insignificant.

Overall, the main results shown in Tables 4.9 and 4.10 for the relationship between sustainability and stock returns seem to be robust to several sample period selections and factor model specifications. Most of the drawn inferences remain consistent through all of these robustness tests. While there has been some degree of learning by investors regarding ESG characteristics, there is enough evidence indicating that sustainability based hedging strategies could have generated consistent abnormal returns in the long run.

4.7 Discussion and Conclusions

This study introduces a corporate sustainability measure *SUS-Index* that represents the attention (+) or lack of attention (–) firms reportedly show towards practices and policies that can influence their triple bottom line. Subsequently, it is found that the highly sustainable firms are associated with superior firm value. In fact, it is this sustainability component from within the broader CSR/CSP measure that completely explains its well-documented relationship with firm value. Both with the dynamic OLS model that includes past firm performances to disentangle simultaneity and with the panel regressions, the same results are observed. Sustainability measure and its two subcomponents seem to capture most of the variations seen in the CSP–firm value relationships for the MSCI sample firms. This result is consistent with the theoretical model proposed in Fatemi, Fooladi, and Tehranian (2015) that captures differential valuation effects of different CSR expenditures. Those CSR activities that are focal to corporate sustainability are shown to have positive valuation effects.

The initial evidence merely supports that the individual sustainability indicators, its composite index and the two subcomponents have significant correlations with firm value but does not indicate causation. Does the firms' attention toward sustainability cause them to be valued higher than the less sustainable firms? I answer this using multiple identification strategies that collectively support the finding that the changes in sustainability scores for a firm can indeed cause changes in its valuation as measured by Tobin's Q. Using regression discontinuity design, Flammer (2015) shows that the passing of CSR engagement proposals can increase firm value in the adopted as well as subsequent years. However, the impact of sustainability initiatives is much higher on Tobin's Q than these broad ESG engagements as shown by the magnitudes of coefficients for SUS-Index in my results.

Additionally, I provide evidence that sustainability and SUS-Index could have generated abnormal returns for investors if appropriate investment strategies were employed. While it is difficult to establish at the firm level if ESG performance is correctly priced by the stock markets, some recent studies (e.g., Flammer, 2015) show that CSR engagements do result in a positive reaction in stock markets resulting in abnormal returns for investors. Krüger (2015), however, has shown that the market reaction can change based on the intensity of the CSR news itself. Since I look at sustainability-based portfolios instead of individual firms, and the sustainability measure itself is an aggregation of multiple initiatives, the impact of individual CSR engagement related firm news and its confounding effects is avoided. It is seen that the SUS-Index based hedge portfolios could have generated risk-adjusted returns of over 4% per year in my sample period. As a word of caution, however, since I have analyzed realized returns to show that a sustainability-based hedge could have generated abnormal returns in the past, it does not imply that the same strategy should necessarily generate similar returns in the future. As the markets and investors become more aware of the benefits from sustainability initiatives, risk-adjusted abnormal returns may eventually diminish and disappear (Borgers et al., 2013).

This study also has regulatory and managerial implications as it identifies a subset of ESG strengths and concerns that are most relevant to the firm's sustainability, which is shown to impact firm performance and shareholders' wealth. On an individual factor level as well, it is found that more than 90% of the identified sustainability indicators have a significant association with firm value. This association remains robust even after controlling for all other ESG indicators. So the value-driving characteristic of sustainability is not merely seen on the aggregate level, but even the individual strength and concern indicators have value-impacting properties. Thus, if regulators introduce policies and directives that target these specific sustainability indicators, they are more likely to influence the overall firm sustainability and its subsequent performance. Similar reasoning also applies for managers and other decision makers who seek to improve corporate sustainability, or for institutional investors who seek sustainable investment portfolios.

By showing that the correlation between CSP and CFP is driven largely by a concentrated subset of ESG components, this study also has an implication for commercial ESG rating agencies such as MSCI and others. For ESG rankings, the more is not the merrier, i.e., increasing the number of ESG indicators does not necessarily enrich the ESG rankings. What essentially matters is whether the included indicators are relevant to corporate sustainability or not.

4.8 References

Altman, E. I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23 (4), 589–609.

Bebchuk, L., Cohen, A., 2005. The costs of entrenched boards. Journal of Financial Economics 78 (2), 409–433.

Bebchuk, L., Cohen, A., Ferrell, A., 2009. What matters in corporate governance? Review of Financial Studies 22 (2), 783–827.

Bebchuk, L., Cohen, A., Wang, C. C., 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics 108 (2), 323–348.

Becchetti, L., Ciciretti, R., Giovannelli, A., 2013. Corporate social responsibility and earnings forecasting unbiasedness. Journal of Banking and Finance 37 (9), 3654–3668.

Becchetti, L., Ciciretti, R., Hasan, I., 2015. Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. Journal of Corporate Finance 35, 297–309.

Bereskin, F., Byun, S. K., Officer, M. S., Oh, J.-M., 2018. The effect of cultural similarity on mergers and acquisitions: Evidence from corporate social responsibility. Journal of Financial and Quantitative Analysis 53 (5), 1995–2039.

Bhagat, S., Bolton, B., 2008. Corporate governance and firm performance. Journal of Corporate Finance 14 (3), 257–273.

Bharath, S. T., Shumway, T., 2008. Forecasting default with the Merton distance to default model. Review of Financial Studies 21 (3), 1339–1369.

Borgers, A., Derwall, J., Koedijk, K., Ter Horst, J., 2013. Stakeholder relations and stock returns: On errors in investors' expectations and learning. Journal of Empirical Finance 22, 159–175.

Bouslah, K., Kryzanowski, L., M'Zali, B., 2013. The impact of the dimensions of social performance on firm risk. Journal of Banking and Finance 37 (4), 1258–1273.

Buchanan, B., Cao, C. X., Chen, C., 2018. Corporate social responsibility, firm value, and influential institutional ownership. Journal of Corporate Finance 52, 73–95.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52 (1), 57–82.

Cheng, B., Ioannou, I., Serafeim, G., 2014. Corporate social responsibility and access to finance. Strategic Management Journal 35 (1), 1–23.

Chung, K. H., Elder, J., Kim, J.-C., 2010. Corporate governance and liquidity. Journal of Financial and Quantitative Analysis 45 (2), 265–291.

Derwall, J., Koedijk, K., Ter Horst, J., 2011. A tale of values-driven and profit-seeking social investors. Journal of Banking and Finance 35 (8), 2137–2147.

Di Giuli, A., Kostovetsky, L., 2014. Are red or blue companies more likely to go green? Politics and corporate social responsibility. Journal of Financial Economics 111 (1), 158–180.

Dyck, A., Lins, K. V., Roth, L., Wagner, H. F., 2018. Do institutional investors drive corporate social responsibility? International evidence. Journal of Financial Economics 131, 693–714.

Eccles, R. G., Ioannou, I., Serafeim, G., 2014. The impact of corporate sustainability on organizational processes and performance. Management Science 60 (11), 2835–2857.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. Journal of Financial Economics 101 (3), 621–640.

El-Ghoul, S., Guedhami, O., Kwok, C. C., Mishra, D. R., 2011. Does corporate social responsibility affect the cost of capital? Journal of Banking and Finance 35 (9), 2388–2406.

Elkington, J., 1994. Towards the sustainable corporation: Win-win-win business strategies for sustainable development. California Management Review 36 (2), 90–100.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33 (1), 3–56.

Fama, E. F., French, K. R., 1997. Industry costs of equity. Journal of Financial Economics 43 (2), 153–193.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies 29 (1), 69–103.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81 (3), 607–636.

Fatemi, A., Fooladi, I., Tehranian, H., 2015. Valuation effects of corporate social responsibility. Journal of Banking and Finance 59, 182–192.

Fernando, C. S., Sharfman, M. P., Uysal, V. B., 2017. Corporate environmental policy and shareholder value: Following the smart money. Journal of Financial and Quantitative Analysis 52 (5), 2023–2051.

Ferrell, A., Liang, H., Renneboog, L., 2016. Socially responsible firms. Journal of Financial Economics 122 (3), 585–606.

Flammer, C., 2015. Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach. Management Science 61 (11), 2549–2568.

Friedman, M., 1970. The social responsibility of business is to increase its profits. New York Times Magazine: 13th September.

Fulton, M., Kahn, B. M., Sharples, C., 2012. Sustainable investing: Establishing long-term value and performance. Unpublished working paper, `http://ssrn.com/abstract=2222740`.

Galema, R., Plantinga, A., Scholtens, B., 2008. The stocks at stake: Return and risk in socially responsible investment. Journal of Banking and Finance 32 (12), 2646–2654.

Girerd-Potin, I., Jimenez-Garcès, S., Louvet, P., 2014. Which dimensions of social responsibility concern financial investors? Journal of Business Ethics 121 (4), 559–576.

Giroud, X., Mueller, H. M., 2011. Corporate governance, product market competition, and equity prices. Journal of Finance 66 (2), 563–600.

Gompers, P. A., Ishii, J. L., Metrick, A., 2003. Corporate governance and equity prices. Quarterly Journal of Economics 118 (1), 107–155.

Gong, N., Grundy, B. D., 2017. Can socially responsible firms survive competition? An analysis of corporate employee matching grant schemes. Review of Finance 23 (1), 199–243.

Gormley, T. A., Matsa, D. A., 2014. Common errors: How to (and not to) control for unobserved heterogeneity. Review of Financial Studies 27 (2), 617–646.

Gregory, A., Whittaker, J., Yan, X., 2016. Corporate social performance, competitive advantage, earnings persistence and firm value. Journal of Business Finance & Accounting 43 (1-2), 3–30.

Hillman, A. J., Keim, G. D., 2001. Shareholder value, stakeholder management, and social issues: What's the bottom line? Strategic Management Journal, 125–139.

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28 (3), 791–837.

Humphrey, J. E., Lee, D. D., Shen, Y., 2012. Does it cost to be sustainable? Journal of Corporate Finance 18 (3), 626–639.

Jha, A., Cox, J., 2015. Corporate social responsibility and social capital. Journal of Banking and Finance 60, 252–270.

Jiao, Y., 2010. Stakeholder welfare and firm value. Journal of Banking and Finance 34 (10), 2549–2561.

Jo, H., Harjoto, M. A., 2011. Corporate governance and firm value: The impact of corporate social responsibility. Journal of Business Ethics 103 (3), 351–383.

Jo, H., Harjoto, M. A., 2012. The causal effect of corporate governance on corporate social responsibility. Journal of Business Ethics 106 (1), 53–72.

Kaptein, M., Wempe, J. F. D. B., 2002. The balanced company: A theory of corporate integrity. Oxford University Press, USA.

Kelly, B., Pruitt, S., 2013. Market expectations in the cross-section of present values. Journal of Finance 68 (5), 1721–1756.

Kelly, B., Pruitt, S., 2015. The three-pass regression filter: A new approach to forecasting using many predictors. Journal of Econometrics 186 (2), 294–316.

Kempf, A., Osthoff, P., 2007. The effect of socially responsible investing on portfolio performance. European Financial Management 13 (5), 908–922.

Khan, M., Serafeim, G., Yoon, A., 2016. Corporate sustainability: First evidence on materiality. The Accounting Review 91 (6), 1697–1724.

Kim, Y., Li, H., Li, S., 2014. Corporate social responsibility and stock price crash risk. Journal of Banking and Finance 43, 1–13.

Konijn, S. J., Kräussl, R., Lucas, A., 2011. Blockholder dispersion and firm value. Journal of Corporate Finance 17 (5), 1330–1339.

Krüger, P., 2015. Corporate goodness and shareholder wealth. Journal of Financial Economics 115 (2), 304–329.

Liang, H., Renneboog, L., 2017. On the foundations of corporate social responsibility. Journal of Finance 72 (2), 853–910.

Lins, K. V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. Journal of Finance 72 (4), 1785–1824.

Loderer, C. F., Waelchli, U., 2010. Firm age and performance. Unpublished working paper, `http://ssrn.com/abstract=1342248`.

Louche, C., 2009. Corporate social responsibility: The investor's perspective. In: Professionals' Perspectives of Corporate Social Responsibility. Springer, pp. 211–231.

McGuire, J. B., Sundgren, A., Schneeweis, T., 1988. Corporate social responsibility and firm financial performance. Academy of Management Journal 31 (4), 854–872.

Morck, R., Shleifer, A., Vishny, R. W., 1988. Management ownership and market valuation: An empirical analysis. Journal of Financial Economics 20, 293–315.

Ng, A. C., Rezaee, Z., 2015. Business sustainability performance and cost of equity capital. Journal of Corporate Finance 34, 128–149.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111 (3), 642–685.

Rahdari, A. H., Rostamy, A. A. A., 2015. Designing a general set of sustainability indicators at the corporate level. Journal of Cleaner Production 108, 757–771.

Solow, R., 1993. An almost practical step toward sustainability. Resources Policy 19 (3), 162–172.

Stock, J. H., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Andrews, D. W., Stock, J. H. (Eds.), Identification and inference for econometric models: Essays in honor of Thomas Rothenberg. Cambridge University Press, pp. 80–108.

Van Beurden, P., Gössling, T., 2008. The worth of values–a literature review on the relation between corporate social and financial performance. Journal of Business Ethics 82 (2), 407–424.

Van Marrewijk, M., 2003. Concepts and definitions of CSR and corporate sustainability: Between agency and communion. Journal of Business Ethics 44 (2), 95–105.

WCED, 1987. Our common future. United Nations World Commission on Environment and Development, Oxford University Press.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica, 817–838.

Wintoki, M. B., Linck, J. S., Netter, J. M., 2012. Endogeneity and the dynamics of internal corporate governance. Journal of Financial Economics 105 (3), 581–606.

4.A Appendices

4.A.1 List of all the MSCI ESG Indicators

Community	
Strengths	*Concerns*
Generous Giving	Investment Controversies
Innovative Giving	Negative Economic/ Community Impact
Support for Housing	**Indigenous Peoples Relations Concern**
Support for Education (added in 1994)	**Tax Disputes (moved from Governance in 2005)**
Indigenous Peoples Relations Strength	Other Concern
Non-US Charitable Giving	
Volunteer Programs Strength	
Community Engagement	
Other Strength	
Employees	
Strengths	*Concerns*
Union Relations Strength	Union Relations Concern
No Layoff Policy (to 1993)	Health and Safety Concern
Cash Profit Sharing	Workforce Reductions
Employee Involvement	Pension/ Retirement Benefits Concern (1992 - 2009)
Strong Retirement Benefits (1991 - 2009)	Supply Chain Controversies
Employee Health and Safety (added in 2003)	Child Labor
Supply Chain Labor Standards	Other Concern/ Labor-Management Relations
Compensation and Benefits	
Employee Relations	
Professional Development	
Human Capital Management/ Developments	
Labor Management	
Controversial Sourcing	
Other Strength	
Environment	
Strengths	*Concerns*
Beneficial Products & Services/ Env. Opportunities	Hazardous Waste
Pollution Prevention/ Waste Management	Regulatory Compliance
Recycling/ Packaging Materials and Waste	Ozone Depleting Chemicals
Climate Change/ Alternative Fuels/ Clean Energy	Toxic Spills and Releases/ Substantial Emissions
Property, Plant, and Equipment (through 1995)	Agricultural Chemicals
Environmental Management Systems	Climate Change (added in 1999)
Water Stress	Negative Impact of Products (from 2010)
Biodiversity and Land Use	Land Use and Biodiversity (from 2010)
Raw Material Sourcing	Non-Carbon Releases/ Operational Waste (from 2010)
Natural Resource Use	Supply Chain Management (from 2012)
Green Buildings	Water Management (from 2012)
Renewable Energy	Other Concern
Waste Management - Electronic Waste	
Climate Change - Energy Efficiency	
Climate Change - Carbon Footprint	
Climate Change - Insuring CC Risk	
Other Strength	

Diversity	
Strengths	*Concerns*
CEO Diversity	Employee Discrimination
Promotion	Non-Representation (1993 - 2011)
Board of Directors - Gender Diversity	Board Diversity - Gender
Work-Life/ Family Benefits	Board of Directors - Minorities
Women and Minority Contracting	Other Concern
Employment of the Disabled	
Progressive Gay/ Lesbian Policies	
Employment of Underrepresented Groups	
Other Strength	
Governance	
Strengths	*Concerns*
Limited Compensation	High Compensation
Ownership Strength	**Tax Disputes (moved to Community 2005)**
Transparency/ Reporting Quality Strength	Ownership Concern
Political Accountability Strength	Accounting Concern
Public Policy Strength	Reporting Quality/ Transparency Concern
Corruption and Political Instability	Political Accountability Concern
Financial System Instability	Public Policy Concern
Other Strength	Governance Structure Controversies
	Controversial Investments
	Business Ethics
	Other Concern
Human Rights	
Strengths	*Concerns*
Positive Operations in South Africa (1994âĂŞ1995)	South Africa Concern (through 1994)
Indigenous Peoples Relations (moved in 2002)	Northern Ireland Concern (through 1994)
Labor Rights Strength	Support for Controversial Regimes
Other Strength	Mexico (1995âĂŞ2002)
	International Labor Rights Concern
	Indigenous Peoples Relations (moved in 2002)
	Operations in Sudan (2010 - 2011)
	Freedom of Expression
	Human Rights Violations
	Other Concern
Product	
Strengths	*Concerns*
Quality	Product Quality and Safety
R & D/ Innovation	Advertising and Marketing/ Contracting Controversy
Benefits to Economically Disadvantaged	Antitrust and Anticompetitive Practices
Access to Capital	Customer Relations
Social Opportunities - Access to Communications	Privacy and Data Security
Social Opportunities - Nutrition and Health	Other Concern
Product Safety - Chemical	
Product Safety - Financial	
Product Safety - Privacy and Data	
Product Safety - Responsible Investment	
Product Safety - Insuring Health & Demographics	
Other Strength	

Note that those indicators which have moved from one category to another are shown in bold. For definitions / explanations of these indicators, check MSCI ESG KLD Stats Methodology guide.

4.A.2 Conceptual Inclusion (Exclusion) of Sustainability (remnant CSP) Indicators

From changes in governance norms to the use of scarce natural resources, from community engagement programs to the human capital development, and from essential human rights to the consumer rights protection; ESG characteristics include a wide array of key stakeholder attributes that the firms and their management should be paying attention towards. With a similar wide variety of ESG initiatives covered by MSCI, the identification of sustainability indicators becomes challenging more so because some of the reported indicators overlap with each other over the years. For example, Employment of the Disabled (DIV-str-F) and Gay & Lesbian Policies (DIV-str-G) were separately evaluated until 2011 but were discontinued thereafter to be covered under a common header Employment Of Underrepresented Groups (DIV-str-H). In this case, since both these diversity strengths fit the selection criteria explained in Section 4.3.3.1, I include all these three as sustainability indicators. In contrast, a few ESG indicators such as freedom of expression, privacy and data security, biodiversity and different dimensions of climate change such as carbon footprint, energy efficiency etc. are relevant to sustainability as per the said criteria, but are excluded from the final list of sustainability indicators since they are reported only after 2012 and are difficult to assess with too many missing values. The only short-lived indicator included purposefully is Operations in Sudan (HUM-con-H), which was assessed for two years i.e., 2010 and 2011, as it broadly fits within another relevant indicator Support for Controversial Regimes (HUM-con-C) that initially reported investments in Burma till 2011. In similar essence, South Africa (HUM-str-A; HUM-con-A) and Northern Ireland (HUM-con-B) indicators are excluded as the data made available by MSCI is restricted to 4 years that includes the end of controversial societal or social regimes in these countries (implying that the nature of these regimes are themselves controversial in this period).

While ESG strength indicators are an assessment of best management practices in relation to stakeholder risk management, the concern indicators make an assessment of ESG-related controversies that the firms were exposed to. For some ESG characteristics, however, there are strength and concern dimensions that are mutually exclusive while being almost exhaustive. Thus, if a specific characteristic is identified as sustainability-relevant, I include only the strength indicator to avoid unbalanced weighting of that characteristic. In other words, the idea is to ensure that all sustainability-related best practices (controversies) are rated either 0 or 1 (-1) in the overall index measure, which will not be the case when one characteristic has its two obverse indicators included resulting in a scale of -1 to +1 in net terms. For instance, within MSCI governance indicators, the Limited Compensation (CGOV-str-A) and Ownership Strength (CGOV-str-C) have their corresponding concern counterparts namely, High Compensation (CGOV-con-B) and Ownership Concern (CGOV-con-F). I find that both the ownership and compensation aspects are important to sustainability as per the selection criteria employed, but to avoid the aforementioned problem of double scaling, I only include the two strength indicators in the sustainability set. Exceptions are the Transparency/ Reporting Quality (CGOV-str-D; CGOV-con-H), Board of Directors - Gender (DIV-str-C; DIV-con-C), Employee Health and Safety (EMP-str-G; EMP-con-B) and Labor Rights (HUM-str-G and HUM-con-F) indicators because either they are asymmetrically defined or they are reported for asymmetric time periods. To illustrate further, while the Labor Rights strengths were evaluated for international or overseas labor-related initiatives, the Labor Rights concerns assessed local controversies. Similarly, while Transparency/ Reporting Quality strengths were reported from 1996 to 2009, its concerns were covered by MSCI from 2005 to 2012.

Certain indicators are prioritized over others for the way they are defined, with the more stringent sustainability-focused indicator preferred. In this light, Generous Giving (COM-str-A) is excluded from the sustainability list as its definition broadly includes social "investments" along with charity and philanthropy. Moreover, in its definition, the 1.5% threshold over three years is set on pre-tax profits that may bias the construct whence the firms engage in such activities for tax-saving motives rather than social or stakeholder engagement motives. On the other hand, Non-US Charitable Giving (COM-str-F) is defined with a substantial minimum (20%) contributed overseas that better reflects sustainability criteria where firms' policies are indeed directed towards community upliftment both locally and internationally. Similarly, while Employee Involvement (EMP-str-D) and Compensation & Benefits (EMP-str-I) are a part of sustainability list for their ability to incentivize all of the employees with a clear welfare objective, Labor Management (EMP-str-M) and Professional Development (EMP-str-K) are excluded from the list as they are either largely profit-oriented activities (EMP-str-M) or are directed only towards mid- / upper-level executives (EMP-str-K).

4.A.3 Definitions of Variables Used in Tobin's Q Regressions

CSPstr: Measures strengths related to corporate social performance. It is constructed as in El-Ghoul et al. (2011); Jha and Cox (2015) as the sum of all ESG strengths available in MSCI dataset (sum total of all strengths given in Appendix 4.A.1). High value indicates high CSR engagements and initiatives for the firm.

CSPcon: Measures concerns related to corporate social performance. It is constructed as in El-Ghoul et al. (2011); Jha and Cox (2015) as the sumtotal of all ESG concerns available in MSCI dataset, or in other words, sum total of all concerns given in Appendix 4.A.1. High value indicates firm is embroiled in CSR controversies.

CSP: Measures the net corporate social performance of the firm in a given year. It is calculated as the difference between ESG strengths and concerns (i.e., $CSP = CSPstr - CSPcon$).

SUSstr: Measures sustainability related strengths for a firm. It is constructed using similar summation as CSPstr but, only the sustainability indicators are included (refer Table 4.1). High value indicates proactiveness for sustainability initiatives in the firm.

SUScon: Measures sustainability related concerns in a firm. It is constructed using similar summation as CSPcon but, only the sustainability indicators are included (refer Table 4.1). High value indicates a disregard for sustainability and triple bottom line by the firm.

SUS: Measures the firm's sustainability score in a given year. It is calculated as the difference between sustainability strengths and concerns (i.e., $SUS = SUSstr - SUScon$).

remCSP: Measures the remnant CSP score after separating the sustainability-related parameters. It is calculated as the difference between the overall net CSP score and the sustainability score (i.e., $remCSP = CSP - SUS$).

Tobin's Q: Calculated as in Bebchuk, Cohen, and Ferrell (2009) as market value of assets divided by book value of assets (Compustat data item 6) with the market value of assets calculated as: (book value of assets + market value of common stock) – (book value of common stock + deferred taxes). Corresponding industry-adjusted (either Fama French 48 or SIC 2-digit) values are obtained by taking the difference of Tobin's Q and the corresponding industry median Tobin's Q values.

ROA: The control used as proxy for operating performance, Return on Assets (ROA) computed as the operating income divided by end of year total assets

(Compustat data item 6). Operating income before depreciation (Compustat data item 13) is used as given in Bhagat and Bolton (2008).

Size: Log transformation of Total Assets (Compustat data item 6).

Leverage: As described in Bhagat and Bolton (2008): Long term debt (Compustat data item 9) / Total Assets (Compustat data item 6). Alternative measure of leverage i.e., Debt/Equity ratio was also used as a means of robustness check.

Volume: Measures liquidity using the volume of trade for the firm's common equity recorded in the fiscal year (in logs).

CAPEX/Total Assets: is the log transformation of the ratio of Capital Expenditures (Compustat data item 31) to Total Assets.

R&D Expense/Total Sales: is the log transformation of the ratio of Research & Development expenses (Compustat data item 47) to Total Revenues.

Sales Growth: The ratio of Total Revenues for current year to that of the year t–2.

Age: Log transformation of firm's age measured in months at the end of each calendar year with reference being the listing month.

Delaware Dummy: Dummy variable indicating whether a firm is incorporated in Delaware or not (coded 1 and 0).

E-Index: The entrenchment index from Bebchuk, Cohen, and Ferrell (2009), which is the sum of the managerial entrenchment provisions (from limits to bylaws, limits to charters, staggered boards, poison pills, golden parachutes and supermajority requirement for mergers) existing in a firm for a given year.

EI Dummy: Dummy variable indicating whether a firm is high or low E-Index value, classified using the median E-Index value for each year.

Institutional Ownership (%): The percentage of shares owned by institutional investors obtained from the quarterly 13f filings, which is annualized using the average of all available quarterly % institutional ownership data.

Blockholders (#): A measure of blockholder dispersion for a firm in a given year, calculated as the average quarterly number of blockholders. The blockholders are classified from institutional investors as the ones that own at least 5% of a firm's equity.

4.A.4 Instrumental Variables for State-Level Political Leanings

% Votes for Democrat Presidential Candidate (PVD): It is the percentage of votes within each state registered in favor of the Democratic presidential candidate.

Congressional Democratic Distribution (CDD): This variable is constructed as shown in Di Giuli and Kostovetsky (2014), for each state, by taking the average of the percentages of Democrat Congressmen and the Democrat Senators.

State Government's Democratic Distribution (SGD): From Di Giuli and Kostovetsky (2014), this variable is calculated as the sum of 0.5 x Democrat governor dummy, 0.25 ÃŮ Democrats-controlled dummy for the state's upper chamber, and 0.25 ÃŮ Democrats-controlled dummy for the state's lower chamber.

4.A.5 Keywords List Used for Google Trends

For each MSCI ESG variable, the related keywords were identified from their respective definitions as given in the MSCI methodology guide. Only those keywords that appeared in Google Trends data are listed below.

4.A.5.1 *Sustainability Indicators:*

"Charitable giving", "community engagement", "education support", "housing support", "gender diversity", "retirement benefits", "employee involvement", "employee safety", "Employment for disabled", "climate change", "alternative fuels", "employee health", "clean energy", "labor rights", "product quality", "product safety", "R & D", "social opportunities", "environmental management system", "tax disputes", "political accountability", "oil spills", "child labor", "hazardous waste", "ozone depletion", "labor relations", "agricultural chemicals", "natural resource", "family benefits", "work-life balance", "pollution prevention", "waste management", "antitrust", "human capital management", "accounting quality", "non-representation", "board compensation", "CSR report", "indigenous people rights"

4.A.5.2 *Remnant ESG Indicators:*

"Generous giving", "volunteer programs", "employee discrimination", "LGBT rights", "gay and lesbian rights", "underrepresented groups", "supply chain issues", "labor management", "water stress", "consumer fraud", "privacy and data security", "data theft", "access to finance", "freedom of expression", "Internet censorship", "human rights violations", "political instability", "regulatory compliance", "community reinvestment act", "green buildings", "public policy issues", "product carbon footprint", "protect biodiversity", "corporate bribery", "business fraud"

4.A.6 Supplementary Results

Table 4.11 Conceptual identification of sustainability indicators

This is a summary list of all indicators identified using three step conceptual filter explained in the Section 4.3.3.1 and Appendix 4.A.2. The selection criteria that were met for each of these indicators are accordingly shown by †, ‡ and ⋇ for Rahdari and Rostamy (2015) 30 sustainability constructs, UNGC Guide to Corporate Sustainability and UNCTAD's 2015 Framework for Sustainable Development respectively.

Community	
Strengths:	*Concerns:*
Support for Housing†‡	Tax Disputes†‡
Support for Education†‡	Other Community Concerns†‡
Non-US Charitable Giving†‡	
Community Engagement†‡	
Diversity	
Strengths:	*Concerns:*
CEO Diversity‡	Board of Directors - Gender Diversity†‡
Board of Directors - Gender Diversity†‡	
Work-Life Balance/ Family Benefits†‡	
Women & Minority Contracting†‡	
Employment of the Disabled†‡	
Progressive Gay/ Lesbian Policies‡	
Employment of Underrepresented Groups†‡	
Employees	
Strengths:	*Concerns:*
Employee Involvement† ‡ ⋇	Health & Safety Concern/ Safety Controversies† ‡ ⋇
Strong Retirement Benefits†	Workforce Reductions†
Employee Health & Safety† ‡ ⋇	Child Labor† ‡ ⋇
Supply Chain Labor Standards† ‡ ⋇	Labor Rights & Supply Chain - Other Concerns/ Labor-Management Relations† ‡ ⋇
Compensation & Benefits†‡	
Human Capital Management/ Developments‡	
Human Capital - Other Strengths† ‡ ⋇	
Environment	
Strengths:	*Concerns:*
Beneficial Products & Services/ Env. Opportunities†	Hazardous Waste† ‡ ⋇
Pollution Prevention/ Waste Management† ‡ ⋇	Regulatory Compliance† ‡ ⋇
Climate Change/ Alternative Fuels/ Clean Energy† ‡ ⋇	Ozone Depleting Chemicals† ‡ ⋇
Environmental Management Systems† ‡ ⋇	Toxic Spills & Releases/ Substantial Emissions† ‡ ⋇
Natural Resource Use‡⋇	Agricultural Chemicals† ‡ ⋇
Governance	
Strengths:	*Concerns:*
Limited Compensation†⋇	Accounting Concern† ‡ ⋇
Ownership Strength† ‡ ⋇	Reporting Quality/ Transparency Concern † ‡ ⋇
Transparency/ Reporting Quality Strength† ‡ ⋇	Other Governance Concerns†⋇
Political Accountability Strength†‡	
Human Rights	
Strengths:	*Concerns:*
Labor Rights Strength† ‡ ⋇	Support for Controversial Regimes⋇
	Labor Rights Concern† ‡ ⋇
	Operations in Sudan⋇
Product	
Strengths:	*Concerns:*
Product Safety & Quality†‡	Advertising & Marketing/ Contracting Controversy†
R & D/ Innovation†‡	Antitrust & Anticompetitive Practices†‡
Social Opportunities - Access to Communications†‡	
Social Opportunities - Nutrition and Health†‡	

Table 4.12 Correlations between the main variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]
CSP [1]	1																			
SUS [2]	0.831***	1																		
$remCSP$ [3]	0.820***	0.363***	1																	
$CSPstr$ [4]	0.709***	0.715***	0.452***	1																
$CSPcon$ [5]	-0.429***	-0.196***	-0.518***	0.332***	1															
$SUSstr$ [6]	0.619***	0.789***	0.225***	0.903***	0.329***	1														
$SUScon$ [7]	-0.423***	-0.446***	-0.250***	0.175***	0.791***	0.198***	1													
Tobin's Q [8]	0.010	0.003	0.013**	-0.012**	-0.029***	-0.010	-0.020***	1												
E-Index [9]	0.044***	-0.014**	0.087***	-0.054***	-0.128***	-0.083***	-0.104***	-0.077***	1											
ROA [10]	0.011**	0.010	0.008	0.013**	0.002	0.011**	0.000	-0.208***	-0.033***	1										
Size [11]	0.200***	0.266***	0.061***	0.475***	0.340***	0.410***	0.171***	-0.026***	0.059***	0.051***	1									
Leverage [12]	-0.047***	-0.033***	-0.046***	-0.012**	0.048***	-0.021***	0.021***	0.027***	0.013**	-0.287***	0.069***	1								
Volume [13]	0.143***	0.200***	0.033***	0.415***	0.340***	0.346***	0.185***	-0.004	0.100***	0.008	0.572***	0.075***	1							
CAPEX/TA [14]	-0.013**	0.016**	-0.088***	0.075***	0.113***	0.073***	0.080***	0.036***	-0.086***	0.043***	-0.110***	0.113***	0.056***	1						
R&D/Sales [15]	-0.018***	-0.072***	0.043***	-0.113***	-0.121***	-0.136***	-0.084***	0.006	-0.031***	-0.026***	-0.020***	0.024***	-0.095***	-0.129***	1					
Sales Growth [16]	-0.002	-0.004	0.001	-0.009	-0.009	-0.008	-0.005	0.001	0.003	-0.000	-0.010**	-0.001	-0.001	-0.000	-0.002	1				
Age [17]	0.104***	0.143***	0.026***	0.235***	0.163***	0.222***	0.095***	-0.014***	0.104***	0.022***	0.311***	0.040***	0.191***	-0.002	-0.126***	-0.042***	1			
Delaware [18]	-0.046***	-0.033***	-0.043***	-0.005	0.055***	-0.017	0.029***	0.002	-0.048***	0.003	-0.073***	0.018***	0.181***	0.068***	-0.052***	0.007	-0.135***	1		
IO (%) [19]	-0.007	-0.010	-0.000	-0.014	-0.009	-0.016**	-0.007	-0.013**	0.050***	0.013**	0.038***	0.010	0.076***	-0.011	-0.006	-0.001	0.036***	0.015**	1	
Blockholders (#) [20]	-0.059***	-0.100***	0.003	-0.208***	-0.190***	-0.213***	-0.158***	-0.073***	0.290***	-0.022***	-0.043***	0.086***	0.127***	-0.082***	-0.027***	0.002	0.091***	0.083***	0.144***	1

$* \rightarrow p < 0.05$

$** \rightarrow p < 0.01$

$*** \rightarrow p < 0.001$

Table 4.13 Tobin's Q regressions on ESG measures (excluding corporate governance indicators)

This table repeats the estimations from Table 4.3, and presents the results when the MSCI corporate governance indicators are excluded from the ESG measures. For details on each of the variables see Appendix 4.A.3. Model 1 shows Tobin's Q regressed on the two ESG measures with all the main controls, and additional year and industry fixed effects. Model 2 adds the past two years' Tobin's Q as regressors in a dynamic OLS for Model 1. Dependent variable is the industry-adjusted Tobin's Q taken as Tobin's Q minus the median Tobin's Q for that industry using SIC 2-digit classification. Coefficients for the constant, year dummies and industry dummies are omitted. Significance levels are represented by *, **, and *** for 10%, 5%, and 1% respectively.

	ESG Aggregate Measures				ESG Subcomponents			
	Model (1)		Model (2)		Model (1)		Model (2)	
CSP	0.0378***		0.0166***					
	(0.005)		(0.003)					
SUS		0.0741***		0.0301***				
		(0.008)		(0.005)				
CSPstr					0.0598***		0.0263***	
					(0.005)		(0.004)	
CSPcon					0.0079		0.0035	
					(0.007)		(0.005)	
SUSstr						0.1010***		0.0428***
						(0.008)		(0.006)
SUScon						-0.0079		0.0012
						(0.010)		(0.007)
Remnant CSP		0.0054		0.0046		0.0058		0.0047
		(0.006)		(0.004)		(0.006)		(0.004)
ROA	-0.0177	-0.0188	-0.6507	-0.6509	0.0080	-0.0032	-0.6385	-0.6428
	(1.016)	(1.016)	(0.769)	(0.769)	(1.018)	(1.017)	(0.771)	(0.770)
Size	-0.4743***	-0.4819***	-0.1391***	-0.1423***	-0.5038***	-0.4973***	-0.1528***	-0.1500***
	(0.014)	(0.014)	(0.026)	(0.026)	(0.016)	(0.015)	(0.028)	(0.027)
Leverage	-0.9812***	-0.9759***	-0.3114**	-0.3099**	-0.9442***	-0.9526***	-0.2958**	-0.2990**
	(0.146)	(0.146)	(0.149)	(0.149)	(0.147)	(0.146)	(0.149)	(0.148)
Volume	0.3953***	0.3960***	0.0960***	0.0965***	0.3889***	0.3922***	0.0936***	0.0949***
	(0.013)	(0.013)	(0.023)	(0.023)	(0.013)	(0.013)	(0.023)	(0.023)
CAPEX / Assets	0.1181***	0.1164***	0.0482**	0.0477**	0.1145***	0.1149***	0.0468**	0.0471**
	(0.029)	(0.029)	(0.020)	(0.020)	(0.029)	(0.029)	(0.020)	(0.020)
R & D / Sales	-0.0048	-0.0039	-0.0076	-0.0073	-0.0016	-0.0018	-0.0062	-0.0063
	(0.016)	(0.016)	(0.012)	(0.012)	(0.017)	(0.016)	(0.012)	(0.012)
Sales Growth	0.0003*	0.0003*	0.0001**	0.0001**	0.0003*	0.0003*	0.0001**	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.0854***	-0.0870***	0.0378***	0.0370***	-0.0896***	-0.0890***	0.0351***	0.0356***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)
Delaware Dummy	0.0225	0.0235	0.0220	0.0223	0.0212	0.0233	0.0213	0.0223
	(0.024)	(0.024)	(0.019)	(0.019)	(0.024)	(0.024)	(0.019)	(0.019)
Lag 1 Tobin's Q			0.5821***	0.5818***			0.5812***	0.5813***
			(0.070)	(0.070)			(0.070)	(0.070)
Lag 2 Tobin's Q			0.0605**	0.0604**			0.0606**	0.0604**
			(0.028)	(0.028)			(0.028)	(0.028)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	32546	32546	30991	30991	32546	32546	30991	30991
R-Squared	0.209	0.210	0.550	0.551	0.212	0.212	0.551	0.551

Table 4.14 Tobin's Q regressions on ESG measures (additional controls)

This table replicates results from Table 4.3 with E-Index, Institutional Ownership and Blockholders' dispersion (#) included as additional controls. Models 1 is static OLS, that includes year and industry fixed effects, whereas Model 2 is dynamic OLS that introduces past two years' Tobin's Q as regressors. For variable definitions, refer Appendix 4.A.3. Significance levels are represented by *, **, and *** for 10%, 5%, and 1% respectively.

Panel A: ESG Aggregate Measures	Model (1)								Model (2)							
CSP	0.0139***		0.0222***		0.0204***		0.0108***		0.0058***		0.0078***		0.0072***		0.0027	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)		(0.002)		(0.002)	
SUS		0.0315***		0.0449***		0.0415***		0.0296***		0.0106***		0.0178***		0.0167***		0.0091**
		(0.005)		(0.005)		(0.005)		(0.005)		(0.003)		(0.004)		(0.004)		(0.004)
remCSP		-0.0031		0.0009		0.0006		-0.0070		0.0011		-0.0016		-0.0016		-0.0034
		(0.004)		(0.005)		(0.005)		(0.005)		(0.003)		(0.003)		(0.003)		(0.003)
E-Index	-0.0656***	-0.0654***					-0.0627***	-0.0623***	-0.0183***	-0.0183***					-0.0136***	-0.0135***
	(0.006)	(0.006)					(0.007)	(0.007)	(0.005)	(0.005)					(0.005)	(0.005)
Institutional Ownership (%)			-0.0079**	-0.0077*			-0.0020**	-0.0019**			-0.0028***	-0.0027***			-0.0009***	-0.0008***
			(0.004)	(0.004)			(0.001)	(0.001)			(0.001)	(0.001)			(0.000)	(0.000)
Blockholders (#)					-0.0697***	-0.0690***	-0.0520***	-0.0515***					-0.0251***	-0.0248***	-0.0165***	-0.0164***
					(0.006)	(0.006)	(0.006)	(0.006)					(0.005)	(0.005)	(0.004)	(0.004)
Lagged Tobin's Q	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	18398	18398	18875	18875	18878	18878	15078	15078	18276	18276	18443	18443	18446	18446	14987	14987
R-Squared	0.404	0.405	0.380	0.381	0.385	0.386	0.423	0.424	0.699	0.699	0.663	0.663	0.664	0.664	0.729	0.729

Panel B: ESG Subcomponents	Model (1)								Model (2)							
CSPstr	0.0187***		0.0361***		0.0327***		0.0161***		0.0089***		0.0148***		0.0137***		0.0046*	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.002)		(0.003)		(0.003)		(0.003)	
CSPcon	-0.0051		0.0038		0.0024		-0.0013		-0.0000		0.0053*		0.0048*		0.0007	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)		(0.003)		(0.003)	
SUSstr		0.0358***		0.0611***		0.0553***		0.0342***		0.0143***		0.0260***		0.0241***		0.0108**
		(0.006)		(0.007)		(0.007)		(0.007)		(0.004)		(0.005)		(0.005)		(0.004)
SUScon		-0.0208***		-0.0030		-0.0060		-0.0178**		-0.0014		0.0033		0.0023		-0.0050
		(0.008)		(0.008)		(0.008)		(0.008)		(0.005)		(0.006)		(0.006)		(0.006)
remCSP		-0.0028		0.0023		0.0018		-0.0065		0.0013		-0.0009		-0.0010		-0.0032
		(0.004)		(0.005)		(0.005)		(0.005)		(0.003)		(0.003)		(0.003)		(0.003)
E-Index	-0.0642***	-0.0644***					-0.0611***	-0.0613***	-0.0174***	-0.0174***					-0.0130***	-0.0131***
	(0.006)	(0.006)					(0.007)	(0.007)	(0.005)	(0.005)					(0.005)	(0.005)
Institutional Ownership (%)			-0.0074**	-0.0074**			-0.0019**	-0.0019**			-0.0026***	-0.0026***			-0.0008***	-0.0008***
			(0.004)	(0.004)			(0.001)	(0.001)			(0.001)	(0.001)			(0.000)	(0.000)
Blockholders (#)					-0.0673***	-0.0671***	-0.0514***	-0.0511***					-0.0239***	-0.0238***	-0.0163***	-0.0162***
					(0.006)	(0.006)	(0.006)	(0.006)					(0.005)	(0.005)	(0.004)	(0.004)
Lagged Tobin's Q	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	18398	18398	18875	18875	18878	18878	15078	15078	18276	18276	18443	18443	18446	18446	14987	14987
R-Squared	0.404	0.405	0.382	0.382	0.386	0.386	0.424	0.424	0.699	0.699	0.664	0.664	0.664	0.664	0.729	0.729

Table 4.15 Annual regressions and time-series averages for Tobin's Q on ESG measures with alternative industry adjustment

As a robustness check, this table replicates the results of Table 4.4 by using Fama and French (1997) 48 industry classification, instead of the SIC 2-Digit industry classification to obtain industry-adjusted Tobin's Q. The annual and time-series average regressions are shown for both the ESG aggregate scores (i.e. SUS and CSP) and their respective strengths and concerns subcomponents. With SUS-Index as the regressor (Model 2 based on Equation 4.8), additional control for remaining CSP indicators ($remCSP$) is applied. All other control variables are the same as before. For each year, only the main regressors coefficients and robust standard errors are shown. Time-series average coefficients and standard errors (using Fama and MacBeth, 1973 methodology) are given at the bottom. *, **, and *** show the significance levels at 10%, 5%, and 1% respectively.

Year	# Observations	ESG Aggregate Measures			ESG Subcomponents				
		Model (1)	Model (2)		Model (1)		Model (2)		
		CSP	SUS	remCSP	CSPstr	CSPcon	SUSstr	SUScon	remCSP
1991	260	0.0174	0.0682	-0.0232	-0.0117	-0.0533	0.0480	-0.1058*	-0.0258
		(0.052)	(0.042)	(0.043)	(0.044)	(0.043)	(0.063)	(0.057)	(0.042)
1992	267	-0.0013	-0.0254	0.0202	-0.0364	-0.0469	-0.0823	-0.0866	0.0111
		(0.046)	(0.035)	(0.040)	(0.033)	(0.040)	(0.053)	(0.068)	(0.035)
1993	274	-0.0240	-0.0546	0.0066	-0.0181	0.0323	-0.0426	0.0728	0.0078
		(0.042)	(0.034)	(0.036)	(0.037)	(0.046)	(0.056)	(0.068)	(0.033)
1994	281	0.0006	0.0200	-0.0203	0.0130	0.0221	0.0339	0.0079	-0.0199
		(0.028)	(0.030)	(0.026)	(0.022)	(0.038)	(0.038)	(0.045)	(0.030)
1995	289	0.0255	0.0320*	0.0187	0.0323	-0.0114	0.0457	0.0106	0.0190
		(0.037)	(0.025)	(0.035)	(0.032)	(0.050)	(0.047)	(0.079)	(0.035)
1996	301	0.0263	0.0243	0.0283	0.0292	-0.0196	0.0275	-0.0136	0.0290
		(0.047)	(0.036)	(0.039)	(0.031)	(0.039)	(0.045)	(0.059)	(0.035)
1997	319	0.0509**	0.0517*	0.0502	0.0599*	-0.0354	0.0560	-0.0378	0.0514
		(0.044)	(0.032)	(0.037)	(0.032)	(0.026)	(0.042)	(0.050)	(0.042)
1998	326	0.0116	0.0068	0.0166	-0.0025	-0.0335	-0.0063	-0.0501	0.0122
		(0.045)	(0.044)	(0.043)	(0.031)	(0.029)	(0.049)	(0.061)	(0.044)
1999	349	-0.0197	0.0202	-0.0659	-0.0149	0.0262	0.0292	-0.0023	-0.0649
		(0.069)	(0.086)	(0.062)	(0.047)	(0.058)	(0.077)	(0.074)	(0.086)
2000	377	0.0119	0.0185	0.0035	-0.0198	-0.0522*	-0.0173	-0.0781	0.0000
		(0.047)	(0.052)	(0.041)	(0.038)	(0.031)	(0.054)	(0.056)	(0.052)
2001	673	0.0101	0.0660**	-0.0637**	0.0279	0.0137	0.0826**	-0.0336	-0.0605**
		(0.032)	(0.027)	(0.026)	(0.022)	(0.020)	(0.033)	(0.031)	(0.027)
2002	704	0.0030	0.0312*	-0.0338*	0.0100	0.0070	0.0404**	-0.0116	-0.0320
		(0.024)	(0.019)	(0.016)	(0.013)	(0.013)	(0.020)	(0.023)	(0.020)
2003	1722	0.0210	0.1129***	-0.0996***	0.0863***	0.0421**	0.1747***	-0.0196	-0.0786***
		(0.029)	(0.028)	(0.026)	(0.021)	(0.018)	(0.032)	(0.030)	(0.028)
2004	2071	0.0528**	0.1537***	-0.0746***	0.0988***	-0.0016	0.1788***	-0.1166***	-0.0716***
		(0.027)	(0.024)	(0.031)	(0.027)	(0.018)	(0.040)	(0.029)	(0.024)
2005	2085	0.0435***	0.0818***	-0.0005	0.0715***	-0.0061	0.1095***	-0.0316	0.0025
		(0.022)	(0.020)	(0.021)	(0.016)	(0.015)	(0.026)	(0.025)	(0.020)
2006	2123	0.0618***	0.0998***	0.0170	0.0890***	-0.0224	0.1265***	-0.0354	0.0217
		(0.021)	(0.019)	(0.022)	(0.016)	(0.014)	(0.025)	(0.026)	(0.019)
2007	2145	0.0526***	0.0760***	0.0273	0.0734***	-0.0218	0.1081***	-0.0030	0.0290
		(0.023)	(0.019)	(0.017)	(0.012)	(0.017)	(0.019)	(0.027)	(0.019)
2008	2263	0.0343***	0.0519***	0.0137	0.0398***	-0.0269**	0.0505***	-0.0551**	0.0135
		(0.019)	(0.016)	(0.015)	(0.011)	(0.013)	(0.017)	(0.027)	(0.016)
2009	2304	0.0369***	0.0439***	0.0291**	0.0443***	-0.0271**	0.0552***	-0.0186	0.0307**
		(0.016)	(0.013)	(0.012)	(0.010)	(0.010)	(0.014)	(0.018)	(0.013)
2010	2383	0.0225**	-0.0008	0.0468***	0.0367***	0.0134	0.0353*	0.0768***	0.0439***
		(0.018)	(0.015)	(0.017)	(0.010)	(0.013)	(0.018)	(0.029)	(0.015)
2011	2288	0.0292***	0.0046	0.0580***	0.0378***	-0.0020	0.0277	0.0531*	0.0587***
		(0.018)	(0.018)	(0.015)	(0.009)	(0.014)	(0.018)	(0.028)	(0.018)
2012	2333	0.0549***	0.0715***	0.0463**	0.0669***	0.0117	0.0955***	0.0735	0.0390*
		(0.027)	(0.022)	(0.026)	(0.014)	(0.032)	(0.028)	(0.048)	(0.022)
2013	2133	0.0260**	-0.0100	0.0450**	0.0380**	0.0373	0.0118	0.1600***	0.0363*
		(0.024)	(0.019)	(0.028)	(0.013)	(0.026)	(0.030)	(0.058)	(0.019)
2014	2213	0.0598**	0.1061***	0.0092	0.0746**	-0.0037	0.1245***	0.0513	0.0111
		(0.036)	(0.032)	(0.032)	(0.025)	(0.032)	(0.033)	(0.070)	(0.032)
2015	2086	0.0978***	0.1265***	0.0709**	0.1103***	-0.0418	0.1413***	0.0300	0.0699**
		(0.033)	(0.031)	(0.031)	(0.022)	(0.031)	(0.033)	(0.052)	(0.030)
Fama-MacBeth	32546	0.0282***	0.0471***	0.0050	0.0376***	-0.0083	0.0582***	-0.0065	0.0053
		(0.005)	(0.010)	(0.009)	(0.008)	(0.006)	(0.013)	(0.013)	(0.008)

Table 4.16 OLS, dynamic OLS and Fama-Macbeth regressions for Tobin's Q on pseudo-sustainability measures

This table replicates the results of OLS, dynamic OLS (from Table 4.3 in the paper) and Fama-Macbeth time series averages (from Table 4.4) for Tobin's Q on the pseudo-sustainability and remnant scores taken in place of the true SUS and $remCSP$ scores. Model 1 applies OLS with all the main controls including year and industry fixed effects. Model 2 includes the past two years' Tobin's Q as regressors in a dynamic OLS model. Model 3 uses Fama-Macbeth regressions to compute time series average coefficients. Dependent variable is the industry-adjusted Tobin's Q taken as Tobin's Q minus the median Tobin's Q for that industry using SIC 2-digit classification. Coefficients for the constant, year dummies and industry dummies are omitted. Significance levels are represented by *, **, and *** for 10%, 5%, and 1% respectively.

	ESG Aggregate Measures			ESG Subcomponents		
	Model (1)	Model (2)	Model (3)	Model (1)	Model (2)	Model (3)
SUS_{pseudo}	0.0297***	0.0121***	0.0378***			
	(0.006)	(0.004)	(0.009)			
$SUSstr_{pseudo}$				0.0689***	0.0289***	0.0597***
				(0.007)	(0.005)	(0.015)
$SUScon_{pseudo}$				0.0618***	0.0271***	0.0162
				(0.009)	(0.006)	(0.010)
$remCSP_{pseudo}$	0.0359***	0.0149***	0.0258***	0.0301***	0.0124***	0.0220***
	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.007)
ROA	-0.0165	-0.6497	4.0927***	0.0055	-0.6391	4.1124***
	(1.017)	(0.770)	(0.826)	(1.017)	(0.770)	(0.824)
Size	-0.4711***	-0.1375***	-0.3407***	-0.5080***	-0.1542***	-0.3578***
	(0.014)	(0.026)	(0.033)	(0.016)	(0.027)	(0.035)
Leverage	-0.9833***	-0.3127**	-1.3064***	-0.9453***	-0.2975**	-1.2926***
	(0.146)	(0.149)	(0.131)	(0.147)	(0.149)	(0.133)
Volume	0.3987***	0.0976***	0.3627***	0.3929***	0.0956***	0.3562***
	(0.013)	(0.023)	(0.047)	(0.013)	(0.023)	(0.048)
CAPEX / Assets	0.1183***	0.0484**	-0.1033***	0.1135***	0.0465**	-0.1092***
	(0.029)	(0.020)	(0.019)	(0.029)	(0.020)	(0.019)
R & D / Sales	-0.0051	-0.0077	0.0713***	-0.0014	-0.0062	0.0743***
	(0.016)	(0.012)	(0.006)	(0.016)	(0.012)	(0.006)
Sales Growth	0.0003*	0.0001*	0.2113**	0.0003*	0.0001**	0.2140**
	(0.000)	(0.000)	(0.084)	(0.000)	(0.000)	(0.085)
Age	-0.0844***	0.0384***	-0.0809***	-0.0905***	0.0346***	-0.0868***
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)
Delaware Dummy	0.0239	0.0224	-0.0683***	0.0236	0.0222	-0.0689***
	(0.024)	(0.019)	(0.020)	(0.024)	(0.019)	(0.020)
Lag 1 Tobin's Q		0.5822***			0.5812***	
		(0.070)			(0.070)	
Lag 2 Tobin's Q		0.0606**			0.0605**	
		(0.028)			(0.028)	
Year Fixed Effects	Yes	Yes	No	Yes	Yes	No
Industry Fixed Effects	Yes	Yes	No	Yes	Yes	No
Number of observations	32546	30991	32546	32546	30991	32546
R-Squared	0.209	0.550	0.364	0.212	0.551	0.367

Table 4.17 Robustness checks for abnormal returns generated using sustainability measure

This table summarizes abnormal returns when industry-adjusted returns are used, alternative sample periods are employed (Panel A) or when alternate asset pricing models are used (Panel B). Abnormal returns using long Green – short Toxic hedge for both value-weighted (shown by VW) and equal-weighted (EW) are reported along with corresponding robust standard errors. The first row in each panel shows the result for baseline model using excess hedge portfolio returns as reported in Table 4.9 for comparison. Panel A reports abnormal industry-adjusted returns followed by abnormal returns when sample period is divided into two equal 12 year periods or 3 equal 8 year periods. Panel B reports α for combinations of Fama and French (1993) three factor model and Fama and French (2016) five factor model along with momentum and the Pástor and Stambaugh (2003) liquidity factors. Significance levels for 10%, 5%, and 1% is shown by *, ** and *** respectively.

Panel A: Alternative Portfolio Characteristics

Portfolios	**Pentile Portfolios**		**Tercile Portfolios**	
	EW	**VW**	**EW**	**VW**
Green – Toxic Hedge	0.0036**	0.0016	0.0021**	0.0012
	(0.002)	(0.002)	(0.001)	(0.001)
Industry adjusted	0.0011*	0.0008	0.0008	-0.0004
	(0.001)	(0.002)	(0.001)	(0.002)
First 12 years	0.0042	0.0041	0.0024	0.0034*
	(0.003)	-0.004	(0.002)	(0.002)
Last 12 years	0.0038*	0.0006	0.0024	0.0005
	(0.002)	(0.002)	(0.002)	(0.002)
First 8 years	0.0021	0.0060	0.0016	0.0038*
	(0.004)	(0.004)	(0.002)	(0.001)
Mid 8 years	0.0027	0.0005	0.0018	0.0006
	(0.003)	(0.004)	(0.002)	(0.002)
Last 8 years	0.0056**	0.0022	0.0037*	0.0024
	(0.003)	(0.003)	(0.002)	(0.002)
$remCSP$-based Hedge	0.0001	-0.0020	0.0003	-0.0006
	(0.001)	(0.004)	(0.001)	(0.003)

Panel B: Alternative Factor Models

Asset Pricing Models	**Pentile Portfolios**		**Tercile Portfolios**	
	EW	**VW**	**EW**	**VW**
FF four factors + liquidity	0.0036**	0.0012	0.0021**	0.0012
	(0.002)	(0.002)	(0.001)	(0.001)
FF three factors	0.0027	-0.0007	0.0016	-0.0002
	(0.002)	(0.002)	(0.001)	(0.001)
FF three factors + liquidity factor	0.0037**	0.0006	0.0025**	0.0004
	(0.002)	(0.002)	(0.001)	(0.001)
FF four factors	0.0026	0.0003	0.0012	0.0005
	(0.002)	(0.002)	(0.001)	(0.001)
FF five factors	0.0036*	-0.0001	0.0019*	0.0007
	(0.002)	(0.002)	(0.001)	(0.002)
FF five factors + liquidity factor	0.0044**	0.0009	0.0029**	0.0012
	(0.002)	(0.002)	(0.001)	(0.002)

CHAPTER 5
Summary and Conclusions

5.1 Summary of Findings

In this dissertation, we set out to study the relationship between corporate governance and returns (Chapter 2), while also drawing attention to the methodological issues plaguing the research in this area (Chapter 3) and the conceptual issues that researchers and investors face when dealing with governance from stakeholders' perspective rather than shareholders' (Chapter 4).

In the chapter, *Governance, Information Flow, and Stock Returns*, we provide a detailed and comprehensive outlook of how governance information continues to be an importance resource for implementing profitable investment strategies.

While Bebchuk, Cohen, and Wang (2013) show that the governance–returns correlation has disappeared after 2002, this chapter reveals that it has a directionally opposite reappearance in recent years i.e., poor governance stocks outperform good governance ones. In other words, the relationship between governance and returns undergoes two structural changes (i.e., dissociation and reversed association). The reappearance of pricing anomalies is seldom identified or studied. Thus, this chapter is one of very few empirical studies that have provided insights on why pricing anomalies reappear. We explain this puzzling reappearance using sophisticated learning that accompanies institutional investors' increased sensitivity to governance information after the 2008 global financial crisis. How did the investors learn that poor governance stocks now have a higher expected returns in equilibrium? We examine and find support for two underlying learning mechanisms that may have aided the sophisticated learning i.e., price and risk channels. Poor governance stocks have lower (higher) price informativeness (future risk) than good governance stocks after the crisis. How did this change in firms' information impounded in stock prices, based on their governance characteristics, influence the investor behavior? We observe that institutional investors react to information flow by adjusting their portfolios based on their investment horizons. Using a quasi-natural experiment, we show that while short-term investors show preference for poor governance stocks after the crisis, long-term investors forgo immediate returns by preferring to invest in good governance stocks.

The chapter titled *The Corporate Governance–Performance Puzzle: New Insights* examines the importance of weights when constructing corporate governance indices. Previously, the literature has introduced governance indices (for e.g., G-Index, E-Index, etc.) applying equal-weighted methodology by simply adding the constituent provisions or governance structures. In this chapter, for the first time, an alternative unequal-weighted approach is introduced for governance index construction. We test multiple new index construction methodologies that can dynamically account for the heterogeneity of individual antitakeover components, and present the nG-Index. This index is found to be less prone to erroneous inferences than a comparable equal-weighted index is. Only with the nG-Index, a monotonic relationship between corporate governance and performance measures is seen. Firms with higher nG-Index scores (i.e., poor governance firms) show worse operating performance and lower firm value. The equal-weighted measure, in contrast, shows conflicting results with operating performance measures and has a statistically insignificant association with firm value. These results hold even when we additionally control for endogeneity.

In the chapter *Sustain and deliver: Capturing the valuation effects of corporate sustainability*, we study firms' environmental, social and governance (ESG) characteristics and how they affect firm valuation. Although the ESG indicators rated by ESG data providers cover a wide array of strengths (indicating socially responsible behavior) and controversies (i.e., socially irresponsible conduct), they are commonly combined using an all-in or kitchen-sink approach to measure corporate social performance/ responsibility (CSP/ CSR). This chapter implements a selective approach to first identify important industry-neutral sustainability indicators from a wide range of firms' ESG characteristics and then show that this subcomponent of CSR is most relevant to valuation benefits. Our findings reveal that the use of sustainability-relevant ESG indicators can help identify a monotonic relationship with both the firm value and abnormal stock returns, unlike the puzzling mixed evidence that was previously shown in related literature. The sustainability-irrelevant indicators, meanwhile, are neither associated with the firm value not with the abnormal returns.

5.2 Limitations and Future Directions

While each of the three manuscripts presented in this dissertation address as many limitations as possible within the framework or approach that is employed, they present opportunities aplenty for future research to address.

Firstly, both the ISS Governance (in Chapters 2 and 3) and MSCI ESG (Chapter 4) data that are used to measure corporate governance and corporate sustainability respectively, are only analyzed for a single country due to their availability. Thus, there is a scope to conduct similar analyses to test whether the benefits of governance and sustainability are available across the globe for investors to exploit. Previously, literature has studied corporate governance–firm value relation for a global sample using an equal-weighted index (Ammann, Oesch, and Schmid, 2011), but the studies on investor returns using governance indices have largely been limited to single-country settings. Moreover, Denis and McConnell (2003) and Martynova and Renneboog (2013) highlight certain challenges that arise when dealing with international corporate governance research. Whether some of these challenges can be addressed using an unequal-weighted governance index remains an open question. When it comes to ESG and CSR, Aouadi and Marsat (2018) and Ferrell, Liang, and Renneboog (2016) show their effect on firm value, and Auer and Schuhmacher (2016) show it on stock returns in cross-country settings. However, the valuation benefits from corporate sustainability across the globe are not yet clearly understood.

Secondly, the focus of this dissertation is on performance outcomes of corporate governance with the investment returns being one of the main performance metrics used. While the impact on risk is partially captured in Chapters 2 and 3 for corporate governance, the third article does not delve into how ESG and corporate sustainability can mitigate or exacerbate firms' riskiness. To address this gap, we have examined the effect of the three ESG dimensions separately on the stock price crash risk (Dumitrescu and Zakriya, 2018) and the distress risk (Dumitrescu, El Hefnawy, and Zakriya, 2019) to understand their importance for the shareholders and debtholders respectively. However, future studies can explore whether corporate sustainability is what drives the relationship between CSR and future firm risk.

Thirdly, and relatedly, instead of performance metrics, the effect of governance and sustainability on other firm outcomes can be determined. Put differently, can the ATPs and ESG information be used by investors and other stakeholder to gauge other firm outcomes such as the ability to innovate or their ability to pay dividends? These outcomes are also important from firms' point of view as they can help us understand how governance and ESG features influence firms' investment and dividend decisions.

Fourthly, the investors' perspective is captured in all the three manuscripts using long-run event studies that obtain risk-adjusted abnormal returns by controlling for common risk factors. Specifically, we have applied calendar-time portfolio approach to obtain the abnormal returns from long/short hedge portfolios. This strategy is employed to mimic real-time investment decisions, and is commonly applied in the literature to study investor gains from corporate policies or decisions. Nevertheless, applying alternate long-run methodologies may provide additional insights (Lyon, Barber, and Tsai, 1999).

Fifthly, the relationship between governance and performance is clouded by endogeneity concerns. The same is true for corporate sustainability and CSR as well. This makes causal identification a major challenge. We overcome this in all the three studies using quasi-natural experiments that exogenously affect either the governance features or socially responsible behavior of the firm. Despite the fact that shock-based design (or natural experiments) can be considered as the best practice in empirical corporate governance (Atanasov and Black, 2016), causal inferences have to be made with caution as it is extremely difficult to assess the shock strength and exogeneity. Future studies can employ other identification strategies such as the regression discontinuity design to assess how investment decisions and investors' preferences are affected by corporate governance and sustainability.

Lastly, each of the three studies were constrained in their scope as the aim was to provide an in-depth assessment of a single explanation of a phenomenon (Chapter 2) or index construction methodology (Chapters 3 and 4). For instance, while we present and examine the sophisticated learning explanation for the reappearance and reversal of governance–returns relation in Chapter 2, ruling out other explanations was beyond the scope. Future research could examine other related mechanisms that may have driven this reappearance. This may be done by simply regressing various outcomes or determinants of corporate governance on the governance measure itself, and then comparing the coefficients around the second structural break point to determine if systematic differences exist (Bebchuk, Cohen, and Wang, 2013; Li and Li, 2016).

5.3 Implications and Concluding Remarks

This dissertation shows that governance and ESG information cannot be ignored by the investors. When it comes to corporate governance, we show that the governance pricing anomaly continues to exist. In recent years, poor governance stocks outperform good governance ones. In theory, this may be driven by increased investor sensitivity to governance information (Pedersen, Fitzgibbons, and Pomorski, 2019), changing governance preferences of investors (Pastor, Stambaugh, and Taylor, 2019), or both. Indeed, our results show that both these factors may have acted in tandem following the 2008 global financial crisis to help institutional investors recognize governance risks and adjust their trading strategies. Through sophisticated learning, investors are able to identify profitable governance-based investment strategies that had earlier disappeared (i.e., before 2008). When it comes to ESG characteristics, we show that investors cannot blindly pay attention to all the ESG strengths or controversies that are commonly reported by the rating agencies. By focusing on important sustainability-relevant ESG subset, investors are more likely to generate abnormal returns. Similarly, managers should also not take it for granted that all ESG investments are beneficial and all ESG controversies are costly.

Since many governance rating agencies apply subjective weights in index construction, this dissertation also has the potential to contribute to the industry by showing that a neutral and objective weight extraction can be useful. Furthermore, the preliminary analysis in Chapter 3, which employs machine learning tools, can be used by ranking agencies to design advanced weight-extraction techniques for their proprietary products. For ESG rating agencies as well, this dissertation has important takeaways. While industry-based ESG rating has been widely implemented following the evidence on materiality by Khan, Serafeim, and Yoon (2016), industry-neutral ESG criteria selection is vastly understudied. In Chapter 4, we make first such attempt to identify important non-industry specific ESG indicators and show that the valuation effect of these are different from others.

This dissertation also makes important contributions to the academia. The topic in focus, i.e., corporate governance and sustainability, is widely studied across many literature streams including finance, economics, accounting, and strategy. Thus, the indices introduced in Chapters 3 and 4 (i.e., the unequal weighted governance measure, nG-Index; and the corporate sustainability measure, SUS-Index) can be used by researchers in multiple fields to raise important research questions. Using the findings of this dissertation as a launch pad, our future research agenda aims to shed further light on the underlying mechanisms that make the corporate governance and ESG data influential for risk and return. Although the idea of "doing well by doing good" is currently widely popular, it is not clear whether and how firms will be able to achieve this. Thus, our goal will be to provide insights by identifying those conditions and firm characteristics that directly influence both the stakeholder- and shareholder-orientations of the firms.

5.4 References

Ammann, M., Oesch, D., Schmid, M. M., 2011. Corporate governance and firm value: International evidence. Journal of Empirical Finance 18 (1), 36–55.

Aouadi, A., Marsat, S., 2018. Do ESG controversies matter for firm value? Evidence from international data. Journal of Business Ethics 151 (4), 1027–1047.

Atanasov, V. A., Black, B. S., 2016. Shock-based causal inference in corporate finance and accounting research. Critical Finance Review 5, 207–304.

Auer, B. R., Schuhmacher, F., 2016. Do socially (ir) responsible investments pay? New evidence from international esg data. Quarterly Review of Economics and Finance 59, 51–62.

Bebchuk, L., Cohen, A., Wang, C. C., 2013. Learning and the disappearing association between governance and returns. Journal of Financial Economics 108 (2), 323–348.

Denis, D. K., McConnell, J. J., 2003. International corporate governance. Journal of Financial and Quantitative Analysis 38 (1), 1–36.

Dumitrescu, A., El Hefnawy, M., Zakriya, M., 2019. Golden geese or black sheep: Are stakeholders the saviors or saboteurs of financial distress? Finance Research Letters, 101371.

Dumitrescu, A., Zakriya, M., 2018. Stakeholders and the stock price crash risk: What matters in corporate social performance? Working Paper Available at: http://ssrn.com/abstract=3305213.

Ferrell, A., Liang, H., Renneboog, L., 2016. Socially responsible firms. Journal of Financial Economics 122 (3), 585–606.

Khan, M., Serafeim, G., Yoon, A., 2016. Corporate sustainability: First evidence on materiality. The Accounting Review 91 (6), 1697–1724.

Li, D., Li, E. X., 2016. Corporate governance and costs of equity: Theory and evidence. Management Science 64 (1), 83–101.

Lyon, J. D., Barber, B. M., Tsai, C.-L., 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 54 (1), 165–201.

Martynova, M., Renneboog, L., 2013. An international corporate governance index. In: The Oxford Handbook of Corporate Governance. Oxford University Press, pp. 97–131.

Pastor, L., Stambaugh, R. F., Taylor, L. A., 2019. Sustainable investing in equilibrium. Tech. rep., National Bureau of Economic Research.

Pedersen, L. H., Fitzgibbons, S., Pomorski, L., 2019. Responsible investing: The ESG-efficient frontier. Unpublished working paper, Available at: http://ssrn.com/abstract=3466417.