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A thesis submitted for the degree of

Doctor of Philosophy
in
Economics, Management, & Organization

Barcelona, 2020

Acknowledgements

My Phd journey has taught me to try and be as "structurally" and "politically" correct as I can. With this in mind, and for the purpose of clarity, the order used in this acknowledgement by no means represents the degree of gratitude that I owe to each and every one mentioned.

The PhD has been a rigorous journey that I could not have endured without guidance. For that, I owe gratitude to my supervisors Professor Miguel Angel Garcia Cestona and Doctor Florina Silaghi for all the help that they have provided me throughout the process. Their inputs were crucial to this dissertation and of course any errors remain my own.

Without my loving wife and her support, this PhD would have been more difficult than it has been. I would like to thank Ghufran for supporting me and being by my side during the ups and downs of this expedition. I am truly indebted to her. Even though, my 3 year old son, Khalid, does not yet know it, his presence has provided me with an additional drive that got me going.

I would like to sincerely thank my parents, Khalid and Hanan, for supporting me in my decision to pursue my PhD in first place. I would also like to thank my sisters, Sahar, Raheem, and Kholoud for all the support that they have provided me and my family throughout the PhD period.

Of course my colleagues can't be left unmentioned. The discussions we had whether in the office, over lunch, or in the corridors were truly invaluable. Indeed, being exposed to them has helped me get alternative points of view on my work as well as insights into different interesting topics.

Abstract

In this dissertation, we approach three unique strands of the crowdfunding literature. In the first chapter, we develop a theoretical model evaluating the entrepreneur's optimal financing and launching choice when choosing between reward-based crowdfunding and debt financing. Contrary to previous literature, we show that when using reward-based crowdfunding, the entrepreneur's optimal pricing strategy involves committing to the future retail price during the crowdfunding campaign and that this unique optimal strategy involves rewarding backers with a discount relative to future retail customers. When choosing between debt financing and reward-based crowdfunding, we show that there is no unique optimal strategy. The optimal strategy would depend on the project capital requirements and the prevailing interest rate. We find that projects with lower capital requirement will prefer to launch via crowdfunding since they do not need to diverge away from the optimal crowdfunding prices. Whereas for higher capital requirements, the optimal strategy depends on the interest rate levels. In the second chapter, we diverge from the classical analysis of non-financial motives in reward-based crowdfunding and investigate how entrepreneurs can financially incentivize backers in order to improve campaign performance. We specifically show how the entrepreneur's pricing strategy can be used to signal the project's quality and the financial reward that backers receive relative to retail customers. Our study involves the analysis of two costly signals, price commitment and discount, and a costless signal, the number of reward classes. Our results show that the use of price commitment and discount by the entrepreneur is positively associated with the campaign performance. The number of reward classes exhibits a similar relationship with crowdfunding performance. However, we highlight that signals do not work in isolation and that in the presence of the costly signals, the effect of the costless signal is weakened. This provides additional support for the argument that when costly and costless signals interact, backers prioritize the former. The third chapter of this thesis extends the nascent literature on serial crowdfunding by accounting for the previously neglected contextual dimension of campaigns on the platform. We investigate the effects of changing contexts (industry and/or geographic location) on the campaign performance. We hypothesize that changing context will adversely affect the campaign outcome as some of the acquired knowledge from previous campaigns is context-specific. Moreover, we posit that entrepreneurs with higher level of crowdfunding experience are better able to make generalizations from previous experience and apply them to different contexts such that they suffer less from changing contexts. An empirical analysis of the universe of serial crowdfunders on Kickstarter provides support for our hypotheses. We additionally show that changing context following failure adds a layer of complexity which intensifies the negative relationship between changing context and campaign outcome.

Keywords: Advance-Purchase Discounts; Crowdfunding Performance; Experience; Information Asymmetry; Price Commitment; Serial Crowdfunding; Signaling

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Introduction

New ventures face difficulties attracting external finance at their initial stages (Cosh et al., 2005). Following the 2008 financial crisis, these difficulties were further amplified and new ventures faced even stricter requirements to acquire financing from banks, angel investors, and venture capital funds (Kuppuswamy & Bayus, 2017; Lee et al., 2015). Among new ventures, those that find it the hardest to raise funds are new innovative firms given their riskier business models, their often reliance on intangible assets, and the presence of asymmetric information and agency problems (Freel, 2007; Lee et al., 2015; Lerner & Hall, 2010; Mina et al., 2013; Schneider & Veugelers, 2010). Thus, this financing constraint limits the launch and growth of new entrepreneurial ventures and threatens their survival (Block et al., 2018). However, it is young innovative firms that play a key role in economic recovery since they are most likely to create new markets, achieve rapid growth, and provide an important source of new jobs (Block et al., 2017; Lee et al., 2015). Given that young innovative firms face tighter financing constraints, we have a financing gap dilemma that could have had adverse effects on economic recovery if no rectifying governmental policies or pure market mechanisms came to action.

In response to this funding gap, and over the past few years, the financing landscape has evolved, and new players have entered the arena to accommodate the needs of entrepreneurs and early-stage new ventures (e.g., crowdfunding, accelerators, angel networks, corporate venture capital, and family offices). Among these new players, some have served as alternative sources of financing while others, such as crowdfunding, have provided new investment approaches. Crowdfunding, in particular, has played a crucial role in filling the funding gap aforementioned and has spread across developed and emerging countries (Block et al., 2018). The crowdfunding market size has grown from $854 million in 2011 to $34 billion in 2015.[1] This tremendous growth in the market size shows that crowdfunding is becoming a viable financing alternative for entrepreneurs and an attractive investment opportunity for individuals. Given its significance as an alternative new source of financing for entrepreneurs worldwide and its non-traditional investment approach, crowdfunding is going to be the focus of this thesis. And more precisely, we will focus on a specific crowdfunding mechanism, reward-based crowdfunding. Even though it does not account for the largest share of the funds raised, the reward-based crowdfunding is an interesting form of crowdfunding to investigate since its contribution to the entrepreneur goes beyond sole financing, as we will elaborate in more detail later.

The most general definition for crowdfunding is given by Ahlers, Cumming, Günther, & Schweizer (2015): "Crowdfunding is an umbrella term used to describe an increasingly widespread form of fundraising, typically via the Internet, whereby groups of people pool money, usually (very) small individual contributions, to support a particular goal". The most striking feature of crowdfunding is the dispersion of the investors, with a reduced role of spatial proximity since the platform mitigates distance-related economic frictions (Agrawal et al., 2015; E. Mollick, 2014). Crowdfunding takes different forms and can generally be grouped into four main categories: lending-based, equity-based, donation-based, and reward-based crowdfunding. Lending-based crowdfunding involves soliciting funds from the public where these funds take the form

[1] Source: Massolution Crowdfunding Industry Reports available at www.crowdsourcing.org/resarch

of a loan, which the entrepreneur would need to pay back with interest (Lin et al., 2013; Lin & Viswanathan, 2016). The interest rate is either set by the platform, where the interest rate would depend on the platform's credit rating criteria, or through an auctioning process. In equity-based crowdfunding, the entrepreneur solicits funds from investors in return for equity in the venture (Belleflamme et al., 2014b; Walthoff-Borm et al., 2018). Prior to April 5th, 2012, firms in the United States were not allowed to use crowdfunding to issue securities. However, President Barack Obama signed the Jobs Act into law to stimulate the funding of small businesses and new entrepreneurial activities, allowing firms to use crowdfunding as a means of issuing securities. Generally, equity crowdfunding tends to be the most regulated type of crowdfunding worldwide. Donation-based crowdfunding involves an altruistic act without any obligation for the recipient to give anything in return; funds are generally being raised for charitable and social causes (Wojciechowski, 2009). Finally, in reward-based crowdfunding supporters back the entrepreneur's project in the promise of a reward. For projects in the music or film category, these rewards usually take the form of early accessing (viewing/listening/ streaming) rights. Whereas for projects where the funds are being raised for the production of a product, backers are essentially pre-ordering the product (E. Mollick, 2014).

Reward-based crowdfunding is of particular interest to us in this thesis given that its role extends beyond sole financing purposes. Entrepreneurs raising funds through reward-based crowdfunding are able to use it as a tool for demand exploration, as well as a way of building a customer base prior to production (Brown et al., 2017), hence serving as a new marketing strategy. Given the role that reward-based crowdfunding plays as a new financing technology and alternative distribution channel, it provides a very interesting context for further investigation. We believe that this interaction between financing and commercialization will play an increasing role in the future given its ability to reduce the risk faced by the entrepreneur. The entrepreneur is no longer required to risk capital in production prior to confirmed pre-orders. Entrepreneurs who turn to crowdfunding their new projects even when there are in no real need for financing, further confirm the attractiveness of this feature. Additionally, the added value of this financing alternative is the openness of the product development process. Entrepreneurs are able to use input from backers suggesting modifications to the product and incorporate these changes to the product during production, leading to a more satisfied and sustainable customer base. Finally, democratizing finance such that the crowd has a say on what kind of projects are financed and launched in the market is an interesting evolution in the financing landscape, and hence investigating the factors influencing the crowd's decision is of real essence.

Kickstarter, the leading reward-based crowdfunding platform, has helped 166,339 projects successfully raise $3.92 billion as of July 10th, 2019 (approximately 10 years since its launch in 2009). Kickstarter employs an "all or nothing" funding mechanism, which requires the project to at least raise the goal set by the entrepreneur before any funds are disbursed. If the project fails to raise the minimum goal set, project supporters are refunded and no funds are transferred to the entrepreneur. An alternative mechanism is the "Keep it all" mechanism, such as that offered under Indiegogo. Under this mechanism, the entrepreneur gets to keep any funds raised during the campaign even if the campaign's goal has not been met (Cumming et al., 2014).

Although incipient, the reward-based crowdfunding literature has grown fast and its focus spans different dimensions. A strand in the literature has developed and proposed different theoretical models addressing the choice of the optimal pricing and financing strategy. Belleflamme et al. (2014) propose a theoretical model in which they compare two types of crowdfunding: reward-based and equity-based crowdfunding. Their model proposes that entrepreneurs can use reward-based crowdfunding to discriminate against campaign supporters and charge them a premium given that campaign supporters enjoy community benefits that increase their utility. A similar pricing strategy is proposed by Kumar, Langberg, & Zvilichovsky (2016), but the price premium is attributed to the pivotal role of consumers. Hu, Li, & Shi (2015) propose different pricing policies (uniform pricing, margin strategy, volume strategy, and intertemporal pricing) for the rewards offered during the campaign. The entrepreneur's optimal pricing policy will depend on the fraction of high to low type buyers. Additionally, Ellman & Hurkens (2014) study the benefits of crowdfunding as a tool for price discrimination and reducing demand uncertainty.

In the first chapter of this thesis, we add to this theoretical literature on crowdfunding and propose a theoretical model on optimal pricing and financing strategy for an entrepreneur choosing between reward-based crowdfunding and debt financing (i.e., bank loans, lending-based crowdfunding). We stress that reward-based crowdfunding is more than just a financing alternative, since it also acts as a launching strategy. Entrepreneurs with no need for financing could opt for crowdfunding as a launching alternative, as it provides them with a tool to discriminate amongst the population of consumers, which is done through segmenting consumers into backers (who pre-order the product) and retail consumers. Therefore, when an entrepreneur is evaluating the available options, he is, in essence, identifying the optimal financing and launching alternative. The model proposed addresses projects offering consumer products such that backers are pre-ordering the product during the campaign.

In the theoretical model we start by determining the entrepreneur's optimal pricing strategy and show that for an entrepreneur opting for reward-based crowdfunding, rewarding backers with a discount relative to the future retail consumers is the optimal pricing strategy. This is in line with the literature on the optimality of advance-purchase discount (Dana, 1998; Gale & Holmes, 1993; Möller & Watanabe, 2010; Nocke et al., 2011). However, it is contrary to Belleflamme et al. (2014) which suggests that entrepreneurs can discriminate against backers by charging them a premium. We believe that the difference in the findings stems from the nature of the projects addressed: we focus on projects offering consumer products, while in their case, their findings are supported by anecdotal evidence from projects in the music category. The novelty in the proposed model is that it employs price commitment. We additionally show that price commitment during the campaign is a possible and dominant strategy and can be achieved by publicizing the future retail price during the campaign. The intuition is that when no information is publicized during the crowdfunding campaign regarding the future retail price, only those who highly value the product would be willing to pre-order the product. Whereas, by price committing the entrepreneur mitigates any uncertainty that the consumer has regarding the future retail price, and financially incentivizes a larger consumer base to pre-order the product. Additionally, when the funds required are beyond what the entrepreneur could optimally raise in pre-orders, we show that the entrepreneur is able to further shift uncertain future demand into pre-orders by increasing the discount offered to campaign backers. Comparing debt obligations and crowdfunding, we find that there is not a unique optimal financing strategy for all projects. The optimal strategy would depend on the project capital requirements and the prevailing interest rate. We find that projects with lower capital requirement will prefer to launch via crowdfunding since they do not need to diverge away from the optimal crowdfunding prices. Whereas for higher capital requirements, the optimal strategy depends on the interest rate levels.

Given that the crowdfunding setting is prone to information asymmetries, another strand in the literature empirically investigates how the use of different signals can alleviate the adverse effects of information asymmetries on campaign performance. For example, Courtney, Dutta, & Li (2017) investigate how signals originating from the entrepreneur (media usage and crowdfunding experience) and from third-party endorsements (backer sentiments) positively affect campaign performance. They additionally study the interaction of these signals investigated and find that signals originating from the same source offset each other, while signals originating from different sources complement each other. Scheaf et al. (2018) similarly investigate other signals (e.g., media coverage and patent ownership) and argue that signals considered effective in one setting might not be as valuable in another setting. With this in mind, they explore the flexibility of the signals across two different crowdfunding mechanisms, reward-based and equity-based crowdfunding. Their findings support their arguments that some signals maintain their effectiveness across different exchange contexts, namely media coverage, while others do not, namely patent ownership.

Although a signal's credibility has been traditionally associated with the cost of acquiring it and the crowdfunding literature has mainly focused on the effectiveness of the costly signals, Anglin et al. (2018) introduce costless signals (psychological capital) to the crowdfunding context and show their effectiveness. This provides the basis for investigating a different type of signals, costless signals, in the crowdfunding setting. Moreover, they show how the relationship between a costless signal and campaign performance is moderated by a costly signal (human capital).

In the second chapter, we draw on information economics theory that proposes multiple ways of dealing with information asymmetry and contribute to the signaling literature in reward-based crowdfunding. During the campaign, relative to potential backers, entrepreneurs possess more information about the quality and the future retail price of the product offered. Thus, backers face the risk of adverse selection regarding two aspects, the product quality and the discount they are rewarded with for their support. The signaling theory, originally proposed by Michael Spence (1973), suggests that entrepreneurs can use signals valued by their counterparty to mitigate this risk. Given that backers are mainly driven by financial motives in their decision to back (Cholakova & Clarysse, 2015), they should particularly value signals conveying information regarding the financial reward offered by the entrepreneur.

We analyze novel signals, both costly and costless, related to financial motives in reward-based crowdfunding. In doing so, we diverge from the classical analysis of non-financial motives in reward-based crowdfunding. We argue that the entrepreneur can resolve issues related to adverse selection by using a pricing strategy that signals not only the quality of the reward (product) offered, but also signals information about the financial reward offered (Bagwell & Riordan, 1991; Chen & Jiang, 2016; Dai, 2016; Stacey, 2016; Yu et al., 2015). Since reward-based crowdfunding platforms do not allow promises of a financial return, this financial reward takes the form of a promised discount relative to future retail price. We propose that this could be signaled by two costly signals, price commitment and discount, and a costless signal, the number of reward classes. In the presence of multiple signals, signals do not work in isolation, they interact. In particular, we expect that the effect of the costless signal is weakened in the presence of a costly signal.

We test our hypotheses on a random sample of 650 projects manually collected from Kickstarter, launched between 2010 and 2016. Our results show that projects publicizing their future retail price, employing price commitment, are more likely to be successful. Moreover, a higher discount is associated with a more favorable funding outcome and the probability of success increases with the size of the discount offered. Additionally, we find that projects offering a larger number of reward classes also enjoy better campaign performance. The intuition is that with more reward classes available, potential backers are better able to construct their expectations regarding the future retail price, which stimulates backing activity. However, our analysis also shows that price commitment and the presence of a discount moderate the effect of the number of reward classes on campaign performance. This is attributed to the fact that the information conveyed by the number of reward classes regarding the expected retail price becomes, somewhat, redundant in the presence of an explicit announcement of the future retail price. This provides additional support for the argument that when costly and costless signals interact, backers prioritize the former (Anglin, Short, et al., 2018).

Another strand in the literature extends serial entrepreneurship studies to the crowdfunding context and investigates the dynamics of serial founders in crowdfunding platforms. Serial founders in the crowdfunding context are entrepreneurs with previous crowdfunding experience, regardless of previous campaigns outcome, and are referred to as serial crowdfunders (Butticè et al., 2017). They account for a significant portion of the funds raised on reward-based crowdfunding platforms. From its inception and up to November 2016, serial crowdfunders raised $859 million on Kickstarter. This represents more than 30% of all the funds raised on Kickstarter during the same period. Kuppuswamy & Mollick (2016) investigate the difference in serial founding rates by gender and find that females are less likely to launch subsequent crowdfunding projects regardless of current campaign outcome. Regarding the performance of serial crowdfunders, Yang & Hahn (2015) find that prior founding experience enhances campaign performance due to accrued learning effects. Skirnevskiy, Bendig, & Brettel (2017) further investigate this advantage by analyzing the effect of previous crowdfunding experience on early campaign performance (number of backers and amount of funds raised). They find a positive effect of prior experience on early campaign performance (the first 1/6th days of total campaign duration) which in turn enhances final campaign outcome. Butticè et al. (2017) turn to the social capital acquired by serial crowdfunders through prior founding experience on the crowdfunding platform, and attribute the outperformance of serial crowdfunders to it. The effect of this social capital is stronger than that acquired by backing others' projects. However, it is worth noting that the effects of this social capital diminishes overtime.

The crowdfunding literature, thus far, has treated the crowdfunding platform as a domain where entrepreneurial learning aids in the accumulation of entrepreneur-specific human capital that is transferable across ventures (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017, 2018; Scheaf et al., 2018). Nevertheless, this is quite a loose generalization since the process of knowledge transfer between campaigns is contingent upon multiple dimensions (Barnett & Ceci, 2002). To be more informative, we need to distinguish between what is learned across ventures (the content-domain), i.e., the tasks required to launch a campaign, and where learning is transferred from and to (the context-domain), i.e., what industry or geographic location, as suggested by Barnett & Ceci (2002).

In the third chapter, we add to the literature on serial crowdfunding by distinguishing between the content and context domains in the crowdfunding setting. Regarding the content-domain, we track the number of previous campaigns launched by the same entrepreneur on the crowdfunding platform and use it as a measure for the task-content similarity between the current campaign and the tasks undergone in previous campaigns. This is a similar approach to the work of Toft-Kehler, Wennberg, & Kim (2014) performed in a traditional setting with serial entrepreneurs. The rationale for this is that entrepreneurs who launched more projects have a wider set of previous experiences that act as a reference for the tasks to be carried out in the current venture (Tversky & Kahneman, 1992). Regarding the contextual domain in crowdfunding, we analyze the two most prominent contextual dimensions identified in the traditional venture launching setting, the industry and geographic location of the venture (Delmar & Shane, 2006; Klepper, 2002; Toft-Kehler et al., 2014).

After identifying the content and context domains in the crowdfunding setting, we investigate the importance of the contextual domain (industrial and geographic) and its effect on the campaign outcome. Specifically, we are interested in analyzing how changing context can act as an obstacle to the appropriate transfer of knowledge among campaigns. We refer to these obstacles as barriers to learning since an entrepreneur not only learns during the campaign, but also learns from previous experience ex-post, as previous experience serves as reference point for the entrepreneur (Tversky & Kahneman, 1992). Changing contexts will adversely affect the entrepreneur's ability to learn and appropriately make inferences applicable to the current venture. We develop arguments for why serial crowdfunders are harmed by changing contexts between campaigns by building upon the serial entrepreneurship literature on industry experience and physical location and their effects on venture performance. In the crowdfunding context, industry is accounted for by the campaign's category and the physical location is the publicized location of the campaign. We additionally explore how task-content similarity between campaigns can alleviate such barriers to learning. Additionally, we cannot investigate learning in the crowdfunding context without considering the previous campaign outcome. In fact, the literature on learning has suggested that learning from failure is far more complex than learning from success (Baumard & Starbuck, 2005). Following a failure, introducing contextual change to the process of new venture creation increases the complexity of the information that an entrepreneur needs to process (Lord & Maher, 1990), which could result in a suboptimal campaign performance. Along these lines, we also develop arguments as to why the previous campaign failure intensifies the barriers to learning stemming from contextual change.

We probe our research questions using the universe of serial crowdfunders on Kickstarter since its start up to November 2016. In that time period, we have a sample of 29,788 serial crowdfunders with 75,654 campaigns. Our analysis reveals that changing contexts (industrial and/or geographic) between campaigns is negatively associated with the subsequent campaign outcome. This suggests that the entrepreneur is less able to effectively utilize the knowledge acquired from previous experience when the context of the current campaign differs from that of the previous campaigns. However, we find evidence that serial crowdfunders with higher levels of crowdfunding experience are less harmed by changing industries between campaigns due to the increased task-content similarity between prior and current ventures. Thus, entrepreneurial experience moderates the negative relationship between industry change and campaign performance. Our main analysis provides no supporting evidence for the presence of a moderation effect of entrepreneurial experience on the negative association between changing physical location and the campaign outcome. This result stimulated us to perform a post hoc analysis and investigate whether entrepreneurs learn from merely launching new campaigns, or if learning benefits accrue differently depending on the previous campaigns' outcomes. As a result, we find that the negative relationship between a change in physical location and the campaign outcome is only attenuated by prior successful experience, while prior unsuccessful experience intensifies this negative relationship. Regarding previous campaign failure, our findings support the notion that contextual change following failure adds another layer of complexity that intensifies the barriers to learning in the crowdfunding context which, in turn, adversely affects the current campaign outcome.

Summing up, the three chapters of this thesis contribute to three unique strands of the crowdfunding literature: theoretical modeling of financing choice, signaling in crowdfunding, and serial crowdfunding. These three chapters are solely focused on reward-based crowdfunding, we do not mix different crowdfunding platform types since different mechanisms could be playing different roles in different crowdfunding settings. In the research conducted in this thesis, unlike most of the previous literature, rather than resorting to phenomena driven and descriptive analysis, we employ an analysis founded on established theoretical frameworks that we extend to the reward-based crowdfunding setting. The nature of the work presented here employs a theoretical and quantitative analysis with the aim to stimulate research in previously unexplored aspects of crowdfunding. Within each chapter, we will discuss in detail the contribution of our work to the state of the art. Moreover, the implications of our findings for future research as well as the limitations of our work are further highlighted. This introduction is followed by three chapters which constitute the main body of this thesis. We conclude this thesis with a "Concluding Remarks" section where we highlight the implications of our work for future research, and we additionally acknowledge the limitations of the work performed.

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Chapter 1
OPTIMAL FINANCING STRATEGIES WITH PRICE COMMITMENT & ADVANCE-PURCHASE DISCOUNTS IN CROWDFUNDING

ABSTRACT

Recent literature has theoretically modelled reward-based crowdfunding using a price discrimination mechanism through which entrepreneurs charge crowdfunders a *premium.* However, more than 50% of the 100 most funded projects on Kickstarter offer a *discount* to early purchasers, with the discount being publicized during the campaign. We contribute to the literature by modeling pre-ordering using an advance-purchase discount while employing retail price commitment. We show that crowdfunding dominates spot selling when the entrepreneur is financially unconstrained. Whereas, when comparing between debt financing and crowdfunding, we find that the entrepreneur's optimal strategy depends on the project's characteristics and the prevailing interest rate.

Content

1. Introduction

The ability of entrepreneurs and innovators to start new ventures is the engine of every economy, or as U.S. Congress representatives Scott Peters, Ron Kind & Patrick Murphy put it "the bedrock of America's economy".[2] Nevertheless, a common issue that most entrepreneurs are facing in the traditional financing market is their inability to access debt financing for their ventures. Innovations in the alternative finance sector has brought crowdfunding to rise as a viable and significant source of funds for entrepreneurs (Schwienbacher and Larralde, 2012). Even though some entrepreneurs might tap crowdfunding to finance their ventures because of their lack of tangible assets that are "required" to access the debt-financing market (Denis, 2004), we observe that some entrepreneurs with previous crowdfunding successes and presentable tangible assets continue to return to crowdfunding for their future projects (Buttice, Colombo, & Wright, 2017). This suggests that crowdfunding is not always the entrepreneur's "last resort".

Since its appearance, crowdfunding has brought to life projects that would not have seen the light otherwise (Kuppuswamy & Bayus, 2018). An example is the Pebble smartwatch project. Eric Migicovsky, the founder of Pebble, envisioned a smartwatch that would be connected to a smartphone and display messages on the go. He was unable to attract traditional investors for his project. Migicovsky then took his idea through the Y Combinator, a business incubator program. During the program, he was able to generate revenues and raise $375,000 through angel investors but he was left hanging, unable to raise further funds to undergo production. On April 11, 2012, Migicovsky launched a Kickstarter campaign to raise $100,000 in the form of pre-orders from the crowd in order to launch his venture. When the campaign ended on May 18, 2012, he had successfully raised $10,266,845 from 68,929 backers.

Eric Migicovsky's Pebble came to life post its crowdfunding campaign's success where crowdfunding served as his *last financing resort*. Whereas, for future projects it is worth noting that despite his ability to raise funds in the form of debt financing, Eric Migicovsky chose to launch his two subsequent projects via crowdfunding, and raised an additional total of $33 million in pre-orders. In this context, a deep understanding of crowdfunding and its underlying mechanisms is of great importance, not only for academics but also for market agents and regulators. The choice of an alternative financing source when traditional financing alternatives are available calls for investigation. To address this issue, we contribute to the scarce literature on crowdfunding by developing a theoretical framework to analyze an entrepreneur's optimal pricing, launching, and financing strategy when offered different options: spot selling, spot selling with standard debt, and reward-based crowdfunding.

It is important to stress that reward-based crowdfunding is more than just a financing alternative, since it also acts as a launching strategy. Entrepreneurs with no need for financing could opt for crowdfunding as a launching alternative, as it provides them with a tool to discriminate amongst the population of consumers which is done through segmenting consumers into backers (who pre-order the product) and retail consumers. Therefore, when an entrepreneur is evaluating the available options, in essence he is identifying the optimal *financing* and *launching* alternative.

[2] The Huffington Post, "Entrepreneurs: Engines of our economic growth", November 18, 2014.

Belleflamme, Lambert, & Schwienbacher (2014) and Kumar, Langberg, & Zvilichovsky (2016) present one of the first attempts to theoretically model crowdfunding. In both models the authors show that crowdfunding enables the entrepreneur to price discriminate against the backers who value the good more than regular consumers. Additionally, in both models, there is no price commitment by the entrepreneur when launching the campaign, such that the entrepreneur does not publicize the future retail price. As shown by Belleflamme et al. (2014), their proposed model is supported by anecdotal evidence from the music category. We observe that their findings hold also for art related projects (music, movies, photography, etc.). However, when analyzing the 100 most funded projects on Kickstarter we find that more than 50% of these projects do publicize future retail prices and, on the contrary to previous models, they offer backers a discount in return for their support. In fact, those projects committing to future retail prices were offering tangible products, which we refer to hereafter as "consumer products".[3] These projects are different in nature from art related projects, thus the need to address and explain the price path and crowdfunding mechanism for a sizable portion of crowdfunding projects so far neglected.

In this paper, we contribute to the crowdfunding literature by building upon theoretical models from the economics literature on advance-purchase discounts, in order to gain insights into the crowdfunding mechanism. Advance-purchase discount has been identified as an optimal profitable strategy in different settings and the optimality of this discount depends on capacity costs and demand uncertainty (Dana, 1998; Gale & Holmes, 1993; Möller & Watanabe, 2010). We specifically build on the general model of Nocke, Peitz, & Rosar (2011), that focuses on advance-purchase discount as a price discrimination device, which can be an optimal pricing strategy when compared to advanced selling and spot selling. We incorporate elements of this general model into a crowdfunding framework to help us derive the optimal crowdfunding pricing strategy.

The novelty in our model is that we employ price commitment, where the entrepreneur publicizes both the pre-ordering and the future retail price during the crowdfunding campaign. Given these prices, rational consumers in an intertemporal setting maximize their utility by choosing whether to pre-order today, or wait until the product is launched in the retail market. We show that rewarding the backers with a price discount is the entrepreneur's optimal pricing policy. Moreover, we compare the different crowdfunding pricing strategies, price commitment and no price commitment, and show that, indeed, price commitment is the dominant crowdfunding pricing strategy. The intuition is that when no information is publicized during the crowdfunding campaign regarding the future retail price, only those who highly value the product would be willing to pre-order the product. Whereas, by price committing the entrepreneur mitigates any uncertainty that the consumer has regarding the future retail price and financially incentivizes a larger consumer base to pre-order the product. Thus, expanding the size of his crowdfunding market. This finding has testable empirical and practical implications for entrepreneurs launching their projects via crowdfunding. It suggests that entrepreneurs can enjoy higher funding amounts when committing to prices, which in turn means that their crowdfunding campaign will enjoy a higher probability of success.

[3] Consumer products is a generalized classification combining projects in the following subcategories: 3D Printing, Accessories, Apparel, Camera Equipment, Childrenswear, Couture, Footwear, Gadgets, Gaming Hardware, Jewelry, Pet Fashion, Playing Cards, Product Design, Puzzles, Ready-to-Wear, Robots, Sound, Tabletop Games, Video Games, and Wearables.

We then proceed by comparing the launching strategies, crowdfunding and spot selling, when the entrepreneur is financially unconstrained. For an entrepreneur to be financially unconstrained means that he can personally provide the required capital to launch his venture and there is no liquidity need. We find that crowdfunding allows the entrepreneur to discriminate against the population of consumers by separating them into retail period customers and pre-ordering customers. By doing so the entrepreneurs is able to shift uncertain future demand into certain pre-orders, as well as expand his market. Crowdfunding comes at a cost which stems from the discount offered to backers for pre-ordering the product. However, it results in increased demand that offsets the cost of the discount yielding higher profits compared to spot selling. Therefore, when the entrepreneur evaluates spot selling and crowdfunding as "pure launching strategies" we find that crowdfunding dominates spot selling.

Moreover, we extend the model to entrepreneurs who require financing to start production. In this case the entrepreneur would be choosing the optimal financing and launching alternative. The financing options available to the entrepreneur are debt obligations (i.e., bank loans, P2P lending) and crowdfunding. Crowdfunding allows the entrepreneur to raise funds in the form of pre-orders, thus acts as a financing source. When the funds required are beyond what the entrepreneur could optimally raise in pre-orders, we show that the entrepreneur is able to further shift uncertain future demand into pre-orders by increasing the discount offered to campaign backers. This increase in the discount would be a result of lowering the crowdfunding period price, as well as increasing the publicized future retail price. In the extreme, by increasing the discount sufficiently, the retail market closes and the entrepreneur would only be selling to backers who pre-order the product. This has testable empirical implications as well as practical implications for entrepreneurs who can increase the discount that they offer to backers in order to raise more in the crowdfunding period and increase the probability of success.

Comparing debt obligations and crowdfunding, we find that there is not a unique optimal financing strategy for all projects. The optimal strategy would depend on the project capital requirements and the prevailing interest rate in the debt market. We find that projects with lower capital requirement will prefer to launch via crowdfunding since they do not need to diverge away from the optimal crowdfunding prices. Whereas for higher capital requirements, the optimal strategy depends on the interest rate. As interest rates increase, crowdfunding becomes a more attractive option for the entrepreneur. This suggests that we would expect to see more and more entrepreneurs tapping crowdfunding as a financing alternative in an environment with increasing interest rates.

Other than the novel testable empirical implications mentioned earlier, the model proposed has other implications which have been supported by empirical findings. Chan and Parhankangas (2017) find that projects with incremental innovation enjoy higher probabilities of success when compared with projects with radical innovation. This is in line with the implications of the model proposed which suggests that projects promising larger shocks to industry standards are more constrained for lower levels of capitals, thus reducing their probability of success. Furthermore, the model proposed implies that riskier projects would find crowdfunding a more attractive financing option when compared to standard debt which is in line with the results of an empirical analysis by Xu (2017) who shows that entrepreneurs tend to launch riskier projects on Kickstarter.

The contribution of our work can be best seen in light of the existing theoretical crowdfunding literature. Miglo & Miglo (2018) present a model of an entrepreneur's choice between different types of crowdfunding and traditional financing. Although closely related to our work, in their model price choice is exogenous. The authors disregard price discrimination between customers even though it is one of the main drivers of opting for crowdfunding. Turning to the theoretical literature on pricing in the crowdfunding context, Hu et al. (2015) explore different pricing decisions given product attributes. However, their proposed model does not extend to show how entrepreneurs choose between different crowdfunding types and traditional financing options given the optimal price choice. Optimal price choice is determined when crowdfunding is the only available option for the entrepreneur. A different strand in the theoretical crowdfunding literature has emphasized the crowdfunding ability to aggregate vague information about consumer preferences and to act as a demand exploration tool (Ellman & Hurkens, 2014; Chemla & Tinn, 2016; Gruener & Siemroth, 2016). Although when looking at the standard debt alternative we assume perfect symmetric information, our results can be related to those of this literature. In particular, Hakenes & Schlegel's (2014) reason that entrepreneurs opt for crowdfunding in order to exploit the consumers' private information rather than their financial sources. They show that good projects are more likely to get funded through crowdfunding rather than through standard debt and that bad firms strictly prefer standard debt. In our model we have seen that entrepreneurs prefer crowdfunding over standard debt for riskier projects while for other projects the entrepreneur's financing strategy depends on the capital requirement and the prevailing interest rate in the credit market.

The rest of the paper is organized as follows: Section 2 describes our proposed basic model. In Section 3 we compare the pricing strategies available under the different launching options. In Section 4 we proceed by determining the optimal launching and financing strategy. In Section 5 we conclude the paper with a discussion of the findings, we provide empirical implications of the theoretical model proposed, we address the limitations of the model proposed, and propose future areas of research.

2. The Model

2.1 The Entrepreneur

Our basic model considers the entrepreneur as a monopolist launching a venture. At $t = 0$ the monopolist chooses whether to spot sell the good or use crowdfunding since the latter provides the possibility of generating demand while raising capital pre-production. The entrepreneur's launching strategy will depend on the venture's capital requirement. When the entrepreneur has no capital constraint, he is essentially choosing between launching through spot selling or launching through reward-based crowdfunding: keep-it-all (KIA). Whereas, if the capital requirement is beyond what the entrepreneur can personally provide, then the entrepreneur is choosing between launching through spot selling financed with standard debt or through reward-based crowdfunding: all-or-nothing (AON). When we refer to the capital requirement, K, hereafter it denotes the project's capital requirement beyond what the entrepreneur can personally provide (Chang, 2016). This capital requirement represents the fixed cost that the entrepreneur needs to invest in order to launch his venture. The entrepreneur will need to evaluate the launching options and accordingly choose the optimal launching strategy at $t = 0$.

2.2 The Consumer

It has been well established in the literature that reward-based backers are motivated by non-monetary incentives (Gerber et al., 2012; Pierrakis & Collins, 2012; Schwienbacher & Larralde, 2012). For example, Belleflame et al. (2014) propose that backers in a reward-based crowdfunding setting enjoy community benefits. However, our focus is to capture the effects of financial incentives in reward-based crowdfunding. Thus, similarly to Miglo & Miglo (2018), we do not incorporate these non-monetary incentives in the proposed model.

Building on Nocke et al. (2011), but assuming a uniform distribution for simplicity, there is a unit mass of consumers with a unit demand. The consumer's type is described by his valuation of the good which is represented by his θ. θ is uniformly distributed between [0,1]. The consumer's ex-post valuation is expressed as $v_Z(\theta) = \theta + \alpha_z$, for $z \in$ {L,H}, which can take one of two values, a high value $v_H(\theta)$ with probability λ and a low value $v_L(\theta)$ with probability 1- λ. Thus, the consumer's ex-post valuation depends on the realized shock, α_z. This shock is independent of the consumer's type where, by construction, the expected value of the shock is zero, $\lambda\alpha_H + (1-\lambda)\alpha_L = 0$, with $\alpha_L \in (-\frac{1}{2},0)$ and $\alpha_H \in (0, \frac{1}{2})$.[4] At t = 0, each consumer privately learns his own type, θ. At t = 1, each consumer privately learns the realization of his valuation $v_Z(\theta)$. Note that in order for the expected value of the shock to be zero, we need to impose some restrictions on the probability of having a positive shock λ. In particular, consider $\lambda > \frac{1}{1+2\alpha_H}$. In such a case the expected value of the shock to quality is always strictly positive, and not equal to zero. We therefore make the following assumption:

Assumption 1.

$$\lambda \leq \frac{1}{1 + 2\alpha_H}$$

2.3 Launching Alternatives & Timing of Events

2.3.1 Spot Selling

When the entrepreneur does not require any capital to launch his venture then he can proceed with production and launch his product in the spot market. The timing of events is as follows:

1. At t = 0: the entrepreneur sets P_S.[5]
2. At t = 1: the product is launched in the spot market, customers realize the shock and make their purchase decision.
3. At t = 2: goods are delivered to customers.

[4] Since we are working with a uniform distribution between [0,1], the parameters have been set in order to guarantee interior solutions for the demand.
[5] In the model that we will propose, similar to Belleflame et al. (2014), the marginal cost of production is zero. Prices set by the entrepreneur can be interpreted as markups above the marginal cost.

2.3.2 Spot Selling with Standard Debt

The entrepreneur is launching the product in the spot market, but the project's capital requirement is beyond what the entrepreneur can personally provide. The entrepreneur taps external sources of funds which are provided in the form of a debt obligation. External sources of funds come at a cost, the cost of capital is denoted by *r,* with *R* denoting (*1+r).* The timeline of this launching strategy is as follows:

1. At t = 0: the entrepreneur takes a loan to cover the capital requirement *K* and invests it, the entrepreneur sets P_S^C.
2. At t = 1: the product is launched in the spot market, customers realize the shock and make purchase decision.
3. At t = 2: loan plus interest is paid back and goods are delivered to customers.

2.3.3 Reward-based Crowdfunding: Keep-it-All (KIA)

When launching a venture through a KIA crowdfunding scheme, the entrepreneur has no capital requirement threshold that he needs to meet in the crowdfunding stage. Thus, he can keep whatever he raises during the crowdfunding campaign period. The timing of events is as follows:

1. At t = 0: the entrepreneur sets the crowdfunding price P_C, publicizes the regular price P_R, and receives pre-orders from backers.
2. At t = 1: the entrepreneur delivers pre-orders, the product is launched in the spot market, regular customers realize the shock and make their purchase decision.
3. At t = 2: goods are delivered to regular customers.

2.3.4 Reward-based Crowdfunding: All-or-Nothing (AON)

For projects opting to launch via an AON scheme, a capital requirement needs to be publicized and funds raised from pre-orders should meet this capital requirement in order for the entrepreneur to have access to the funds. In case this capital threshold is not met, then the project fails and the entrepreneur does not receive the amounts pledged by the backers. The timing of events in AON crowdfunding is as follows:

1. At t = 0: the entrepreneur sets the capital requirement *K*, sets the crowdfunding price P_C^C, publicizes the regular price P_R^C, and receives pre-orders from backers.
2. At t = 1: the entrepreneur delivers pre-orders, the product is launched in the spot market, regular customers realize the shock and make purchase decision.
3. At t = 2: goods are delivered to regular customers.

A list of the variables and their corresponding notations is provided in Table 1.1.

3. Pricing Strategy of Different Launching Options

3.1 Spot Selling

When spot selling, following Nocke et al. (2011), the entrepreneur sets the price P_S at t=0. The entrepreneur is uncertain regarding the consumers' realization of the shock at t = 1. The marginal consumer who would purchase the good at t = 1 if a negative shock

Table 1.1: Definition of Variables

Variable	Definition
θ	Consumer's valuation of the product, this variable is uniformly distributed between [0,1].
α_H, α_L	α_H (α_L) is the positive (negative) realized by the consumer when product is delivered.
λ	The probability that the positive shock is realized when product is delivered.
K	Capital required to launch venture.
Variables specific to the model of Spot Selling:	
θ_H, θ_L	The marginal consumer in case a negative (positive) shock is realized is denoted by θ_H (θ_L).
$P_S, E[Q_S]$	Price charged to consumers (P_S) and expected demand in the spot market ($E[Q_S]$).
$E[\pi_S]$	Expected profits in the spot market.
Variables specific to the model of Spot Selling with Standard Debt:	
$P_S^C, E[Q_S^C]$	Price charged to consumers (P_S^C) and expected demand in the spot market ($E[P_S^C]$).
$E[\pi_S^C]$	Expected profits in the spot market.
r, R	r is the interest rate of the debt obligation; by definition: $R = 1 + r$
$\overline{K}_S$	This is the maximum amount that the entrepreneur is able to solicit in debt obligations.
Variables specific to the model of Reward-based Crowdfunding Keep it All (KIA):	
θ_C, θ_R	The marginal consumer in the crowdfunding period (θ_C) and the retail period (θ_R).
P_C, P_R	Price charged to crowdfunders (P_C) and regular consumers (P_R).
$Q_C, E[Q_R], E[Q_{CF}]$	Crowdfunding demand (Q_C), retail period demand ($E[Q_R]$), and total demand ($E[Q_{CF}]$).
$\pi_C, E[\pi_R], E[\pi_{CF}]$	Crowdfunding period profits (π_C), retail period profits ($E[\pi_R]$), and total profits ($E[\pi_{CF}]$).
Variables specific to the model of Reward-based Crowdfunding All or Nothing (AON):	
θ_C^C, θ_R^C	The marginal consumer in the crowdfunding period (θ_C^C) and the retail period (θ_R^C).
P_C^C, P_R^C	Price charged to crowdfunders (P_C^C) and regular consumers (P_R^C).
$Q_C^C, E[Q_R^C], E[Q_{CF}^C]$	Crowdfunding demand (Q_C^C), retail period demand ($E[Q_R^C]$), and total demand (Q_{CF}^C).
$\pi_C^C, E[\pi_R^C], E[\pi_{CF}^C]$	Crowdfunding period profits (π_C), retail period profits ($E[\pi_R]$), and total profits after investment ($E[\pi_{CF}]$).
$\underline{K}_{CF}$	Capital that can be raised in pre-orders without diverging from optimal KIA pricing strategy.
$\overline{K}_{CF}$	Maximum capital that can be raised through crowdfunding.

is observed is defined by $\theta_H = P_S - \alpha_L$ and will be referred to as the high type.[6] Whereas the marginal consumer who would only purchase the good in case of a positive shock is defined by $\theta_L = P_S - \alpha_H$ and will be referred to as the low type hereafter, where $\theta_H \geq \theta_L$ (see Figure 1.1).

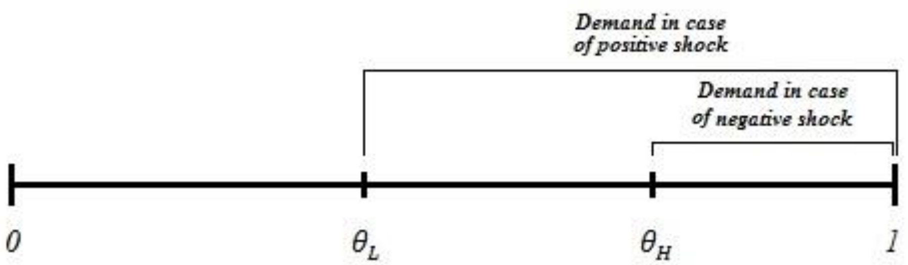

Figure 1.1: Demand in case of positive and negative shock.

When setting P_S the entrepreneur faces a trade-off. On the one hand, if the price is set low enough, then he will attract demand from consumers with valuation $\theta \geq \theta_H$ in case of a negative shock. However, in case of a positive shock he foregoes the possibility

[6] Hereafter we will be abusing the terminology, even though in the uniform distribution there is a continuum of types and not just two types, we will refer to those with $\theta \geq \theta_H$ as the high type and those with with $\theta_L \leq \theta < \theta_H$ as the low type consumers.

of charging a high price. On the other hand, setting a high price in order to extract more rents from consumers in case of a positive shock would imply foregoing demand in case of a negative shock. The available strategies are characterized below.

Strategy A: Attract demand for both the positive and negative shock.

Under this strategy, the entrepreneur's maximization problem can be written as follows:

$$\max_{P_S} \boldsymbol{\pi(P_S) = \lambda P_S(1-\theta_L) + (1-\lambda)P_S(1-\theta_H)}$$

$$s.t.\ \theta_H = P_S - \alpha_L\ ;\ \theta_L = P_S - \alpha_H\ ;\ \theta_H \in [0,1]\ ;\ \theta_L \in [0,1] \quad (1)$$

Here we have that the profit maximizing price $\hat{P}_S \leq \theta_H + \alpha_L$. In this case, the low type consumers (with $\theta_L \leq \theta < \theta_H$) participate only when observing a positive shock. The high type consumers (with $\theta \geq \theta_H$) participate both in case of a positive and of a negative shock. The first order conditions yield that the profit maximizing spot selling price is characterized by $\hat{P}_S = \frac{1}{2}$. The expected quantity demanded at t = 1 is $E[\hat{Q}_S] = \frac{1}{2}$. The expected profits in this case are $E[\hat{\pi}_S] = \frac{1}{4}$.[7]

Strategy B: Attract demand for the positive shock only.

Under this strategy, the entrepreneur's maximization problem is as follows:

$$\max_{P_S} \boldsymbol{\pi(P_S) = \lambda P_S(1-\theta_L)}$$

$$s.t. \quad \theta_L = P_S - \alpha_H;\ \theta_L \in [0,1] \quad (2)$$

Here we have that the profit maximizing price $\check{P}_S > \theta_H + \alpha_L$. In this case, both the high type and the low type will only purchase the product when a positive shock is realized. The profit maximizing spot selling price is characterized by $\check{P}_S = \frac{1+\alpha_H}{2}$. The expected quantity demanded at t = 1 is $E[\check{Q}_S] = \frac{\lambda(1+\alpha_H)}{2}$. The expected profits given this case are $E[\check{\pi}_S] = \frac{\lambda(1+\alpha_H)^2}{4}$.

Comparing the two strategies we note that when $\lambda \geq \frac{1}{(1+\alpha_H)^2}$ the entrepreneur will not find it optimal to attract the high type consumers in case a negative shock is observed. Indeed, the profit generated by charging a price premium for a positive shock would dominate the profit generated by offering a price discount in order to ensure demand in case of a negative shock. Thus, ventures with a relatively high probability of delivering a positive shock would implement Strategy B, only attracting consumers in case a positive shock is realized. Additionally, entrepreneurs promising larger positive shocks to industry standards will more likely implement strategy B.[8] According to Mollick's (2016) empirical study on the impact of Kickstarter funding "over 50% of the projects were reported as being innovative by both backers and creators, and projects produced over 2,601 patent applications". Therefore, crowdfunding projects have a relatively high probability of delivering a positive shock to the industry standards since they are creative and innovative. This suggests that the comparable spot selling strategy

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[7] See the Appendix for a proof of these results.

[8] $\frac{\partial\lambda}{\partial\alpha_H} < 0$.

is Strategy B.[9] In order to focus on the comparable spot selling strategy we make the following assumption:

Assumption 2.

$$\lambda > \frac{1}{(1+\alpha_H)^2}$$

3.2 Spot Selling with Standard Debt

Entrepreneurs unable to launch their project via the spot market due to the lack of personal financial endowments can take a loan in order to start production. Following Kumar et al. (2016), we assume that lenders have perfect information regarding the venture's expected profits. The information that both the lender and the entrepreneur have regarding the future profitability of the venture is symmetric. The entrepreneur has no motive to provide false information regarding the profitability of the venture since these loans take the form of a personal liability. The entrepreneur's maximization problem is:

$$\max_{\boldsymbol{P_S^C}} \boldsymbol{\pi}\left(\boldsymbol{P_S^C}\right) = \boldsymbol{\lambda P_S^C(1-\theta_L) - R * K}$$
$$s.t. \quad \theta_L = P_S^C - \alpha_H \tag{3}$$

The optimal price and quantities are the same as that under spot selling, $\breve{P}_S^C = \frac{(1+\alpha_H)}{2}$ and $E\left[\breve{Q}_S^C\right] = \frac{\lambda(1+\alpha_H)}{2}$. Expected profits will be profits after the payment of the loan and interest, $E[\breve{\pi}_S^C] = \frac{\lambda(1+\alpha_H)^2}{4} - R * K$. The maximum capital that an entrepreneur is able to raise under this strategy is $\overline{K}_S = \frac{\lambda(1+\alpha_H)^2}{4R}$. For higher levels of capital, $K > \overline{K}_S$, the venture will be expected to make losses and suppliers of funds will not provide capital. Thus, the venture would fail to launch.

3.3 Reward-based Crowdfunding: Keep-it-All (KIA)

In this section we will derive the optimal crowdfunding contract offered by the entrepreneur assuming that at t = 0 the entrepreneur commits to the prices for both the crowdfunding and the spot selling period. Previous literature assumes no price commitment and maximizes profits in two stages backwards. In our case, following the literature on advance-purchase discount (Nocke et al., 2011) and drawing on anecdotal evidence from projects offering tangible products, the entrepreneur commits to the pre-ordering and the future retail prices and maximizes his profits at t = 0.

At t = 0, the entrepreneur publicizes the crowdfunding price, P_C, and the retail price, P_R. Let us assume $P_C > P_R$, a rational crowdfunder will not back the project given the premium since the realization of the positive shock is uncertain. Thus, consumers wait for the retail period to make their purchasing decision and the crowdfunding market closes. Therefore, when committing to prices the entrepreneur commits to offering a discount, $P_C < P_R$. A rational consumer that intends to purchase the good irrespective of the shock will pre-order, taking advantage of the backer's discount (as the expected value

[9] Since for simplicity we abstract from any crowdfunding costs such as platform fees or reputation costs, as will be shown later on, comparing crowdfunding with the spot selling Strategy A will result in crowdfunding always dominating. We thus focus on the more interesting and comparable spot selling alternative to crowdfunding, that is, Strategy B.

of the shock is zero). The decision to purchase the good is delayed to t = 1 only if the consumer is not planning to buy the good in case a negative shock is realized. On the one hand, the discount offered to backers compensates them for the uncertainty they are facing in regard to the shock. While on the other hand, publicizing the discount removes the uncertainty that potential backers might have regarding the product's future retail price. Thus, we have the following conditions describing the marginal consumer at the crowdfunding period, θ_C, and the marginal consumer in the retail market, θ_R:

$$t=0: \qquad \theta - P_C \geq \lambda(\theta + \alpha_H - P_R) \quad \rightarrow \quad \theta_C \geq \frac{P_C - \lambda(P_R - \alpha_H)}{1-\lambda} \tag{4}$$

$$t=1: \qquad \theta + \alpha_H - P_R \geq 0 \quad \rightarrow \quad \theta_R \geq P_R - \alpha_H \tag{5}$$

A consumer pre-ordering at t = 0 expects a utility of $\theta + E[\alpha_Z] - P_C = \theta - P_C$, while a consumer buying later expects $\lambda(\theta + \alpha_H - P_R)$, as he buys in the spot market only when a positive shock is realized. $\theta_C > \theta_R$, therefore we observe that crowdfunders have a higher valuation relative to consumers who wait to observe a positive realization of the shock, α_H. Demand at t = 0 is *(1 -θ_C)*, while expected demand at t = 1 is $\lambda(\theta_C - \theta_R)$. Thus, at t = 0 the entrepreneur has certain demand from crowdfunders and uncertain future demand depending on the realization of the positive shock. The entrepreneur´s maximization problem is:

$$\max_{P_C, P_R} \boldsymbol{\pi}(\boldsymbol{P_C}, \boldsymbol{P_R}) = \boldsymbol{P_C}(\mathbf{1} - \boldsymbol{\theta_C}) + \boldsymbol{\lambda P_R}(\boldsymbol{\theta_C} - \boldsymbol{\theta_R})$$

$$s.t. \quad \theta_C = \frac{P_C - \lambda(P_R - \alpha_H)}{1-\lambda}; \theta_R = P_R - \alpha_H \tag{6}$$

From the first order conditions we obtain that the entrepreneur maximizes his profit by setting $\hat{P}_C = \frac{1}{2}$ and $\hat{P}_R = \frac{1+\alpha_H}{2}$. The quantity demanded in pre-orders during the crowdfunding period is $\hat{Q}_C = \frac{1}{2} - \frac{\lambda\alpha_H}{2(1-\lambda)}$, while the expected demand in the retail market is $E[\hat{Q}_R] = \frac{\lambda\alpha_H}{2(1-\lambda)}$. The total expected quantity demanded during both periods is $E[\hat{Q}_{CF}] = \frac{1}{2}$. Profits during the crowdfunding period are $\hat{\pi}_C = \frac{1}{4} - \frac{\lambda\alpha_H}{4(1-\lambda)}$, while during the retail period expected profits are $E[\hat{\pi}_R] = \frac{\lambda\alpha_H + \lambda\alpha_H{}^2}{4(1-\lambda)}$. Total profits during both periods are $E[\hat{\pi}_{CF}] = \frac{1}{4} + \frac{\lambda\alpha_H{}^2}{4(1-\lambda)}$, which increase as the probability of fulfilling the promised shock increases.[10]

A benchmark strategy available to the entrepreneur when tapping crowdfunding as the financing and launching alternative is not to commit to prices prior to the respective period. Thus, during the crowdfunding period the entrepreneur sets the crowdfunding price only and does not publicize the future retail price. The retail price is set later on when launching the product in the retail market. Hence, the entrepreneur maximizes his profits in two stages backward. When comparing commitment versus no commitment, we find similar to Belleflame et al. (2014) that commitment dominates. This result is summarized in the following proposition.

[10] Comparative statics are provided in Table 1.A in the Appendix.

Proposition 1.
The optimal crowdfunding strategy is to commit to both the crowdfunding and retail period prices during the crowdfunding campaign.

Proof. See Appendix.

This illustrates a crucial point. From the entrepreneur's perspective price commitment dominates the alternative strategy of not committing. It is worth noting that even when not committing to future retail prices, backers still enjoy a discount relative to future retail consumers. When the entrepreneur commits to prices during the campaign he is able to charge a higher crowdfunding period price, relative to that without commitment, while attracting more in pre-orders. In essence, this follows intuitively since the entrepreneur now exploits the fact that backers face less uncertainty in regards to the future retail price compared to the case of no price commitment. The publicized discount helps stimulate the backing decision and attracts more in pre-orders compared to no commitment. When there is no price commitment by the entrepreneur, the entrepreneur enjoys higher retail period profits. The higher retail period profits do not offset the lower crowdfunding period profits; thus, demonstrating the dominance of price commitment as an optimal crowdfunding strategy.

Kickstarter stresses on being a community built on trust, but it should not be neglected that there is an incentive for entrepreneurs to deviate from the initially publicized retail price given that there are no legal consequences. However, in Kickstarter, a significant portion of projects are accounted for by serial entrepreneurs who return to crowdfunding for their future ventures (Butticè et al., 2017). We argue that reputation costs from deviating are high such that commitment is feasible in such a context of repeated interaction between the entrepreneurs and the crowdfunders (Fudenberg & Levine, 1989).

3.4 Reward-based Crowdfunding: All-or-Nothing (AON)

The optimal contract proposed earlier under the KIA scheme is the contract which maximizes total profits from both periods. Now when the entrepreneur uses an AON, he will have to meet the required capital threshold during the crowdfunding stage in order to access the funds pledged by backers. When the capital requirement is met by the pre-orders under the optimal contract proposed by the KIA scheme, $K \leq \underline{K}_{CF} = \frac{1}{4} - \frac{\lambda \alpha_H}{4(1-\lambda)}$, we have that the optimal KIA contract holds under the AON. Whereas, for $K > \underline{K}_{CF}$, the entrepreneurs faces a constrained maximization problem: maximize total profits under the constraint of raising the necessary capital during the crowdfunding period. Expected profits of crowdfunding will be the sum of both periods profits less the required capital. Therefore, the contract under the AON will differ from that under KIA and will involve departing from the optimal pricing strategy. The entrepreneur manipulates prices in order to raise more in pre-orders to meet his capital requirement. Through this strategy the entrepreneur is shifting future demand to pre-orders beyond the optimal levels suggested by the optimal KIA contract. Thus, for levels of $K > \underline{K}_{CF}$ the entrepreneur's problem is defined below:

$$\max_{\boldsymbol{P_C^C, P_R^C}} \boldsymbol{\pi\left(P_C^C, P_R^C\right) = P_C^C(1-\theta_C) + \lambda P_R^C(\theta_C - \theta_R) - K}$$

$$s.t.\ P_C^C(1-\theta_C) = K;\ \theta_C = \frac{P_C^C - \lambda(P_R^C - \alpha_H)}{1-\lambda};\ \theta_R = P_R^C - \alpha_H \tag{7}$$

P_C^C and P_R^C denote the AON crowdfunding and future retail price respectively. Since the constraint is binding, the optimal crowdfunding price is such that the entrepreneur is able to successfully raise his capital requirement during the crowdfunding period, $P_C^C(1-\theta_C) = K$. We can thus express the optimal crowdfunding price as a function of the retail price by solving the polynomial $P_C^C\left(1 - \frac{P_C^C - \lambda(P_R^C - \alpha_H)}{1-\lambda}\right) = K$. We obtain the optimal constrained crowdfunding price, $\hat{P}_C^C$, as a function of the future retail and capital requirement.[11]

Plugging $\hat{P}_C^C$ back into the entrepreneur's objective function we solve for the optimal crowdfunding and future retail price through maximizing total profits given the other two constraints. This maximization problem in general has no analytical solution and has to be solved numerically. Nevertheless, we can derive simple analytical solutions for the polar case where the entrepreneur maximizes first period profits by shifting all future demand to pre-orders such that $\theta_R = \theta_C$. For this to hold we have that $P_R^C = P_C^C + \alpha_H$ and $\theta_C = P_C^C$.[12] The publicized price should be high enough such that no consumer finds it optimal to wait for the retail period to open. Thus, the entrepreneur foregoes any profits in the second period in order to undergo production. This is relevant indeed, since in many cases the crowdfunding demand is high to an extent that the retail market does not open as firms focus on delivering their pre-orders (Miglo & Miglo, 2018). The corresponding maximization problem is:

$$\max_{P_C^C} \boldsymbol{\pi}(\boldsymbol{P_C^C}) = \boldsymbol{P_C^C}(\mathbf{1} - \boldsymbol{\theta_C}) - \boldsymbol{K}$$
$$s.t. \quad \theta_C = P_C^C \tag{8}$$

The maximum capital raised under crowdfunding is always $\overline{K}_{CF} = \frac{1}{4}$ regardless of the shock and the probability of the shock being delivered. At this level $P_C^C = \frac{1}{2}$ and $P_R^C = \frac{1}{2} + \alpha_H$. We have no retail demand and the market shrinks to just one period.[13]

For levels of capital below the maximum, $K < \overline{K}_{CF}$, numerical simulations show that the crowdfunding price and demand exhibit a non-monotonic relationship with the capital requirement (see Figure 1.2). We denote the level of capital where there is an inflection in the behavior of the crowdfunding price and demand by $\widetilde{K}_{CF}$. The benchmark results representing the optimal outcomes for different capital requirements are provided below in Table 1.2.

We note that for different levels of capital requirement, the entrepreneur pursues different strategies. For low levels of capital requirement, $K \leq \underline{K}_{CF}$, the entrepreneur does not diverge away from the optimal KIA contract when using AON. For higher capital requirements, the entrepreneur decides to expand the crowdfunding market in order to raise more money in pre-orders. The entrepreneur finds it optimal to increase the backer's discount through lowering the crowdfunding price, while increasing the premium that the retail consumers would have to pay. The future expected demand

[11] $\hat{P}_C^C = \frac{1-\lambda(1+\alpha_H)+\sqrt{(1+\lambda P_R^C)^2+\lambda(1+\alpha_H)[\lambda(1+\alpha_H-2P_R^C)-2]-4K(1-\lambda)}}{2}$

[12] θ_c and θ_R are defined by our consumer participation constraints. For $\theta_R = \theta_C$ we have that $P_R^C - \alpha_H = \frac{P_C^C - \lambda\left(P_R^C - \alpha_H\right)}{1-\lambda}$. Solving for P_R^C we arrive at $P_R^C = P_C^C + \alpha_H$. Plugging P_R^C in θ_C we obtain $\theta_C = P_C^C$.

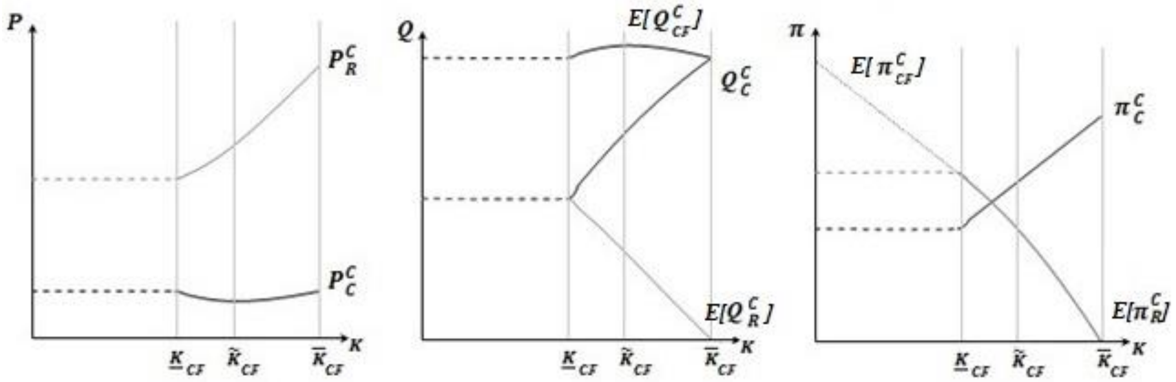
[13] Proof in the Appendix.

shrinks, but is offset by the demand gains in preorders, such that total expected quantity demanded increases. This holds for intermediate levels of capital requirement, $\underline{K}_{CF} < K \leq \widetilde{K}_{CF}$. Whereas for high levels of capital requirement, $\widetilde{K}_{CF} < K < \overline{K}_{CF}$, the previous strategy is no longer optimal. The decrease in the crowdfunding price does not generate enough demand to compensate for the discount offered to the backer. Thus, the entrepreneur starts raising the crowdfunding price as the capital requirement increases, while raising the future retail price even more. This results in a higher discount level for the consumer relative to the future retail price. As the entrepreneur raises the crowdfunding and retail price the market size starts shrinking. The amount raised in pre-orders increases since the loss in demand is offset by the higher price charged by the entrepreneur. Total expected demand is still larger than that under the KIA scheme.

Table 1.2: Benchmark numerical simulation for constrained crowdfunding

		No Capital	$\underline{K}_{CF}$	$\widetilde{K}_{CF}$	$\overline{K}_{CF}$
		0	***0.1375***	***0.1881***	***0.2500***
Crowdfunding Price	$(\widehat{\boldsymbol{P}}_C^C)$	*0.5000*	*0.5000*	*0.4816*	*0.5000*
Retail Price	$(\widehat{\boldsymbol{P}}_R^C)$	*0.7250*	*0.7250*	*0.8038*	*0.9500*
Crowdfunder's Discount		*0.2250*	*0.2250*	*0.3222*	*0.4500*
Crowdfunding Demand	$(\widehat{\boldsymbol{Q}}_C^C)$	*0.2750*	*0.2750*	*0.3906*	*0.5000*
Expected Retail Demand	$(\boldsymbol{E}[\widehat{\boldsymbol{Q}}_R^C])$	*0.2250*	*0.2250*	*0.1278*	*0*
Aggregate Demand	$(\boldsymbol{E}[\widehat{\boldsymbol{Q}}_{CF}^C])$	*0.5000*	*0.5000*	*0.5184*	*0.5000*
Crowdfunding Profit	$(\widehat{\boldsymbol{\pi}}_C^C)$	*0.1375*	*0.1375*	*0.1881*	*0.2500*
Expected Retail Profit	$(\boldsymbol{E}[\widehat{\boldsymbol{\pi}}_R^C])$	*0.1631*	*0.1631*	*0.1027*	*0*
Residual Profit	$(\boldsymbol{E}[\boldsymbol{\pi}_{CF}^C])$	*0.3006*	*0.1631*	*0.1027*	*0.0000*

$\alpha_H = 0.45,\ \lambda = 0.50$



a) Prices b) Demands c) Profits

Figure 1.2: Relationship of Optimal Prices, Demand and Profits with Capital Requirement.

We now analyze the effect of a change in the probability of the shock being delivered and the size of the shock that the entrepreneur claims to deliver on our previous results. At $\underline{K}_{CF}$ and $\overline{K}_{CF}$, we are able to provide analytical comparative statics which are summarized in Table 1.B in the Appendix. We notice that the level of capital starting with which the entrepreneur becomes constrained, $\underline{K}_{CF}$, decreases in both λ and

α_H. Thus for higher λ and α_H the entrepreneur becomes constrained for lower capital requirements and needs to diverge away from the optimal KIA contract. At $\underline{K}_{CF}$ and $\overline{K}_{CF}$, as α_H increases the retail price increases but this does not have any effect on the crowdfunding price. The probability of the shock being delivered does not affect prices but does affect demand at $\underline{K}_{CF}$. As λ or α_H increase there is a decrease in the crowdfunding demand but profits increase since demand is shifted to the retail period at which the price is higher. In Table 1.3 and Table 1.4 we numerically present comparative statics for AON crowdfunding.

Table 1.3: Comparative statics for different probabilities λ given the benchmark α_H= 0.45

	λ = 0.48				*λ = 0.52*			
	No Capital	$\underline{K}_{CF}$	$\widetilde{K}_{CF}$	$\overline{K}_{CF}$	*No Capital*	$\underline{K}_{CF}$	$\widetilde{K}_{CF}$	$\overline{K}_{CF}$
Capital Requirement (K)	*0*	*0.1462*	*0.1903*	*0.2500*	*0*	*0.1281*	*0.1830*	*0.2500*
Crowdfunding Price $(\widehat{P}_C^C)$	*0.5000*	*0.5000*	*0.4830*	*0.5000*	*0.5000*	*0.5000*	*0.4800*	*0.5000*
Retail Price $(\widehat{P}_R^C)$	*0.7250*	*0.7250*	*0.7997*	*0.9500*	*0.7250*	*0.7250*	*0.8019*	*0.9500*
Crowdfunders' Discount	*0.2250*	*0.2250*	*0.3167*	*0.4500*	*0.2250*	*0.2250*	*0.3219*	*0.4500*
Crowdfunding Demand $(\widehat{Q}_C^C)$	*0.2923*	*0.2923*	*0.3940*	*0.5000*	*0.2562*	*0.2562*	*0.3812*	*0.5000*
Expected Retail Demand $(E[\widehat{Q}_R^C])$	*0.2077*	*0.2077*	*0.1230*	*0*	*0.2438*	*0.2438*	*0.1288*	*0*
Aggregate Demand $(E[\widehat{Q}_{CF}^C])$	*0.5000*	*0.5000*	*0.5170*	*0.5000*	*0.5000*	*0.5000*	*0.5200*	*0.5000*
Crowdfunding Profits $(\widehat{\pi}_C^C)$	*0.1462*	*0.1462*	*0.1905*	*0.2500*	*0.1281*	*0.1667*	*0.1830*	*0.2500*
Expected Retail Profit $(E[\widehat{\pi}_R^C])$	*0.1506*	*0.1506*	*0.0984*	*0*	*0.1767*	*0.1250*	*0.1113*	*0*
Residual Profit $(E[\pi_{CF}^C])$	*0.2967*	*0.1506*	*0.0984*	*0*	*0.3048*	*0.1250*	*0.1113*	*0*

Table 1.4: Comparative statics for different shock levels α_H given the benchmark λ = 0.50

	α_H *= 0.425*				α_H *= 0.475*			
	No Capital	$\underline{K}_{CF}$	$\widetilde{K}_{CF}$	$\overline{K}_{CF}$	*No Capital*	$\underline{K}_{CF}$	$\widetilde{K}_{CF}$	$\overline{K}_{CF}$
Capital Requirement (K)	*0*	*0.1437*	*0.1916*	*0.2500*	*0*	*0.1312*	*0.1817*	*0.2500*
Crowdfunding Price $(\widehat{P}_C^C)$	*0.5000*	*0.5000*	*0.4834*	*0.5000*	*0.5000*	*0.5000*	*0.4798*	*0.5000*
Retail Price $(\widehat{P}_R^C)$	*0.7125*	*0.7125*	*0.7881*	*0.9250*	*0.7375*	*0.7375*	*0.8133*	*0.9750*
Crowdfunders' Discount	*0.2125*	*0.2125*	*0.3047*	*0.4250*	*0.2375*	*0.2375*	*0.3335*	*0.4750*
Crowdfunding Demand $(\widehat{Q}_C^C)$	*0.2875*	*0.2875*	*0.3963*	*0.5000*	*0.2625*	*0.2625*	*0.3788*	*0.5000*
Expected Retail Demand $(E[\widehat{Q}_R^C])$	*0.2125*	*0.2125*	*0.1203*	*0*	*0.2375*	*0.2375*	*0.1415*	*0*
Aggregate Demand $(E[\widehat{Q}_{CF}^C])$	*0.5000*	*0.5000*	*0.5166*	*0.5000*	*0.5000*	*0.5000*	*0.5202*	*0.5000*
Crowdfunding Profits $(\widehat{\pi}_C^C)$	*0.1437*	*0.1437*	*0.1916*	*0.2500*	*0.1312*	*0.1312*	*0.1817*	*0.2500*
Expected Retail Profit $(E[\widehat{\pi}_R^C])$	*0.1514*	*0.1514*	*0.0948*	*0*	*0.1752*	*0.1752*	*0.1151*	*0*
Residual Profit $(E[\pi_{CF}^C])$	*0.2952*	*0.1514*	*0.0948*	*0*	*0.3064*	*0.1752*	*0.1151*	*0*

4. Optimal Launching Strategy

In our prior analysis we were able to identify the optimal pricing strategy corresponding to each launching option. Before the launch of the venture, the entrepreneur needs to decide on the optimal launching strategy given the project's capital requirement. For projects where the entrepreneur is able to personally provide funds for executing the project, such that there is no capital requirement, three launching strategies are available: spot selling, KIA, and AON. In this case, we have seen that the optimal crowdfunding contract under the KIA and AON scheme are identical. Therefore, in our subsequent analysis for projects with no capital requirement we compare spot selling and KIA. For projects requiring capital beyond what the entrepreneur can personally provide, capital can be acquired in the form of a debt obligation or via pre-orders in crowdfunding. When the capital requirement is less than what the entrepreneur can optimally raise in pre-orders, we have identical optimal contracts under KIA and AON schemes. Whereas, for higher levels of capital only AON is feasible as a crowdfunding launching alternative. Therefore, for projects that require capital to initiate we compare spot selling with standard debt and AON crowdfunding.

4.1 Spot Selling and KIA

Entrepreneurs not requiring external sources of capital to launch their project are considered to be "unconstrained". Given the optimal pricing strategies identified earlier, the entrepreneur chooses the alternative that maximizes his profits. These optimal strategies are from the entrepreneur's perspective and do not imply optimality from a welfare standpoint.

Proposition 2.

a) *The unconstrained entrepreneur's unique optimal strategy is to use crowdfunding.*
b) $\hat{P}_C$ *&* $\hat{P}_R$ *set by the unconstrained entrepreneur are indeed such that* $\hat{P}_C < \hat{P}_R$ *, thus the optimal pricing strategy is such that crowdfunders are rewarded with a price discount compared to retail consumers.*
c) *Total demand under crowdfunding dominates the one under spot selling.*

Proof. See Appendix.

Part (a) poses that the unconstrained entrepreneur is always better off using crowdfunding than spot selling.[14] It is due to the fact that, by construction, the unconstrained entrepreneur is able to mimic spot selling when using crowdfunding. This can be achieved by having $(P_C, P_R) = (\infty, \frac{1+\alpha_H}{2})$ where the crowdfunding market closes and the entrepreneur only caters to consumers in the retail market. Whereas, when the market opens in both periods we have that crowdfunders enjoy a price discount as stated by part (b). The opportunity cost of crowdfunding is the discount offered to backers pre-ordering the product. However, this cost is outweighed by the benefits clarified in part (c). The entrepreneur expands the market, due to the crowdfunding's ability to shift uncertain future demand into certain pre-orders, offsetting the cost of the discount offered to backers.

4.2 Spot Selling with Standard Debt and AON

Thus far we know that the maximum capital that an entrepreneur can raise under AON is reached by shifting all uncertain future demand into certain pre-orders which yields $\overline{K}_{CF} = \frac{1}{4}$. Whereas, the maximum amount that the entrepreneur can take in loans is $\overline{K}_S = \frac{\lambda(1+\alpha_H)^2}{4R}$. In the extreme, for $r = 0$, we have that $\overline{K}_{CF} < \overline{\overline{K}}_S = \frac{\lambda(1+\alpha_H)^2}{4}$. For a given capital requirement, a project is feasible through standard debt financing if the interest

[14] Note that this holds for KIA and AON no matter if we compare to spot selling strategy A or to strategy B. Indeed, when analyzing this further, we see that crowdfunding dominates both spot selling strategies, A and B, for all admissible values of λ.

rate is below a certain threshold. This interest rate threshold, denoted by r_F, is expressed below:

$$r_F = \frac{\lambda(1+\alpha_H)^2}{4K} - 1 \tag{9}$$

Thus, intuitively, the entrepreneur faces different financing and launching alternatives depending on the required capital and prevailing interest rate. Below we identify the four possible situations and the respective strategies available:

i. $r \leq r_F$ and $0 < K \leq \underline{K}_{CF}$; Spot Selling with Standard Debt vs AON (or KIA).
ii. $r \leq r_F$ and $\underline{K}_{CF} < K \leq \overline{K}_{CF}$; Spot Selling with Standard Debt vs AON.
iii. $r \leq r_F$ and $\overline{K}_{CF} < K \leq \overline{K}_S$; Spot Selling with Standard Debt only.
iv. $r > r_F$ and $0 < K \leq \overline{K}_{CF}$; AON only.

These scenarios are illustrated below in Figure 1.3.

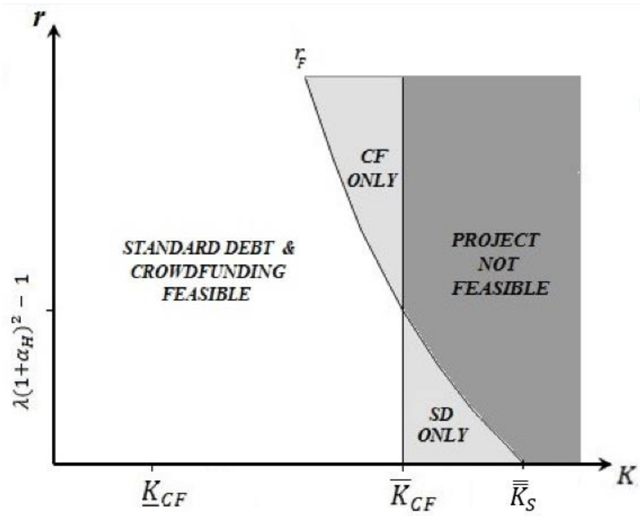


Figure 1.3: Entrepreneur's available strategies given the capital requirement and interest rate.

The optimal strategy for each of the scenarios is discussed below.

i. $r \leq r_F$ and $0 < K \leq \underline{K}_{CF}$; Spot Selling with Standard Debt vs AON (or KIA).

The optimal AON contract for $K \leq \underline{K}_{CF}$ is identical to the optimal KIA contract. We have seen that projects with low capital requirements, $K \leq \underline{K}_{CF}$, always find it optimal to launch via crowdfunding. Since KIA dominates spot selling it can be easily verified that expected profits are higher for AON when compared to spot selling with debt obligations, $E[\hat{\pi}_{CF}] > E[\breve{\pi}_S^C]$. This result holds regardless of the size of the shock that the entrepreneur promises or the probability that the shock is fulfilled.

ii. $r \leq r_F$ and $\underline{K}_{CF} < K \leq \overline{K}_{CF}$; Spot Selling with Standard Debt vs AON.

Now the entrepreneur is diverging away from his optimal prices when opting for AON, therefore, it does not always follow that the entrepreneur is better off under crowdfunding. The entrepreneur's optimal choice involves comparing expected profits under both strategies. The choice will depend on the interest rate that he faces in the credit market which brings to the analysis a critical interest rate that we will denote with r_O.

$$r_O = \frac{\left(\frac{\lambda(1+\alpha_H)^2}{4} - E\left[\pi_{CF}^C(K)\right]\right)}{K} - 1 \tag{10}$$

It is when both options are feasible for the entrepreneur where r_O comes into play. r_O represents the interest rate threshold at which the entrepreneur is indifferent between the two financing options. If interest rates are low enough, $r < r_O$, the entrepreneur finds it optimal to launch using debt obligations. Otherwise, the entrepreneur would prefer crowdfunding and would meet the project's capital requirement by manipulating prices to secure capital in the pre-ordering stage.

iii. $r \leq r_F$ *and* $\overline{K}_{CF} < K \leq \overline{K}_S$*; Spot Selling with Standard Debt only.*

For $K > \overline{K}_{CF}$ and $r \leq r_F$, the entrepreneur's capital requirement can not be met through AON and standard debt is the only launching option available to the entrepreneur.

iv. $r > r_F$ *and* $0 < K \leq \overline{K}_{CF}$*; AON only.*

For $0 < K \leq \overline{K}_{CF}$ and $r > r_F$, the entrepreneur's capital requirement can not be met through standard debt and AON crowdfunding is the only launching option available to the entrepreneur.

The result of this analysis is summarized in Proposition 3 and are graphically presented in Figure 1.4.

Proposition 3.

1. *For* $0 < K \leq \overline{K}_{CF}$ *and* $r > r_F$*, only crowdfunding is feasible.*
2. *For* $0 < K \leq \overline{K}_{CF}$ *and* $r < r_O$*, the entrepreneur's unique optimal strategy is to use standard debt.*
3. *For* $0 < K \leq \overline{K}_{CF}$ *and* $r_O \leq r \leq r_F$*, the entrepreneur's unique optimal strategy is to use AON.*
4. *For* $\overline{K}_{CF} < K \leq \overline{\overline{K}}_S$ *and* $r \leq r_F$*, only standard debt is feasible.*

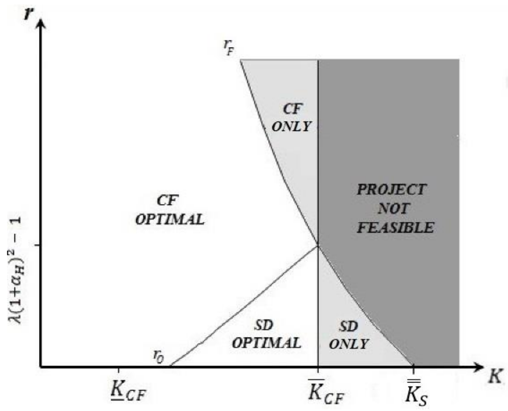


Figure 1.4: Entrepreneur's optimal strategy given the capital requirement and interest rate.

From the comparative statics of key variables presented earlier in Table 1.3 and 1.4 we arrive at interesting results that we mention in the corollary below and proceed by further discussing their implications.

Corollary 1: *Projects that promise higher positive shocks or are more probable to deliver on their promises have a lower $\underline{K}_{CF}$, higher $\overline{\overline{K}}_S$ and higher interest rate thresholds (r_F and r_O).*

This poses important implications. From our corollary we can infer that projects promising higher shock to industry standards are constrained for lower levels of capital requirement under crowdfunding. Thus, they are more probable to diverge away from their optimal crowdfunding strategy making standard debt more attractive. This is consistent with the findings of Chan & Parhankangas (2017) who investigated the effect of innovativeness on crowdfunding outcomes. They found that projects with incremental innovativeness, lower α_H, result in favorable crowdfunding outcomes when compared to projects with radical innovativeness, higher α_H. Given this, we expect to see that more radically innovative projects launch through the use of debt obligations. Further on we depict that projects with lower probability of delivering on their promises would more likely opt for crowdfunding, which is in line with the results of an empirical analysis by Xu (2017) who shows that entrepreneurs tend to launch riskier projects on Kickstarter. Thus, we expect to see that entrepreneurs who are more likely to deliver on their promised shocks launch their projects through the use of standard debt. Moreover, our model further implies that when both financing options are available to the entrepreneur, standard debt becomes more attractive as the funding needs increase. Thus, entrepreneurs with larger funding requirements would more likely prefer to raise their capital in the form of debt obligations.

5. Discussion

In this paper we fill a gap in the literature by developing a theoretical framework that explains the crowdfunding mechanism for projects offering "consumer products", since previous theoretical models do not specifically address them. In the framework that we propose we have that consumers with high expected valuation pre-order the product, while consumers with low expected valuation wait to observe the shock and make their purchase decision in the retail period. In contrast to previous literature, and supported by anecdotal evidence, we show that committing to a price discount is the entrepreneur's optimal strategy. Thus, we highlight a managerial recommendation for a pricing strategy to be implemented by entrepreneurs tapping crowdfunding as their financing and launching alternative. We also compare crowdfunding to spot selling and show when it would be optimal for an entrepreneur to opt for crowdfunding.

The proposed model has some important novel testable implications. The model shows that projects committing to prices are able to raise more capital in pre-orders during the crowdfunding period. This can be verified through the study of launched crowdfunding projects by analyzing the effect of price commitment on the project's crowdfunding outcome. Another main testable implication of the proposed model is that the entrepreneur can increase the amount of capital raised during the crowdfunding period through increasing the discount offered to potential backers. Similar to price commitment, this can be verified by testing the effect of the size of the discount on the project's crowdfunding outcome. Other implications derived from the comparative statics of key variables in our proposed model have been supported by empirical findings.

As mentioned earlier, projects promising larger shocks to industry standards are more constrained for lower levels of capitals, thus reducing their probability of success which is consistent with the findings of Chan & Parhankangas (2017). Moreover, as previously highlighted we expect that projects with lower probability of delivering on their promises would more likely opt for crowdfunding, which is in line with the results of an empirical analysis by Xu (2017) who shows that entrepreneurs tend to launch riskier projects on Kickstarter.

An implication for platforms driven from our theoretical analysis is related to the credibility of the entrepreneur's price commitment. In our model we see that entrepreneurs find it optimal to commit to the retail price during the crowdfunding campaign and then diverge in the retail period. In other words, entrepreneurs find it optimal to initially publicize a high future retail price to attract demand during the crowdfunding stage and then later lower the retail price in order to attract more demand in the retail period. We have argued that serial crowdfunding is common, entrepreneurs might need to return to the platform for future projects and, hence, they need to maintain their reputation. In case they diverge, backers will penalize them in future crowdfunding endeavors. However, there are entrepreneurs who do not return to the platform for subsequent campaigns and their reputation might not constrain them from diverging away from their commitment. Through a joint effort between government business bureaus and crowdfunding platforms, this can be regulated such that entrepreneurs are held accountable for deviating from the promised discount. If commitment became legally binding through regulation, this would enhance its credibility. Given that most products are launched online, regulating this is achievable through regular monitoring of crowdfunded campaigns in the marketplace and through allowing backers to file complaints if an entrepreneur fails to deliver the promises made during the campaign. This would also require platforms to collect proper identification from the entrepreneurs posting projects on the platform.

Our model abstracts from several important aspects and our analytical framework relies on several restrictive assumptions. First, we have assumed that all projects deliver no shock to the industry standards ex-ante and at $t = 0$ the expected value of the shock is zero. What if entrepreneurs have patents or quality certifications that demonstrate that they are more probable to deliver a shock to the industry standards and that the expected value of the shock is no longer zero? Or what if lower quality entrepreneurs are attracted by the platform such that the expected realized shock to the industry standards is negative? Relaxing these assumption would affect the implications of the model. In case, the expected shock was positive this would imply that the entrepreneur's optimal pricing policy would entail offering a lower level of discount compared to the benchmark case where no shock to industry standards is expected. Moreover, the entrepreneur will only be constrained at higher levels of capital and crowdfunding would be a more favorable financing alternative even when prevailing interest rates are low. On the contrary, if the expected shock to industry standards was negative, the entrepreneur would need to offer a high level of discount to backers in order to compensate them for the associated risk. The entrepreneur will be more constrained for lower levels of capital requirements and crowdfunding will be a less attractive option even when prevailing interest rates are high.

Second, in the base model that we provided we assume that there are two selling dates when using crowdfunding: $t=0$ for pre-orders and $t=1$ for retail orders. For retail orders the consumers know their ex post valuation as they observe the shock. On crowdfunding platforms, entrepreneurs usually offer the same reward at multiple prices in limited quantities (i.e., Super Early Bird Price, Early Bird Price, and Campaign Special

Price). Usually the earliest backers opt for the super early bird price, then after it has been fully subscribed new backers opt for the early bird price, and finally remaining backers only have the campaign special price available to them. Signals stemming from early backers can additionally incentivize later backers to pre-order the product. If we add multiple stages to the theoretical model, this can lead to further insights into the optimal number of reward classes and the associated prices. Future research could also relax our symmetric information assumption and apply a mechanism design approach, similar to Strausz (2017), to analyze such an extension to the base model.

Third, relaxing the assumption of perfect information could be an interesting extension since consumers' private information is an important ingredient of crowdfunding. Entrepreneurs have better information regarding the product quality that will be delivered, while backers have better information regarding their valuation of the product. Crowdfunding does play a role in aggregating this private information and incorporating this in the model can provide us with further implications. This is left for future research.

6. Conclusion

The literature on crowdfunding is developing rapidly. To this point, the major focus of this research is on drivers of success of crowdfunding campaigns and how entrepreneurs can enhance their campaign performance. Less well studied are the issues of when do entrepreneurs opt for crowdfunding when traditional sources of financing are available and what type of projects are more likely to be launched on the crowdfunding platform. In this paper we highlight that crowdfunding is a launching option and opting for crowdfunding might not necessarily be driven by liquidity needs. In the case of entrepreneurs with no liquidity needs, crowdfunding is an optimal launching strategy since the cost of opting for crowdfunding is outweighed by the benefits of expanding the market and discriminating between campaign backers and retail period consumers. However, for projects with high levels of capital requirement, entrepreneurs would need to compare the cost of the discount offered to backers to raise the required capital, to the benefits of expanding the market, and the prevailing interest rate in the debt market. Additionally, we highlight that crowdfunding would more probably attract riskier projects.

Appendix

Proof. [Proposition 1]

With Commitment:

Participating Consumers

t = 0 : $\theta - P_C \geq \lambda(\theta + \alpha_H - P_R) \quad \rightarrow \quad \theta_C \geq \frac{P_C - \lambda(P_R - \alpha_H)}{1-\lambda}$

t = 1 : $\theta + \alpha_H - P_R \geq 0 \quad \rightarrow \quad \theta_R \geq P_R - \alpha_H$

The entrepreneur commits to prices that maximize profits at time 0. The optimal crowdfunding pricing strategy is the one that solves the following maximization problem:

$$\max_{P_C, P_R} \pi(P_C, P_R) = P_C(1 - \theta_C) + \lambda P_R(\theta_C - \theta_R)$$

$$s.t. \quad \theta_C = \frac{P_C - \lambda(P_R - \alpha_H)}{1-\lambda}; \theta_R = P_R - \alpha_H$$

From the first order conditions we obtain the following:

Prices: $\hat{P}_C = \frac{1}{2}$, $\hat{P}_R = \frac{1+\alpha_H}{2}$

Quantities: $\hat{Q}_C = \frac{1}{2} - \frac{\lambda\alpha_H}{2(1-\lambda)}, E[\hat{Q}_R] = \frac{\lambda\alpha_H}{2(1-\lambda)}, E[\hat{Q}_{CF}] = \frac{1}{2}$

Profits: $\hat{\pi}_C = \frac{1}{4} - \frac{\lambda\alpha_H}{4(1-\lambda)}, E[\hat{\pi}_R] = \frac{\lambda\alpha_H + \lambda{\alpha_H}^2}{4(1-\lambda)}, E[\hat{\pi}_{CF}] = \frac{1}{4} + \frac{\lambda{\alpha_H}^2}{4(1-\lambda)}$

Without Commitment:

The entrepreneur does not commit to prices and sets the profit maximizing price at its respective period. Thus, we solve the entrepreneur's problem backward. At the retail period the entrepreneur's problem is:

$$\max_{P_C, P_R} \pi(P_R) = P_R(\theta_C - \theta_R)$$

$$s.t. \quad \theta_R = P_R - \alpha_H$$

The solution gives us $P_R = \frac{\theta_C + \alpha_H}{2}$. Since the consumers anticipate that this will be the future retail price, the participating consumer in the crowdfunding period would be:

t = 0 : $\theta_C - P_C \geq \lambda(\theta_C + \alpha_H - \frac{\theta_C + \alpha_H}{2}) \quad \rightarrow \quad \theta_C \geq \frac{2P_C + \lambda\alpha_H}{2-\lambda}$

Plugging P_R and θ_C into $\pi(P_C, P_R) = P_C(1 - \theta_C) + \lambda P_R(\theta_C - \theta_R)$ and solving for the profit maximizing prices, we have that:

$$P_C = \frac{4(1-\lambda) + \lambda^2(1+\alpha_H)}{8-6\lambda}$$

$$P_R = \frac{2(1+2\alpha_H) - \lambda(1+\alpha_H)}{8-6\lambda}.$$

For all admissible values of λ we have the following:

1. Crowdfunding Demand, *1-* θ_C, and Crowdfunding Profits, $P_C(1 - \theta_C)$, are higher under commitment.
2. Retail Period Profits, $P_R(\theta_C - \theta_R)$, are higher when the entrepreneur does not commit to prices.
3. Under both strategies $P_C < P_R$.

4. Total profits are higher under price commitment, thus, the optimality of price commitment when launching a crowdfunding strategy.

Proof. [Proposition 2]

Optimal Spot Selling Strategy

- Spot Selling Strategy A

$$\max_{P_S} \pi(P_S) = \lambda P_S(1-\theta_L) + (1-\lambda)P_S(1-\theta_H)$$

$$s.t.\ \theta_H \geq P_S - \alpha_L\ ;\ \theta_L \geq P_S - \alpha_H\ ;\ \theta_H \in (0,1)\ ;\ \theta_L \in (0,1)$$

Solution:

$\hat{P}_S = \frac{1}{2}$ $\quad E[Q_S] = \frac{1}{2}$ $\quad E[\hat{\pi}_S] = \frac{1}{4}$

- Spot Selling Strategy B

$$\max_{P_S} \pi(P_S) = \lambda P_S(1-\theta_L)$$

$$s.t.\ \theta_L \geq P_S - \alpha_H\ ;\ \theta_L \in (0,1)$$

Solution:

$\breve{P}_S = \frac{1+\alpha_H}{2}$ $\quad E[\breve{Q}_S] = \frac{\lambda(1+\alpha_H)}{2}$ $\quad E[\breve{\pi}_S] = \frac{\lambda(1+\alpha_H)^2}{4}$.

Comparing both strategies:

$$E[\breve{\pi}_S] > E[\hat{\pi}_S] \text{ for } \lambda > \frac{1}{(1+\alpha_H)^2}$$

Strategy B dominates Strategy A for $\lambda > \frac{1}{(1+\alpha_H)^2}$.

Spot Selling vs KIA

$\mathrm{E}[\hat{\pi}_{\mathrm{CF}}] = \frac{1}{4} + \frac{\lambda \alpha_{\mathrm{H}}{}^2}{4(1-\lambda)} > \mathrm{E}[\breve{\pi}_{\mathrm{S}}] = \frac{\lambda(1+\alpha_{\mathrm{H}})^2}{4}$, for all admissible values of λ.

$\hat{\mathrm{P}}_{\mathrm{C}}$ & $\hat{\mathrm{P}}_{\mathrm{R}}$ set by the unconstrained entrepreneur are indeed such that $\hat{\mathrm{P}}_{\mathrm{C}} < \hat{\mathrm{P}}_{\mathrm{R}}$.

$\mathrm{E}\left[\hat{\mathrm{Q}}_{\mathrm{CF}}\right] = \frac{1}{2} > \mathrm{E}[\breve{\mathrm{Q}}_{\mathrm{S}}] = \frac{\lambda(1+\alpha_{\mathrm{H}})}{2}$, which holds for all admissible values of λ.

Proof. [Proposition 3]

Spot Selling with Standard Debt

$$\max_{P_S^C} \pi(P_S^C) = \lambda P_S^C(1-\theta_L) - R * K$$

$$s.t. \quad \theta_L = P_S^C - \alpha_H$$

Solution:

$\breve{P}_S^C = \frac{1+\alpha_H}{2}$ $\quad E\left[\breve{Q}_S^C\right] = \frac{\lambda(1+\alpha_H)}{2}$ $\quad$ for $\quad \leq \overline{K}_S = \frac{\lambda(1+\alpha_H)^2}{4R}$.

For levels of $K > \overline{K}_S$ the project is not feasible under spot selling.

Rearranging, $r_F = \frac{\lambda(1+\alpha_H)^2}{4K} - 1$. r_F is the interest rate threshold above which the project is not feasible.

-For $0 < K < \frac{1}{4}$ and $r > r_F$, the project is only feasible under crowdfunding.

-For $0 < K < \frac{1}{4}$ and $r \leq r_F$, the project is feasible using standard debt and crowdfunding.

-For $K \leq \underline{K}_{CF} = \frac{1}{4} - \frac{\lambda\alpha_H}{4(1-\lambda)}$, same optimal prices and quantities as those determined under proposition 1 (with commitment).

-For $\underline{K}_{CF} < K < \overline{K}_{CF}$;

$$\max_{P_C^C, P_R^C} \pi(P_C^C, P_R^C) = P_C^C(1-\theta_C) + \lambda P_R^C(\theta_C - \theta_R) - K$$
$$s.t.\; P_C^C(1-\theta_C) = K; \theta_C = \frac{P_C^C - \lambda(P_C^R - \alpha_H)}{1-\lambda}; \theta_R = P_R^C - \alpha_H$$

Substituting θ_C in to the capital constraint and solving for P_C^C we have that:

$$\widehat{P}_C^C = \frac{1-\lambda(1+\alpha_H) + \sqrt{(1+\lambda P_R^C)^2 + \lambda(1+\alpha_H)[\lambda(1+\alpha_H - 2P_R^C) - 2] - 4K(1-\lambda)}}{2}$$

Plugging back $\widehat{P}_C^C$ into the objective function we solve for the optimal retail price. There exists no analytical solution due to a polynomial of forth degree. But numerical simulations have been presented in the main text.

- For $K = \overline{K}_{CF}$; The maximum capital ($\overline{K}_{CF}$) to be raised is such that all future demand is shifted to the pre-ordering period $\frac{P_C^C - \lambda(P_R^C - \alpha_H)}{1-\lambda} = P_R^C - \alpha_H$.

Solving for P_R^C we have that the $P_R^C = P_C^C + \alpha_H$.

Plugging P_R^C into the entrepreneur's objective function:

$$\max_{P_C^C, P_R^C} \pi(P_C^C) = P_C^C(1-\theta_C) - K$$
$$s.t.\quad \theta_C = P_C^C$$

Solution:

$P_C^C = \frac{1}{2}$ $\qquad P_R^C = \frac{1}{2} + \alpha_H$ $\qquad Q_C^C = \frac{1}{2}$ $\qquad \overline{K}_{CF} = \frac{1}{4}$

- For $\frac{1}{4} < K \leq \overline{\overline{K}}_S$ and $r \leq r_F$, Standard Debt Only.

Having established the optimal strategies under the constrained case we can now proceed with proving Proposition 3.

For $0 < K \leq \frac{1}{4}$ and $r > r_F$, crowdfunding is the optimal strategy

For $0 < K \leq \frac{1}{4}$ and $r < r_O$, both strategies are feasible and the constrained entrepreneur's unique optimal strategy is to use standard debt.

r_O is the interest rate below which the entrepreneur finds standard debt optimal.

$E\left[\pi_{CF}^{C}(K)\right] < \frac{\lambda(1+\alpha_H)^2}{4} - R * K$. Through rearranging we arrive at this interest rate threshold below.

$$r_O = \frac{\left(\frac{\lambda(1+\alpha_H)^2}{4} - E\left[\pi_{CF}^{C}(K)\right]\right)}{K} - 1$$

For $0 < K \leq \frac{1}{4}$ and $r_O \leq r \leq r_F$, the entrepreneur's unique optimal strategy is to use AON.

For $r_O \leq r$ we have that $E\left[\pi_{CF}^{C}(K)\right] \geq \frac{\lambda(1+\alpha_H)^2}{4} - R * K$ such that the entrepreneur prefers to use crowdfunding as the financing option for his venture.

For $\frac{1}{4} < K \leq \overline{\overline{K}}_S$ and $r \leq r_F$, the entrepreneur's optimal strategy is to use standard debt.

Appendix Tables

Table 1.A: Comparative Statics for KIA Crowdfunding

	$\partial(.)/\partial\alpha_H$	$\partial(.)/\partial\lambda$
Crowdfunding Price ($\hat{P}_C$)	0	0
Retail Price ($\hat{P}_R$)	+	0
Crowdfunding Demand ($\hat{Q}_C$)	-	-
Expected Retail Demand ($E[\hat{Q}_R]$)	+	+
Crowdfunding Profits ($\hat{\pi}_C$)	-	-
Expected Retail Profit ($E[\hat{\pi}_R]$)	+	+

Table 1.B: Comparative Statics at $\underline{K}_{CF}$ and $\overline{K}_{CF}$ for AON Crowdfunding.

	$\underline{K}_{CF}$		$\overline{K}_{CF}$	
	$\partial(.)/\partial\alpha_H$	$\partial(.)/\partial\lambda$	$\partial(.)/\partial\alpha_h$	$\partial(.)/\partial\lambda$
Crowdfunding Price ($\hat{P}_C^C$)	0	0	0	0
Retail Price ($\hat{P}_R^C$)	+	0	+	0
Crowdfunding Demand ($\hat{Q}_C^C$)	-	-	0	0
Expected Retail Demand ($E[\hat{Q}_R^C]$)	+	+	0	0
Crowdfunding Profits ($\hat{\pi}_C^C$)	-	-	0	0
Expected Retail Profit ($E[\hat{\pi}_R^C]$)	+	+	0	0
Expected Profits ($\pi_{CF}^c(K)$)	+	+	0	0
Maximum Unconstrained Capital ($\underline{K}_{CF}$)	-	-	0	0
Maximum Constrained Capital ($\overline{K}_{CF}$)	0	0	0	0

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Chapter 2
SIGNALING AND FINANCIAL MOTIVES IN REWARD-BASED CROWDFUNDING

ABSTRACT

We draw on information economics to examine how costly signals (price commitment and discount) and costless signals (reward classes) play a role in conveying information about product quality and the financial compensation that backers receive for pre-ordering the product. Our empirical analysis covers detailed hand-collected information on a random sample of 650 Kickstarter campaigns. We extend the crowdfunding literature by shedding light on how backers' financial motives are stimulated through signaling information regarding the future retail price, enhancing crowdfunding performance. Moreover, we show that backers prioritize these signals such that costly signals partially offset the effect of costless signals.

Content

1. Introduction

Along other innovations in the alternative finance sector, crowdfunding has come to rise as a viable and significant source of funds for entrepreneurs (Schwienbacher & Larralde, 2012). Kickstarter, the leading reward-based crowdfunding platform, helped 151,606 projects from around the world meet their goals and raise almost $3.49 billion dollars.[15] Considering the total number of projects launched on Kickstarter, this corresponds to a success rate of 36.42%. A growing body of literature explores the determinants of success in crowdfunding campaigns. Success in "all or nothing" crowdfunding platforms is achieved when the campaign collects enough capital to reach its goal (Cumming et al., 2019). A major challenge faced by the entrepreneur to achieve success in crowdfunding is the information asymmetry between himself/herself and potential investors regarding the venture's quality and his/her own competence (an adverse selection problem). Recent literature on the determinants of crowdfunding success has analyzed both costly and costless signals that the entrepreneur can use to disclose information to potential backers such as media content, founder's crowdfunding experience, social and human capital, positive psychological capital, and language-based costless signals (Ahlers et al., 2015; Anglin, Short, et al., 2018; Courtney et al., 2017b).

Although there is an extended perception in the crowdfunding literature that backers in reward-based crowdfunding platforms are mainly stimulated by intrinsic, non-financial motives (e.g., community benefits, help others …), while backers in equity-based crowdfunding platforms are stimulated by extrinsic, financial motives (Gerber et al., 2012; Schwienbacher & Larralde, 2012), recent evidence from Cholakova & Clarysse (2015) challenges this view. In particular, the authors show that the motivation to support a project for both reward-based crowdfunding and equity investing is mainly driven by financial motives: collect rewards in the case of reward-based crowdfunding and get a return on investment for equity crowdfunding. Non-financial motivations such as helping others, supporting ideas or belonging to a community only play a secondary role. Thus, supporters in reward-based crowdfunding usually back the entrepreneur's project in exchange for the promise of a reward, which in many cases is the product itself since funds are being raised for production. Therefore, backers are essentially pre-ordering the product during the crowdfunding campaign (advance purchase) in exchange for a lower price relative to the future retail price (Butticè et al., 2018; E. Mollick, 2014).

Since backers are mainly driven by financial motives in their decision to back, they should particularly value signals conveying information regarding the financial reward offered by the entrepreneur. In this paper, we draw on signaling theory to analyze novel signals, both costly and costless, related to financial motives in reward-based crowdfunding.[16] In doing so, we diverge from the classical analysis of non-financial motives in reward-based crowdfunding. Instead, we highlight the role of financial motives and study how signaling financial rewards, through the reward section of the campaign, can be used to incentivize the backers' contribution and act eventually as a determinant of success. To our knowledge, this is the first paper to empirically analyze

[15] The total amount raised is as of October 9th, 2018 and does not include live projects.

[16] The signaling theory was originally proposed by Michael Spence (1973) as a solution to an adverse selection problem. It suggests that entrepreneurs can signal their quality through the use of signals. Signaling, along with screening and principal-agent problems, is part of a broader literature on information economics and contract theory.

how entrepreneurs utilize backers' financial motives to enhance their campaigns outcome.

Drawing on signaling theory, we argue that the entrepreneur can resolve issues related to adverse selection through the use of a pricing strategy that signals not only the quality of the reward offered , but also to signal information about the financial reward[17] offered to backers (Bagwell & Riordan, 1991; Chen & Jiang, 2016; Dai, 2016; Stacey, 2016; Yu et al., 2015). We propose that the pricing strategy includes two high-cost (from now on, costly) signals, price commitment and discount, and a low-cost (from now on, costless) signal, the number of reward classes. We analyze to what extent these signals related to the financial reward influence crowdfunding performance. We do not have sufficient information regarding the entrepreneur and their project prior to campaign launch. Hence, we do not investigate the determinants of price commitment, the discount degree and the number of reward classes. These variables of interest are treated as exogenous variables in our proposed model.

Price commitment is defined as the entrepreneur setting and publicizing both the crowdfunding and the future retail price/spot price prior to the launch of the crowdfunding campaign. As in the advance-purchase discount literature, the spot price itself can be used as a signal of venture quality (Yu et al., 2015), since by committing to a high spot price the entrepreneur is signaling the high quality of the product to potential backers. Moreover, the financial reward that takes the form of a discount incentivizes backers to pre-order the product during the campaign. Employing price commitment is nevertheless costly. By committing to a high future price, the entrepreneur risks having few buyers if the committed price is too high with respect to quality (Bagwell & Riordan, 1991). This cost will prevent low-quality ventures from imitating high-quality ones by mimicking their pricing strategy. Although this commitment is non-binding and non-verifiable during the campaign, the credibility of commitment is achievable in crowdfunding since this is a context of repeated interaction between backers and entrepreneurs (Fudenberg & Levine, 1989), given that a considerable portion of entrepreneurs return to the platform for their future ventures. By failing to deliver on their commitment, entrepreneurs would incur a reputation cost which makes non-binding contracts a credible resolution of issues arising from information asymmetry (Sharpe, 1990).

A less costly alternative to signaling information about the future retail price, with no commitment by the entrepreneur, is through the construction of the reward classes. Typically, rewards are constructed using three dimensions: timing (Super Early Bird Price, Early Bird Price, and Campaign Special Price), quantity (1 unit, 2 units, Wholesale Quantity), and product variations (different colors or sizes). Given these dimensions, potential backers can infer information about the future retail price and can construct their expectations regarding the discount offered for their support during the campaign. For instance, potential backers would expect the future retail price to be higher than both the campaign special price and the quantity discounted price. The more reward classes constructed along these dimensions, the more information potential backers have regarding the future retail price of the product. Thus, we argue that signaling the discount

[17] Since in reward-based crowdfunding no monetary rewards are allowed, the entrepreneur cannot make any financial promises. However, the entrepreneur is able to embed the financial compensation in the rewards offered in the form of a discount relative to the future retail price. We refer to this as the financial reward.

through the reward classes is costless for multiple reasons. First, the same product being offered by the entrepreneur at multiple price levels (according to the timing or quantity) does not impose any cost to create and deliver the product. Second, this pricing strategy is easy to replicate since any entrepreneur can offer their product during the campaign at multiple prices at no additional cost. Third, the potential discount is initially signaled to potential backers implicitly through the price pattern in the reward classes with no explicit commitment to the future retail price. Since the entrepreneur did not commit to any specific future price, the entrepreneur does not incur any reputation costs when diverging away from potential backers' expectations. It also gives the entrepreneur the freedom to set the retail price during the retail period depending on the realized product quality and demand. Thus, this lack of commitment makes it a costless signal.

However, multiple signals often operate at the same time, and not in isolation (Anglin, Short, et al., 2018; Courtney et al., 2017b). Since reward classes are used by potential backers to construct their expectation regarding the retail price of the product offered, the information provided by them might be redundant when the entrepreneur employs price commitment and explicitly announces the discount that backers will enjoy relative to the retail price. When information about the future retail price is explicitly mentioned, we believe that the implicit information offered through the construct of the reward classes becomes redundant, and loses importance. The influence of the costless signal might thus be weakened by the impact of the costly signal. Therefore, we investigate the interaction between the costly signals, price commitment and discount, and the costless signal, reward classes.

We test our hypotheses on a random sample of 650 projects manually collected from Kickstarter offering consumer products, for which rewards are actually pre-orders. This allows us to study advance-purchase discounts and financial motives within reward-based crowdfunding. Projects with other offerings usually have rewards that are not pre-orders such as thank you notes, online acknowledgements, exclusive scenes etc. and hence not the focus of this study. Our results show that projects employing price commitment are more likely to be successful. Moreover, the probability of success increases with the size of the discount offered. Projects offering a larger number of reward classes also enjoy better campaign performance. However, our analysis shows that price commitment and the presence of a discount moderate the effect of reward classes on campaign performance, confirming that when costly and costless signals interact, backers prioritize the former (Anglin, Short, et al., 2018).

Our work makes important contributions to several literatures. First, we contribute to the crowdfunding literature by building upon theoretical models from the economics literature on advance-purchase discounts and price commitment as a signaling device (Chen & Jiang, 2016; Yu et al., 2015), to gain insights into signaling in crowdfunding. Second, we extend current research on signaling theory in reward-based crowdfunding by focusing on financial motives, departing from the classical analysis of intrinsic, non-financial motives in reward-based crowdfunding (Cholakova & Clarysse, 2015). Third, we advance the theoretical understanding of the role of costless signals in crowdfunding, a stream of the literature still at a very incipient phase (Anglin, Short, et al., 2018). Lastly, we extend the crowdfunding literature that has mostly focused on signals in isolation, by investigating the interaction of costly and costless signals.

Finally, our findings have important implications for entrepreneurs planning to launch their ventures via reward-based crowdfunding, particularly those offering consumer products. Price commitment, the size of the discount, and the design of the reward levels are critical for their fundraising success. Committing to the future retail price during the campaign and rewarding potential backers with a discount positively enhances the campaign performance. Moreover, our paper stresses the importance of the joint decision of whether to price commit and how to design the reward levels, since they seem to provide partially substitute information to consumers.

The rest of this paper is organized as follows. In Section 2 we present the underlying theoretical framework and in Section 3 we develop the hypotheses that we will empirically test in this paper. In Section 4 we present the data that we will build our analysis on as well as define the variables of interest to us in this study. The results and their analysis are discussed in Section 5. We end the paper by discussing the implications of our study, limitations, and areas for fruitful future research in Section 6.

2. Theoretical Background

There is growing literature examining different determinants of success in reward-based crowdfunding. One strand in this literature examines and identifies entrepreneur related factors that increase the campaign's probability of success; i.e. education, social capital, previous crowdfunding performance (Butticè et al., 2017; Colombo et al., 2015; E. Mollick, 2014). Another strand in the literature examines factors related to the funders' contribution to the campaign and notices that funders' support increases as the goal is approached and decreases once the goal is attained (Kuppuswamy & Bayus, 2017; Zvilichovsky et al., 2018). The funding campaign itself has also been investigated to determine factors affecting success (Chan & Parhankangas, 2017; Davis et al., 2017). The product offering is not the only factor related to the crowdfunding campaign, but the pitch itself plays a huge role. Exploiting this idea, additional research illustrates the effects of different linguistic cues on the campaign's performance (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Moss et al., 2018; Parhankangas & Renko, 2017).

2.1 Information Asymmetry and Signaling

Information asymmetry is an issue that arises in exchange environments where one party possesses more information than the other. This can potentially lead to market failures, where exchange transactions either fail to form or are inefficient (as in Akerlof's, 1970 lemon market). In the context of entrepreneurial finance, potential investors typically possess incomplete and imperfect information regarding the quality of a venture or the credibility of an entrepreneur when compared to the entrepreneur.

The signaling theory offers a possible solution to information asymmetries (Spence, 1973). The entrepreneur (the informed party in the transaction) can send signals to the investors (the uninformed party) which disclose information about the prospects of the start-up alleviating some of the information asymmetries. Traditionally, the effectiveness of a signal depended on how costly it is to imitate that signal. The cost to acquire and send the signal is key to prevent lower quality signalers from mimicking higher quality signalers. For example, patents, granted by property rights institutions to entrepreneurs who have developed something unique, are indicative of the time and effort invested by the entrepreneur in the firm, are credible costly signals of the underlying quality of the innovation. On the contrary, an entrepreneur's statement, deemed to be costless and easy to imitate, is considered to have little value in helping investors to separate high quality ventures from low quality ventures. Nevertheless, recent signaling research has identified the conditions under which costless signals can be used to infer information about the entrepreneur's/venture's quality (Danilov & Sliwka, 2017). The three conditions identified are: when the environment has less explicit behavioral norms (Danilov & Sliwka, 2017), when the uninformed party lacks sophistication (Loewenstein et al., 2014), and when there is a lack of objective information about the venture (Lin et al., 2013)..

2.2 Information Asymmetry in Crowdfunding

In the crowdfunding context, several costly signals have been shown to credibly reveal information to backers enhancing crowdfunding performance: media usage (such as a video and images), entrepreneur's experience (previously successful crowdfunding campaigns), or product prototype (Courtney et al., 2017b; Devaraj, 2014). Moreover, crowdfunding also seems to be an appropriate context for costless signals to be useful in revealing information about the venture to investors, as it satisfies the three conditions previously mentioned. First, crowdfunding occurs at very early stages of the venture and through an online platform, which implies that there is little objective information available about the venture. Second, backers supporting crowdfunding projects usually have little or no investment experience and thus are financially unsophisticated investors. Third, investors have no formal vetting processes compared to more traditional fundraising settings. However, the existing literature on costless signals in crowdfunding is still incipient. Anglin, Short, et al. (2018) are the first to introduce costless signals to the crowdfunding context, and show how positive psychological capital language (with its four dimensions: hope, optimism, resilience and confidence) influences crowdfunding performance.

All the signals investigated in the crowdfunding context, thus far, are used to provide information about important aspects of the venture such as the project quality, the entrepreneur's credibility and characteristics. Nevertheless, a potentially key piece of information also valued by crowdfunding investors is the financial reward that they receive for their support. Unlike equity crowdfunding and peer to peer lending, in reward-based crowdfunding potential backers are not investors per se. Supporters usually back the entrepreneur's project in exchange for the promise of a reward. For projects offering consumer products, the reward is the product itself since funds are being raised for production, thus backers are essentially pre-ordering the product during the crowdfunding campaign in exchange for a lower price (Butticè et al., 2018; E. Mollick, 2014). Therefore, in this setting, backers possess incomplete information regarding not only the quality of the product, but also the financial reward that they will enjoy in the form of a discount relative to the future retail price of the product.

To this end, we introduce new signals, both costly and costless to the crowdfunding literature. In particular, we look at signals related to financial motives in reward-based crowdfunding: the entrepreneur can signal information not only about the product's quality and his/her own effort and dedication, but also about the discount offered to backers in return for their support through his/her pricing strategy. The pricing strategy includes two costly signals, price commitment and price discount, and a costless signal, the number of reward classes. Through the use of the costly signals, price commitment (publishing the future retail price) and price discount (discount for backers relative to future retail price), the entrepreneur reveals his/her private information about the product's quality and the discount offered to backers for pre-ordering the product. Moreover, although the design of different reward classes is less costly and offers no explicit information about the discount that backers receive, backers can use these reward classes to deduce information about the future retail price and hence the discount offered. In the next sections, we elaborate on why these variables act as important information mechanisms, and how costly and costless signals interact to influence crowdfunding performance.

3. Hypotheses development

3.1 Costly signals: Price commitment and Price Discount

Potential backers usually have few information available during the campaign about the product's quality and how their support during the campaign is rewarded relative to those who will order the product later on in the retail market. Entrepreneurs can take actions to signal the quality of the project as well as the financial reward to attract funders and increase the likelihood of success. For example, the entrepreneur can advertise the future retail price of the product when designing the rewards or can publish the discount that backers obtain off the future retail price. Phrases such as "future retail price: $90", "20% off future retail price", or "save up to $50 off the future retail price" are sometimes employed when designing the reward section in reward-based crowdfunding campaigns. By committing to a high future retail price, the entrepreneur is revealing private information, signaling to backers that the quality of the product is high. As argued by Bagwell and Riordan (1991), consumers infer high quality from high prices. Additionally, committing to the future retail price reveals information about the financial reward that the entrepreneur is offering to potential backers when they pre-order the product during the campaign.

Publishing and advertising the future retail price is commonly denoted as price commitment. Drawing on the information economics literature, we know that under incomplete information, price commitment serves as a signaling device (Bagwell & Riordan, 1991; Chen & Jiang, 2016; Dai, 2016; Stacey, 2016; Yu et al., 2015). A stream of this literature focuses on advance selling where advance-purchase discounts are offered to buyers. In this case, if an entrepreneur can commit to a spot price during advance selling, the spot price itself can be used as a signal of quality (Yu et al., 2015). Advance-purchase discounts also apply to new experience goods where consumers face uncertainty about the product's characteristics (Nocke et al., 2011).[18] For example, premium French vineries recur to advance selling for their wine. That is, they offer consumers the possibility of buying the new vintage at a discount before it is bottled. Wine quality is uncertain to buyers during advance sales since the product does not exist yet (Nocke et al., 2011; Yu et al., 2015).

In the crowdfunding context, backers pre-order the product and buy at the crowdfunding stage before production (i.e., advance purchase), where they face a lot of uncertainty regarding the yet inexistent product (at most the entrepreneur can present a prototype). Backers can only determine the quality of these innovative products after delivery. Thus, products offered through crowdfunding campaigns can also be considered experience goods. In contrast, the entrepreneur has much more information available about the quality of the product (e.g., the materials used to produce it, etc.). Consequently,

[18] An experience good is defined as a product whose quality consumers cannot readily determine until they have used the product after purchase.

the information on product quality is asymmetric in advance. Like for many other experience goods, the entrepreneur can signal the quality of the product by publicizing the future retail price (i.e., price commitment), and by offering an advance-purchase discount.

Price commitment will be an efficient way for the high-quality venture to signal its true quality under two conditions. First, price commitment must be credible. As argued in Sewaid, Garcia-Cestona, & Silaghi (2018), credibility of commitment is achievable in crowdfunding since this is a context of repeated interaction between backers and entrepreneurs (Fudenberg & Levine, 1989). Indeed, a third of the funds raised on Kickstarter are accounted for by serial entrepreneurs that return several times to the market (Butticè et al., 2017). Thus, although this commitment is non-binding, since there are currently no legal consequences of failing to commit to the publicized prices, the entrepreneur would incur substantial costs in terms of reputation or lost customers in case of deviation. Non-binding contracts are shown to resolve information asymmetry issues when backed by reputation (Sharpe, 1990).

Second, it should be difficult for entrepreneurs with low-quality projects to imitate entrepreneurs with high-quality projects by mimicking their pricing strategy. This is indeed the case since employing price commitment is costly. If the future retail price committed is too high with respect to quality, not many consumers will buy the product in the retail period. The consequent loss of volume will be more damaging for the low-quality venture (Bagwell & Riordan, 1991). Thus, it will be costlier for the low-quality venture to mimic the high-quality venture's high future price.

Because ventures of different quality levels have different optimal pricing strategies, price commitment is an efficient tool for the high-quality venture to signal its quality and differentiate from the low-quality one (Chen & Jiang, 2016). Moreover, since those backers pre-ordering the product during the crowdfunding campaign do so in expectation of a lower price relative to the retail price (Butticè et al., 2018; E. Mollick, 2014) they are incentivized by the embedded financial reward that takes the form of a discount. We, therefore, hypothesize:

Hypothesis 1a: Price commitment by the entrepreneur is positively associated with the campaign performance.

Hypothesis 1b: Rewarding potential backers with a higher discount, relative to future retail consumers, is positively associated with the campaign performance.

3.2 Costless signals: Reward classes

In some situations, price commitment is difficult since the spot price of the product will be influenced by the production process that has not yet taken place (Yu et al., 2015). In this case, the entrepreneur could signal its quality through the design of the rewards.

In the campaign's webpage, the rewards are typically presented in increasing order of price, with lower priced reward classes offered in limited capacity. For example, an entrepreneur could offer the product at 10 dollars for the first 100 backers in the first reward class, while in the second reward class the same product can be offered at 11 dollars with no limit on the quantity available. Although the entrepreneur might find it difficult to commit to a future retail price, the information provided through the increasing price pattern of the rewards could be a valuable signal for backers regarding the quality of the product and the embedded financial reward. If the entrepreneur offers the reward at only one price level, backers will expect that the price in the retail period would be higher but it will be difficult for them to predict how much higher the retail price would be. However, by offering the same reward at different price levels, backers could infer, with more confidence, the retail price range from the increasing price pattern that the reward classes exhibit. Therefore, by offering a larger number of reward classes, the entrepreneur can solve some of the information asymmetries and signal more information regarding the expected retail price without explicit commitment. Thus, the entrepreneur provides backers with a larger information set to construct their expectation concerning the future retail price. However, if the entrepreneur faces lower than expected demand in the retail period, he/she can adjust the price accordingly since he/she did not publicize any future price during the crowdfunding campaign. Therefore, the lack of reputation costs associated with diverging from backers' expectations makes it a costless signal of quality and financial reward.

Communicating information about the future retail price by designing the reward section in increasing price order is not costly per se since offering the same product at multiple prices (Super Early Bird Price, Early Bird Price, and Kickstarter Special Price, Quantity Discount) does not entail any additional production or delivery costs, and it is relatively cheap to publish text on the campaign website. Thus, signaling a venture's quality and the financial reward offered to backers through appropriate presentation of the rewards could be considered costless. Similarly, Anglin, Short et al. (2018) argue that communicating positive psychological capital (such as hope, optimism, resilience and confidence) through use of language is costless. Even though it is a costless signal, these authors show that it does positively influence crowdfunding success. In a similar vein, we argue that, despite its low cost, signaling through reward classes could also have a positive influence on the crowdfunding performance. If rewards are designed in multiple classes in increasing price order, a high last reward price could signal a high future retail price. Backers could infer from this a high product quality and a high financial reward in return for their backing activity. Additionally, since the entrepreneur did not commit to any specific future price, the entrepreneur does not incur any reputation costs when diverging away from potential backers' expectations regarding the future price. Moreover, having multiple rewards could also signal effort, motivation, preparation and dedication from the side of the entrepreneur, potentially attracting more support from backers. In fact, reward classes actually serve two purposes in the campaign. On the one hand, they signal information regarding the future retail price and are therefore costless as argued earlier as there is no explicit commitment by the entrepreneur. On the other hand, these rewards could be offering different product variations, which could further enhance campaign performance. We accordingly hypothesize:

Hypothesis 2: The number of reward classes is positively associated with the campaign performance.

3.3 Interaction Between Costly and Costless Signals

Signals rarely act in isolation, they rather interact with other signals (Anglin, Short, et al., 2018; Courtney et al., 2017b). For example, signals originating from the same source of information such as media usage and founder's past success, have been shown to partially offset each other's informational value (Courtney et al., 2017b). On the contrary, signals originating from different sources of information such as media usage and backers' positive comments, or founder's past success and backers' positive comments validate and complement each other's information. Similarly, Anglin, Short et al. (2018) show that costly signals, may, at times, enhance the influence of costless signals. While increases in human capital (a costly signal) strengthen the relationship between the use of positive psychological capital (a costless signal) and crowdfunding success, social capital (another costly signal) does not moderate this relationship.

In our case, signals in the form of price commitment and discount operate simultaneously with reward classes. As mentioned earlier, reward classes play two roles in affecting the campaign performance. First, they provide implicit information regarding the discount that backers enjoy relative to future retail consumers. Having more reward classes helps potential backers better form their expectations regarding the future retail price. Second, they offer different product variations that increases the chances of appealing to a wider set of backers. Since the increasing price pattern of rewards can offer partial information regarding the future retail price, the information content of the rewards could be partially redundant in the presence of price commitment. Thus, in this case, reward classes would only affect the crowdfunding performance through the product variety that it offers (more choice), and not through the information that backers could infer about the discount. Hence, the effect of reward classes on the crowdfunding performance might be partially offset. Therefore, when costly signals are available, backers might prioritize them, weakening the influence of costless signals. This suggests the following:

Hypothesis 3: The positive effect of a costless signal (number of reward classes in our case) on the campaign performance is weakened in the presence of the costly signals (price commitment and discount in our case).

4. Data and Methodology

4.1 Data Source and Sample Construction

We collect data from Kickstarter, the leading reward-based crowdfunding platform which has been widely used in previous crowdfunding research (e.g. Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017; Kuppuswamy et al., 2017; Mollick, 2014). Our initial dataset covers all observations *(297,884 projects)* between April 21st, 2009 and November 29th, 2016. Out of these, 109,707 projects (36.83%) were successful. Similar to previous studies we eliminate those projects not denominated in USD currency, projects with goals less than $1,000, and projects which were in progress, cancelled, or suspended (Butticè et al., 2017; Courtney et al., 2017b; E. Mollick, 2014). This reduces the sample to 194,058 observations out of which 79,699 projects (41.07%) were successful, raising a total of $1.92 billion USD. Hereafter, we refer to this refined sample as our initial sample.

To test our hypotheses we focus our attention, similarly to earlier studies, on those projects offering consumer products.[19] We have a final sample of 30,751 projects offering consumer products out of which 12,497 projects (40.64%) were successful. The success rate in our final sample closely mirrors that of the initial sample. Even though our final

[19] Projects offering consumer products are projects in the following subcategories: 3D Printing, Accessories, Apparel, Camera Equipment, Childrenswear, Couture, Footwear, Gadgets, Gaming Hardware, Hardware, Jewelry, Pet Fashion, Playing Cards, Product Design, Puzzles, Ready-to-Wear, Robots, Sound, Tabletop Games, Video Games, and Wearables.

sample only represents 15.84% of the total number of observations in the initial sample it accounts, nevertheless, for more than 50% of the funds raised in the initial sample (1.02 billion USD). Hereafter, we will refer to the final sample as the population, since it includes all the projects in the subcategories of interest to us.

Unfortunately, to fully capture information regarding price commitment, discount degree, and reward classes, we need data that is not readily available. We have collected this information manually.[20] Since this is a very time-consuming process, we proceed by taking a random sample of 650 observations for which we have hand collected this information.[21] We have also used mean comparison tests and regression analysis to verify that our random sample (650 observations) does not differ significantly from the population (30,751 observations), and thus closely represents the projects in the mentioned subcategories. Additionally, we have checked for differences in the subcategory representation between the population and the random sample, and no significant differences have been found.

4.2 Measures

4.2.1 Dependent Variables

In our analysis we proceed using two proxies for the crowdfunding campaign performance to test our hypothesis. Since Kickstarter is a reward-based crowdfunding platform that uses an all-or-nothing mechanism, an appropriate measure of the campaign performance is whether the campaign was successful in reaching its goal or not (e.g., Butticè et al., 2017; Colombo et al. , 2015; Courtney et al., 2017). Given this we have our dependent variable defined as *Success* (*0 = Failure, 1 = Success*). Additionally, previous literature has occasionally used the amount of capital raised as a measure of crowdfunding performance (e.g., Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017). The amount of capital raised is positively skewed we would like to apply the natural log transformation to correct for the skewness, but we faced zero values in the data which prevented the use of the natural logarithm transformation. To overcome this, and following the transformation proposed by Anglin, Short et al. (2018), we use an inverse hyperbolic sine transformation. This transformation allows us to correct for the right skew, and its interpretation remains identical to that of variables transformed using the natural log (Burbidge, Magee, and Robb, 1988; Franke and Richey, 2010; Sauerwald, Lin, and Peng, 2016). The inverse hyperbolic sine transformation is computed as follows: $\sinh^{-1}(y) = \log(y + (y^2 + 1)^{1/2})$. We denote this measure of crowdfunding performance as *Amount Raised*.

4.2.2 Independent Variables

For the independent variables, we have hand-collected information regarding price commitment, the discount degree, and the number of reward classes. More specifically, *Price Commitment* is constructed as a dummy variable where *Price Commitment = 1* if the entrepreneur publicizes either the future retail price or the

[20] Text mining is another alternative; however, we do not consider it as it is more prone to type I and type II errors and to underestimation bias.

[21] When deciding on the sample size we were willing to accept a 5% margin of error with 99% confidence level hence our choice of 650 observations.

discount that backers will enjoy when compared to future retail customers. For projects with price commitment, we construct the variable *Discount Degree,* which is the discount that campaign backers enjoy when compared to the specified retail price. Since there are multiple reward classes usually in increasing price order, there will be different discount degrees for each of these classes. As the early reward classes are typically capped in quantity, we aggregate this information into a unique discount measure per project. This discount is computed as the difference between the total future value [(*# of Backers/Reward)* x *Future Retail Price*] and the corresponding total value of the backing activity [(*# of Backers/Reward)* x *Reward Price*], divided by the former one, and is expressed in percentage (see Appendix).[22] For projects offering their rewards at a premium, this *Discount Degree* becomes negative. For those reward levels where the future retail price is not specified, we assume that there is no discount, i.e., the retail price is the same as the reward price.[23] For the number of reward classes, we manually analyzed the rewards offered by the entrepreneur. Since we focus on financial motives, rewards offering a variation of the same product (just different color or size) at the same reward price were consolidated into one reward class (see Appendix for an illustration). Due to the skewness of the number of reward classes identified, we operationalize the variable *Rewards* as the log transformation of the number of reward classes identified.[24] To investigate the presence of the moderation effects that price commitment and discount might have on the influence of the number of rewards on the campaign performance, we also construct the interaction terms *Price Commitment* x *Rewards* and *Discount Degree* x *Rewards*.

4.2.3 Control Variables

We include a number of control variables that might influence crowdfunding performance and which are consistent with the previous literature on crowdfunding. Following Butticè et al. (2017), Colombo et al. (2015), Courtney et al. (2017), and Mollick (2014) we control for the project goal size, using the natural logarithm of the project goal, and denote this variable by *Project Goal*. To control for the entrepreneur's specific attributes on the crowdfunding platform, we account for the entrepreneur's previous successes and failures (e.g., Butticè et al. 2017; Courtney et al. 2017). These are denoted by *Previous Success* and *Previous Failure* respectively. The variables *Previous Success* and *Previous Failure* are the inverse hyperbolic sine transformation of the entrepreneur's previous successes and failures.[25] For campaign content variables we control for whether the project has a video pitch or not, using a dummy variable *Video Pitch (0 = no video pitch, 1 = video pitch available)*. We also control for the count of videos on the campaign page and denote it by *Video Count*. The variable *Image Count* refers to the number of

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[22] We acknowledge that when a backer decides whether to support a project, he/she will look at the individual discount for a given reward class and not at the aggregate one weighted by the ultimate outcome of the campaign. Nevertheless, aggregating this information using a weighted average seems more sensible than making a simple equally weighted average of the discounts across reward classes since a very high discount for the first reward class might be capped in quantity, so that only few early backers can enjoy it.

[23] This assumption allows us to use the whole random sample to test our hypothesis. Nevertheless, to verify that our results are not driven by this assumption, we also test our hypothesis on the subsample of projects with Price commitment=1, the only situations in which we observe the discount.

[24] Some projects also have some low-level rewards like "thanks" or t-shirts for small contributions, e.g., $5. Although they are not the focus of our study, we include them in the reward classes. However, they do not affect our measure of discount since no future retail price is publicized for these rewards.

[25] $Previous\ Success = log(Previous\ Success + (Previous\ Success^2 + 1)^{1/2})$

$Previous\ Failure = log(Previous\ Failure + (Previous\ Failure^2 + 1)^{1/2})$

images in the campaign webpage and *Word Count* is the number of words. Additional control variables in our analysis are the *Duration* of the campaign, *Category* to which the project belongs, and the *Year* of launch.

4.3 Random sample vs Population

We now perform a check to address potential concerns regarding the representativeness of our random sample. In Table 2.1 we present first the means of the variables for the population and the random sample, and then we perform a test of difference in means. We only note a significant difference for the video count at the 10% level. Other than that, we note no significant differences among both samples. Thus, this suggests the representativeness of our random sample.

Table 2.1
Difference in Means (Population and Random Sample)

	Population	Random Sample	Two tails t-test
Observations	30,751	650	
Success (%)	0.41	0.40	
Amount Raised (in $000s)	36.00	25.00	
Project Goal (in $000s)	46.00	110.00	
Number of Previous Failures	0.21	0.22	
Number of Previous Successes	0.49	0.60	
Video Pitch (Yes/No)	0.82	0.81	
Video Count	0.47	0.56	*
Image Count	12.49	11.72	
Word Count (in 000s)	3.63	3.67	
Duration (in days)	34.23	34.49	

** p-value < 0.10*

4.4 Descriptive Statistics and Correlations

Table 2.2 provides the descriptive statistics and correlations for our sample, as well as the variance inflation factors (VIFs) of our independent variables. The average VIF (1.58) and the maximum VIF (3.04) are well below the thresholds established in the literature (Hair et al., 2010; McDonald & Moffitt, 1980; Neter et al., 2018; Tabachnick & Fidell, 2007). Therefore, these results indicate no concerns in regard to multicollinearity issues with our subsequent analyses. Even though our VIF scores pose no multicollinearity issues, we further investigate the two relatively high VIFs (*Price Commitment* and *Discount Degree*) that we observe. It is worth noting that the two relatively high VIFs are for variables that will be used in separate estimation models, not

Table 2.2

Descriptive Statistics, Correlation Matrix, & VIFs

	Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	VIF
1	Success	0.40	0.49	0.00	1.00	1.00													DV
2	Amount Raised	7.08	3.42	0.00	14.31	0.69 ***	1.00												DV
3	Price Commitment	0.15	0.36	0.00	1.00	0.17 ***	0.26 ***	1.00											3.04
4	Discount Degree	0.04	0.12	-0.60	0.68	0.20 ***	0.26 ***	0.81 ***	1.00										2.99
5	Rewards	1.88	0.70	0.00	3.22	0.35 ***	0.51 ***	0.10 ***	0.09 **	1.00									1.27
6	Project Goal	9.38	1.30	6.91	17.73	-0.14 ***	0.18 ***	0.15 ***	0.11 ***	0.17 ***	1.00								1.16
7	Previous Failure	0.17	0.41	0.00	2.89	0.08 **	0.06	0.05	0.06	-0.07 **	-0.15 ***	1.00							1.27
8	Previous Success	0.22	0.65	0.00	4.64	0.31 ***	0.26 ***	0.12 ***	0.12 ***	0.05	-0.09 **	0.43 ***	1.00						1.31
9	Video Pitch	0.81	0.39	0.00	1.00	0.28 ***	0.47 ***	0.17 ***	0.14 ***	0.35 ***	0.10 **	-0.03	0.09 **	1.00					1.16
10	Video Count	0.56	1.46	0.00	17.00	0.14 ***	0.27 ***	0.07 *	0.06	0.17 ***	0.18 ***	0.02	0.12 ***	0.14 ***	1.00				1.13
11	Image Count	11.72	12.87	0.00	107.00	0.31 ***	0.47 ***	0.24 ***	0.23 ***	0.38 ***	0.15 ***	0.08 **	0.14 ***	0.27 ***	0.25 ***	1.00			1.50
12	Word Count	3.67	3.31	0.00	17.53	0.27 ***	0.39 ***	0.10 **	0.07 *	0.36 ***	0.25 ***	-0.02	0.04	0.24 ***	0.24 ***	0.46 ***	1.00		1.43
13	Duration	34.49	10.85	5.00	65.00	-0.07 *	0.01	0.05	0.05	0.03	0.13 ***	-0.02	-0.16 ***	0.02	0.02	-0.04	-0.01	1.00	1.05

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

jointly. Once we include one but not the other in the model, we have a significant drop in both the average VIF (1.24) and the maximum VIF (1.49).

The projects in our sample were launched during the years 2010 to 2016. Out of the 650 projects in our sample we have 260 successful projects (40%). The average campaign in our sample was public for a period of 34.5 days and offered 8 unique reward classes. We also know that 99 projects (15%) committed to prices during the campaign and offered, on average, a discount of 26.39% off retail price. Also, entrepreneurs with previous projects launched 154 projects (23.69%) in our sample. Concerning media content, 81% of the projects in our sample featured a video pitch in their campaign webpage and, on average, they had 0.56 videos and 11.72 images within the campaign description section.

4.5 Estimation Models

To test the association of price commitment, discount, reward classes, and their interaction with the crowdfunding success, we model the probability of crowdfunding success using a logistic regression model which we denote as Model A. We report the coefficients and robust standard errors (the latter ones in between brackets) in Model A and follow with an analysis of the marginal effects. The conditional marginal effects of independent variables discussed in the analysis below holds all continuous variables at their mean values, the categorical variables at their mode values, and the dummy variables at their median value, which is more appropriate than reporting the average marginal effects. It also helps to provide a clearer intuition. This approach is also adopted by Butticè et al. (2017). In Model B, we investigate the effects of price commitment, discount, reward classes, and the interaction terms on the amount of capital raised (*Amount Raised*). The estimation procedure applied is the robust ordinary least squares (OLS) estimation.

5. Empirical Results

In Table 2.3 and Table 2.4 we present the results of the logistic regression, Model A, and the robust ordinary least squares (OLS) estimation, Model B. In Model A (control), we first consider the control variables and their effect on the probability of success. The average project in our sample has a 35.77% probability of success. The signs in the model presented are consistent with previous literature. We note that increasing the value of *Project Goal* by one standard deviation (SD) is associated with a decrease in the probability of success from 35.77% to 20.46%. Regarding *Previous Failure*, even though weakly significant ($p < 0.10$), we observe that a one SD increase reduces the probability of success from 35.77% to 30.39%, while a one SD increase in *Previous Success* increases the probability of success from 35.77% to 58.09%. Thus, our findings are consistent with earlier evidence that previous success and previous failure indeed affect the probability of success (Butticè et al., 2017). For projects where the entrepreneur does not have a video pitch in the campaign page, the probability of success decreases from 35.77% to 9.45%. Regarding the image content of the campaign's page, for a one SD increase in *Image Count* the probability of success increases from 35.77% to 36.96%. When looking at the text length of these campaigns, we observe that a one SD increase in the text length increases the probability of success from 35.77% to 46.76%. The number of videos included in the campaign content and the duration of the campaign had no significant effects on the campaign's success.

In Model B (control) we observe a similar effect of the control variables on the *Amount Raised* except for the variables: *Project Goal*, *Previous Failure*, and *Video Count*. We have that the campaign's goal is positively associated with the amount of capital raised at the 10% significance level, previous failure does not affect the amount of capital raised, and the more videos incorporated in the campaign page the higher is the amount of capital raised.

5.1 Costly Signals: Price Commitment and Price Discount

In Model A (I) we add entrepreneur's price commitment. The explanatory and the diagnostic power of the model increases, as shown by the McFadden's Pseudo R^2 (from 25.18% 26.06%) and the Receiver Operating Characteristics (ROC) curves (from 81.89% to 82.06%). It is worth noting that, even though only 99 projects (15.23%) out of the 650 projects commit to the future retail price we find supporting evidence that price commitment by the entrepreneur is associated with an increase in the probability of success from 33.84% to 52.53% and the coefficient of *Price Commitment* is significant ($p < 0.01$). We find a similar positive and significant coefficient for *Price Commitment* in the robust ordinary least squares regression in Model B (I), that considers *Amount Raised* as the dependent variable. Furthermore, looking at the difference in the means of projects that commit versus projects without commitment, we see that 60.12% of projects that commit to prices are successful while only 36.40% of projects that do not commit succeed and this difference is significant ($p < 0.01$). Thus, our results provide a clear support for *Hypothesis 1a*.

We have shown that the entrepreneur's price commitment is positively associated with the probability of success and the amount raised. This result follows because providing more information to the backers regarding the future price of the product signals information about the quality of the project and the financial reward that backers will enjoy in the form of a discount. In line with the advance-purchase discount literature and the theoretical model proposed by Sewaid et al. (2018), we verify empirically that almost all projects that commit do offer a discount and not a premium.[26] In order to investigate further the effect of the discount on the campaign's crowdfunding success, we have also considered the *Discount Degree* variable in Model A. The results are shown under Model A (II). We find that a one SD increase in the discount offered to backers is associated with an increase in the probability of success from 36.87% to 43.40% and the coefficient of the *Discount Degree* is significant ($p < 0.01$). We cannot test the joint effect of *Price Commitment* and *Discount Degree* since they are highly correlated. Regarding other variables, we have the same effects as those discussed under Model A (control). The explanatory and diagnostic power of the model further improve significantly as it can be seen through the significant improvement in the model's McFadden's Pseudo R^2 (from

[26] In fact, only 1 out of 99 projects in our sample charges backers a premium. Moreover, the project charging a premium failed to meet its funding goal.

Table 2.3
Logistic Regression Models

	Model A (Dependent Variable : Success)						
	Control	I	II	III	IV	V	VI
Price Commitment		0.7721***		0.8027***		3.5357***	
		(0.2908)		(0.2951)		(0.9957)	
Discount Degree			3.5620***		3.6769***		10.1555***
			(0.9778)		(1.0455)		(3.6400)
Rewards				1.3101***	1.3194***	1.6786***	1.5800***
				(0.2337)	(0.2339)	(0.2855)	(0.2680)
Price Commitment x Rewards						-1.3134***	
						(0.4514)	
Discount Degree x Rewards						-1.3134***	-3.1884**
						(0.4514)	(1.6157)
Project Goal	-0.5931***	-0.6297***	-0.6428***	-0.7481***	-0.7631***	-0.7557***	-0.7652***
	(0.0879)	(0.0889)	(0.0906)	(0.1034)	(0.1060)	(0.1049)	(0.1066)
Previous Failure	-0.5960*	-0.6261**	-0.6689**	-0.4632	-0.4977	-0.4717	-0.5085
	(0.3071)	(0.3166)	(0.3211)	(0.3146)	(0.3168)	(0.3151)	(0.3172)
Previous Success	1.3964***	1.3871***	1.4353***	1.4178***	1.4622***	1.3891***	1.4566***
	(0.2574)	(0.2595)	(0.2556)	(0.2412)	(0.2380)	(0.2461)	(0.2420)
Video Pitch	1.6744***	1.6323***	1.6177***	1.5353***	1.5257***	1.5220***	1.5113***
	(0.3155)	(0.3171)	(0.3192)	(0.3290)	(0.3319)	(0.3315)	(0.3341)
Video Count	0.0961	0.0999	0.1061	0.0993	0.1066	0.0815	0.0955
	(0.0679)	(0.0671)	(0.0673)	(0.0679)	(0.0684)	(0.0679)	(0.0683)
Image Count	0.0446***	0.0404***	0.0397***	0.0274***	0.0266***	0.0278***	0.0269***
	(0.0103)	(0.0101)	(0.0099)	(0.0102)	(0.0100)	(0.0105)	(0.0102)
Word Count	0.1377***	0.1377***	0.1401***	0.1136***	0.1162***	0.1042***	0.1093***
	(0.0411)	(0.0411)	(0.0413)	(0.0415)	(0.0417)	(0.0415)	(0.0416)
Duration	0.0010	-0.0003	-0.0014	-0.0037	-0.0047	-0.0038	-0.0049
	(0.0086)	(0.0087)	(0.0088)	(0.0088)	(0.0090)	(0.0089)	(0.0090)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	650	650	650	650
Mc Fadden's Pseudo R^2	0.2518	0.2606	0.2707	0.3085	0.3183	0.3175	0.3246
Log pseudolikelihood	-327.30	-323.45	-319.05	-302.50	-298.24	-298.58	-295.46

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 2.4
Robust Ordinary Least Squares Regression Models

	Model B (Dependent Variable : Amount Raised)						
	Control	I	II	III	IV	V	VI
Price Commitment		0.9175***		0.9162***		2.9132***	
		(0.2975)		(0.2926)		(0.8795)	
Discount Degree			3.7415***		3.6922***		9.7599***
			(0.8865)		(0.8634)		(2.3570)
Rewards				1.3006***	1.2960***	1.4689***	1.4325***
				(0.1657)	(0.16377)	(0.1780)	(0.1732)
Price Commitment x Rewards						-0.9889**	
						(0.4260)	
Discount Degree x Rewards							-3.0082***
							(1.1103)
Project Goal	0.1610*	0.1331	0.1369	0.0880	0.0922	0.0900	0.0957
	(0.0918)	(0.0923)	(0.0929)	(0.0848)	(0.0855)	(0.0841)	(0.0846)
Previous Failure	-0.2998	-0.3214	-0.3251	-0.1193	-0.1234	-0.1165	-0.1230
	(0.2283)	(0.2306)	(0.2291)	(0.2136)	(0.2118)	(0.2094)	(0.2074)
Previous Success	1.2040***	1.1477***	1.1352***	1.1123***	1.1007***	1.0567***	1.0553***
	(0.1447)	(0.1450)	(0.1438)	(0.1375)	(0.1352)	(0.1374)	(0.1357)
Video Pitch	2.5510***	2.4641***	2.4496***	1.9856***	1.9740***	1.9259***	1.9184***
	(0.2930)	(0.2920)	(0.2913)	(0.2800)	(0.2779)	(0.2819)	(0.2787)
Video Count	0.1493**	0.1512**	0.1536**	0.1454**	0.1477**	0.1332**	0.1375**
	(0.0644)	(0.0646)	(0.0654)	(0.0608)	(0.0616)	(0.0610)	(0.0614)
Image Count	0.0766***	0.0715***	0.0693***	0.0536***	0.0515***	0.0546***	0.0526***
	(0.0112)	(0.0110)	(0.0113)	(0.0099)	(0.0102)	(0.0098)	(0.0101)
Word Count	0.1166***	0.1155***	0.1186***	0.0797**	0.0829**	0.0743**	0.0786**
	(0.0397)	(0.0387)	(0.0386)	(0.0357)	(0.0356)	(0.0356)	(0.0353)
Duration	0.0132	0.0120	0.0112	0.0078	0.0072	0.0081	0.0074
	(0.0094)	(0.0094)	(0.0094)	(0.0087)	(0.0089)	(0.0087)	(0.0087)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	650	650	650	650	650	650	650
Mc Fadden's Pseudo R^2	0.4571	0.4651	0.4713	0.5149	0.5207	0.5191	0.5248

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

25.18% to 27.07%) and the ROC curves (from 81.89% to 82.65%). Similar results can be observed for the effect of *Discount Degree* on the amount of capital raised in Model B (II). The results of Model A (II) along with Model B (II) support *Hypothesis 1b.* By publicizing a higher future retail price, the entrepreneur signals higher quality of the offered product and a larger financial reward to backers in return for their support, improving the campaign performance.

5.2 Costless Signals: Reward Classes

In Model A (III) we add the independent variable *Rewards* to Model A (I). The explanatory power of the model increases as depicted by the increase in the McFadden's Pseudo R^2 (from 26.06% to 30.85%). We also note that the diagnostic ability of the model significantly improves since the area under the ROC curve increases (from 82.06% to 84.81%). For a one SD increase in *Rewards*, the probability of success shifts from 27.99% to 49.27%. Similarly, if we add *Rewards* to Model A (II), the same effect of *Rewards* on the probability of success occurs. Now, a one SD increase in the number of rewards is associated with an increase in the probability of success from 30.99% to 53.05%. Thus, we see that when the entrepreneur conveys more information about the venture through offering more reward classes, he/she seems able to capture more backers and the probability of success does increase. The same effects can be observed for the amount of capital raised, presented in Models B (III - IV). Thus, these findings provide support for *Hypothesis 2*, the number of rewards is positively associated with the campaign performance.

5.3 Interaction Between Costly and Costless Signals

We are now interested in checking the effects of the simultaneous use of signals. Model A (V) analyzes the interaction between price commitment and the number of reward classes. For this purpose, we add the interaction term, *Price Commitment* x *Rewards* to Model A (III). Once again, the explanatory power of the model increases as depicted by McFadden's Pseudo R^2 (from 30.85% to 31.75%) and the diagnostic ability of the model significantly improves since the area under the ROC curve increases (from 84.81% to 85.36%). The coefficient of the interaction term is negative and significant, $p < 0.01$, suggesting that, indeed, a moderation effect exists. For projects without price commitment, a one SD increase in *Rewards* enhances the probability of success from 26.25% to 53.51%. However, for projects with price commitment, a one SD increase in *Rewards* only improves the probability of success from 50.87% to 57.20%. These results suggest that backers prioritize the signals available to them, where the costly signal, price commitment, weakens the influence of the costless signal, reward classes. Since looking at the coefficient of the interaction term in non-linear models is not sufficient, we have additionally proceeded to plot the relationships in Figures 2.1 and 2.2 (following Ai and Norton, 2003), and confirmed the previous results. Furthermore, the same effect can be seen in Model A (VI), that analyzes the moderating effect of the discount on the probability of success. The previous results, along with the results shown under Model B (V) and (VI), provide support for *Hypothesis 3*.

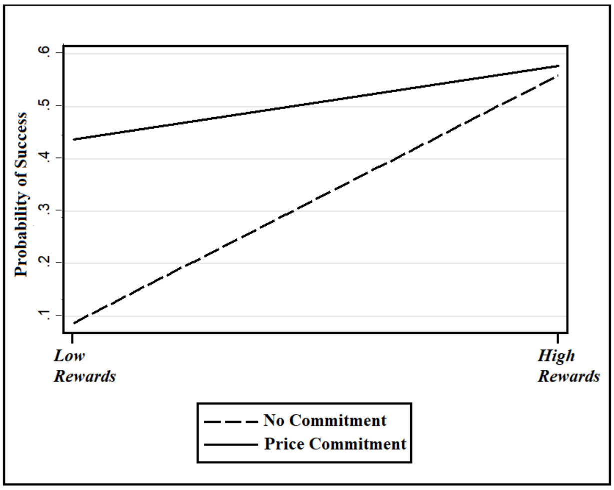

Figure 2.1: Conditional Marginal Effects of Reward Classes on the Probability of Success with Interaction Term

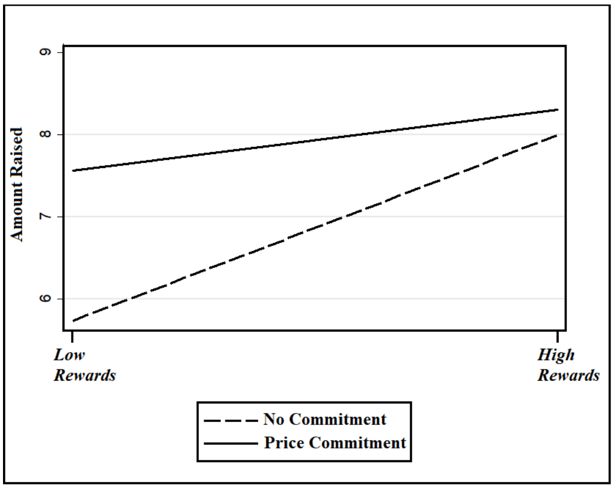

Figure 2.2: Conditional Marginal Effects of Reward Classes on the Amount Raised with Interaction Term

5.4 Robustness Checks

To ensure the robustness of our results in this section, we have run additional tests.[27] First, we run propensity score matching and use the nearest neighbor matching algorithm between projects that commit and projects that do not. Every matching is performed with replacement to reduce possible biases (Abadie and Imbens, 2012). We find that after matching our 99 projects that committed to prices during the crowdfunding campaign with their nearest neighbors, we obtain that *Price Commitment* is still a very significant factor ($p < 0.01$) affecting the campaign's success. To further validate the robustness of our results we have also repeated this process using the nearest two and three neighbors. Similar results still hold.

Second, we perform a Heckman 2 Stage Model, where in the first stage we investigate the effect of *Price Commitment* on *Success* and in the second stage we investigate the effect of the *Discount Degree* on *Amount Raised*. The result of this analysis

[27] The results of the robustness checks are available upon request.

shows that indeed price commitment is positively associated with the success of the campaign ($p < 0.01$). Moreover, among the successful campaigns, the level of discount is positively associated with the amount of funds raised during the campaign ($p < 0.01$). Regarding *Rewards*, we find that it is positively associated with campaign's success ($p <$ 0.01). However, among the successful campaigns, increasing the number of reward classes is not significantly associated with the amount of funds raised.

Third, we have created alternative measures of campaign performance and check the significance of our findings when using these additional measures. Various studies have used ratio-based measures of crowdfunding performance (Belleflamme, Lambert, and Schwienbacher, 2013; Cholakova and Clarysse, 2015; Frydrych, Bock, Kinder, and Koeck, 2014; Mollick, 2014; Scheaf et al., 2018). Like Scheaf et al. (2018), we have used the campaign's funded percentage as a measure of success, since the campaign goal is a valuable reference point. This variable is operationalized as the inverse hyperbolic sine transformation of $[(Amount\ Raised)/(Funding\ Goal)]$. Then we have run robust ordinary least squares (OLS) estimations and the results provide further support for our hypotheses and confirm the robustness of our results. Additionally, we use the number of backers as an additional measure of campaign performance (Anglin, Wolfe, et al., 2018; Viotto da Cruz, 2018). The results are also robust to this additional measure of campaign performance.

As a fourth check for the robustness of our results, we have used the raw reward count, as well as its log transformation, instead of the variable *Rewards*. That is, we have used the total number of reward levels as presented in the campaign website, and not the number of reward classes where levels offering a variation of the same product (different color or size) at the same reward price have been consolidated into one class. We also conclude that all the results discussed in our analysis still hold. We have gone a step further by dissecting the reward count into reward classes (which we constructed earlier) and repeated rewards (consolidated into reward classes in our prior analysis). We find that the number of reward classes has a significant effect on the campaign's success, but the number of repeated rewards has no effect on the campaign's success. Moreover, we compare the two models and find that the model using reward classes outperforms the model using the raw reward count.

Fifth, we have controlled for possible biases due to outliers. In the first approach of outliers control we have winsorized the continuous variables in our model at the 1st and 99th percentile. As a second approach we have trimmed the data at the 1st and 99th percentile to remove the extreme values from the estimation model. The results from both treatments are fully consistent with the outcomes of our main model. Finally, we have repeated all our logit estimations using probit as suggested by Butticè et al. (2018) and our results still hold.

6. Discussion and Conclusion

Due to the scarcity of information regarding the quality of the product and the financial reward for pre-ordering the product during the campaign, potential backers face information uncertainty. In this paper, we examine how the entrepreneur can alleviate some of the informational uncertainty by using signals. Specifically, we explore three signals related to financial motives present in the rewards section of the crowdfunding campaign. First, we start by investigating how costly signals, such as price commitment and discount, affect the campaign performance. This empirically contributes to both the economics literature on price commitment (Chen & Jiang, 2016; Davis et al., 2017; Sewaid et al., 2018; Yu et al., 2015) and the signaling literature in crowdfunding (Anglin, Short, et al., 2018; Courtney et al., 2017b; Davis et al., 2017; Piva & Rossi-Lamastra, 2018; Scheaf et al., 2018). Second, we also contribute to the literature on the effectiveness of costless signals (Anglin, Short, et al., 2018; Danilov & Sliwka, 2017; Lin et al., 2013; Loewenstein et al., 2014) by investigating the effect of costless signals such as reward classes in the crowdfunding context. We find that the number of reward classes significantly enhances the campaign's outcome given its ability to serve as a costless signal to reveal information about the product. Our findings also shed some light on previous conflicting evidence regarding the effect of the number of rewards on the campaign's outcome (Butticè et al., 2017; Courtney et al., 2017b; Du et al., 2018; Kunz et al., 2017). By consolidating the different reward levels we show that the reward classes drive crowdfunding performance, while repeated rewards have no effect. Third, we add to the literature on the interaction of signals and show that signals do not work in isolation (Anglin, Short, et al., 2018; Plummer, et al., 2016; Stern, et al., 2014). We show that when signals overlap in the information that they convey, they are prioritized by the receiver, and that the effect of the costly signal partially offsets that of the costless signal.

A post-hoc analysis compared the use of price commitment in the successful campaigns in our random sample and the top 100 funded campaigns in the same categories. We find that 54.50% of the top funded campaigns utilize price commitment, while only 22.70% of the successful campaigns in our random sample commit to prices. This difference is statistically significant at the 1% level. The more common use of price commitment among the top funded projects provides further support for our findings that stimulating potential backers' financial motives by the explicit disclosure of the discount is a dominating strategy when it is feasible for the entrepreneur to commit and not diverge in the retail period. An alternative explanation for the dominance of the price commitment strategy is that it could be a signal of the product's stage of development. For projects at an advanced stage of development, the entrepreneur is better able to estimate production costs and, hence, publicize the expected future retail price. This would lead us to argue that price commitment could be influencing campaign performance, since it resolves some of the information asymmetry associated with the actual delivery of the product to backers. Products at a late stage of development are more likely to be produced and delivered to backers on time, and the risk associated with pre-ordering the product is minimized. However, the discount degree is positively associated with campaign performance and is not reflective of the product's stage of development. This leads us to argue that price commitment enhances campaign performance due to its ability to signal the financial reward to backers rather than serving as an indicator of the product's stage of development.

We are aware of some limitations of our study that encourage future research. The first limitation is that, having empirically established that signaling through the use of a costly signal (price commitment) considerably enhances the outcome of the crowdfunding campaign, we do not investigate why some entrepreneurs commit to prices while others do not. Further research into the determinants of entrepreneurs' price commitment in the crowdfunding context should be conducted, since we observe that 45.50% of the top 100 funded campaigns on Kickstarter do not publicize their future retail prices. Along a similar line, a second limitation of our analysis is that we do not investigate the determinants of the number of reward classes constructed by the entrepreneur. Reward classes of the same product can be constructed by differentiating amongst consumers through their timing of backing (i.e. super early bird price, early bird price, not too late price, campaign special price) or the quantity that they order (1 unit, 2 units ...). On the one hand, this has a relatively low cost for the entrepreneur. While, on the other hand, it seems to provide valuable information for potential backers that stimulates their backing activity. Therefore, it would be relevant to know more about what factors play a role in determining the optimal number of reward classes for a given campaign. A third concern is the static nature of our analysis, as we do not investigate the dynamics of signaling through price commitment. Do entrepreneurs use a costly signal, like price commitment, in their first campaigns and then abandon it in subsequent campaigns once they have established their reputation on the platform? Given the proportion of campaigns launched by serial entrepreneurs, this could provide the setting for investigating the dynamics of price commitment. A final limitation is that we build our analysis using data from Kickstarter. Even though data from a single platform provides important insights, the generalizability of its results should be treated with caution. Testing our results using data from different platforms could provide fruitful insights on the flexibility of the signals investigated across platforms.

Our main implication for entrepreneurs is that, by signaling the product's quality and the financial reward through committing to future prices during the campaign, entrepreneurs can incentivize potential backers, leading to better fundraising outcomes. Nevertheless, an entrepreneur should note that committing to prices will require a higher level of planning. Such planning is associated with determining and estimating production costs before starting production. Therefore, a well-developed project, with a clear future plan, will allow the entrepreneur to commit to prices during the crowdfunding campaign. Even though there are no legal consequences of not committing to the publicized prices, failure to maintain the publicized price could adversely affect the entrepreneur's reputation and future crowdfunding campaign performance. Another implication is that an entrepreneur should carefully construct rewards in order to appeal to a wider set of potential backers. We see that constructing different reward classes along the dimensions of timing and quantity is less costly than committing to prices as the entrepreneur still maintains some flexibility to adjust future prices to demand, while signaling some information about the future retail price.

Overall, this paper contributes to the literature on the determinants of success in crowdfunding by analyzing financial motives in reward-based crowdfunding. Contrary to the popular view that backers in reward-based crowdfunding are mostly incentivized by non-financial motivations, recent evidence from Cholakova and Clarysse (2015) shows that backers are mainly driven by financial motives. Our paper is a first step into this direction. Nevertheless, further research on financial motives in reward-based crowdfunding should be welcome.

Appendix

Example of a reward section in a crowdfunding campaign.

<u>Support</u> Pledge \$100 or more Smartwatch black. Regular retail price will be \$200. Limited to 30 backers 30 backers Pledge \$150 or more Smartwatch black Regular retail price will be \$200. 112 backers Pledge \$150 or more Smartwatch blue. Regular retail price will be \$200. 87 backers

Our measures for independent variables in this example are as follows:

Price commitment = 1

Discount Degree = $\frac{(30\times200+112\times200+87\times200)-(30\times100+112\times150+87\times150)}{30\times200+112\times200+87\times200}\times 100 = 28.28\%$

Reward Count = 3 reward levels

Reward Classes = 2 reward classes

Note that different variations of the same product offered at the same price, black and blue at \$150 were consolidated into one reward class.

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Chapter 3

SERIAL CROWDFUNDERS: THE EFFECT OF CHANGING INDUSTRY AND LOCATION ON CROWDFUNDING PERFORMANCE AND THE MODERATING ROLE OF CROWDFUNDING EXPERIENCE

ABSTRACT

As part of the recent interest in serial entrepreneurship in the crowdfunding setting, studies have investigated the effects of the entrepreneur's crowdfunding experience on the campaign outcome. Nevertheless, there are multiple contextual dimensions that may make the entrepreneur's current campaign different from his/her previous campaigns affecting its outcome. In our study we extend the literature on serial crowdfunding by investigating the effects of changing industry and/or geographic location on the campaign performance. We hypothesize that changing context will adversely affect the campaign outcome as some of the acquired knowledge from previous campaigns is context-specific. Moreover, we posit that entrepreneurs with higher level of crowdfunding experience are better able to make generalizations from previous experience and apply them to different contexts such that they suffer less from changing contexts. Additionally, changing context following failure adds a layer of complexity which intensifies the negative relationship between changing context and campaign outcome. An empirical analysis of 75,654 Kickstarter campaigns launched by 29,788 serial crowdfunders confirms our claims.

Content

1. Introduction

Crowdfunding has emerged as a viable source of funding for entrepreneurs. The number of entrepreneurs that have returned to crowdfunding for their subsequent ventures has grown rapidly in recent years (Butticè et al., 2017). On Kickstarter, serial crowdfunders, that is, entrepreneurs who launch multiple projects on the platform, have successfully raised $859 million up to November 2016 which accounts for more than 30% of the amount successfully raised on the platform. Similar to the findings about serial entrepreneurs, research in serial crowdfunding has shown that serial crowdfunders outperform novice entrepreneurs in the crowdfunding setting (Butticè et al., 2017, 2018; Skirnevskiy et al., 2017) due to their ability to use their platform-specific human capital as a costly signal of their qualities, and, additionally, due to their ability to mobilize their platform-accumulated social capital to different campaigns. Although these factors play a significant role in the subsequent campaign performance, we should note that, similar to serial entrepreneurs, serial crowdfunders learn by repeatedly launching more than one campaign. Through this learning the entrepreneur accumulates knowledge that can be utilized when launching a subsequent campaign. The transfer of this acquired knowledge is not a simple process and depends on multiple dimensions as suggested by the literature on learning transfer (Barnett & Ceci, 2002). In our study, we aim to disentangle some of the dimensions of knowledge transfer in the crowdfunding setting and investigate how the benefits of learning from prior experience can be amplified or hindered.

"Learning-by-doing" theory has been a preeminent theory in explaining the outperformance of serial entrepreneurs. According to "learning-by-doing" theories, the entrepreneur learns how to identify opportunities by repeatedly launching more than one venture. Additionally, he becomes more knowledgeable about what it takes to launch a venture and gains the experience required to run a venture (Alsos et al., 2006; Baron & Ensley, 2006; Ucbasaran et al., 2008). However, it has been suggested that serial crowdfunders differ from serial entrepreneurs and that the effects of entrepreneurial learning is diluted due to the public availability of information regarding other crowdfunders' campaigns (Butticè et al., 2018). That is, crowdfunders can learn by observing campaigns of other crowdfunders and identify the "winning" strategies without the need to have prior campaign launching experience. Nevertheless, the benefits of learning by experience differ from that of learning by observation, and only those who experience an event reap the learning benefits of the experience (Alvarez & Parker, 2009). This leads us to believe that, although novice crowdfunders could learn by observing prior campaigns launched on the platform, observation itself does not give them a competitive edge, nor does it level playing field between novice and serial crowdfunders since serial crowdfunders have this public information available to them in addition to the knowledge acquired from experiencing the "hidden" dynamics of the campaign that are exclusive to the campaign launcher. Therefore, we believe that the effects of entrepreneurial learning are not necessarily diluted in the crowdfunding setting.

Crowdfunding literature, thus far, has treated the crowdfunding platform as a *domain* where entrepreneurial learning aids in the accumulation of *entrepreneur-specific human capital* that is transferable across ventures (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017, 2018; Scheaf et al., 2018). Nevertheless, this is quite a loose generalization since the process of knowledge transfer between campaigns is contingent upon multiple dimensions (Barnett & Ceci, 2002). To be more informative, we need to distinguish between what is learned across ventures (*the content-domain*), i.e., the tasks required to launch a campaign, and where learning is transferred from and to (*the context-domain*), i.e., what industry or geographic location, as suggested by Barnett & Ceci (2002). Regarding the content-domain, we track the number of previous campaigns launched by the same entrepreneur on the crowdfunding platform and use it as a measure for the task-content similarity between the current campaign and the tasks undergone in previous campaigns. This is a similar approach to the work of Toft-Kehler, Wennberg, & Kim (2014) performed in a traditional setting with serial entrepreneurs.[28] The rationale for this is that entrepreneurs who launched more projects have a wider set of previous experiences that act as a reference for the tasks to be carried out in the current venture (Tversky & Kahneman, 1992). Regarding the contextual domain in crowdfunding, we analyze the two most prominent contextual dimensions identified in the traditional venture launching setting, the industry[29] and geographic location of the venture (Delmar & Shane, 2006; Klepper, 2002; Toft-Kehler et al., 2014).

The purpose of our study is to investigate the importance of the contextual domain (industrial and geographic) and its effect on the campaign outcome. Previous studies that looked into the effect of changing context overlooked the value that learning from prior crowdfunding experience might have (Lee & Chiravuri, 2019). In contrast, those studies that have investigated the role of learning from prior crowdfunding experience on campaign performance have failed to account for contextual changes between campaigns (Yang & Hahn, 2015). If we turn to the findings from the serial entrepreneurship literature, they cannot carry over directly to crowdfunding due to salient differences between serial entrepreneurship and serial crowdfunding. Namely, in the context of our study, we identify three main differences: 1) crowdfunders' time commitment to a specific project and time between successive projects is relatively short, 2) changing context is relatively easy and does not require mobilizing resources, and 3) the population of backers on the platform is relatively stable across categories and reputation from prior campaign launching activity is public. With this in mind, in our study we are interested in analyzing how changing context can act as an obstacle to the appropriate transfer of knowledge among campaigns. We refer to these obstacles as barriers to learning since an entrepreneur not only learns during the campaign, but also learns from previous experience ex-post, as previous experience serves as reference point for the entrepreneur (Tversky & Kahneman, 1992). Changing contexts will adversely affect the entrepreneur's ability to learn and appropriately make inferences applicable to the current venture. We develop arguments for why serial crowdfunders are harmed by changing contexts between campaigns by building upon the serial entrepreneurship literature on industry experience and physical location and their effects on venture performance. Moreover, we explore how task-content similarity between campaigns can alleviate such barriers to learning. Additionally, we cannot investigate learning in the crowdfunding context without considering the previous campaign outcome. In fact, the literature on learning has suggested that learning from failure is more complex than

[28] We perform additional analysis to validate the appropriateness of this measure in the crowdfunding setting by investigating the effect of entrepreneurial experience on the campaign preparation time given the increased similarity of the tasks required to launch a campaign as crowdfunding experience is accumulated. A brief discussion of the approach used and the results are provided in the appendix.
[29] Similar to previous literature, in our analysis we use the crowdfunding campaign's category as our proxy for the campaign's industry (Allison et al., 2017; Butticè et al., 2017; Oo et al., 2019; Scheaf et al., 2018).

learning from success (Baumard & Starbuck, 2005). Following failure, introducing contextual change to the process of new venture creation increases the complexity of the information that an entrepreneur needs to process (Lord & Maher, 1990), which could result in a suboptimal campaign performance. Along these lines, we also develop arguments as to why the previous campaign failure intensifies the barriers to learning stemming from contextual change.

We probe our research questions using the universe of serial crowdfunders on Kickstarter since its start up to November 2016. In that time period, we have a sample of 29,788 serial crowdfunders with 75,654 campaigns. Our analysis reveals that changing contexts (industrial and/or geographic) between campaigns is negatively associated with the subsequent campaign outcome. This suggests that the entrepreneur is less able to effectively utilize the knowledge acquired from previous experience when the context of the current campaign differs from that of the previous campaigns. However, we find evidence that serial crowdfunders with higher levels of crowdfunding experience are less harmed by changing industries between campaigns due to the increased task-content similarity between prior and current ventures. Thus, entrepreneurial experience moderates the negative relationship between industry change and campaign performance. Our main analysis provides no supporting evidence for the presence of a moderation effect of entrepreneurial experience on the negative association between changing physical location and the campaign outcome. This result stimulated us to perform a post hoc analysis and investigate whether entrepreneurs learn from merely launching new campaigns, or if learning benefits accrue differently depending on the previous campaigns' outcomes. As a result, we find that the negative relationship between a change in physical location and the campaign outcome is only attenuated by prior successful experience, while prior unsuccessful experience intensifies this negative relationship. Regarding previous campaign failure, our findings support the notion that contextual change following failure adds another layer of complexity that intensifies the barriers to learning in the crowdfunding context which, in turn, adversely affects the current campaign outcome.

Our work provides a twofold contribution to the entrepreneurship and the crowdfunding literature. First, we apply a new theoretical lens to further develop the literature on serial crowdfunding. Specifically, we differentiate between content and contextual factors in the transfer of learning between campaigns (Barnett & Ceci, 2002). In our study, we show that a change in context (industrial and/or geographic) has a significant effect on the campaign outcome suggesting the importance of the contextual dimension in the crowdfunding setting, specifically our work suggests that what is learned in one industry/location is not fully transferable to a different industry/location. Our findings complement those of Butticè et al. (2018) who show that the effects of different antecedents of campaign performance differ by industry, i.e., different factors play different roles in different industries, which indicates the need to account for the context of the campaign. This finding is particularly relevant since an emerging stream of literature is utilizing crowdfunding platforms for the study of serial entrepreneurship and it is important to acknowledge the contextual domain of each campaign and not to treat each crowdfunding platform as a context by itself. Although the crowdfunding platform can be seen as a context by itself, we stress the importance of accounting for the multiple contextual dimensions within any given crowdfunding platform. Second, in addition to the direct effects of entrepreneurial experience, we suggest a moderating role that entrepreneurial experience could play in alleviating barriers to learning, providing new insights that complement the serial entrepreneurship literature. In such literature, contextual similarities alleviate the barriers to learning from content-domain differences (Gick & Holyoak, 1987; Toft-Kehler et al., 2014). On the contrary, we investigate how content similarity can alleviate barriers to learning stemming from contextual changes. Our results indicate that in contrast to novice entrepreneurs, experienced entrepreneurs are able to make better generalizations and apply them, more effectively, to different contexts such that they are less harmed by contextual change.

The rest of this paper is organized as follows. In Section 2 we present the underlying theoretical framework and in Section 3 we develop the hypotheses that we will empirically test in this paper. In Section 4 we present the data that we will build our analysis on, as well as define the variables of interest to us in this study. The results of our main analysis along with a post hoc analysis and the robustness checks, are discussed in Section 5. In Section 6 we discuss the implications of our findings, limitations, and areas for fruitful future research. Section 7 concludes our paper.

2. Theoretical Background

2.1 Serial Entrepreneurship and Crowdfunding

Serial entrepreneurs have been shown to outperform novice entrepreneurs in different contextual settings. A strand in the literature explains this outperformance by building upon theories of entrepreneurial "learning-by-doing". According to "learning-by-doing" theories, repeatedly launching more than one venture exposes the entrepreneur to the entrepreneurial process. Throughout the process, the entrepreneur learns how to identify opportunities, becomes more knowledgeable about what it takes to launch a venture, and gains the experience required to run a venture (Alsos et al., 2006; Baron & Ensley, 2006; Ucbasaran et al., 2008). This helps develop the entrepreneur's human capital specific to the entrepreneurial process, while education develops the general human capital. Additionally, since entrepreneurial processes are embedded in a system of social relationships, the serial entrepreneur is able to establish social ties that novice entrepreneurs do not have, such as access to client pools from previous ventures, relationship with investors, or even connection to suppliers. Therefore, unlike novice entrepreneurs, serial entrepreneurs have access to the social capital stock accumulated over their past ventures. In terms of raising capital, Zhang (2011) suggested that serial entrepreneurs are more skillful and socially connected than novice entrepreneurs. This view is also shared by Hsu (2007) who found that entrepreneurs with prior start-up experience are more likely to receive venture capital funding. With this in mind, and as crowdfunding has become a viable financing alternative for entrepreneurs, we look at serial entrepreneurs in the crowdfunding context.

Crowdfunding has recently emerged as a financing alternative for entrepreneurs planning to launch their venture. Lately, reward-based crowdfunding has evolved as an interesting context for the study of serial entrepreneurship. In crowdfunding platforms, a significant portion of projects are launched by "*serial crowdfunders*", that is, entrepreneurs who launch more than one project on a crowdfunding platform. Previous literature has used crowdfunding experience as a proxy for entrepreneurial experience, which is a costly indicator of human capital (Anglin, Short, et al., 2018). Human capital represents the skills and capabilities that an entrepreneur has at the time of launching a venture through crowdfunding (Martin et al., 2013). In fact, findings in the crowdfunding literature show that previous experience in launching campaigns on a crowdfunding platform is positively associated with the crowdfunding campaign outcome (Anglin, Short, et al., 2018; Butticè et al., 2017; Scheaf et al., 2018). However, crowdfunding platforms do not only act as financial intermediators, they also provide an ideal setting for interaction between backers and entrepreneurs (Skirnevskiy et al., 2017). The entrepreneur is able to establish ties with the backer community, accumulating social capital which can prove to be beneficial in future crowdfunding efforts. Social capital refers to the value received from those social relationships created through personal ties (Gedajlovic et al., 2013; Grichnik et al., 2014), which could facilitate the building of relationships between investors and entrepreneurs (Florin et al., 2003). In this concern, some studies suggest that the social capital accrued over prior campaigns influences the campaign outcome. Despite prior research on serial crowdfunders, the determinants of success for serial crowdfunders have been primarily investigated without accounting for the contextual factors (industrial and geographic) that have been identified to be important dimensions for the transfer of capital (human and social) among ventures in the traditional setting. In this paper, we extend the literature on serial crowdfunders by investigating the effects of contextual change on campaign performance. Moreover, we investigate how previous crowdfunding experience (accumulated crowdfunding experience and previous campaign outcome) could moderate the effects of contextual change on campaign performance.

2.2 Entrepreneurial Learning: Task-Content and Contextual Domains

In the literature encompassing entrepreneurial learning, Deakins & Freel (2009) assert that even though it is not fully understood how entrepreneurs learn, it is accepted that they learn from merely establishing new ventures. Over ventures, serial entrepreneurs learn how to recognize new opportunities (Alsos et al., 2006; Baron & Ensley, 2006; Ucbasaran et al., 2010) and develop reputations and networks (Politis, 2005; Wright et al., 1997). In the crowdfunding setting, the effects of entrepreneurial learning is thought to be diluted due to the public availability of information regarding other crowdfunders' campaigns (Butticè et al., 2018) such that there are no significant private gains from having previous experience. However, we should note that the benefits of learning by experiencing differs from that of learning by observing, and only those who experience an event can really capture the learning benefits of the experience (Alvarez & Parker, 2009). To shed light on entrepreneurial learning in the crowdfunding setting, we ought to point out that the crowdfunding literature, so far, has treated the crowdfunding platform as a *domain* where entrepreneurial learning aids in the accumulation of *entrepreneur-specific human capital* that is transferable across ventures (Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017, 2018; Scheaf et al., 2018). However, as suggested by Barnett & Ceci (2002) the content and the context of learning are two dimensions that affect the transfer of knowledge among ventures. Therefore, there is the need to distinguish between what is being learned across ventures (*the content-domain*), that is, the tasks required to launch a campaign; and where this learning is transferred from and to (*the context-domain*), that is, what industry or geographic location.

The process of launching multiple ventures enhances the accumulation of entrepreneur-specific human capital through entrepreneurial learning (Ucbasaran et al., 2008). This entrepreneur-specific human capital can be transferred across ventures given the similarity of the tasks required to launch a new venture. Task-content domain in the venture creation process refers to what is being learned from experience with a given task. Launching a project on a crowdfunding platform entails making many decisions related to the design of the campaign. Naturally, having previous crowdfunding experience aids the entrepreneur in acquiring skills related to launching a new campaign, such as conducting market research, designing a product, and setting up the crowdfunding campaign. This "learned skill" regarding the tasks involved can be transferred across ventures. Unlike mechanical tasks, the task-content domain of launching a new venture is rather complex since similar tasks could differ across ventures. The tasks involved in the creation of a new venture are not a pure repetition of what has been done before in an earlier venture. Thus, the entrepreneur does not only relate to the last launched project, but rather draws upon different elements of his entire venture-launching experience. As an entrepreneur launches more ventures, the degree of task-content similarity of launching a new venture increases since the entrepreneur has a wider set of previous experiences that can be used to draw inferences applicable to the launch of the current venture (Tversky & Kahneman, 1992). In this essence, we capture the task-content similarity of launching a new venture by tracking the number of previous campaigns launched by the same entrepreneur on the crowdfunding platform.

In contrast, the contextual domain refers to where the knowledge acquired through entrepreneurial learning is being transferred, and more specifically in our analysis, to which industry or geographic location. As some authors suggest, the knowledge acquired through the launch of prior campaigns is not exclusive to the task-content and this entrepreneurial learning remains context specific (Cope, 2005) and thus cannot be fully captured by only looking at the number of previously launched campaigns. Thus, a portion of the knowledge acquired is task-content specific, while the other portion is context specific. When launching a crowdfunding campaign, a serial entrepreneur could launch a campaign in an industry where he has previous crowdfunding experience or in a new industry. Similarly, the location of the current campaign could be in the same city where the previous campaign was launched or in a different location. Changing context, in industrial or geographic terms, can act as a barrier to the effective application of knowledge from previous crowdfunding efforts (Toft-Kehler et al., 2014). We argue that contextual change adversely affects the campaign performance. Moreover, we argue that this negative effect varies depending on the entrepreneur's previous crowdfunding experience. Finally, we also acknowledge that learning from failure differs from learning from success and that it is more difficult to gain the same learning benefits from a failure than from a success, as already anticipated by some authors (Cannon & Edmondson, 2001; Denrell & March, 2001; Eggers, 2012; Shepherd, 2003). Therefore, we investigate how the adverse effects of contextual change vary with the previous campaign outcome.

3. Hypotheses Development

In the following section, we discuss how contextual change can act as a barrier to learning in the crowdfunding setting. We also look into how an increase in content similarity, due to previous entrepreneurial experience, can alleviate the barriers to learning generated by a contextual change. Finally, we address how changing the context relative to the last previous campaign harms more entrepreneurs whose previous campaign was a failure than other entrepreneurs.

3.1 Effects of Contextual Change on Campaign Performance

The most prominent indicator of context-specific entrepreneurial experience is the industry similarity (Delmar & Shane, 2006; Klepper, 2002). The benefit of having industry experience has been investigated in different settings. An analysis of the survival rate of firms shows that prior industry experience is positively associated with the survival of the firm (Brüderl, Preisendörfer, & Ziegler, 1992; Van Praag, 2003; Wicker & King, 1989). In addition to the effects on the firm's survival, other research has also found a positive association of industry experience with key performance indicators such as profits, sales growth, economic performance, and employment (Bosma, Van Praag, Thurik, & de Wit, 2004; Brüderl & Preisendörfer, 1998; Gimeno, Folta, Cooper, & Woo, 1997). An explanation for these findings is that many of the skills required to launch a venture and effectively exploit an opportunity are industry-specific (Delmar & Shane, 2006). Besides, an entrepreneur's industry experience has been associated with more accurate expectations of a new firm's performance (Cassar, 2014). All of these arguments suggest that a portion of the human capital developed through prior entrepreneurial experience is industry-specific. Therefore, one can expect that a change in the industry will hinder the entrepreneur's ability to benefit fully from this previous experience, which could then impact performance. Indeed, through an analysis of a survey of serial entrepreneurs located in China, Eggers & Song (2015) find that changing industries between ventures reduces the performance of subsequent ventures.

So far, the industry context of serial crowdfunders' projects has attracted limited scholarly attention (Butticè et al., 2018). When launching a project on Kickstarter, an entrepreneur identifies the category to which his project belongs. Currently, there are 15 categories identified by Kickstarter covering a wide range of projects.[30] The category to which a project belongs has been widely used as a proxy for the industry (Allison et al., 2017; Butticè et al., 2017; Oo et al., 2019; Scheaf et al., 2018). We will also use these categories as our industry proxy in this paper. By launching a subsequent campaign in the same category, we understand that entrepreneurs can better utilize what they have learned from previous campaigns due to the contextual similarity. This similarity helps in the appropriate transfer of knowledge across ventures. However, changing industry can lead to a suboptimal crowdfunding campaign outcome. We investigate the effect that switching industries between ventures has on the campaign performance. Similar to entrepreneurs in the traditional setting, we expect to see that a portion of entrepreneurial learning is industry-specific. Thus, those serial crowdfunders changing industries between ventures will suffer from abandoning their previous industry knowledge. Therefore, we posit:

Hypothesis 1a: Changing industries between crowdfunding campaigns is negatively associated with the campaign performance.

In addition to changes in the industry context, a change in the geographic location context can impede learning from venture to venture as well. In the traditional setting, by launching a new venture in the same location as a prior venture, an entrepreneur can benefit from the knowledge previously acquired. Research shows that, by establishing ventures in close proximity to previous ventures, an entrepreneur can benefit from the value of knowing "who knows what and who knows whom" (Klepper, 2002; Stuart & Sorenson, 2003a). Additionally, this local experience facilitates the transfer of knowledge from prior ventures to new ventures (Ingram & Baum, 1997; Pe'er et al., 2008).

[30] The categories available on Kickstarter are: art, comics, crafts, dance, design, fashion, film and video, food, games, journalism, music, photography, publishing, technology, and theater.

In an online setting, various studies have investigated the significance of the physical location on different forms of transactions (Agrawal et al., 2015; Giudici et al., 2018; Guo et al., 2018; Hortaçsu et al., 2009; Lin & Viswanathan, 2016). A striking feature of crowdfunding is the great distance between crowdfunders and backers. In a study conducted by Agrawal, Catalini, & Goldfarb (2015), they find that the average distance between a crowdfunder and a backer on Sellaband, a platform dedicated to new musical artists, is 5,000 kilometers. At first glance, we would expect the effect of geographic proximity between ventures to be less prevalent in an online setting. However, their study suggests that distant funders rely on information revealed by the investment decisions of early funders. Similarly, a study of projects launched on Kickstarter shows that the average distance between backers and the entrepreneur increases as funding progresses (Guo et al., 2018). Thus, people with close proximity to the entrepreneur serve as the campaign's early backers which, in turn, signals credibility to distant backers and stimulates their investing activity. This would suggest the presence of a backers' home bias earlier on in the campaign, with the entrepreneur first needing to appeal and secure funds from those in closest proximity to him.

In crowdfunding, friends and family usually constitute a significant portion of the early contributions made to the campaign (E. Mollick, 2014; Skirnevskiy et al., 2017). By changing physical location in a subsequent venture, the entrepreneur distances himself from his initial base of early backers. In turn, this could make it more difficult to attract capital from distant funders given the path dependency of accessing distant funders online. Also, one might argue that given the online setting, an entrepreneur could still remain in contact with his close network from the previous location. However, there is a difference between online and offline social connectedness (Grieve et al., 2013): face to face communication could prove to be more effective than online communication (Johnson et al., 2000) in the persuasion of a larger portion of the close network to provide early support to the campaign. Additionally, by remaining in the same physical location, the entrepreneur can further grow his established local network. On the contrary, by changing physical location the entrepreneur will need to develop new local ties and build a local community to support his upcoming venture, something that will be relatively more difficult. Therefore, we hypothesize:

Hypothesis 1b: Changing geographic location between crowdfunding campaigns is negatively associated with the campaign performance.

3.2 Moderating Effects of Entrepreneurial Experience

Although Cope (2005) defines entrepreneurial learning as a task where much of the learning is context-specific, task-content similarity (as a result of accumulated entrepreneurial experience) enhances the performance of new ventures as previously argued. Besides the direct effects of entrepreneurial experience on firm performance, a strand in the literature also suggests that entrepreneurial experience plays a moderating role in different contexts (Anglin, Short, et al., 2018; Brunel et al., 2017; Farmer et al., 2011; Hmieleski & Baron, 2009; Sommer & Haug, 2011). Among serial entrepreneurs, entrepreneurs with higher levels of prior experience are able to respond quicker to a challenge and generate fast and effective heuristics (Ucbasaran et al., 2008). They are also better able to effectively apply knowledge from their prior efforts to their current endeavors (Toft-Kehler et al., 2014). Learning from prior experiences also strengthen entrepreneurs' ability to process and respond to complex information (Lord & Maher, 1990) and stimulates creativity (Amabile, 1997). Along similar lines, we argue that crowdfunders with higher levels of experience are able to draw better inferences from the knowledge acquired through previous exposure to the tasks involved in launching a crowdfunding campaign and they seem able to apply this knowledge more effectively. Additionally, given their familiarity with the crowdfunding platform and its dynamics, they are able to identify better opportunities even if it is not within the same context of their prior ventures. Therefore, in addition to the direct effect of entrepreneurial experience on the crowdfunding campaign outcome, we also expect entrepreneurial experience to moderate the negative relationship between contextual change and the campaign performance, such that entrepreneurs with higher levels of entrepreneurial experience will suffer less when they change their industry or their geographic location. Therefore, we predict:

Hypothesis 2a: Entrepreneurial experience moderates the relationship between industry change and crowdfunding campaign performance: the relationship is less negative for those with high, as opposed to low, levels of entrepreneurial experience.

Hypothesis 2b: Entrepreneurial experience moderates the relationship between geographic location change and crowdfunding campaign performance: the relationship is less negative for those with high, as opposed to low, levels of entrepreneurial experience.

3.3 Moderating Effect of Previous Venture Failure

The literature on learning from failure shows that improper inferences can be made from unsuccessful prior experience which will affect the current venture's outcome (Denrell & March, 2001; Eggers, 2012). Learning from failure is not a straight forward process since, as a result of failure, an entrepreneur learns what does not work rather than what works. Learning from failure would also require the recognition of the causes of failure for this learning to yield any benefits (Cannon & Edmondson, 2001). This suggests that learning from failure is more complex than learning from success (Baumard & Starbuck, 2005). In any case, introducing a contextual change to the process of new venture creation increases the complexity of the information that an entrepreneur needs to process (Lord & Maher, 1990). When we combine more complexity with previous venture failure, an entrepreneur will face more obstacles in transferring knowledge among ventures. As a result, transferring knowledge from a previous venture to a current venture becomes more complicated when the previous venture has failed and when the new venture is launched in a different context. Following this, we expect that serial crowdfunders are less effective in the transfer of their knowledge between campaigns when the previous campaign was a failure and when the new campaign is launched in a different context (industrial and/or geographic). Therefore, the negative association between changing context and campaign performance is amplified by the failure of the previous venture. Along these lines, we posit:

Hypothesis 3: Previous campaign failure moderates the relationship between context change (industrial and/or geographic) and crowdfunding campaign performance: the relationship becomes more negative for entrepreneurs who failed in their previous crowdfunding campaign.

4. Data and Methodology

To examine the role of contextual change on the crowdfunding campaign performance of serial crowdfunders we collect data from Kickstarter, the leading reward-based crowdfunding platform which has been widely used in previous crowdfunding research (e.g. Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017; Kuppuswamy et al., 2017; Mollick, 2014). Our initial dataset covers all observations (297,884 projects) between April 21st, 2009 and November 29th, 2016. Out of these, 75,654 projects were launched by 29,788 serial crowdfunders. During that period, serial crowdfunders successfully raised $859 million, accounting for more than 30% of the funds raised on Kickstarter. Since context change is defined as a change in context from that of the prior venture we drop the first observation for all entrepreneurs where no prior venture exists. This reduces the sample to 45,866 projects.

In Table 3.1 we provide some insight into the serial crowdfunders' performance presented by the number of projects launched by each serial entrepreneur. The average success rate of entrepreneurs with 5 projects or more is 61.72% compared to a 38.65% success rate of entrepreneurs with 2 projects. Additionally, successful entrepreneurs with 5 projects or more raise on average $30,376 compared to $20,571 raised on average by entrepreneurs with 2 projects. This preliminary insight suggests that entrepreneurs with higher levels of experience are more likely to be successful in their crowdfunding efforts and raise more funds on average.

Table 3.1: Insight on Serial Crowdfunders in Kickstarter

Projects Launched by Entrepreneur	Number of Entrepreneurs		Number of Projects		Success Rate	Successful Amount Raised (in thousands)		Average Amount Raised
2	22,116	(74.24%)	44,232	(58.47%)	38.65%	$ 351,668	(40.91%)	$ 20,571
3	4,570	(15.34%)	13,710	(18.12%)	45.50%	$ 199,304	(23.18%)	$ 31,950
4	1,498	(5.03%)	5,992	(7.92%)	49.62%	$ 88,932	(10.35%)	$ 29,911
5 or more	1,604	(5.38%)	11,720	(15.49%)	61.72%	$ 219,725	(25.56%)	$ 30,376
Totals	29,788		75,654			$ 859,629		

4.1 Dependent Variables

We examine the effect that a change of context change has on two outcomes of interest in crowdfunding research: the success of the campaign and the amount raised. Unlike other platforms with a Keep-it-All mechanism, Kickstarter is a crowdfunding platform with an All-or Nothing mechanism. In such a setting, the campaign goal has to be met in order for the funds to be disbursed to the entrepreneur. This suggests that an appropriate measure of campaign performance is whether the campaign was successful in reaching its goal or not. Given this, we have our dependent variable defined as *Success*, which takes the value 1 if the campaign goal is met and 0 otherwise. Past crowdfunding research has also used continuous measures of success for evaluating the performance of crowdfunding campaigns, such as the amount of funds raised and the number of backers (e.g., Anglin, Short, et al., 2018; Anglin, Wolfe, et al., 2018; Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017). In line with this research, we additionally measure the crowdfunding performance with a continuous variable accounting for the amount of funds raised during the campaign. Due to the positive skewness of this variable and the zero values encountered, we follow Anglin, Short et al. (2018) and use the inverse hyperbolic sine transformation to treat this variable.[31] This transformation allows us to correct for the right skew, and its interpretation remains identical to that of variables transformed using the natural log (Burbidge, Magee, and Robb, 1988; Franke and Richey,

[31] $\sinh^{-1}(y) = \log\left[y + (y^2 + 1)^{1/2}\right]$

2010; Sauerwald, Lin, and Peng, 2016). We denote this additional measure of crowdfunding performance as *Amount Raised*.

4.2 Independent Variables

In our study we examine the effect of two dimensions of context change: industry change and a change in geographic location. Entrepreneurs on the crowdfunding platform have the freedom to launch campaigns in different industries and locations, with no platform-specific barriers. To capture the effect of a change in industry on the campaign performance, we operationalize our independent variable, *Industry Change*, as a dummy variable that takes the value 1 if the current campaign category differs from the previous campaign's category and 0 otherwise. Similarly, we operationalize our independent variable, *Location Change*, as a dummy variable that takes the value 1 if the current campaign is launched in a different city and 0 otherwise. Out of the 45,866 projects launched by serial entrepreneurs there are 7,025 projects (15.32%) with industry changes, 8,750 projects (19.08%) with location changes, and 3,522 projects (7.68%) with both industry and location changes. In total, a significant portion of the projects (42%) exhibit some form of contextual change. In Figure 3.1 we present the persistence of contextual changes over the number of ventures.

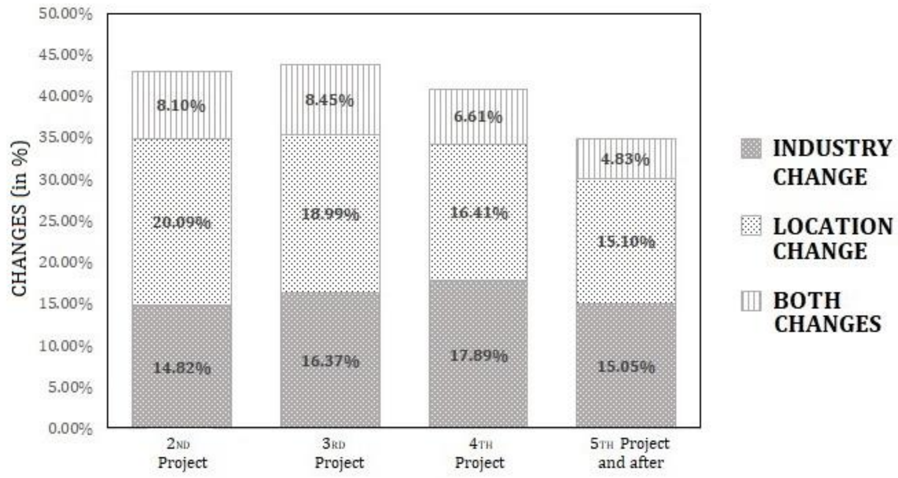

Figure 3.1: Percentage of Context Changes Over the Number of Ventures

To account for the entrepreneur's crowdfunding experience we collect information on the number of campaigns launched by the entrepreneur prior to the current project. We denote it by *Entrepreneurial Experience*. This measure of entrepreneurial experience is treated by the inverse hyperbolic sine transformation due to the right skewness of the variable.

4.3 Interaction Variables

In our hypothesis we posit that more experienced entrepreneurs, those with a larger number of previous crowdfunding campaigns, suffer less from changing context. Thus, we expect that the degree of task-content similarity arising from prior experience will moderate the negative effects of context changes. To account for this, we examine two interaction terms. The first interaction term examines the effect of previous entrepreneurial experience and how it moderates the effect of industry change. It is denoted by: *Entrepreneurial Experience* x *Industry Change*. The other interaction term examines the moderation effect of entrepreneurial experience on the negative effects of location change. It is denoted by: *Entrepreneurial Experience* x *Location Change*. In Figure 3.2 we present the success rate of projects (with and without context changes) over the number of ventures launched and can see an increasing pattern in the success rate over the number of ventures. However, this increasing pattern does not exhibit the same slope for projects with and without contextual changes.

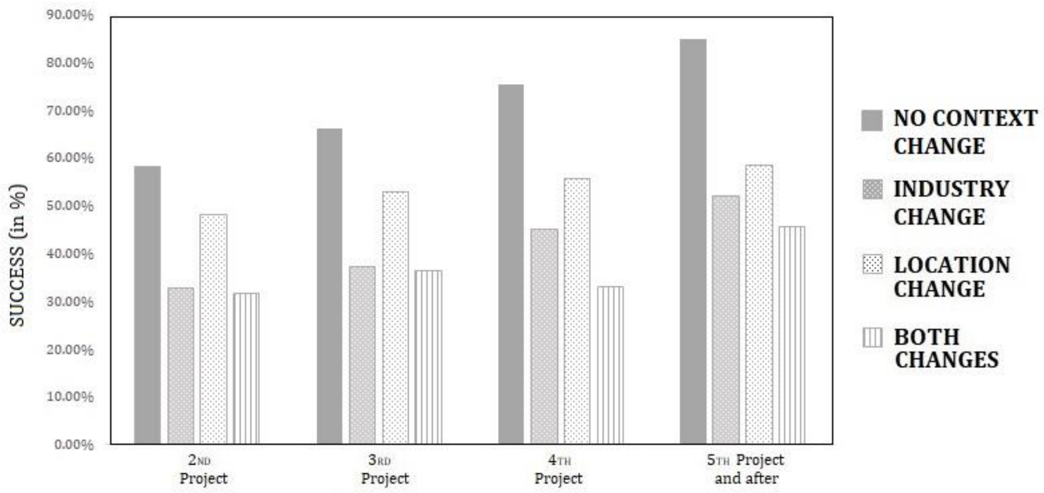

Figure 3.2: Success Rate for Projects Over the Number of Ventures

We also hypothesize that the effect of changing context following an immediate campaign failure is more severe since failure acts as a barrier to learning. To capture this effect, we start by controlling for the previous campaign outcome using the variable *Failure* which takes the value 1 if the previous campaign goal is not met and 0 otherwise. We continue by examining two additional interaction terms: *Failure* x *Industry Change* and *Failure* x *Location Change*. In Table 3.2, we present the percentage of changes in context grouped by the previous campaign outcome along with the success rate of their current campaigns. Following either success or failure, the effect of changing industry is more severe than changing location. However, this effect is even more severe following failure where the average success rate is 41.18% lower (from 35.27% to 20.75%) than that of campaigns that do not change industry, while following success the average success rate is only 14.17% lower (from 76.43% to 65.60%) than that of campaigns that do not change industry.

Table 3.2: Context Change and Success Rate by Previous Campaign's Outcome

Previous Campaign Outcome	**Failure**		**Success**	
	% Change	% Success	% Change	% Success
Context:				
No Context Change	55.31%	35.27%	61.27%	76.43%
Industry Change	17.49%	20.75%	12.54%	65.60%
Location Change	17.88%	28.98%	20.60%	74.10%
Both Changes	9.31%	19.36%	5.59%	64.00%
Observations	25,739		20,127	

4.4 Control Variables

To account for other determinants of crowdfunding performance, we include several control variables that are consistent with previous literature on crowdfunding (Anglin, Wolfe, et al., 2018; Butticè et al., 2017; Colombo et al., 2015; Courtney et al., 2017b; E. Mollick, 2014). We start by accounting for the *Time between Projects* by counting the number of days that have passed since the end of the previous campaign and the start of the current campaign. We control for the project goal size and call it *Project Goal*. Due to the significance of the number of rewards offered by an entrepreneur in a reward-based crowdfunding setting, we control for the number of rewards by using the variable *Rewards.* We additionally account for whether the project has a video pitch or not, using a dummy variable *Video Pitch (0 = no video pitch, 1 = video pitch available)*. We also control for the count of videos on the campaign page and denote it by *Video Count*. The variable *Image Count* refers to the number of images in the campaign webpage and *Text Length* is the length of the text included in the campaign's webpage in thousands. Additional control variables in our analysis are the *Duration* of the campaign, *Industry* to which the project belongs, and the *Year* of launch. Due to the right skewed distribution and the zero values observed in some of the continuous variables in our control (*Time between Projects*, *Project Goal*, *Rewards*, *Video Count*, *Image Count*, and *Text Length*), we treat these variables using the inverse hyperbolic sine transformation (Anglin, Short, et al., 2018).

4.5 Estimation Models

To test the effects of context change (industry and location), previous campaign outcome, and the interaction terms on the crowdfunding success, we model the probability of crowdfunding success using a panel logistic regression model which we denote as Model A in Table 3.5. We report the coefficients and clustered standard errors (the latter ones in between brackets) and continue with an analysis of the conditional marginal effects. The conditional marginal effects of independent variables discussed in the results section holds all continuous variables at their mean values, the categorical variables at their mode values, and the dummy variables at their median value, which is more appropriate than reporting the average marginal effects. This approach is also adopted by Butticè et al. (2017). In Model B in Table 3.6, we investigate the effects of context change (industry and location), previous campaign outcome, and the interaction terms on the amount of capital raised (*Amount Raised*). The estimation procedure applied is a panel ordinary least squares (OLS) estimation with clustered standard errors. Both Models A and B are specified with random effects because including individual fixed effects will eliminate the variance in our individual-level predictor, entrepreneurial experience (Toft-Kehler et al., 2014).

5. Results

Table 3.3 provides the descriptive statistics of our sample and Table 3.4 presents the correlations and the variance inflation factors (VIFs) of our independent variables.[32] The average VIF (1.22) and the maximum VIF (1.50) are well below the thresholds

[32] We notice the presence of non-serious crowdfunding efforts categorized by project goals less than $100 or project goals greater than $1,000,000 (E. Mollick, 2014). In order to minimize distortions to the structure of our panel data, we run our analysis on all observations. As a robustness check, we eliminate 1,460 non-serious crowdfunding efforts from our dataset and repeat the estimation process. Our main results hold.

Table 3.3
Descriptive Statistics

Variable	Mean	S.D.	Min	Max	Variable	Frequency	% of Sample	Variable	Frequency	% of Sample
Success	0.49	0.50	0	1	Year:			Category:		
Amount Raised	$14,496.24	$156,047.70	0	$20,338,986	2009	131	0.29%	Art	3,429	7.48%
Industry Change	0.23	0.42	0	1	2010	988	2.15%	Comics	2,751	6.00%
Location Change	0.27	0.44	0	1	2011	3,288	7.17%	Crafts	966	2.11%
Failure	0.56	0.50	0	1	2012	5,630	12.27%	Dance	591	1.29%
Entrepreneurial Experience	2.28	4.84	1	110	2013	7,370	16.07%	Design	3,928	8.56%
Time between Projeccts	275.93	318.04	0	2516	2014	11,204	24.43%	Fashion	2,041	4.45%
Rewards	8.93	6.51	1	179	2015	10,350	22.57%	Film and Video	7,627	16.63%
Project Goal	$33,522.16	$1,018,943	0	$100,000,000	2016	6,905	15.05%	Food	1,829	3.99%
Video Pitch	0.73	0.44	0	1				Games	6,886	15.01%
Video Count	0.33	1.07	0	21				Journalism	351	0.77%
Image Count	7.30	11.61	0	166				Music	5,315	11.59%
Text Length	2.79	2.95	0	186.97				Photography	1,221	2.66%
Duration	33.04	13.47	1	92				Publishing	4,488	9.79%
								Technology	2,979	6.50%
								Theater	1,464	3.19%

Table 3.4

Correlation Matrix & VIFs

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	VIF
1	Success	1.0000														DV
2	Amount Raised	0.6407 ***	1.0000													DV
3	Industry Change	-0.1482 ***	-0.1861 ***	1.0000												1.03
4	Location Change	-0.0456 ***	-0.0592 ***	0.0819 ***	1.0000											1.04
5	Failure	-0.4345 ***	-0.4650 ***	0.1023 ***	0.0112 *	1.0000										1.32
6	Entrepreneurial Experience	0.1410 ***	0.1204 ***	-0.0284 ***	-0.0565 ***	-0.2161 ***	1.0000									1.15
7	Time between Projeccts	0.2068 ***	0.3215 ***	0.0042	0.1291 ***	-0.3490 ***	-0.1421 ***	1.0000								1.29
8	Rewards	0.2521 ***	0.4371 ***	-0.0921 ***	-0.0217 ***	-0.2310 ***	0.0454 ***	0.2035 ***	1.0000							1.29
9	Project Goal	-0.1631 ***	0.2177 ***	-0.0308 ***	0.0328 ***	0.0141 **	-0.1094 ***	0.1267 ***	0.2013 ***	1.0000						1.20
10	Video Pitch	0.1910 ***	0.3384 ***	-0.0872 ***	-0.0033	-0.1540 ***	-0.0136 **	0.1971 ***	0.2721 ***	0.1902 ***	1.0000					1.16
11	Video Count	0.1015 ***	0.2165 ***	-0.0691 ***	-0.0130 **	-0.0695 ***	0.0483 ***	0.0737 ***	0.1411 ***	0.1552 ***	0.1419 ***	1.0000				1.12
12	Image Count	0.2077 ***	0.4477 ***	-0.0581 ***	-0.0780 ***	-0.1919 ***	0.1468 ***	0.1245 ***	0.3514 ***	0.1885 ***	0.2028 ***	0.2687 ***	1.0000			1.50
13	Text Length	0.1942 ***	0.3848 ***	-0.0744 ***	-0.0238 ***	-0.1649 ***	0.0357 ***	0.1458 ***	0.3401 ***	0.2470 ***	0.2430 ***	0.2499 ***	0.4994 ***	1.0000		1.47
14	Duration	-0.1795 ***	-0.0651 ***	0.0179 ***	0.0116 *	0.1392 ***	-0.1247 ***	-0.0445 ***	0.0097 *	0.2221 ***	0.0045	-0.0068	-0.0563 ***	0.0133 **	1.0000	1.09

** p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001*

established in the literature (Hair et al., 2010; McDonald & Moffitt, 1980; Neter et al., 2018; Tabachnick & Fidell, 2007). Therefore, these results indicate no concerns in regard to multicollinearity issues with our subsequent analyses. In Model A (I), presented in Table 3.5, we consider the effects of entrepreneurial experience and the control variables on the probability of success. In Model B (I), presented in Table 3.6, we observe similar effects on the amount of funds raised. The only difference is that although a larger campaign goal is negatively associated with the probability of success, it exhibits an opposite relationship with the amount of funds raised. The results provided for these two dependent variables are consistent with the findings of previous literature.

Hypothesis 1a suggested that changing industries will be negatively associated with the campaign performance. In Model A (II) and Model B (II), the coefficient of *Industry Change* was negative and significant ($p < 0.01$). This provides support for hypothesis 1a. The results of the conditional marginal effects indicate that, on average, changing industries is associated with a 42.64% reduction in the probability of success (from 45.15% to 25.90%) and $206.92 (49.28%) decrease in the amount of funds raised (from $407.23 to $206.54). Hypothesis 1b suggested that changing location will be negatively associated with the campaign performance. In Model A (II) and Model B(II), the coefficient of *Location Change* was negative and significant ($p < 0.01$), supporting hypothesis 1b. Our findings show that changing location is associated with a 13.27% decrease in the probability of success (from 45.15% to 39.16%) and $85.19 (20.92%) decrease in the amount of funds raised (from $407.23 to $322.04).

Hypothesis 2a suggested that the negative effect of changing industry becomes less severe with an increase in campaign launching experience. In Model A (III), the interaction term between *Entrepreneurial Experience* and *Industry Change* is positive and significant ($p < 0.05$). In Model B (III), the moderating effect of entrepreneurial experience on the amount of funds raised is also positive and significant ($p < 0.01$). This supports Hypothesis 2a. We plot the interactions in Figures 3.3a and 3.3b. At the average entrepreneurial experience, we find that change in industry is associated with a 42.70% decrease in the probability of success (from 45.02% to 25.79%) and a 50.10% decrease in the amount of funds raised (from $405.53 to 202.35). When we increase entrepreneurial experience by 1 SD (standard deviation), we find that the effects of change in industry are relatively less severe, such that a change in the industry is now associated with a 37.25% decrease in the probability of success (from 48.18% to 30.22%) and a 40.42% decrease in the amounts of funds raised (from $444.13 to $264.60). From the interaction plots, we note that for extremely high levels of entrepreneurial experience the entrepreneur is able to raise higher levels of funding when he changes industry. However, this higher level of funding is associated with a lower probability of success.

Hypothesis 2b suggested that entrepreneurial experience moderates the negative effect of changing geographic location. The coefficient of the interaction term between *Entrepreneurial Experience* and *Location Change* is not significant in neither Models A (IV) and B (IV). Therefore, the findings fail to support Hypothesis 2b. In our post hoc analyses, we dig deeper into how the benefits of learning from prior experience accrues differently for successful versus unsuccessful prior campaigns (Eggers & Song, 2015; Gompers et al., 2010). We are specifically interested in how different experiences moderate the effects of a change in context.

Table 3.5
Panel Logistic Regression

	Model A (Dependent Variable : Success)							
	I	II	III	IV	V	VI	VII	VIII
Industry Change		-0.8567*** (0.0396)	-1.0426*** (0.0902)	-0.8567*** (0.0396)	-1.0458*** (0.0903)	-0.5357*** (0.0484)	-0.6612*** (0.0327)	-0.5435*** (0.0485)
Location Change		-0.2461*** (0.0359)	-0.2454*** (0.0360)	-0.2106** (0.0835)	-0.1979** (0.0837)	-0.1841*** (0.0298)	-0.0374 (0.0438)	-0.0425 (0.0438)
Entrepreneurial Experience x Industry Change			0.1495** (0.0650)		0.1522** (0.0651)			
Entrepreneurial Experience x Location Change				-0.0300 (0.0637)	-0.0401 (0.0638)			
Failure x Industry Change						-0.2247*** (0.0632)		-0.2081*** (0.0634)
Failure x Location Change							-0.2728*** (0.0587)	-0.2611*** (0.0588)
Failure						-1.2761*** (0.0323)	-1.2503*** (0.0333)	-1.2063*** (0.0360)
Entrepreneurial Experience	0.2185*** (0.0343)	0.2362*** (0.0341)	0.2033*** (0.0370)	0.2430*** (0.0371)	0.2119*** (0.0394)	0.1290*** (0.0271)	0.1328*** (0.0272)	0.1343*** (0.0272)
Time between Projects	0.3349*** (0.0116)	0.3665*** (0.0118)	0.3671*** (0.0118)	0.3663*** (0.0118)	0.3669*** (0.0118)	0.1795*** (0.0102)	0.1802*** (0.0102)	0.1824*** (0.0102)
Rewards	1.0102*** (0.0310)	0.9819*** (0.0306)	0.9835*** (0.0307)	0.9818*** (0.0306)	0.9834*** (0.0307)	0.7114*** (0.0248)	0.7123*** (0.0249)	0.7126*** (0.0249)
Project Goal	-0.6495*** (0.0147)	-0.6443*** (0.0145)	-0.6457*** (0.0146)	-0.6442*** (0.0145)	-0.6455*** (0.0146)	-0.5043*** (0.0114)	-0.5055*** (0.0114)	-0.5061*** (0.0114)
Video Pitch	1.0457*** (0.0429)	1.0150*** (0.0425)	1.0163*** (0.0426)	1.0151*** (0.0425)	1.0164*** (0.0426)	0.7786*** (0.0345)	0.7811*** (0.0346)	0.7791*** (0.0346)
Video Count	0.2303*** (0.0317)	0.2205*** (0.0313)	0.2217*** (0.0314)	0.2205*** (0.0313)	0.2217*** (0.0314)	0.1998*** (0.0258)	0.2001*** (0.0259)	0.2003*** (0.0259)
Image Count	0.2716*** (0.0155)	0.2614*** (0.0153)	0.2613*** (0.0154)	0.2613*** (0.0153)	0.2613*** (0.0154)	0.1999*** (0.0126)	0.2007*** (0.0126)	0.2002*** (0.0126)
Text Length	0.3875*** (0.0254)	0.3732*** (0.0251)	0.3735*** (0.0252)	0.3732*** (0.0251)	0.3735*** (0.0252)	0.2894*** (0.0205)	0.2892*** (0.0206)	0.2891*** (0.0206)
Duration	-0.0292*** (0.0013)	-0.0288*** (0.0013)	-0.0289*** (0.0013)	-0.0288*** (0.0013)	-0.0289*** (0.0013)	-0.0216*** (0.0011)	-0.0216*** (0.0011)	-0.0216*** (0.0011)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,866	45,866	45,866	45,866	45,866	45,866	45,866	45,866
Wald Chi^2	4406.72	4609.80	4585.80	4611.35	4587.42	7710.47	7693.15	7685.63
LR Test		vs (1) 558.31***	vs (2) 5.33**	vs (2) 0.22	vs (2) 5.72*	vs (2) 1678.22***	vs (2) 1687.31***	vs (2) 1698.14***

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

Table 3.6

Panel Ordinary Least Squares Regression

	Model B (Dependent Variable : Amount Raised)							
	I	II	III	IV	V	VI	VII	VIII
Industry Change		-0.6789***	-1.0481***	-0.6789***	-1.0485***	-0.4290***	-0.6378***	-0.4399***
		(0.0277)	(0.0607)	(0.0277)	(0.0609)	(0.0426)	(0.0275)	(0.0426)
Location Change		-0.2347***	-0.2334***	-0.2621***	-0.2299***	-0.2165***	0.0036	-0.0042
		(0.0261)	(0.0261)	(0.0572)	(0.0573)	(0.0259)	(0.0374)	(0.0374)
Entrepreneurial Experience x Industry Change			0.2840***		0.2842**			
			(0.0416)		(0.0417)			
Entrepreneurial Experience x Location Change				-0.0217	-0.0028			
				(0.0403)	(0.0404)			
Failure x Industry Change						-0.3494***		-0.3236***
						(0.0530)		(0.0531)
Failure x Location Change							-0.4058***	-0.3872*
							(0.0491)	(0.0492)
Failure						-0.8821***	-0.8493***	-.7827***
						(0.0285)	(0.0292)	(0.0313)
Entrepreneurial Experience	0.2041***	0.2054***	0.1456***	0.2006***	0.1462***	0.1443***	0.1496***	0.1498***
	(0.0242)	(0.0241)	(0.0256)	(0.0256)	(0.0268)	(0.0240)	(0.0240)	(0.0240)
Time between Projects	0.3033***	0.3281***	0.3276***	0.3282***	0.3276***	0.2528***	0.2536***	0.2559***
	(0.0078)	(0.0079)	(0.0079)	(0.0079)	(0.0079)	(0.0081)	(0.0081)	(0.0081)
Rewards	1.0606***	1.0402***	1.0384***	1.0401***	1.0384***	0.9909***	0.9899***	0.9896***
	(0.0202)	(0.0201)	(0.0201)	(0.0201)	(0.0201)	(0.0199)	(0.0199)	(0.0199)
Project Goal	0.1038***	0.1087***	0.1096***	0.1088***	0.1096***	0.1110***	0.1105***	0.1111***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0077)	(0.0077)	(0.0077)
Video Pitch	1.0785***	1.0484***	1.0467***	1.0483***	1.0467***	1.0216***	1.0228***	1.0179***
	(0.0294)	(0.0293)	(0.0293)	(0.0293)	(0.0293)	(0.0289)	(0.0289)	(0.0289)
Video Count	0.2618***	0.2547***	0.2561***	0.2547***	0.2562***	0.2675***	0.2660***	0.2667***
	(0.0233)	(0.0231)	(0.0231)	(0.0231)	(0.0231)	(0.0229)	(0.0229)	(0.0229)
Image Count	0.4082***	0.4012***	0.3998***	0.4012***	0.3998***	0.3896***	0.3900***	0.3891***
	(0.0114)	(0.0113)	(0.0113)	(0.0113)	(0.0113)	(0.0111)	(0.0111)	(0.0111)
Text Length	0.3615***	0.3559***	0.3546***	0.3559***	0.3546***	0.3466***	0.3458***	0.3452***
	(0.0184)	(0.0183)	(0.0183)	(0.0183)	(0.0183)	(0.0181)	(0.0181)	(0.0181)
Duration	-0.0092***	-0.0090***	-0.0091***	-0.0090***	-0.0091***	-0.0076***	-0.0075***	-0.0076***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Category Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,866	45,866	45,866	45,866	45,866	45,866	45,866	45,866
Wald Chi^2	21791.29	23074.73	23149.45	23076.64	23150.50	26083.25	26113.56	26200.58
R-Squared: Within	0.1020	0.1026	0.1026	0.1026	0.1026	0.0658	0.0666	0.0658
Between	0.4332	0.4490	0.4490	0.4490	0.4490	0.4997	0.4999	0.5008
Overall	0.4142	0.4293	0.4287	0.4292	0.4288	0.4779	0.4779	0.4786

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

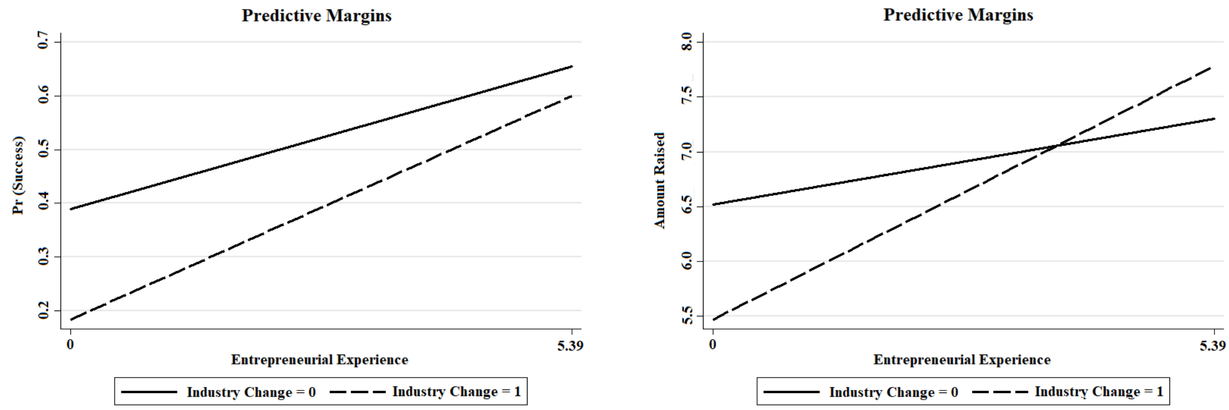

Figure 3.3a and 3.3b. Interactions between Industry Change and Entrepreneurial Experience

Hypothesis 3 suggested that the negative effects of changing context is more severe if it follows a failed campaign. In Model A (VI) and Model B (VI), the coefficient of the interaction term between *Failure* and *Industry Change* is negative and significant ($p < 0.01$). Changing industry after a failed campaign is associated with a 42.89% decrease in the probability of success (from 34.09% to19.47%) and a 54.09% decrease in the amount of funds raised (from $288.35 to $132.38). However, following success, changing industry is only associated with a 19.85% decrease in the probability of success (from 64.95% to 52.06%) and a 34.85% decrease in the amount of capital raised (from $696.25 to $453.61). Our results indicate that changing industry is negatively associated with the campaign performance regardless of the previous campaign outcome. However, this negative effect becomes more severe following a failure. Equally, the interaction term between *Failure* and *Location Change* is negative and significant ($p < 0.01$) in Models A (VII) and B (VII). Following failure, changing location is associated with a 19.27% decrease in the probability of success (from 34.36% to 27.74%) and a 33.11% decrease in the amount of funds raised (from $293.52 to $196.33). Worth noting, the negative effect of location change is only realized if it occurs following a failed campaign. Overall, the negative effect of changing contexts is more severe for campaigns following a failure, providing support for Hypothesis 3.

5.1 Post Hoc Analysis

In our main analysis, we have investigated the moderating effects of learning from previous crowdfunding experience. However, a strand in the literature suggests that entrepreneurial learning accrues differently depending on previous venture's performance (Eggers & Song, 2015; Gompers et al., 2010). This suggests that we should dig deeper into the effects of entrepreneurial learning from previous venture launching by tracking successful and unsuccessful crowdfunding experience separately. As a post-hoc test, we perform the same tests presented in Models A (I-V), but dissect our variable *Entrepreneurial Experience* into two variables: *Entrepreneurial Experience from Successful Campaigns* and *Entrepreneurial Experience from Unsuccessful Campaigns*.[33] Our results are presented in Table 3.7.

In Models C (I-V) we observe that the coefficient of *Entrepreneurial Experience from Successful Campaigns* is positive and significant ($p < 0.01$). This finding suggests

[33] Our post-hoc analysis results are robust to the measure of the campaign outcome. We obtain the same results when using the amount raised and number of backers as our measures of campaign performance.

that learning benefits only accrue from successful venture launching experience (Gompers et al., 2010). Whereas the coefficient of *Entrepreneurial Experience from Unsuccessful Campaigns* is negative and significant ($p < 0.01$). Our results suggest that experience from unsuccessful ventures leads to improper inferences that result in worse subsequent venture performance (Eggers, 2012). This is attributed to the small sample of experiences and the noisy cues that typically accompany failure (Rerup, 2009).

In Model C (III) we add interaction terms for both measures of entrepreneurial experience with industry change. The interaction term between *Entrepreneurial Experience from Successful Campaigns* and *Industry Change* is positive and significant ($p < 0.01$) suggesting that an increase in the number of previous successful campaigns alleviates the barrier to learning caused by a change in industry. We note that, at the average entrepreneurial experience from previous successful campaigns, a change in industry is associated with a 29.13% decrease in the probability of success (from 49.11% to 34.81%). When we increase entrepreneurial experience from previous successful campaigns by 1 SD (standard deviation), we find that the effects of change in industry are relatively less severe, such that a change in the industry is now only associated with an 18.06% decrease in the probability of success (from 65.24% to 53.246%). However, the negative coefficient associated with the interaction term between *Entrepreneurial Experience from Unsuccessful Campaigns* and *Industry Change* is not significant, this suggests that *Entrepreneurial Experience from Unsuccessful Campaigns* plays no moderating role on the effects of *Industry Change*.

In Model C (IV) we investigate the interaction between both measures of entrepreneurial experience and location change. The coefficient of the interaction term between *Entrepreneurial Experience from Successful Campaigns* and *Location Change* is positive and significant ($p < 0.05$). At the average entrepreneurial experience from previous successful campaigns, a change in location is associated with a 10.05% decrease in the probability of success (from 32.84% to 29.54%). When we increase entrepreneurial experience from previous successful campaigns by 1 SD we find that the effects of change in location is diminished, such that a change in location is now only associated with a 3.45% decrease in the probability of success (from 48.78% to 47.10%). Additionally, the coefficient of the interaction term between *Entrepreneurial Experience from Unsuccessful Campaigns* and *Location Change is negative and significant* ($p < 0.10$). At the average entrepreneurial experience from previous unsuccessful campaigns, a change in location is associated with a 10.05% decrease in the probability of success (from 32.84% to 29.54%). When we increase entrepreneurial experience from previous unsuccessful campaigns by 1 SD, we find that the effect of change in location is intensified and that a change in location is now associated with a 15.27% decrease in the probability of success (from 22.86% to 19.37%).

5.2 Robustness Tests

To ensure the robustness of our results, we run a series of additional tests. First, in our analysis we look at a change in industry or geographic location relative to the previous campaign. However, what we measure as a change in context could be, in fact, a return by the entrepreneur to an industry where he has previous experience or a return to a prior geographic location. To avoid accounting for these changes as a change in context and in order to get a more “pure” measure of change in context, we only look

Table 3.7
Panel Logistic Regression

	Model A (Dependent Variable : Success)				
	I	II	III	IV	V
Industry Change		-0.5970 *** (0.0304)	-0.6445 *** (0.0581)	-0.5959 *** (0.0304)	-0.6415 *** (0.0581)
Location Change		-0.1568 *** (0.0277)	-0.1551 *** (0.0278)	-0.1588 *** (0.0528)	-0.1552 *** (0.0529)
Entrepreneurial Experience from Successful Campaigns x Industry Change			0.1246 *** (0.0440)		0.1162 *** (0.0441)
Entrepreneurial Experience from Unsuccessful Campaigns x Industry Change			-0.0388 (0.0509)		-0.0346 (0.0510)
Entrepreneurial Experience from Successful Campaigns x Location Change				0.1069 ** (0.0426)	0.0995 ** (0.0426)
Entrepreneurial Experience from Unsuccessful Campaigns x Location Change				-0.0901 * (0.0475)	-0.0870 * (0.0476)
Entrepreneurial Experience from Successful Campaigns	0.8542 *** (0.0188)	0.8486 *** (0.0187)	0.8235 *** (0.0206)	0.8251 *** (0.0209)	0.8033 *** (0.0224)
Entrepreneurial Experience from Unsuccessful Campaigns	-0.8573 *** (0.0233)	-0.8314 *** (0.0233)	-0.8211 *** (0.0258)	-0.8036 *** (0.0266)	-0.7955 *** (0.0288)
Time between Projects	0.1307 *** (0.0090)	0.1550 *** (0.0092)	0.1563 *** (0.0092)	0.1565 *** (0.0092)	0.1576 *** (0.0092)
Rewards	0.6286 *** (0.0228)	0.6194 *** (0.0228)	0.6199 *** (0.0228)	0.6196 *** (0.0228)	0.6201 *** (0.0229)
Project Goal	-0.4688 *** (0.0103)	-0.4720 *** (0.0103)	-0.4726 *** (0.0103)	-0.4729 *** (0.0103)	-0.4735 *** (0.0104)
Video Pitch	0.6897 *** (0.0318)	0.6826 *** (0.0318)	0.6811 *** (0.0319)	0.6821 *** (0.0319)	0.6807 *** (0.0319)
Video Count	0.1956 *** (0.0241)	0.1891 *** (0.0240)	0.1896 *** (0.0240)	0.1894 *** (0.0241)	0.1898 *** (0.0241)
Image Count	0.1874 *** (0.0116)	0.1832 *** (0.0117)	0.1826 *** (0.0117)	0.1833 *** (0.0117)	0.1828 *** (0.0117)
Text Length	0.2582 *** (0.0191)	0.2498 *** (0.0191)	0.2498 *** (0.0191)	0.2494 *** (0.0191)	0.2494 *** (0.0191)
Duration	-0.0177 *** (0.0010)	-0.0178 *** (0.0010)	-0.0178 *** (0.0010)	-0.0178 *** (0.0010)	-0.0179 *** (0.0010)
Category Dummies	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Observations	45,866	45,866	45,866	45,866	45,866
Wald chi^2	8,531.42***	8,612.73 ***	8,603.29 ***	8,597.43 ***	8,588.78 ***
LR Test (null model in brackets)		vs (1) 447.53 ***	vs (2) 10.24 ***	vs (2) 13.21 ***	vs (2) 21.96 ***

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

at the serial crowdfunders' second campaign and identify whether there is a change in the context relative to the first campaign launched by the serial crowdfunder. This approach also helps in isolating any differences that could rise due to differences in the level of crowdfunding experience by the entrepreneur. We run a pooled logistic regression and our initial results regarding the adverse effects of contextual change hold. Second, in our analysis we have used panel regressions to account for the panel-level variance component. However, an alternate approach is to discard the panel-level variance component and run pooled estimation models. As a robustness check, we replicate the process used to yield the results in Table 3.5 and 3.6 by using pooled logistic and OLS regression models (without panel effects). The results are in line with our prior findings. Third, in our main analysis we have defined context change as change in category or location of the current project. Between projects entrepreneurs could also change the subcategory. The effect of changing subcategory should be less severe than changing category since projects within the same category are more similar than projects in different categories. Moreover, in our main analysis a change in location could mean that the entrepreneur has either changed city or state/country. We would expect the adverse effects of changing city not to be as severe as changing state/country. Therefore, we introduce additional measures to account for the different degrees of contextual change. The first measure is adding *Sub-Category Change* to our regression analysis. The second measure involves dissecting *Location Change* into *City Change,* which is city change within the same state/country, and *State/Country Change.* We replicate the process used in our main analysis and the results are in line with what we expected that a higher degree of contextual change has more severe adverse effects. Fourth, the crowdfunding literature has used different proxies for campaign performance. Although in our analysis we had consistent results for the two dependent variables investigated, success and amount raised, we proceed by investigating the main effects discussed earlier on an alternative campaign performance measure, the number of backers. We find no differences in the effects presented in the main results. Fifth, we control for outliers generated by non-serious crowdfunding efforts as indicated by Mollick (2014). We remove campaigns with goals less than $100 or goals greater than $1,000,000. This left us with a total of 74,116 campaign launched by 29,364 entrepreneurs. We drop the first observation for each entrepreneur and repeat our estimation process on 44,752 observations. We also find similar results to the ones discussed in the main analysis. As a final robustness check, we limit our sample to activity during the period 2009 – 2015. We drop observations in 2016 from our sample since our data does not cover the full year. We repeat all the analyses conducted earlier and all prior findings hold.

6. Discussion

In this study we examine how changing contexts (industrial and geographic) can act as a barrier to learning and how this barrier can either be alleviated by task-content similarity or intensified by previous campaign failure. Similar to Toft-Kehler et al. (2014), we gauge the degree of task-content similarity between campaigns using the number of previous campaigns launched by the same entrepreneur, the rationale being that entrepreneurs who launched more projects have a wider set of previous experiences that act as a reference for the tasks to be carried out in the current venture. We hypothesize that serial crowdfunders with higher levels of crowdfunding experience are less harmed by changing contexts. We find supporting evidence that the effect of changing industry is moderated by entrepreneurial experience, but we find no supporting evidence that this moderation effect holds for the change in geographic location. Regarding previous campaign failure, studies suggest that learning from failure is not a straightforward process and that it is, in fact, more complex than learning from success. Thus, we hypothesize that changing context following a failure adds another level of complexity to the process of knowledge transfer which intensifies the barrier to learning. We find evidence supporting our claims.

In our study we were surprised by two of the findings contrary to our hypothesis on the changes in geographical context. The first finding is the absence of a moderation effect of entrepreneurial experience on the effect of physical location change. A potential explanation for this unexpected finding is that the relevance of the physical location is related to the ability to establish local ties with stakeholders, that is. customers, suppliers (Klepper, 2002; Stuart & Sorenson, 2003b). This network is an important determinant of the venture performance. Merely having previous venture launching experience is not an indicator of the ability to establish local ties that could, in turn, impact the venture performance. If an entrepreneur was unable to establish ties in a prior location, then it is more probable that the entrepreneur would be unable to establish such ties when switching to a new location. Therefore, the negative effect of changing location is not moderated by the crowdfunding launching experience per se, but is rather moderated by the entrepreneur's ability of developing a network of campaign backers during previous campaign launching experience. To disentangle this issue, we propose that we should focus on previous *successful* venture launching experience since an entrepreneur's ability to develop a network of early supporters for the crowdfunding campaign would only benefit from successful prior experience in developing a network of early supporters (Gompers et al., 2010). Additionally, this ability would moderate the adverse effects of changing location. In our post hoc analysis, presented earlier, we have tracked previous successful and unsuccessful crowdfunding experience separately which helps us in unravelling the dynamics behind the issue we have at hand. Indeed, we find that previous successful campaign launching experience moderates the effect of change in physical location and alleviates the obstacles encountered by changing physical location. Moreover, we find that the barrier to learning as a result of change in physical location is amplified by the number of previous unsuccessful campaigns.

The second unexpected finding was that changing location following success does not harm the serial crowdfunder in the current campaign, whereas, changing the location of a new crowdfunding campaign following failure hurts the entrepreneur. A possible explanation for this finding is that entrepreneurs changing their location following a successful campaign could be doing so for potentially good reasons and do not suffer a performance penalty, while lower quality entrepreneurs could be attributing failure to the location of their campaign and react by changing location. This explanation builds upon the literature on attributional biases which suggests that entrepreneurs are likely to blame external factors for their failure (Jones & Harris, 1967; Weiner, 1985). Based on this external attribution of failure, serial entrepreneurs who failed are likely to change external factors between ventures (Eggers & Song, 2015). Let alone that learning from failure is complex, lower-quality entrepreneurs add additional complexity to the knowledge transfer process by changing location. Thus, they fall victim to their desire to change location between ventures which adversely affects their subsequent campaign performance. Due to the inadequacy of the data that we have at hand in determining the entrepreneurs' attribution of previous campaigns' failure, as well as our inability to match entrepreneurs by their qualities, we are unable to decompose and investigate this finding further.

Our post hoc analysis digs deeper into how the benefits of learning from prior experience accrues differently for successful versus unsuccessful campaigns. The results provide important insights into learning in crowdfunding. Although, in general, entrepreneurs learn from the process of launching new ventures, we find that entrepreneurs only reap the benefits of learning from prior successful experience (Gompers et al., 2010), whereas prior failure might have an adverse effect on the current campaign performance. We additionally find that successful experience tempers the negative relationship between contextual change (either industrial or geographic) and the campaign outcome. This suggests that learning from previous successful campaigns is transferred across campaigns since entrepreneurs use this previous successful experiences as their reference points when constructing a new campaign. They aim to replicate their previous successes in their current campaigns by building upon what they have learned from prior successes, while trying to avoid, at the same time, what they have implemented in previous unsuccessful campaigns. The results suggest that entrepreneurs are not fully able to do so since previous unsuccessful experience imposes noisy cues that distort the effective transfer of knowledge among campaigns (Rerup, 2009). This is more apparent when changing location since, aside from the negative direct effect of previous unsuccessful experience, we find that previous unsuccessful experience strengthens the negative association between change in physical location and campaign outcome.

Our study seeks to make a twofold contribution to the literature on crowdfunding and serial entrepreneurship. First, we apply a new theoretical lens to further extend the literature on serial crowdfunding. Specifically, we differentiate between content and contextual factors in the transfer of learning between campaigns (Barnett & Ceci, 2002). Past work in crowdfunding has stressed the importance of human capital acquired through the launch of previous campaigns on the crowdfunding campaign outcome (Anglin, Short, et al., 2018; Butticè et al., 2017, 2018). We argue that this crowdfunding-specific human capital is a valuable asset for the entrepreneur since entrepreneurs with higher levels of crowdfunding experience exhibit higher levels of task-content similarity between their current and previous ventures, which in turn facilitates the transfer of knowledge between campaigns. Needless to say, a contextual change could affect the transfer of knowledge. By adopting two dimensions of context prominently used in the study of serial entrepreneurs, the industrial and the geographic contexts, we show that a change in context acts as a barrier to the transfer of knowledge leading to suboptimal campaign outcomes. This finding is important since an emerging stream of literature is utilizing crowdfunding platforms for the study of serial entrepreneurship without accounting for the contextual dimensions of each campaign. To illustrate this, consider the case of an entrepreneur launching a successful product in the design category on a crowdfunding platform. She might not effectively use the knowledge acquired from this campaign to launch another campaign soliciting funds for developing a movie. But she would be more effective in using the prior knowledge of product development to launch a new campaign soliciting funds for the development of a new product. A similar intuition could follow in regards to the study of social capital acquired in previous campaigns. For instance, a local artist with a successfully funded musical performance cannot mobilize, as effectively, the social capital acquired in the current geographic location if she launches a campaign soliciting funds for a musical performance in a different geographic context.

Second, in addition to the direct effects of entrepreneurial experience, we suggest a moderating role that entrepreneurial experience could play in alleviating barriers to learning, which provides new insights for the serial entrepreneurship literature. Barriers to learning from content-domain differences were shown to be alleviated by contextual similarities (Gick & Holyoak, 1987; Toft-Kehler et al., 2014). Our work complements these results since we investigate how content similarity can alleviate barriers to learning stemming from contextual changes. We suggest that as an entrepreneur accumulates venture launching experience, the tasks required to launch a new venture become more similar due to the multiple reference points that he has (Tversky & Kahneman, 1992). An increase in the task-content similarity can in turn facilitate the transfer of knowledge between contexts. Thus, in contrast to novice entrepreneurs, experienced entrepreneurs are able to make better generalizations and more effectively apply them to different contexts. We find supporting evidence for the moderating role of task-content similarity on the effects of industry change. Our results indicate that entrepreneurs benefit from the knowledge drawn from their prior experience even if it is not within the same industry. Moreover, for higher levels of experience a change in context has a less severe effect on the new venture performance.

Fruitful venues for future research are best viewed in light of the limitations of our current work. First, we focus our research on a single reward-based crowdfunding platform, Kickstarter. Hence, we cannot control for missing activity outside the platform. This could possibly lead to an underestimation in the actual number of serial crowdfunders who have launched other campaigns on different platforms. Nevertheless, we think that we have found relevant results and opened an approach which is definitely worthy to keep on exploring. Moreover, a change in platform by the serial entrepreneur would imply a third change in context worth analyzing. Although we conjecture that our findings for industry and location change are generalizable to a change in crowdfunding platform, a cross-platform analysis addressing whether learning is transferable across reward-based crowdfunding platforms is needed. Second, in our main analysis we have investigated two dimensions for context-domain differences among prior and current campaigns in crowdfunding. Although these are the most prominent contextual dimensions in the traditional venture launching setting, there exists other dimensions for contextual domain differences that can be considered in future serial crowdfunding studies. Previous research has investigated the moderating effect of the temporal context on the transfer of social capital between campaigns (Butticè et al., 2017). A similar approach can be used to investigate if the temporal context affects the transfer of learning between campaigns. Additionally, differences in the functional context of the campaign could be another dimension worth investigating, such as if the current campaign is a sequel of a previous campaign, or if it is a totally new campaign with a different function. Third, another limitation of our analysis is that some projects could be a follow up for a project launched in a different industry, but we fail to capture this. For instance, after raising funds for producing a movie in the Film category, an entrepreneur could solicit funds to record the music tracks associated with the movie in the Music category. In such situation, these two projects are in fact related; however, our analysis would consider this example as a change in context. Although we do not expect this to be a widespread practice, future studies should take this into account to identify more carefully the different effects of changing industries when the project is a follow-up and when the project is a new standalone project. Fourth, given our findings, we encourage research on how entrepreneurs can utilize task-content similarity to effectively launch ventures in different contexts, for instance, can using a standardized approach regarding the processes required to launching a venture attenuate some of the barriers faced when changing industry or location? Fifth, our analysis investigates barriers to learning in reward-based crowdfunding and how these barriers could be alleviated. It would be particularly interesting to see how these effects are generalizable to different crowdfunding platform types. Specifically, it would be interesting to see if learning is transferable across different crowdfunding platform types (equity, peer to peer lending, donation-based crowdfunding) or if it is specific to the type of crowdfunding platform. Finally, future research can investigate the generalizability of our findings to different learning transfer contexts.

There are other venues for fruitful research related to the essence of our study. Given that we investigate the effects of context change on campaign performance, it would be interesting and relevant to know the reasons driving the entrepreneur's change of context. Is this change in context an opportunity-driven decision, such that the entrepreneur has identified opportunities in different industries or locations? Or is this change of context a strategy implemented by the entrepreneur to expand his exposure to a different set of backers? Even more, this change of context could also be driven by previous campaign performance. To gain insights into the determinants of context change between campaigns, future research should resort to the use of additional primary data; i.e. the use of surveys or interviews to entrepreneurs. A similar approach could also be used to investigate learning dynamics in the crowdfunding context. Primary data could be used to examine how entrepreneurs learn from prior experiences. Is the learning related to the campaign planning and marketing process? Or do entrepreneurs learn from the production and logistic processes related to fulfilling the delivery of the promised reward? Or do entrepreneurs learn strategies related to maintaining their social network acquired over previous campaigns? The analysis of these issues could involve a mixed method empirical strategy that builds on the secondary data available regarding serial entrepreneurs' campaign performance and the primary data collected.

7. Conclusion

Our study is the first to investigate the adverse effects of changes in contextual factors between campaigns for serial entrepreneurs on the campaign performance in reward-based crowdfunding, focusing on industry and location change. From our analysis of 29,788 serial crowdfunders on Kickstarter we show how task-content similarity can moderate the adverse effects of changing context. Moreover, we find evidence that the interaction between previous failure and contextual change is negative suggesting that failure adds a new level of complexity to the effective application of prior knowledge which intensifies the barriers to learning resulting from changing contexts. For scholars, our study motivates the need to differentiate between content and context when analyzing campaigns launched by serial crowdfunders. We also suggest that task-content similarity can be used to alleviate barriers to learning which we hope will lead to further academic inquiry in different knowledge transfer settings. For entrepreneurs, our study suggests that entrepreneurs would benefit from remaining in the same context and that this is particularly important following failure. An entrepreneur should not focus on blaming external factors following failure but rather consider changing aspects regarding the campaign such as the campaign design, product attributes, and fundraising pitch style. Entrepreneurs can improve their subsequent venture performance by extensively launching campaigns in the same context, i.e. category and physical location.

Appendix

We were able to extract information from Kickstarter on the number of days since the campaign was created until the day it goes public. Interestingly, this provides a measure of the entrepreneur's time to prepare the campaign. In a more traditional setting, this can be referred to as the business gestation period (Alsos & Kolvereid, 1998). We utilize this information to validate entrepreneurial experience as a measure of task-content similarity by investigating its effect on the campaign preparation time while controlling for campaign-specific features. As an entrepreneur has more experience launching campaigns, we expect to see that less time is required on average to prepare the campaign due to the similarity of the tasks required in setting up the campaign.

In Table 3.A we present the results of a fixed effects and a random effects panel ordinary least squares regression of the campaign preparation time (the number of days elapsed since campaign creation to campaign launch) on entrepreneurial experience and campaign specific variables (more concretely, number of rewards offered, project goal, whether the campaign has a video pitch, the number of videos in the content section of the campaign, image count, and the text length). The regressions control for category and year. Due to the skewness of the control variables, all continuous variables were transformed using the inverse hyperbolic sine transformation. A detailed description of the independent and control variables is provided in the main body of the text in Section 4. Our findings provide support for the appropriateness of the measure used to gauge task-content similarity. We additionally depict the relationship between the campaign preparation time and entrepreneurial experience in Figure 3.A, where we can see that an increase in entrepreneurial experience is associated with a decrease in the campaign preparation time. Figure 3.A shows the predictive output of the fixed effects model and the axes are the inverse hyperbolic sine transformation of campaign preparation time and entrepreneurial experience.

Table 3.A
Panel Ordinary Least Squares Regression

Dependent Variable : Preparation Time	I	II
Entrepreneurial Experience	-0.3128***	-0.1798***
	(0.0132)	(0.0092)
Rewards	0.1198***	0.2192***
	(0.0161)	(0.0104)
Project Goal	0.1642***	0.1246***
	(0.0060)	(0.0039)
Video Pitch	0.2399***	0.4859***
	(0.0222)	(0.0150)
Video Count	0.0344**	0.0824***
	(0.0171)	(0.0126)
Image Count	0.0685***	0.1489***
	(0.0090)	(0.0059)
Text Length	0.0415***	0.1296***
	(0.0139)	(0.0096)
Category Dummies	Yes	Yes
Year Dummies	Yes	Yes
Fixed Effects	Yes	No
Observations	75,653	75,653
R-squared: Within	0.1037	0.0883
Between	0.2034	0.3008
Overall	0.1723	0.2228

** p-value < 0.10, ** p-value < 0.05, *** p-value < 0.01*

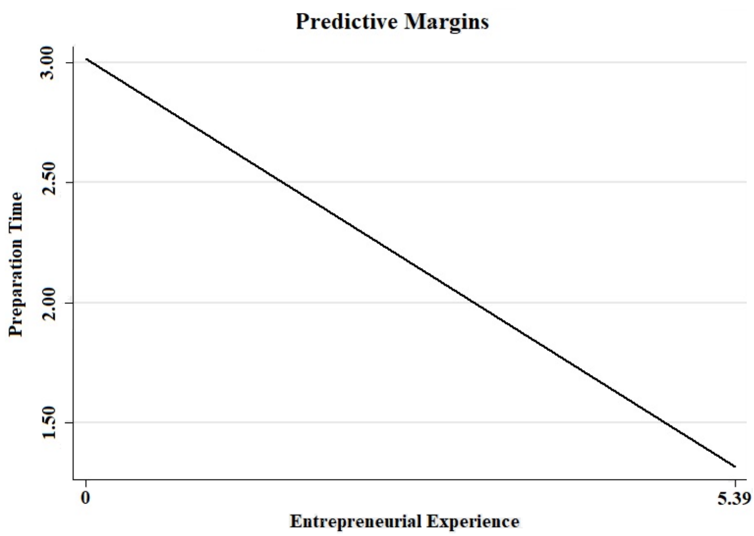

Figure 3.A. Predictive Margins of the Effect of Entrepreneurial Experience on Campaign Preparation Time

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Concluding Remarks

In this PhD we have aimed to contribute to three unique strands of the crowdfunding literature: theoretical modeling of financing choice, signaling in crowdfunding, and serial crowdfunding. Our work adds to the current academic debate in the crowdfunding literature and identifies fruitful areas of research to further extend our knowledge of crowdfunding.

In the first chapter, we fill a gap in the literature by developing a theoretical framework that explains the crowdfunding mechanism for projects offering "consumer products", since previous theoretical models do not specifically address them (Belleflamme, Lambert, & Schwienbacher, 2014; Hu, Li, & Shi, 2015; Kumar, Langberg, & Zvilichovsky, 2016; Miglo & Miglo, 2018). We highlight a managerial recommendation for a pricing strategy to be implemented by entrepreneurs tapping crowdfunding as their financing and launching alternative. We also compare crowdfunding to spot selling and show when it would be optimal for an entrepreneur to opt for crowdfunding. The work performed adds to the theoretical literature on entrepreneurs optimal financing strategy (Schwienbacher, 2007; Schwienbacher & Larralde, 2012). It also contributes to the debate on when do entrepreneurs tap crowdfunding to finance their ventures (Blaseg, Cumming, & Koetter, 2020; Walthoff-Borm, Schwienbacher, & Vanacker, 2018). The implications of the model proposed suggests that factors affecting the choice of crowdfunding need not only be entrepreneur-specific. External factors, such as the prevailing interest rate and customers' valuation of the product play a significant role in determining the optimality of crowdfunding as a financing and launching alternative. Future research should take external factors into consideration when analyzing drivers of an entrepreneurs' financing choice.

In the second chapter, we contribute to the literature on signaling in crowdfunding. The crowdfunding context is prone to information asymmetries regarding the entrepreneur's offering where potential backers have access to limited information regarding the product's quality. Previous literature has investigated how entrepreneurs can signal the quality of their offerings through signaling their own qualities (Courtney, Dutta, & Li, 2017; Piva & Rossi-Lamastra, 2018; Scheaf et al., 2018). In our paper, we show how the entrepreneur can signal the product's quality through their pricing strategy. Specifically, we argue that backers can infer the product's quality through its expected retail price. The entrepreneur can signal the product's retail price through an explicit commitment to the future retail price or through the construction of different reward levels in an ascending price order. We contend that an explicit commitment is costly since divergence is associated with reputation costs, while the use of different reward levels to convey some information regarding the product's future retail price is less costly since it does not involve an explicit commitment. We show that price signals are indeed effective in the crowdfunding context. Moreover, similar to Anglin et al. (2018), we show that both costly and costless signals are valued by potential backers. However, in the presence of the costly signal, the effect of the less costly signal is weakened. This adds to the managerial literature on the interaction of signals (Plummer, Allison, & Connelly, 2016; Stern, Dukerich, & Zajac, 2014). The factors affecting the choice of commitment and the number of rewards by the entrepreneur remain unexplored. Knowledge of drivers of these choices can provide fruitful insights into signaling choices by entrepreneurs.

In the third chapter, we apply a new theoretical lens and differentiate between content and contextual factors in the transfer of learning between campaigns (Barnett & Ceci, 2002). This further extends the nascent literature on serial crowdfunding (Butticè, Colombo, & Wright, 2017; Butticè, Orsenigo, & Wright, 2018; Lee & Chiravuri, 2019; Yang & Hahn, 2015). In our paper, we highlight that a change in context adversely affects the process of transferring knowledge between campaigns which is indicated by lower campaign performance following a contextual change (industry or location). Moreover, we show that entrepreneurial experience could play a moderating role in alleviating barriers to learning due to contextual changes between campaigns. This provides new insights for the serial entrepreneurship literature. However, what we do not know is what drives crowdfunders to change contexts between campaigns. Is this change in context an opportunity-driven decision? Or is this change of context a strategy implemented by the entrepreneur to expand his exposure to a different set of backers? Insights into drivers of contextual change between campaigns can help further this academic inquiry.

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