THE LOGIC OF MARKETS: FROM MICRO TO MACRO DYNAMICS

Report submitted by Rocco Caferra in order to be eligible for a doctoral degree awarded under joint supervision by Universitat Jaume I and Università degli Studi di Bari Aldo Moro

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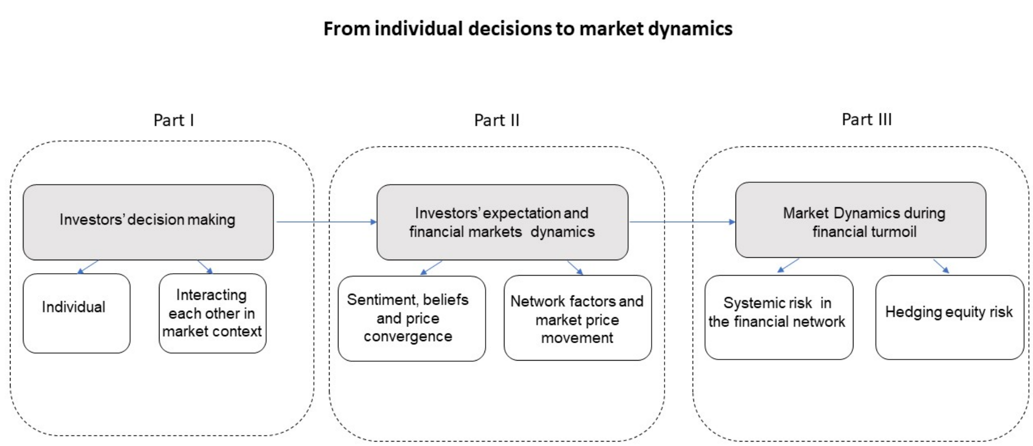
Contents

Preface

Every day we are called to take risks in different troubling situations. Behind every individual choice, there is a complex decision-making process, continuously fluctuating between rationality and irrationality, often influenced by the beliefs of other agents.
This thesis proposes a series of experimental and empirical works considering traders from "isolate atoms" to heterogeneous "interacting particles" operating in the marketplace.
The figure below summarizes the different proposed themes.



Inspired by the recent development of behavioral studies, where the *homo economicus* is far from being always rational, efficient and infallible, but it

seems an agent influenced by the environment (e.g. sentiments), the first section of the thesis proposes two experimental works where the investors' decision-making process is analyzed.
Therefore, I study the (i) context-dependence of the risk assessment and (ii) the cruciality of the agents' interaction in explaining the vulnerability of the price dynamics. Firstly, investors' risk propensity is measured considering different stakeholders' financial constraints. Afterward, in a second different experiment, the price dynamics resulting from the interaction of traders in market context is analyzed.
In the other two sections of the thesis, a series of empirical works are proposed to infer investors' expectations and behavior from different market conditions, proposing a variety of empirical strategies.
In section II, inspired by the huge amount of ICT data available, I show the linkage between market sentiments and the convergence of beliefs. Therefore, in a similar vein, the work is extended proposing a series of network-based measure explaining agents' price forecasting. Specifically, the network-based measures come from the financial network architecture, the communication (social and press media) world, and the exchanges places. Once again, the importance of interconnection of the different information released is prominent to dig out into agents' expectations and subsequent price formation.
After having studied the factors driving decisions and expectations, Section III explores how expectations vary under financial turmoil and the main implications on asset management. The recent vicissitudes of COVID-19, and then the stress test undertaken to the whole economic and financial world, has offered the possibility to investigate the reaction of a global interconnected financial landscape. Here, two empirical works are proposed to investigate the extent of the systemic risk in the financial network and the possibility to hedge equity risk with the recent developed financial instruments (e.g. cryptocurrencies).
In conclusion, the current work proposes -through a mixture of experimental and econometric approaches- a comprehension of a complex and continuously evolving economic and financial ecosystem, moving "from the individual to the system", that is, from the single investor' decision-making process to the market system where she acts.

Part I

No Man is an Island

Overview

The thesis starts with an individual decision-making problem. A subjects' pool composed of professional traders involved in the commodity sector participate in a risk elicitation task. Assuming an extremely realistic scenario, different treatments consider a targeted group on which the choice fall, characterized by different financial constraints (poor/rich groups). Furthermore, depending on the treatment, the trader is included (or not) in the targeted group. These scenarios stylized the case of risk management of fund managers, where the stakeholder (that can be private savers or companies), have different portfolio size/financial constraints.
The results show that risk aversion decreases when income-wealth conditions in the group increase. The inclusion of the decision maker in the group mitigate extremely risk averse decision (in the low-income case) and avoid gambling in the opposite (high-income) case. From here, different policies implications are drawn.
The readers can find the published version of this paper on *Annals of Public and Cooperative Economics (APCE)*. I would like to thank the other co-authors: Prof. Piergiuseppe Morone, Prof. Andrea Morone and Mr Paolo Storelli, who significantly helped us in the recruitment of the professional traders involved in the project.
In the second section, I move from individual to market context. Here, an experimental double auction is ran with the typical students' pool. In this work I study an asset market by combining two different approaches. On the one hand, experimental economics is able to create a laboratory environment where it is possible to control agent behaviour under different risk levels, given by the different levels of precision of the information released. On the other hand, the interaction among subjects is reconstructed by employing network theory. The idea is to analyze the network generated by experimental data and the effects on price dynamics. Our results prove that the emerging empirical networks are far away from a random topology.
Moreover, when the network is very centralized we observe a higher level of price volatility, and the speculation activity of the guru (i.e. the most central subject in the market network) determines the market efficiency, meant as the price-fundamental value gap.
Once again, I would like to thank both of my supervisors involved in this working paper and all the precious comments received at the international conferences where it has been presented: the *Workshop on Economic Sci-*

ence with Heterogeneous Interacting Agents (WEHIA 2021), the *International Coference in Computing Economics and Finance (CEF 2021)*, and the *Economic Science Association Global Online Conference (ESA 2020).*
Related Publications:

- Caferra, R., Morone, A., Morone, P., & Storelli, P. (2021). Professional traders' individual and social preferences under risk: Does group's wealth matter?. Annals of Public and Cooperative Economics.

Chapter 1

Professional traders' individual and social preferences under risk

abstract

We studied whether professional traders' risk attitudes varied according to social context. To this extent, we examined whether the level of wealth in the relevant group influenced traders' risky decisions. The results showed that risk aversion decreased with increased income/wealth conditions in the group context.

1.1 Introduction

Modern economies are characterized by complex causal structures, in which choices frequently impact not only the individual decision maker, but also groups of individuals, to whom the decision maker may be strongly or weakly connected. In this regard, many studies have demonstrated that, when making decisions, individuals consider not only their own payoff, but also the payoff of other individuals in their social environment (Rohde and Rohde; 2011). Previous research on social risk attitudes has generated contrasting results (Baker et al.; 2008,Shupp and Williams; 2008,Zhang and Casari; 2012,Morone et al.; 2021). Since many decisions—particularly in economic and political spheres—target different segments of the population, we sought to analyze whether the wealth of a target population might influence the risk attitude of an individual decision maker. Specifically, we aimed at examining whether professional traders' risk propensity varied based on the target population's level of wealth. The literature on risk taking on behalf of others (Andersson et al.; 2020) includes both economic and financial perspectives. However, to the best of our knowledge, no prior study has presented a combined consideration of both: (i) the professional role of decision makers and (ii) the wealth of "others." To this end, the present study analyzed the decision making behavior of professional versus non-professional traders, with reference to target populations reflecting varying economic conditions.

1.2 Literature review

Before proceeding to the main working hypotheses, in this section, we discuss the state of the art with respect to the main aspects of the present work. Specifically:

- section 1.2.1 overviews the existing studies of professional traders' behavior under risk, motivating the need to further investigate their behavior;

- section 1.2.2. links the relationship between the decision makers/fund managers and the group of interest affected by their risky choice, motivating the analysis of both group financial wealth and risk sharing between shareholders and capital managers;

- section 1.2.3. briefly motivates the implications deriving from the features proposed in section 1.2.2. in term of contract structure and incentive schemes mitigating risk (i.e. risk sharing).

1.2.1 Decision Makers, Professional Decision Makers and Experiments

As is well depicted in the recent contribution of Cipriani et al. (2020), the literature is lacking analyses of the potential behavioral differences between professional investors and students (i.e., the typical sample recruited for laboratory experiments). The authors note that only a few studies have involved professional traders, in research on the emergence of financial bubbles: King et al. (1993), Smith et al. (1988) and Weitzel et al. (2020). They further found that professional traders aggregate information significantly better than students, and are linked to more attenuated financial bubbles (Cipriani et al.; 2020). Accordingly, we were motivated to investigate the behavior of professional traders, given their prominent role in making risky and potentially costly decisions. Although some studies (e.g., those referenced above) have examined the behavior of professional traders in market contexts, to our knowledge, no research has measured risk attitudes among this specific population. However, in one example of related research, Masclet et al. (2009) compared the risk preferences of self-employed people (who take daily decisions that directly affect their personal outcomes) with those of employees (who take decisions for others daily). Beside the specific aim of the experiment conducted, the comparison between the two subjects pool, i.e. the professional traders and the non-professional decision makers (other participants), will contribute to the debate on external validity of experiments guala2005experiments (Guala and Mittone; 2005). In case of statistical differences among the behavior of the two subjects' pool, it would be noteworthy that lab results based on traditional subjects' pool might lack of representativeness of real-life risk management. Indeed, risk management is a task usually performed by professional traders, hence all the experiments assessing the effectiveness of some incentive scheme to lessen gambling in investing must consider the category of subjects doing this activity in a real-life context. If the behavior of such category is different from the typical subjects' pool recruited in experiments, the lab results would be difficult to be generalized if this aspect is not taken into account. Otherwise, the similarity of behavior will favor the laboratory results based on traditional subjects' pool, highlighting the relevance of experiments in stylizing real context. Hence, as an interesting corollary, we might contribute on how such type of experiments should be conducted in the future in order to obtain results that can be valid proxy of real-life risk management.

1.2.2 Social Context and Risk Preferences

Undoubtedly, daily decisions affect not only the decision makers, themselves, but also one or more groups of interest. This is evidently the case when, for example, policy makers craft policies targeting a specific group (e.g. poor classes, retired people) or investors/bankers propose strategies to manage family savings or company capital. For this reason, there has been much research on decision making in a collective context within the socio-economic sciences [1]. From here, the concept of individual and social preferences has been introduced: while the first considers only individual pay-off determined by the decision made, the second one includes the reference group pay-off in the decision made by the individual. In this case, we consider individual preferences over social risk, that is the risk faced by a reference group ()Harrison et al.; 2013). In these studies, as in real life, groups are typically defined on the basis of a discriminating factor, such as gender, national characteristics (See Lane (2016) for a review), political affiliation (Kranton et al.; 2020 or, as in the case of this paper, income (Guiso and Paiella (2008); Lei and Vesely (2010)). Since the pioneering studies of Samuelson (1937) and Von Neumann and Morgenstern (1947), analyses of decision making under conditions of risk and uncertainty have been successfully extended from the individual to the collective context. The literature provides plenty of comparisons between group and individual decisions (see, e.g., Baker et al.; 2008; Morone et al.; 2021; Rockenbach et al.; 2007; Shupp and Williams; 2008). Some scholars have reported that groups are more risk averse than individuals (Baker et al.; 2008;Masclet et al.; 2009 ;Shupp and Williams; 2008), while other studies have found the opposite (Zhang and Casari; 2012). Since we stylize the scenario of fund management under risk, we consider how traders/investors decisions can be affected by the characteristics of the group of interests. In particular, how their attitude varies on the basis of the financial resources of

[1] Comprehensive surveys comparing group and individual decision making can be found in Charness and Sutter (2012) .

savers, or, more generally, shareholders. With regards to the personal traits of the decision makers dealing with risky resource management, Andersson et al. (2020) provided a review. The authors also reported that risk taking on behalf of others is common in many economic and financial decisions, such as when fund managers invest their clients' money (as proposed in the present study). Previously, the importance of understanding risk attitudes in relation to collective wealth was proposed by Chakravarty et al. (2011), who found a connection between individual and expected preferences of the reference group and risk levels that varied in accordance with the degree of detachment between the decision maker and the population of interest. With regard to job title, Masclet et al. (2009) found a link between the employment sector and risk attitude of the decision maker. This aspect deserves further investigation in sectors in which risky decisions are a daily occurrence (e.g. professional trading). Andersson et al. (2020) questioned the relevance of the risky decisions made by professional traders, though the authors focused on personal traits, rather than the employment sector. We aimed at investigating professional traders, specifically, in order to differentiate this particular employment sector. Additionally, we sought to disentangle the problem by considering different facets of a target group defined by income, assuming that wealth in the target group would contribute to the risk propensity of the decision maker (as in Guiso and Paiella; 2008). Both of these aspects, merged together, defined the novelty of the present research. Considering the range of income proposed in our study (i.e. per capita net income of 800–5000 euros), the stylized scenario closely resembled situations in which fund managers invest their clients' money; more extensively, we conceived the target population as all persons impacted by the investment (in a broad stakeholder perspective). Ultimately, we aimed at representing the risk management of traders acting on behalf of a group of interest, where gains and losses would have a differential impact according to the group's actual financial and economic resources. Additionally, it is noteworthy to analyze the general relationship between decision makers and the affected group. In existing studies, the individual decision maker has sometimes—but not always—belonged to the affected group (see Andreoni and Miller; 2002; Eckel and Grossman; 1996,Harrison et al.; 2013), while, as introduced, some studies consider the degree of detachment of the decision maker (Chakravarty et al.; 2011). Taking together these aspects, we will consider the case where the traders share the risk with the group of interest (Risk-Sharing, hereafter RS), and the case where he/she is not included in the targeted group (Non-

Risk-Sharing, hereafter NRS). This will be important to draw different policy implication in regulating contract of capital management, mitigating risk.

1.2.3 Risk, Investment Choice and Contract Structure

The prominent role of the decision maker, the characteristics of the target population and the degree of risk outlined for the decision maker's investment decisions determine several policy implications for contracts (Hart and Holmström; 1987). In particular, as discussed in several works (see, e.g., Fischer; 2013), it is crucial to mitigate risk with respect to investment choices (e.g., Karlan et al.; 2011;Stiglitz; 1990). Additionally, the present study sought to uncover further implications, asking (for example): Can "risk sharing" (i.e. the inclusion of the investor in the target group) mitigate risky decisions? Does level of risk change based on group wealth and/or available capital? The answers to these questions are likely to have important implications for the regulation of contracts.

1.3 Experimental Design

The experiment involved 121 subjects recruited though social networking services, including both risk professional (RP) and non-professional (NP) agents [2]. In total, there were 48 RPs and 73 NPs. Most RPs were from the commodities trading sector, which is characterized by relatively high risk, due to market volatility. All subjects were asked to complete a questionnaire [3] divided into two main parts: part one collected demographic and professional data and part two elicited participants' risk preferences. More specifically, demographic and professional data pertained to gender, nationality, age, number of family members, number of brothers/sisters, relationship status (i.e. single, engaged, married), population of the city of residence, educational level (i.e. secondary school, university, PhD), area of study (only for university graduates and PhDs), employment status (i.e. student, inactive, unemployed, employed, freelance) and monthly net income. The second part

[2] To preserve the anonymity of the data, we limit ourselves to specifying that participants were recruited through the internal network channels of a company operating in a sector in which such decisions are taken.

[3] https://docs.google.com/forms/d/1qz7-Md2lLmxB-4SXAtG9nlISiGAnNEOcd4FtwUr82No/edit

of the questionnaire employed Holt and Laury (2002) mechanism to elicit risk attitudes. Here, subjects examined the same multiple choice problem in five different contexts, expressing their preference for 10 successive lottery choices with a probability [4] of winning a first prize ranging from p = 0.1 to p = 1 (see the table in Fig. 1.1). For instance, in the first decision problem (Table 1), subjects were asked to choose between lottery A, which had a 90% chance of returning 40k euros and a 10% chance of returning 50k euros, and lottery B, which had a 10% chance of returning 100k euros and a 90% chance of returning nothing. Clearly, lottery B was riskier and had a lower expected value (EV(B)); accordingly, lottery A (with a higher EV(A)) was defined as the safe option. Therefore, the problem scheme was as follows: in each choice i, the expected value for both lotteries was shown together with the difference between the two. According to Holt and Laury (2002), risk neutral agents would choose lottery A for their first four choices and switch to lottery B starting with their fifth choice, since the expected value of lottery B was higher (as shown in the EV delta column of figure 1.1). Agents who switched to lottery B earlier would be relatively risk loving and those who switched later would be relatively risk averse. The final three columns in figure 1.1 present the constant relative risk aversion parameter (cRRA) r for subjects switching from lottery A to lottery B. As is evident, agents who switched in their fifth choice had r = 0 (i.e. risk neutrality), whereas risk loving and risk averse agents had negative and positive r values, respectively.

Subjects were asked to indicate their preferences for the above multiple-choice problem in five contexts, each involving a different target population for the risky decision. The target populations included both low-income and high-income cases, with scenarios that included (i.e. Risk Sharing-RS cases) or did not include (i.e. Non-Risk-Sharing NRS decision cases) the decision maker (see Appendix B). All experimental payoffs were hypothetical, in the sense that subjects were asked to answer "as if" they were actually participating in the lotteries with real payment. Despite the significant discussion of the use of financial incentives in experimental economics (see Camerer and Hogarth; 1999), we did not feel our hypothetical treatment threatened the validity of the results, for two reasons: (i) the main purpose of the research was not to study the absolute values of risk aversion, but the differences be-

[4] Probabilities were obtained by changing the composition of the white/black balls inside a hypothetical urn. Each agent made a random draw, knowing that he/she would win the first prize by extracting a white ball and the second prize by extracting a black ball.

i	Lottery A				Lottery B				EV(A)	EV(B)	EV delta	Implied *r* for a subject switching from the lottery A to the lottery B in the choice number *i*		
	p	prize (k€)	*p*	prize (k€)	*p*	prize (k€)	*p*	prize (k€)	(k€)	(k€)	(k€)	lower limit	upper limit	estimation
1	0.1	50	0.9	40	0.1	100	0.9	0	41	10	31	-∞	-1.595	**-2.00**
2	0.2	50	0.8	40	0.2	100	0.8	0	42	20	22	-1.595	-0.864	**-1.23**
3	0.3	50	0.7	40	0.3	100	0.7	0	43	30	13	-0.864	-0.431	**-0.65**
4	0.4	50	0.6	40	0.4	100	0.6	0	44	40	4	-0.431	-0.117	**-0.27**
5	0.5	50	0.5	40	0.5	100	0.5	0	45	50	-5	-0.117	0.133	**0.01**
6	0.6	50	0.4	40	0.6	100	0.4	0	46	60	-14	0.133	0.344	**0.24**
7	0.7	50	0.3	40	0.7	100	0.3	0	47	70	-23	0.344	0.529	**0.44**
8	0.8	50	0.2	40	0.8	100	0.2	0	48	80	-32	0.529	0.697	**0.61**
9	0.9	50	0.1	40	0.9	100	0.1	0	49	90	-41	0.697	0.853	**0.78**
10	1	50	0	40	1	100	0	0	50	100	-50	0.853	+∞	**0.95**

Figure. 1.1: Holt and Laury (2002) mechanism, as adapted for the present questionnaire.

tween various types of agents and frameworks for risky decisions [5]; and (ii) given participants' high income levels , a monetary incentive was assumed ineffective to ensuring pay-off dominance (Harrison; 1994), since it would be difficult and extremely costly to achieve an adequate reward level to finance an incentivized scheme [6]. Based on the proposed literature, we built the main working hypotheses in accordance with the novel aspects of the research, examining: (i) the role of professional traders in risk decision contexts, as discussed in Cipriani et al. (2020); (ii) the importance of the degree of detachment from the target group (following the suggestion of Chakravarty et al. (2011)); and (iii) the relevance of the wealth of the target group (Guiso and Paiella; 2008).

- **H1. RPs and NPs would exhibit the same level of risk aversion, independent of the social context.** Should this hypothesis be rejected, it could be inferred that job title plays a significant role in shaping risk attitude, as suggested by Masclet et al. (2009). In particular, as proposed by Cipriani et al. (2020), we might expect professional traders to be less prone to risky decision making. This finding would be

[5] Any hypothetical bias was assumed constant, and therefore insignificant in the comparison across treatments.

[6] Different from the vast majority of experiments involving students, all subjects in the present sample had stable jobs. Incentives of only a few euros would have been considered very insignificant, relative to participants' monthly earnings.

of extreme interest, considering that decisions could be optimized for risk neutrality to preserve the integrity of the capital invested, thereby limiting the potential for loss due to gambling.

- **H2. The inclusion of the decision maker in the target group would not impact the decision maker's risk attitude.** Putting it differently, we would observe no statistical differences between RS and NRS scenarios. Should this hypothesis be rejected, it could be inferred that the level of detachment between the decision maker and the target group significantly affects decision making, as in Chakravarty et al. (2011). In that paper, the authors suggested: "individuals tend to be significantly less risk averse when they make decisions over another person's money, compared to decisions that they make over their own money." This result may have implications for contracts (Hart and Holmström; 1987), contributing to the debate over the inclusion of terms (see, e.g., Prosser; 2005) to regulate risk sharing (Fischer; 2013). To wit, further policy implications may be inferred, with reference to the appropriateness of including (or not) a portion of the decision makers' gains/losses in their proposed investment outcomes, in order to attenuate risk. In other words, it would be important to understand if there is a significant benefit to including risk managers/traders in investments.

- **H3. Decision makers' risk aversion is independent of the level of wealth in the social context.** This hypothesis, adapted from Guiso and Paiella (2008) main idea that greater income and uncertainty might reduce risk propensity, has never been tested in the literature. Should this hypothesis be rejected, it could be inferred that decision makers account for the wealth of the target population. For instance, the likelihood of taking a risky decision might be lower for low-income target populations, who would suffer more from a possible loss in earnings. Once again, any finding along these lines might generate several policy implications, including contract wording to prevent risk seeking decisions on the basis of the target group's wealth. As an example, contracts might include more (or less) stringent clauses and penalties linked to the financial constraints of stakeholders.

All of these aspects will be discussed further below, in the context of the results presented in the following section.

1.4 Results

The majority of the participants were male (81 out of 121) and younger than 40 years old (82%). With respect to education, 72% had a university degree in Economics (50 out of 121) or Engineering (38 out of 121), and 48 participants were RPs. Net monthly income was equally split between the ranges of 1000–2000 and 2000–5000 euros, and most subjects lived with a nuclear family comprised of four members. [7]. In the first step of the analysis, we examined the proportion of subjects who chose the safe lottery A for all scenarios. As discussed in the "Experimental Design" section, risk neutral agents (r = 0) shifted their selection to lottery B after the fourth choice. Figure 1.2 compares all 121 responses for each of the five scenarios (for a total of 605 observations). Individual choices can be considered reference points for comparison with the other scenarios. Table 1.1 summarizes the results, showing the average switching points for RPs and NPs. Figure 1.2 presents the ordered lotteries (following the first column of the table in Fig. 1.1) on the x-axis and the cumulative fraction of respondents choosing lottery A on the y-axis. , The dashed black line indicates the risk neutrality theoretical prediction. Figure 1.3 repeats the same graph, differentiating between RPs and NPs.[8][9].

Risk neutral = 4	NP	RP	Total	KS test-p value
Individual	6.38 (1.96)	6.02 (1.907)	6.24 (1.945)	0.631
Low-income NRS decision	7.51 (1.864)	7.42 (1.622)	7.47 (1.765)	0.291
High-income NRS decision	5.29 (2.365)	4.71 (2.230)	5.06 (2.321)	0.718
Low-income RS decision	6.93 (2.057)	6.81 (1.758)	6.88 (1.937)	0.81
High-income RS decision	5.93 (2.097)	5.56 (1.934)	5.79 (2.033)	0.47
Number of observations per response	73	48	121	

Table 1.1: Average switching point per group and scenario. Risk neutral agents were theorized to shift from lottery A to lottery B after the fourth choice.

[7]The suitability of the sample size is discussed in Appendix A, which presents the results of post-hoc power tests for two group comparisons, employed using the GPower software

[8]This reflects the standard graphical representation employed in Holt and Laury (2002) and later studies.

[9]As can be inferred from the theoretical prediction, all subjects chose A up to the fourth decision problem; hence, the fraction was always 1 to that point, and 0 afterwards, when no subjects opted for lottery A.

Figure. 1.2: Total proportion of participants choosing the safe lottery A for each choice (y-axis) and decision (x-axis).

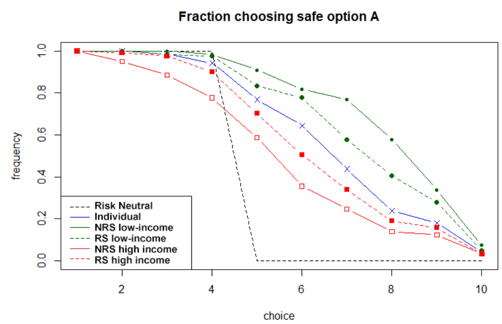
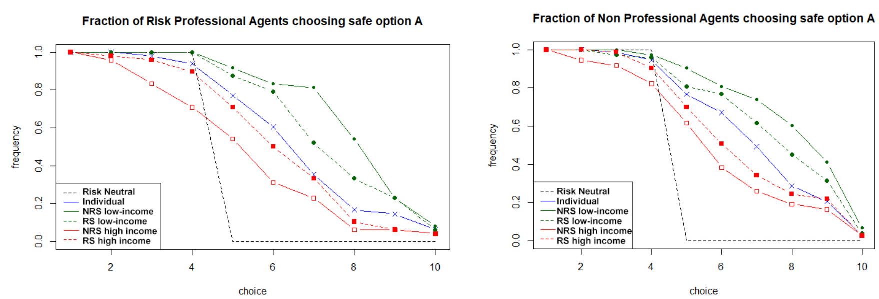


Figure. 1.3: Total proportion (y-axis) of RPs (left) and NPs (right) choosing the safe lottery A for each choice (x-axis).



As is evident, individual choices in both groups were far from risk neutral. Indeed, the average switching point for both NPs and RPs (6.38 and 6.02, respectively) were statistically different from the risk neutral switching point of 4. [10]. Additionally, considering Table 1.1 and Figure 1.3, it is possible to observe a lack of statistical difference between RPs and NPs. This result was also confirmed by our regression models.

Hence, with respect to the first hypothesis, no statistical behavioral differences emerged between RPs and NPs. With respect to the second hypothesis, it was observed that the effect of including the decision maker in the target

[10] Here, we employed both t-tests and Kolmogorov Smirnov (KS) tests, based on the differences between the empirical observations and the theoretical expectation of risk neutrality. The resulting distribution of differences was statistically different from 0 at all levels.

group mitigated the effect on risk attitude. This was inferred from the finding that both low- and high-income RS decisions were closer to individual preferences than were low- and high-income NRS decisions.

Finally, with respect to the third hypothesis, we found that social context mattered. Indeed, we observed that subjects tended to be more risk averse when the decision targeted a poorer group (green lines) and more risk seeking in the opposite scenario (red lines).

All in all, no differences were found with respect to employment sector, while risk attitude was found to be strongly impacted by the level of wealth in the target population. To test this experimental framework more formally, we employed an interval random effect regression model (Andersen et al.; 2006; Coller and Williams; 1999; Harrison et al.; 2013) (Table 1.2). This model can be considered an extension of the Tobit regression model, which considers interval-censored variables. In the present case, the response variable was represented by the cRRA interval associated with the switch from lottery A to lottery B. That is, we constructed a dependent variable base on the lower and upper limit of the interval, corresponding to the switching point from lottery A to lottery B, as reported in the table in figure 1.1.[11] We proposed four versions of the model, to better investigate our hypotheses. First, two reduced forms of the model were proposed (1–2, Table 1.2).

[11] Here, we used the Stata intreg command (https://www.stata.com/manuals/rintreg.pdf).

Dependent variable: cRRA intervals	Coefficients (standard errors)							
Variables	Reduced model				Full model			
	(1)		(2)		(3)		(4)	
Constant	0.3494**	(0.06)	0.387***	(0.077)	0.356	(0.48)	0.359***	(0.485)
Low-income NRS decision	0.377***	(0.06)	0.348 ***	(0.064)	0.377***	(0.05)	0.347***	(0.064)
High-income NRS decision	-0.395***	(0.06)	-0.357 ***	(0.064)	-1.41***	(0.05)	-0.357 ***	(0.064)
Low-income RS decision	0.196***	(0.05)	0.164 **	(0.064)	0.196***	(0.05)	0.164 ***	(0.064)
High income RS decision	-0.141***	(0.05)	-0.133 **	(0.064)	-0.394***	(0.05)	-0.133 ***	(0.064)
Risk professional (RP)								
RP*constant			-0.094	(0.122)			-0.122	(0.131)
RP*Low-income NRS decision			0.075	(0.102)			0.075	(0.102)
RP*High-income NRS decision			-0.093	(0.102)			-0.093	(0.102)
RP*Low-income RS decision			0.082	(0.102)			0.081	(0.102)
RP*High income RS decision			-0.019	(0.103)			-0.020	(0.102)
Income								
1000–2000					-0.167	(0.4)	-0.167	(0.404)
2001–5000					-0.017	(0.42)	-0.016	(0.416)
Up to 1000					-0.113	(0.42)	-0.113	(0.422)
More than 5000					0.167	(0.48)	0.166	(0.479)
risk					-0.114	(0.11)		
University degree					-0.284	(0.26)	-0.284	(0.262)
PhD					-0.348	(0.28)	-0.348	(0.278)
Single					-0.079	(0.13)	-0.080	(0.128)
Married					-0.113	(0.14)	-0.114	(0.138)
Family members								
2					0.428**	(0.19)	0.429 **	(0.186)
3					0.283	(0.19)	0.284	(0.186)
4					0.368**	(0.17)	0.368 **	(0.170)
5					0.336	(0.22)	0.335	(0.219)
More than 5					0.605*	(0.35)	0.604 *	(0.348)
Age								
30–39					-0.008	(0.14)	-0.009	(0.137)
40–49					0.141	(0.27)	0.141	(0.267)
50–59					0.185	(0.35)	0.185	(0.350)
More than 60					0.414	(0.56)	0.412	(0.561)
male					0.172	(0.12)	0.172	(0.124)
Log likelihood	-1080.7412		-1078.4038		-1072.0581		-1070.0698	
obs/groups	605(121)		605 (121)		605(121)		605 (121)	

Table 1.2: Regression Results.***,**,* refer to 99%, 95% and 90% statistically significant coefficients, respectively. Response variable: cRRA interval corresponding to the first switch from lottery A to lottery B.

In model 1, we confirmed the statistical differences between individual choices (i.e. the model constant) and choices made in other scenarios. In model 2, we accounted for potential differences between RPs and NPs, interacting the RP variable (i.e. a dummy variable indicating whether the unit was operating (1) or not (0) in the risk sector) with the categorical variable indicating each scenario.[12] Subsequently, model 3 (4), representing

[12] Again, the constant indicated the individual decision case.

an extension of model 1 (2), introduced a set of control variables: gender (male, female), income (none [13] , up to 1000, 1000–2000, 2001–5000, more than 5000 euro), educational level (secondary school, university, PhD), marital status (single, engaged, married), number of family members (1, 2, 3, 4, 5, more than 5) and age (up to 30, 30–39,40–49, 50–59, more than 60 years)[14]. The selection of control variables was motivated by the literature on risk taking and age (Mata et al.; 2011), income (Guiso and Paiella; 2008), gender (Maxfield et al.; 2010) and other variables, including household size, marital status and education (e.g.Spicka; 2020). Of note, the literature is mixed with regards to the effects of each variable on the outcome (see, e.g., Fehr-Duda et al.; 2006 for a significant discussion on the gender effect). As it is evident: (i) there were no statistical differences between RPs and NPs (models 2 and 4), (ii) group decision coefficients were most similar to individual choices (i.e. constant terms) and (iii) subjects were most risk seeking when decision making for high-income target populations, and increasingly risk averse as the average wealth of the target population decreased. Of note, the response variable was not affected by decision makers' socio-demographic characteristics.

In summary:

- R1. RPs and NPs exhibited the same level of risk aversion, independent of the social context. Although there was weak evidence of reduced risk aversion for RPs, this result was not supported by the statistical tests or regression models.

- R2. The inclusion of the decision maker in the target group mitigated the decision maker's risk attitude.

- R3. Subject risk aversion was strongly dependent on the wealth of the target group.

From the first result, we can draw two conclusions. First, the finding lends support to the claim that laboratory experiments represent valid conditions

[13]Here, we included those who had not yet received a job contract but were trainees or trial period trainees.

[14]The constant term included, as a reference category: females, trainees (baseline income category), those with a secondary school education, those who were engaged, those who were not living with family and those who were younger than 30 years. Additionally, in model 3, the status of "non-operating in risky sectors" was included in the reference category.

to hypothesize real world scenarios, independent of the subject pool involved, since non-professional decision makers act similar to professional ones when facing a decision-making problem. Hence, the success of the proposed risk elicitation procedure does not depend on the decision maker's professional status. Second, the result suggests that professional status does not guarantee against risky behavior with investments (i.e. gambling). Therefore, it might be useful to insert a penalty/incentive into contracts, or to consider the propensity to seek risk with higher capital when evaluating the potential payoff of an investment. The second result suggests that the level of involvement in each project leads investors to reveal their own preferences. In particular, we identified an asymmetric effect: investors were extremely risk adverse when dealing with low-income groups, while showing the opposite behavior when dealing with high-income groups. Accordingly, "risk sharing" is likely to: (i) prevent an excess of risk aversion in the former cases and (ii) mitigate extreme risk seeking in the latter. Finally, participants were more careful when their choices affected low-income groups, and they assumed greater risk when their choices impacted wealthier ones. This suggests that the income of the target population contributes to shaping decision makers' risk attitudes. In a similar vein to Guiso and Paiella (2008), we might extend these results to cases in which subjects must manage not only their own money, but also the money of others (i.e. group contexts) (Andersson et al.; 2020). Given the finding that low wealth in the target group mitigated the risk attitude of decision makers (and vice versa), investors should be encouraged to be more cautious when dealing with target groups possessing large sums of capital.

1.5 Conclusions

The present study aimed at investigating attitudes towards risk, with particular reference to professional background and social context. A survey was administered to a sample of 121 subjects, and Holt and Laury (2002) lottery choice problem was exploited to elicit subjects' constant relative risk aversion (cRRA) in different scenarios. The influence of professional background on risk preference was analyzed by recruiting sample workers from the risk management sector—in particular, financial traders and analysts operating in commodities markets. The introduction of groups with different income levels reflected a range of social contexts, alternatively including and excluding the decision maker from the group. Although risk professionals showed generally lower levels of risk aversion, the effect was not statistically significant. Furthermore, subjects' risk attitudes were strongly correlated with the target group's financial constraints. In particular, the higher the income of the target group, the greater risk was allocated to them by decision makers; in contrast, the lower the income of the target group, the less risk was allocated. All in all, we observed an inverse relation between risk and group wealth. Interestingly, we also found a "risk sharing" asymmetric effect: when decision makers were affected by their own decisions, they were less risk seeking in high-income cases and less risk adverse in low-income cases. This result has important implications for contracts, as the inclusion of investors in the target group is likely to mitigate risky decisions.

1.6 Appendix A1

Tables A1–A3 report: (i) the p-value (α) of the Kolmogorov tests and (ii) the power of the results (1-β), accounting for the possibility of Type II errors (result in brackets). Hence, we jointly consider: (i) the statistical significance of the differences found and (ii) the probability of correctly accepting the alternative hypothesis.

Category=RP	Individual	Low-income NRS decision	High-income NRS decision	Low-income RS decision	High-income RS decision
Individual	-				
Low-income NRS decision	0.000 (0.988)	-			
High-incomeNRS decision	0.03 (0.715)	0.000 (0.99)	-		
Low-income RS decision	0.185 (0.701)	0.03 (0.451)	0.000 (0.99)	-	
High-income RS decision	0.59 (0.13)	0.000 (0.99)	0.180 (0.51)	0.03 (0.85)	-

Table 1.3: Pairwise comparisons of the results for professional traders (RP).

Category=NP	Individual	Low-income NRS decision	High-income NRS decision	Low-income RS decision	High-income RS decision
Individual	-				
Low-income NRS decision	0.001 (0.810)	-			
High-income NRS decision	0.004 (0.803)	0.000 (0.99)	-		
Low-income RS decision	0.130 (0.381)	0.195 (0.445)	0.000 (0.979)	-	
High-income RS decision	0.130 (0.297)	0.000 (0.99)	0.316 (0.561)	0.004 (0.891)	-

Table 1.4: Pairwise comparisons of the results for those employed in non-risky sectors (NP).

Category=ALL	Individual	Low-income NRS decision	High-income NRS decision	Low-income RS decision	High-income RS decision
Individual	-				
Low-income NRS decision	0.000 (0.99)	-			
High-income NRS decision	0.000 (0.996)	0.000 (0.999)	-		
Low-income RS decision	0.075 (0.812)	0.025 (0.73)	0.000 (0.999)	-	
High-income RS decision	0.091 (0.561)	0.000 (0.999)	0.065 (0.854)	0.001 (0.92)	-

Table 1.5: Pairwise comparisons of the results for the full sample.

1.7 Appendix A2: the Questionnaire

TEST

Indicate your preferences in the 5 following lotteries: the structure is always the same, what changes are the players . There are no correct answers, only subjective opinions: imagine yourself in the described situations.

You are invited to a lottery where the prize is established by randomly drawing a ball from an urn: white you win the first prize, black the second. The urn contains exactly 10 balls, with assortments varying between black and white. Before playing, you must choose whether to participate in Lottery A or Lottery B, which have different first and second prize, see table:

Lottery A		Lottery B:	
WHITE ball	BLACK ball	WHITE ball	BLACK ball
50'000 €	40'000 €	100'000 €	0 €

16. **Express your preference on the lottery in which to play for different assortments of the 10 balls inside the urn:** *

Contrassegna solo un ovale per riga.

	Lottery A: white 50'000€ - black 40'000€	Lottery B: white 100'000€ - black 0€
White 1 - Black 9		
White 2 - Black 8		
White 3 - Black 7		
White 4 - Black 6		
White 5 - Black 5		
White 6 - Black 4		
White 7 - Black 3		
White 8 - Black 2		
White 9 - Black 1		
White 10 - Black 0		

17. **Repeat the choices in the case you are not playing the lotteries, but a group of 10 people with a net income per capita of € 800 per month will play:** *

In this case, you choose on their behalf, without participating in the lotteries. Based on your choices, each member of the group will participate individually for the prizes available.

Contrassegna solo un ovale per riga.

	Lottery A: white 50'000€ - black 40'000€	Lottery B: white 100'000€ - black 0€
White 1 - Black 9		
White 2 - Black 8		
White 3 - Black 7		
White 4 - Black 6		
White 5 - Black 5		
White 6 - Black 4		
White 7 - Black 3		
White 8 - Black 2		
White 9 - Black 1		
White 10 - Black 0		

18. **Repeat the choices in the case you are not playing the lotteries, but a group of 10 people with a net income per capita of € 5'000 per month will play:** *

As in the previous case, you choose on their behalf, without participating in the lotteries. Based on your choices, each member of the group will participate individually for the prizes available.

Contrassegna solo un ovale per riga.

	Lottery A: white 50'000€ - black 40'000€	Lottery B: white 100'000€ - black 0€
White 1 - Black 9		
White 2 - Black 8		
White 3 - Black 7		
White 4 - Black 6		
White 5 - Black 5		
White 6 - Black 4		
White 7 - Black 3		
White 8 - Black 2		
White 9 - Black 1		
White 10 - Black 0		

19. **Repeat the choices in the case a group of 10 people, made up by YOU and 9 other people with a net income per capita of € 800 per month, will play:** *

In this case you choose for the whole group. Based on your choices, each member of the group (including yourself) will participate individually for the prizes available.
Contrassegna solo un ovale per riga.

	Lottery A: white 50'000€ - black 40'000€	Lottery B: white 100'000€ - black 0€
White 1 - Black 9	◯	◯
White 2 - Black 8	◯	◯
White 3 - Black 7	◯	◯
White 4 - Black 6	◯	◯
White 5 - Black 5	◯	◯
White 6 - Black 4	◯	◯
White 7 - Black 3	◯	◯
White 8 - Black 2	◯	◯
White 9 - Black 1	◯	◯
White 10 - Black 0	◯	◯

20. **Repeat the choices in the case a group of 10 people, made up by YOU and 9 other people with a net income per capita of € 5000 per month, will play:** *

In this case you choose for the whole group. Based on your choices, each member of the group (including yourself) will participate individually for the prizes available.
Contrassegna solo un ovale per riga.

	Lottery A: white 50'000€ - black 40'000€	Lottery B: white 100'000€ - black 0€
White 1 - Black 9	◯	◯
White 2 - Black 8	◯	◯
White 3 - Black 7	◯	◯
White 4 - Black 6	◯	◯
White 5 - Black 5	◯	◯
White 6 - Black 4	◯	◯
White 7 - Black 3	◯	◯
White 8 - Black 2	◯	◯
White 9 - Black 1	◯	◯
White 10 - Black 0	◯	◯

Chapter 2

Agents interaction and price dynamics: evidence from the lab

abstract

Using data collected from an experimental double auction market, we study the dynamics of interaction among traders. Our focus is on the effect the trading network has on price dynamics and price-fundamental convergence. At the aggregate level, the network of empirical exchanges reveals properties that are dissimilar from random graphs and, in particular, high centrality and high clustering. Precisely, these properties are identifiable as the cause of price volatility and divergence from the fundamental value. At the microscopic level, we find out how the topological properties of the network derive from the behavior of traders. In fact, our findings show that it is the unbridled trading action of very centralized players, called gurus, who implement a minority game, to give rise to volatility clustering and arbitrage opportunities.

2.1 Introduction

The mainstream economics relies on the hypothesis that the exhaustiveness of prices ensures the efficiency of the market and, therefore, it makes unnecessary to comprehend its functioning (see Fama; 1965a). Moreover, even in a context of incomplete information, uninformed traders can achieve full knowledge through the pricing system in such a way that private information is aggregated correctly and efficiently (see Grossman and Stiglitz (1976) and Smith et al.; 1982). However, "this approach reduces, via reductionism, aggregate entities to concepts and knowledge for the lower-level domain of the individual agent. By doing so, the reductionist paradigm blocks from the outset any understanding of the interplay between the micro and macro levels. As a consequence, the differences between the overall system and its parts remain simply incomprehensible given the assumption of equilibrium" (see Tedeschi et al.; 2012a).

Decades of empirical evidence have undermined these assumptions and demonstrated that "markets do not automatically work well and that design matters" (see Stiglitz; 2004). Among the first to show the importance of the markets institutional structure and the exchange linkages to gather the price formation mechanism, we should remember the seminal papers of North (1991) and Kirman (1991). In this vein, several papers have shown that prices dynamics reflect the interaction among agents and are not, instead, the result of a central coordination (see Kirman (2010) for a review). Since interaction depends on differences in information, motives, knowledge and capabilities, this implies heterogeneity of agents and, as a consequence, for externalities. Therefore, the literature has focused on two key aspects capable of generating heterogeneity and, consequently, moving prices away from equilibrium, namely the aggregation of information and the individual behavior. About the first element, the research has focused on the effect that agents' reaction to signals has on the price informativeness (see, for instance, Smith et al.; 1988; Morris and Shin; 2002; Allen et al.; 2006; Ferri and Morone; 2014; Halim et al.; 2019; Steiger and Pelster; 2020; Steiger and Pelster; 2020; Ruiz-Buforn et al.; 2021). Regarding the second aspect, a vast literature has shown how markets are dominated by "epidemic attitudes". These "mass-uniform" behaviors that cause coordination of expectations and collective beliefs lead to large aggregate fluctuations (see Banerjee; 1992; Bikhchandani et al.; 1992; Kirman; 1993; Smith et al.; 1988; Hey and Morone; 2004).

Some insights into fluctuations in prices and agents coordination have been provided by agent-based models. These models, replacing the isolated representative agent with heterogeneous interacting agents in a context of dynamic markets, are able to generate price hikes, out of equilibrium patterns and many other financial stylized facts (see Hommes; 2006; LeBaron; 2006; LeBaron; 2006; Grilli and Tedeschi; 2016, for extensive surveys). In whatever way coordination is represented, via behavioral switching models (see Brock et al.; 1997;Brock and Hommes (1997); Brock and Hommes (1998); Lux and Marchesi; 2000; Chiarella et al.; 2009) or herding mechanisms (see Banerjee; 1992; Banerjee; 1993; Yamamoto and Lebaron; 2010 ; Tedeschi et al.; 2009a; Tedeschi et al.; 2012a), it generates strong synchronization in the individual actions that affect price dynamics. Furthermore, a more recent literature has focused on the relationship between agents' coordination and price fluctuations using network theory. This tool has proved to be particularly suitable for describing the relationship between the organization of interaction among individuals within different components of the economy (see Bargigli and Tedeschi (2014a) for a review) In light of this, some papers have studied the effects that static or dynamic networks have on price dynamics, information dissemination and price convergence to the fundamental (see Tedeschi et al.; 2009a; Tedeschi et al.; 2012a; Panchenko et al.; 2013; Wang et al.; 2019). In fact, depending on the adopted/obtained network topology, these works have highlighted the impact that the interaction between traders has on market efficiency and financial time series. Also experimental economics has recently incorporated into laboratory experiments different network architectures to better understand, in a controlled environment, how several mechanisms of information spreading impact the financial markets dynamics. Specifically, these studies have focused on the effects that different levels of attachment probability between players have on market efficiency (see Attanasi et al.; 2016; Alfarno et al.; 2019; Halim et al.; 2019). Following this line of research, this work analyzes two important aspects related to interaction in an experimental double action market. **Firstly**, we analyze the network architecture emerging from the buying and selling transactions among individuals in the lab. Therefore, differently from the previously mentioned works, we do not introduce a network topology into the experimental design, but we reconstruct the network architecture through players' transactions. The reason behind this modeling choice is simple: we are not interested in understanding how an ex-ante graph impacts on the information dissemination, but what the emerging market structure is and its impact on price dynamics. Our results reveal a very centralized network topology made up of few but populous

communities. Precisely, these network characteristics are shown to impact prices and generate volatility clustering and price divergence from the fundamental. Furthermore, to better understand the topology of the network generated through empirical exchanges, we compare it with a random network simulated by taking into account the key characteristics introduced in the experimental design, namely the number of players and the probability of the dividend signal accuracy. Specifically, we use a two step Bayesian approach to formalize the probability of attachment of the trading network and, thus, to reconstruct the theoretical random graph. Interestingly, the empirical and theoretical networks (i.e. the network derived from the exchanges in the lab and the one reconstructed with the Bayesian approach) considerably diverge in terms of topological characteristics. This result has two important implications. On the one hand, it strengthens empirical evidences that social networks are scale free (see Caldarelli (2007) and Newman (2010) for extensive surveys). On the other hand, it highlights that exchanges are not random as in the case in which agents just use prices to decide whether to buy or sell, but follow different behavioral rules (for example loyalty relationships as shown in Kirman and Vriend; 2000;Kirman and Vriend; 2001; Cirillo et al.; 2012). **Secondly**, we study the behavioral rules that determine the creation of the exchange links and, consequently, define the architecture of the network. Curiously, our findings highlight the emergence of a player who make a high number of transactions. The presence of this subject (called guru) who plays against the crowd implementing a minority game, explains on the one hand the network centrality and, on the other hand, motivates the divergence of the price from the fundamental and the creation of volatility.
In conclusion this work aims i) to highlight how the dynamics that define the interactions among economic agents are essential to explain financial stylized facts; ii) to enrich the vast literature revealing that the market design matters and is the result of the endogenous interaction among the elements that compose it.
The rest of the paper is organized as follows. In Section 2.2, we present the experimental design and reconstruct the theoretical random network associated with it. In Section 2.3, we present the empirical results on aggregate dynamics and micro behaviors. Finally, in Section 2.4, we draw conclusions.

2.2 The experimental double action market: expected vs empirical trading network architecture

In this section we present an experimental double action market where participants may make public offers both to buy (”bids”) and to sell (”asks”). The goal is to investigate how the emerging market topology impacts on price dynamics and individual behavior. To this end, we compare the empirical transactions network, emerging from agents trade, with an expected theoretical graph, and verify if agents act independently of each other and link only through the price system or apply different behavioral rules in the exchange process.

2.2.1 Experimental Design

We run a double action market experiment where a population of N traders can either place market orders, which are immediately executed at the current best listed price, or they can place limit orders. Limit orders are stored in the exchange's book and executed using time priority at a given price and price priority across prices. A transaction occurs when a market order hits a quote on the opposite side of the market.

The experiment, programmed using the Z-tree software (see Fischbacher; 2007), is run at the laboratory LEE at the University Jaume I of Castellon. After reading the instructions, participants get involved in a test session where they become familiar with the exchange mechanism. This preliminary session, which includes reading the instructions, answering any doubts and testing the auction, takes approximately 20 minutes. After the test, the double action market experiment begins, and it includes 48 students who play about 21 minutes and earn an average of 14 euros.

Let us now describe the details of the experimental design. $N = 8$ agents trades, over a time span of 7 periods, one-period life asset, which pays an uncertain dividend. Each period consists in 180 seconds of trading activity. Consequently, there are $T = 7$ periods, and $\tau = 180$ intra-period trading activities. At the beginning of each period, T, the experimenter i) endows each agent with the same balance-sheet, composed by cash, $C = 2000$ experimental Currency Unit, and $S = 10$ stocks; ii) draws, with probability 0.5, the dividend value d, which might be either 10 or 20; iii) gives each player a signal on the value of the dividend. Regarding this last point, two different scenarios (Treatments) are considered, and they vary depending on the signal accuracy: in the first scenario, T1, the probability of receiving the correct dividend value is $p(d) = 6/8$, while, in the second scenario, T2, $p(d) = 5/8$. Whereas the signal on the dividend value received by each agent is a private information, the probability of the signal accuracy, p(d), is common knowledge. At the end of each period, i.e. in $\tau = 180$, the dividend true value is publicly announced.

Finally, in order to check the robustness of our qualitative results, three independent sessions for each scenario are run, using different subjects.

2.2.2 The expected theoretical trading network formation

Keeping in mind the experiment design described above, and remembering that the traded stocks are homogeneous goods and the probability of the dividend signal accuracy, p(d), is common knowledge, one could conjecture that linkages among agents and, consequently, exchanges, take place randomly and just considering prices. On the basis of these simple considerations, we model the trading connections among subjects as a random network and, specifically we hypothesize that the expected theoretical network is the Erdős and Rényi (1959) model.

Let us now explain the approach used to reconstruct the exchange relationships. As already mentioned, the probabilistic distribution of the dividend signal accuracy, p(d), is common knowledge, while the realization coming from that distribution is agent specific. In fact, some subjects, with probability p(d), receive an information reveling the dividend true value, while others, with probability $(1 - p(d))$, have a wrong information. We assume that traders trust (or not) the agent-specific signal received on the dividend value with a probability corresponding to $p(d)$ (or 1-p(d)). In our context, two naive strategies are hypothesized. On the one hand, agents following their signal (regardless of its correctness) submit a buy (sell) order when receiving the signal $d = 20$ ($d = 10$). On the other hand, players refusing the received information apply the opposite strategy. This assumption comes from both the empirical analysis obtained by our experimental data and the literature on trader belief heterogeneity inferring the same information (see Harris and Raviv; 1993; Carlé et al.; 2019). We model this aspect consid-

ering the probability of giving different interpretations of the same signal in accordance with its accuracy level. A trading connection is created when a buyer meets a seller.
Let us now formalize how the expected theoretical trading network is formed. We define with $D \sim \{10,20;0.5,\ 0.5\}$ the dividend distribution, d the dividend realization and $\bar{d}$ the opposite event. Moreover, let I=$\{I_m|I_m \sim (d,\bar{d};p(d),1-p(d))\}$ be the generic signal informational distribution received by each agent. I_m is the signal realization coming from the distribution, where $m=1$ ($m=0$) indicates the coincidence (divergence) between signal and dividend[1]. Once received the signal, the trader can choose the action A_m=$\{A_1,\ A_0\}$, where $m=1$ ($m=0$) refers to an action consistent (not consistent) with the signal. Consequently, we define "coherent" the player who acts in accordance with her signal regardless of its correctness, that is received the correct (incorrect) signal, I_1 (I_0), her action follows the signal (A_1). Symmetrically, an incoherent trader is the one who discards her signal, that is received the correct (incorrect) signal, I_1 (I_0), she always takes the opposite action, A_0. Let us suppose the signal on the dividend to be 20 (10), the coherent player will place an order to buy (sell), at any price, p $\leq$ 20 (p $\geq$ 10). Otherwise the incoherent agent, received the signal of a dividend equal to 20 (10), will not trust the information truthfulness and place a sell (buy) order, at any price p $\geq$ 10 (p $\leq$ 20).
By using a Bayesian approach, and in particular a two step methodology, we can now formalize the trading network bayesian probability of attachment, $p(g)$. In the first step, we assume that the probability to follow the received signal (I_m) coincides with the signal precision ($p(d)$). In other words, we hypothesize that the signal is given without including its distribution. In the second step, we incorporate in the equation obtained in the first step, the signal distribution, that is the probability to receive a signal (in)coherent, (I_0) I_1, with the dividend true value. In this way, agents behavior jointly considers i) the probability to follow the received signal and ii) the probability to receive a signal in line with the dividend true value.
Let us start by describing the first step. As known agents' action lead to a binomial outcome, that is a buy or sell order. Both orders can be modeled

[1]Specifically, if the dividend is 20, d=20, $\bar{d}$=10, I_1=20 and I_0=10

with the following Bayesian distribution:

$$P(A = A_m|I = I_m) = \frac{P(A) \times P(I = I_m|A = A_m)}{P(I)} \propto P(A) \times P(I = I_m|A = A_m), \tag{2.1}$$

where the probability to take an action on the basis of the received signal, P(A=A_m|I=I_m), is given by the prior distribution, $P(A)$, that represents the probability to do the action independently from the received signal, the likelihood, $P(I = I_m|A = A_m)$, that is the probability to correctly infer the signal, and the marginal probability, $P(I)$, that is the probability to choose one of the two actions. Firstly, $P(A)$ can be defined as a flat uninformative prior distribution, since traders have no preference between the two actions. $P(A)$ is uninformative due to the fact that the only available information is both dividends to have an equal chance of happening. Secondly, $P(I)$ is equal to 1 since, in line with the empirical analysis on our experimental data, traders always take an action. Consequently, Eq. 2.1 becomes:

$$P(A = A_m|I = I_m) = P(I = I_m|A = A_m) = \begin{cases} p(d), & \text{if } A_m = A_1 \; \forall \; I_m \in I, \\ 1 - p(d), & \text{if } A_m = A_0 \; \forall \; I_m \in I, \end{cases} \tag{2.2}$$

where the first (second) line of Eq. 2.2 right hand side denotes the coherent (incoherent) strategy.

Let us now move to the second step, where we reintroduce I_m, that is the probability to receive a signal (in)coherent, (I_0) I_1, with the dividend true value. This implies a modification of Eq. (2) in such a way as to introduce $P(I = I_m)$, that is the probability to receive a specific signal. Consequently, by multiplying Eq.2.2 by $P(I = I_m)$, we obtain the joint probability to take a specific action, that is $P(I = I_m) \times P(A = A_m|I = I_m)$. Theoretically the probability to create a trading link, $p(g)$, depends on the probability of drawing two players making different actions. The different possible combinations in the links' creation depend i) on the information received ii) on the strategy adopted by traders (coherent vs incoherent). Tab. 2.1 summarizes all the essential ingredients to reconstruct the links. Moving from left to right we find: the probability to receive a signal coinciding or not with the dividend; the probability to make a specific action (buy or sell) depending on the coherency (incoherency) of the player (see Eq. 2.2); the joint probability; the agent market position and, finally the trader strategy profile.

Signal received	Probability to make a specific action (Eq. 2)	Joint probability	Market Order		Strategy profile
$P(I = I_m)$	$P(A = A_m \vert I = I_m)$	$P(I = I_m) \times P(A = A_m \vert I = I_m)$	$d = 10$	$d = 20$	
$P(I_1) = p(d)$	$P(A_1 \vert I_1) = p(d)$	$p(d) \times p(d)$	Sell	Buy	W1
$P(I_1) = p(d)$	$P(A_0 \vert I_1) = 1 - p(d)$	$p(d) \times (1 - p(d))$	Buy	Sell	W2
$P(I_0) = 1 - p(d)$	$P(A_1 \vert I_0) = p(d)$	$(1 - p(d)) \times p(d)$	Buy	Sell	B1
$P(I_0) = 1 - p(d)$	$P(A_0 \vert I_0) = 1 - p(d)$	$(1 - p(d)) \times (1 - p(d))$	Sell	Buy	B2

Table 2.1: Summary table of the probability to make a buy or a sell order. Specifically, the first column identifies the different signal realizations; the second one models the probability to make an action based on the given signal. The third column summarizes the joint probability of these events, shaping the signal-coherent (or signal-incoherent) strategy profile (fifth column) and the corresponding market order (fourth column).

Basically, four options are possible: coherent players who may be well (badly) informed, i.e. W1 (B1). These traders, who always follow the signal, buy (sell) if the information reveals a dividend equal to 20 (10). Incoherent players who may be well (badly) informed, i.e. W2 (B2). These traders, who never follow the signal, sell (buy) if the information reveals a dividend equal to 20 (10).
Let us now compute the probability of attachment p(g), considering all the available combinations and the compatibility of events. This implies that all possible events, occurring simultaneously in the market, can be added together. Specifically, trading happens when a couple of agents belonging to one of these two trading strategy profiles groups, (W1, W2, B1) or (W2, B2), meet. Obviously there is no interaction between a couple of agents with the same strategy profile belonging to the same group. Hence the probability of attachment is given by:

$$p(g) = W1 \times B1 + W1 \times W2 + W2 \times B1 + W2 \times B2. \qquad (2.3)$$

By substituting each strategy profile with the corresponding joint probability in Tab. 2.1, and after some algebra, we obtain:

$$p(g) = 2 \times p(d)(1 - p(d))[p(d)^2 + (1 - (p(d))^2)]. \qquad (2.4)$$

Recalling that in the first scenario p(d)=6/8 and in the second one p(d)=5/8, we easily obtain the probability of attachments, that are $p(g)$=0.234 in T1, and $p(g)$=0.249 in T2.

2.3 Empirical results

In this session we analyze the emerging market structure and the arising trading strategies. Firstly, our study deals with the market microstructure. Here we mainly focus on the similarities/differences between the theoretical network (see Sec. 2.2.2) and the empirical exchanges. The goal is to understand the impact of the network topology on price dynamics, its volatility and equilibrium. Secondly, we look at agents strategies, focusing on those behaviors that move the price away from equilibrium and motivate the discrepancies between the theoretical and the empirical network.

2.3.1 Market microstructure: theoretical vs empirical configuration

Using the attachment probability, $p(g)$, calculated in Sec. 2.2.2, we simulate, for the two treatments, the Erdòs-Renyi theoretical networks with $N = 8$ vertices and study their topological properties.

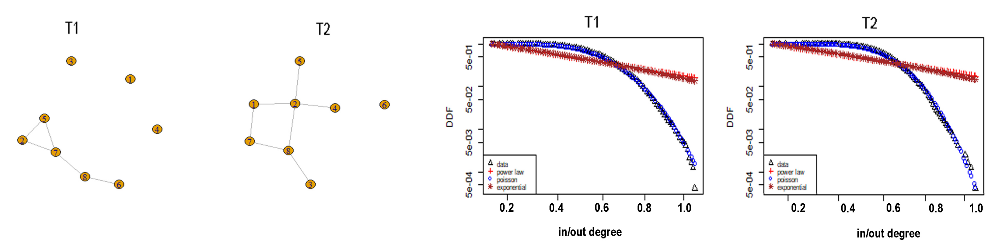


Figure. 2.1: Theoretical network configuration (left side), and decumulative distribution function (DDF) of the degree (right side), for $p(g) = 0.234$ in T1 and $p(g) = 0.249$ in T2.

In Fig.2.1 we plot one shot of the configuration of the theoretical network for T1 & T2 (left side) and the corresponding degree distribution (right side). The graphs show that the network architecture depend on the probability of attachment: the higher p(g), the more connected the network. Obviously, the simulated degrees follows a poisson distribution in both scenarios, as shown by the decumulative distribution functions (DDF). By applying the well-known properties of random graphs (see Newman; 2003), we identify other important characteristics of the theoretical trading network. Firstly, we define the approximate mean degree, z, for each of the N vertexes as $z = p(g)(N-1)$. The mean degree, which coincides with the network average degree and its degree centrality, is equal to 1.638 (1.743) in T1 (T2). Once the mean degree and the probability of attachment are known, we can calculate the fraction of nodes (traders) joined together in a single giant component. The size of the largest component S, is numerically[2] obtained by solving $S = 1-e^{-zS}$. Our theoretical graph exhibits a giant component made up of 66% (70%) of agents in T1 (T2), demonstrating the network to cross the percolation threshold. Finally, we focus our attention on the diameter index, d, which shows the shortest distance between the two most distant nodes in the network. This index, defined as $d = log(N)/log(z)$, is equal to 4.213 (3.742) in T1 (T2).

In summary, theoretical exchanges generate a high connected network with a high probability of trading between each pair of agents. Obviously this result strongly depends on the attachment probability described in Sec. 2.2. The expected structure of the random graph, in fact, varies with the value of the connectivity $p(g)$. The links join nodes (i.e traders) together to form components, i.e., (maximal) subsets of nodes that are connected by paths through the network. Random graphs possess an important property, called phase transition, from a low-density, low-$p(g)$ state in which there are few edges and all components are small, to a high-density, high-$p(g)$ state in which an extensive fraction of all traders is joined together in a single giant component. As we have seen, our theoretical network crosses this threshold by displaying a giant component. The impact of the attachment probability on the network topology is shown in Fig 2.2. The black solid line in Fig 2.2 (left side) shows the dependence of the attachment probability, $p(g)$, on the probability of the dividend signal accuracy, $p(d)$. It is worthy of note that the probability of creating a trading link is a symmetrical function with respect to the informativeness of the dividend signal, with a maximum in $p(d) = 0.5$ and two minima in $p(d) = 0$ and $p(d) = 1$. Intuitively, when half of the players think the dividend is 20 and the other half it is 10, 50% of agents buys and the other 50% sells, thus reaching the maximum number of exchanges. Instead, in the case of missing or complete information (i.e. $p(d) = 0$ and $p(d) = 1$), traders assume the same market position, thus leaving no room for transactions. Finally, a signal corrected to 25% or 75% generates exactly the same number of transactions given the reciprocity between the number of

[2] Numerical solutions are obtained by applying the Newton-Rapson algorithm.

buyers and sellers. Obviously, the motion of the giant component is strictly correlated with the connectivity dynamics, as shown in the black dashed line of Fig.2.2, left side. The variation of the network properties as a function of connectivity are shown in the right side of the Fig 2.2. As expected, as $p(g)$ grows, the network centrality increases and its diameter decreases.
Having shown the topological characteristics for the expected theoretical trading network, we can test affinities and dissimilarities with experimental empirical exchanges. The empirical network is simply defined as the sell/buy orders matrix recorded during the experiment, between the players. Consequently, the nodes represent the $N = 8$ traders and the links the transactions among them. Specifically, the agent i incoming links show her buying positions, while the outgoing links the selling positions. In Fig. 2.3 we plot one shot of the configuration of the empirical trading network (left side) and the in-out degree distribution (right side) for T1 and T2. As we can easy recognize, empirical exchanges considerably diverge from the random configuration. The network architecture, in fact, appears denser than the Erdos-Renyi graph and the degree distribution[3] well approximated by an exponential function rather than a Poisson one. The robustness of the

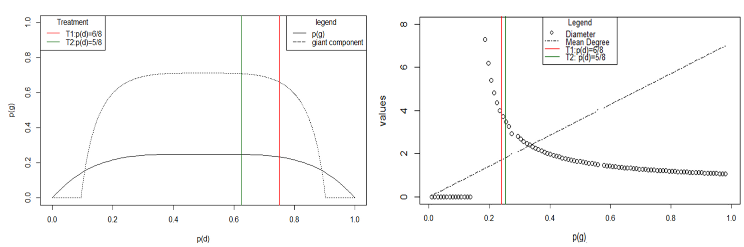


Figure. 2.2: Left side: Evolution of attachment probability,$p(g)$, and of the giant component as a function of the dividend signal accuracy, $p(d)$. Right side: variation of the network mean degree and diameter as a function of $p(d)$. The vertical red (green) line refers to T1 (T2) where $p(d) = 6/8$ ($p(d) = 5/8$). Results refer to the theoretical network.

empirical network topology is displayed in Tab.2.2 where we estimate the empirical degree distribution with the exponent α of the power law function and its standard error and the rate parameter λ of the exponential function and its standard error by means of the Maximum Likelihood Method (MLM)

[3]The sample, made up of 168 observations, collects the information of the 8 subjects, in the 7 periods for each of the three sessions.

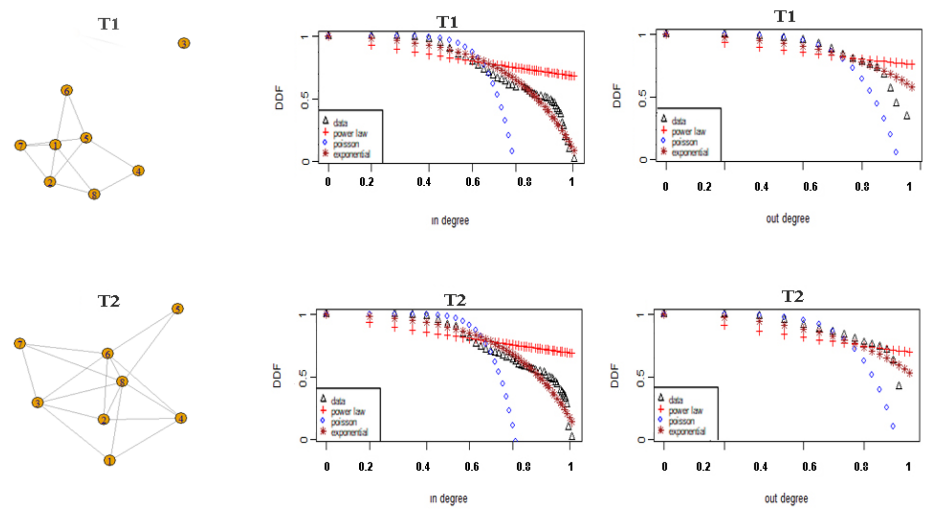


Figure. 2.3: Empirical network configuration (left side), and decumulative distribution function (DDF) of the in-out degree (right side), in T1 and in T2.

as in Clauset et al. (2009). The estimated α and λ parameters of the in/out degrees, for each treatment, are displayed in the third and fourth columns respectively. The comparison via the Vuong (1989) test between the two distributions is shown in the fifth column of Tab.2.2. Given the null hypothesis that the empirical data are equally far from a power law or an exponential distribution, and the alternative hypothesis that the exponential function best represents the "truth" degree distribution, the p-value identifies the exponential function as the degree best fit[4].
Let us now focus on the other properties of the empirical exchanges network and the comparison with the theoretical graph. Tab. 2.3 shows the main properties of the theoretical and empirical network and their statistical comparison through the t-test for both treatments. It is worthy of note that the empirical network, compared to the theoretical one, is more centralized, and more than 90% of traders are clasterized in a large community and very close to each other. These aspects suggest that empirical transactions are influenced by some central traders around which the others crowd and not, instead, only by the information contained in prices. Finally, a t-test on the

[4]We also estimate the empirical degree distribution with the λ parameter of the Poisson distribution. Results, omitted here, reconfirm the supremacy of the exponential distribution.

Treatment	Type	Estimated power law coefficient (MLM)	Estimated Exponential coefficient (MLM)	p-value
T1	In	1.292	0.070	0.000
T1	Out	1.429	0.148	0.045
T2	In	1.312	0.067	0.000
T2	Out	1.436	0.143	0.000

Table 2.2: Maximum Likelihood Method (MLM) estimation of the power law exponents α and the exponential function λ parameter of in-out degree distributions in T1 and T2. p-value of the Vuong's test, with H0 defining both classes of distributions to be equally far from the true distribution, and H1 identifying the exponential function as closer to the "truth".

	T1			T2		
	Theoretical	Empirical	Diff	Theoretical	Empirical	Diff
Degree Centrality	1.638	6.238 (0.95)	-4.600***	1.743	6.017 (1.422)	-4.274***
Density	0.234	0.445 (0.068)	-0.211***	0.249	0.433 (0.105)	-0.184***
Diameter	4.213	2.142 (0.654)	2.071***	3.742	1.857 (0.792)	1.885***
Giant Component	0.661	0.976 (0.050)	-0.315***	0.709	0.952 (0.062)	-0.243***

Table 2.3: Theoretical and empirical network properties. T-test on the statistical difference between the properties of the two networks. Results refer to both treatments.

statistical differences between the two graphs topological properties shows the robustness of our results, that is the existence of considerable divergences between empirical exchanges and the Erdos-Renyi graph, as shown in the column "Diff" of Tab.2.3. Curiously, however, considering the two treatments distinguishing the empirical network, we notice a close similarity between their topological measures. The t-test, omitted here, on the statistical differences between T1 and T2 proves the two sets of data are significantly no different from each other.

Let us now analyze the effect that the empirical network topology has on market prices. Specifically, we focus on two key prices characteristics, namely the volatility and the convergence to the fundamental value. On the one hand, price volatility is a good proxy of financial and macroeconomic uncer-

tainty, often generated by the emergence of systemic instability (see Baum et al.; 2008; Berardi and Tedeschi; 2017; Ghosal and Loungani; 2000; Grilli et al.; 2020a; Tedeschi et al.; 2020b). Understanding, therefore, whether specific network configurations boost systemic risk is useful for safeguarding systemic resilience. On the other hand, the price-fundamental juxtaposition indicates the network topology ability in spreading the signal and, consequently, reveals the market efficiency (see Fama; 1965a).
To create time series with a sufficient length to conduct the analysis, we sample data every 60 seconds. Since there are 7 trading periods of 180 seconds, and these 7 periods are repeated three times (i.e. there are three independent sessions) for each of the two scenarios (T1& T2), we obtain historical series of network measures, prices variance and deviation from the dividend made up of 126 observations[5]. A preliminary empirical analysis reveals that market prices are affected by great volatility and hardly converge to the dividend which, in our experiment, coincides with the fundamental. Specifically, remembering that individual prices always oscillate between 10 and 20, the average prices standard deviation is 0.99, indicating that prices have an average dispersion of about 10%. Furthermore, the dividend price deviation, defined as $e = |p - d|$, is on average equal to 4.85 (st.dev 2.65), indicating that the market prices do not match the dividend. The empirical evidence on prices indicates that, on the one hand, traders do not seem to follow mainstream rational strategies, but rather behave like keynesian animal spirits, and on the other hand, information does not properly flow into the market. The question, therefore, is whether these "anomalies" depend, in some way, on the market architecture. An affirmative answer can be found in Tab 2.4, where we correlate the main network measures with prices dynamics.

[5]By sampling every $\tau = 60$ seconds, we obtain a minimum of 20 and a maximum of 52 transactions every τ.

Market measure	Empirical network	Correlation	p-value
volatility	closeness centrality	0.11	0.007
volatility	mean degree	0.091	0.044
volatility	number of cluster	-0.405	0.000
Price Deviation	closeness centrality	-0.010	0.511
Price Deviation	mean degree	0.191	0.000
Price Deviation	number of cluster	-0.151	0.001

Table 2.4: Correlation between prices dynamics and network properties. The analysis refers to time series made up of 126 observations.

Specifically, we observe that the high centrality of the empirical network (the average closeness centrality is in fact equal to 0.375 with standard deviation of 0.031) has a positive impact on price volatility, as shown by the positive and significant correlation, equal to 0.11, between the two variables. Obviously, when the network is very centralized, few communities (clusters) emerge, and traders tend to clusterize themselves into few, but very populated, groups. In particular, our market is characterized by an average number of groups[6] equal to 1.5 (st. dev. 0.01), and by the materialization of a giant component made up of 96% of players (see Tab.2.3). As expected, therefore, given the inverse relationship between the two network properties, we observe a negative and significant correlation between price volatility and the number of communities in the order of -40%. This result is in line with other studies showing that in high centralized trading networks, congestion phenomena can emerge and these foster volatility clustering (see Tedeschi et al.; 2009a; Grilli et al.; 2014; Grilli et al.; 2015). Furthermore, the high number of transactions, the mean degree is in fact 4.42 (st. dev. 1.45), generates a positive and significant impact on price volatility equal to 0.091. Finally, regarding the impact of network architecture on the information dissemination, in Tab 2.4 we observe that the separation between price and dividend depends, for 19%, on the high number of transactions and for 15% on the presence of a few communities.
The results collected so far reveal the emergence of a highly centralized market where traders clasterize into a few communities generating strong prices volatility and poor convergence to the fundamental value. However, it is worthy of note that the emerging empirical network is a dynamic process,

[6] We implements the "leading eigenvector" method.

depending on the trading strategies adopted by agents. Consequently, understanding its dynamics requires the study of the strategies adopted by players which, in turn, determinate links formation.

2.3.2 From agents behavior to trading links formation

As mentioned above, the strategies adopted by traders define their trading links and, consequently, determine the evolution of the empirical network. Understanding how players use the received signal and interpret other subjects' actions is, therefore, the key ingredient to comprehend the network dynamics. In this subsection, we study the evolution of players' strategies and the impact they have on traders' performance, on the one hand, and on the deviation of the price from the dividend on the other hand. Before starting this analysis some general remarks are essential: **i)** to create time series with a sufficient length to conduct the analysis, we sample data every 10 seconds. Since there are 7 trading periods of 180 seconds, and these 7 periods are repeated three times (i.e. there are three independent sessions) for each of the two scenarios (T1& T2), we obtain historical series made up of 756 observations **ii)** we introduce a new agent-specific variable: the trading net position. When the dividend is equal to 20, this variable is calculated as the difference between incoming and outgoing links, since buying is the best strategy the trader can implement. Conversely, when the dividend is equal to 10, the trading net position is given by the difference between outgoing and incoming links, since selling is the best strategy the trader can implement. Consequently, this variable increases (decreases) each time the player takes the correct market position. **iii)** we rank agents according to their network centrality. Specifically, traders are sorted, within the considered time window (ie every 10 seconds), in descending order using the betweenness centrality[7] and, the most central node is named guru/hub.

In the bottom panel of Fig 2.4 we plot the index of the current guru with the identifier of the strategy she adopts. Following the approach used in the theoretical network, the **well** (badly) informed guru can be "coherent" and, therefore, follow the received signal, ie **W1** (B1), or "incoherent" and, consequently, not be consistent with the signal, ie **W2** (B2). The figure shows that agents alternate as the guru during the experiment. However, it is worthy of

[7] The traders descending order is also robust using other centrality measures such as the closeness and degree centrality.

note that there are long time periods where the guru is stable, as shown, for example, in the last two experimental sessions. The persistence of this agent denotes her aggressiveness in the market, highlighted by her high volume of transactions. In fact, the hub trading volume is 28% higher than that of other players.

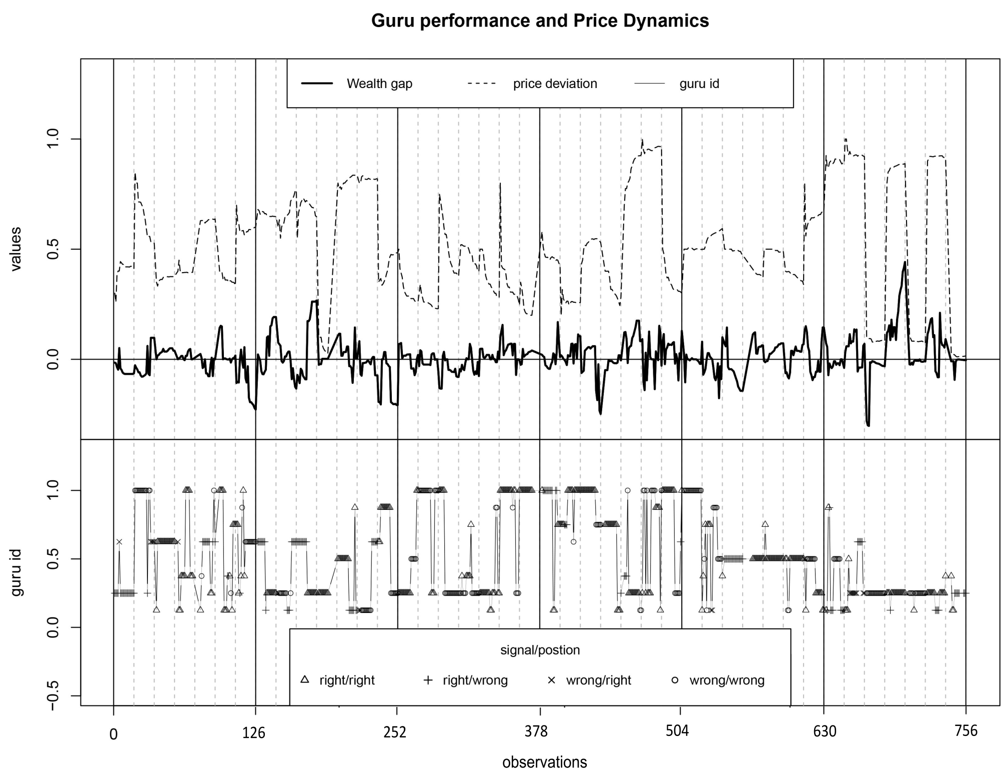


Figure. 2.4: Top Panel: normalized time series of i) the distance between the guru wealth and that of the second most central trader (black solid line), ii) the price deviation from the fundamental value (black dotted line). Bottom Panel: the index of current guru (black line), identified by her coherence/incoherence: triangles and circles identifies coherent strategies, W1 and B1 respectively; plus and times incoherent strategies, W2 and B2 respectively. Vertical solid lines identify the independent sessions for each scenario. Dashed vertical lines refer to the 7 periods of 180 seconds making up each session.

One might expect the hub's highest volume of transactions to depend on her particular trading tactic. A possible answer is in Tab. 2.5, where we report the average strategy adopted by each of the 8 traders arranged in

descending order with respect to their centrality (with S1 to be the guru). As is clear, most of the time, 66%, players follow the coherent strategy, that is, regardless of the correctness of the signal, they follow it. Despite the position taken by the player in the network, this strategy is therefore the most common. Nevertheless, a not negligible percentage of time, 24.5%, agents reject the received information. The manifestation of the non-coherent tactic has a double value. On the one hand, it legitimizes the introduction of this strategy in the calculation of the probability of attachment used in the theoretical network. On the other hand, it justifies the existence of the high volume of transactions in the market. In fact we know that the interaction between coherent agents represents only 1 out of 4 possible trading combinations. The other 3 possible interactions necessarily involve the non-coherent agents, as shown in Eq. 3. On the whole, we can conclude that the guru, which is similar to other players for the adopted strategies, differs in her "aggressiveness" in placing market orders.
Another characteristic distinguishes the hub from other traders, that is her market position. This peculiarity is shown in Tab. 2.6, where we report the

	ALL	S1	S2	S3	S4	S5	S6	S7	S8
W1	44.1%	44.4%	41.9%	42.1%	39.0%	39.6%	49.6%	47.2%	49.5%
W2	24.5%	23.0%	21.4%	23.5%	31.2%	23.9%	25.4%	22.5%	25.7%
B1	21.9%	28.4%	31.2%	28.6%	21.8%	25.8%	13.4%	16.3%	10.1%
B2	0.09%	4.1%	5.4%	5.8%	7.9%	10.7%	11.6%	14.0%	14.8%

Table 2.5: Average strategy adopted by each of the 8 traders arranged in descending order with respect to their centrality (with S1 to be the guru). W1 & B1 refer to well (badly) informed agents following their signal (coherent strategy). W2 & B2 refer to well (badly) informed agents not following their signal (incoherent strategy).

correlation of trading net positions of each pair of players ranked according to their centrality[8] (with S1 to be the guru). As the reader can observe the guru trading net position is always negatively correlated with the other players one. This indicates that the hub plays against the crowd, that is when she submits a market order to buy (sell), other traders give the instruction to sell (buy). Interestingly, however, other traders are perfectly synchronized when placing their orders, as demonstrated by the positive and significant

[8]The 4 most peripheral agents have similar correlations to those reported here. Results are available upon request.

correlation among their trading net positions. The fact that the guru plays a minority game has important systemic consequences. On the one hand, in fact, this strategy gives rise to important stylized facts, such as fat tails and volatility clustering (see Galla and Zhang; 2009; Tedeschi et al.; 2009a). In this regard, it is sufficient to recall the positive and significant correlation between the volatility and the network centrality shown in Tab. 2.4. On the other hand, minority game allows guru for the possibility of arbitrage opportunities (see Challet et al.; 2005). This second point is shown in the top panel of Fig. 2.4, where we display the difference between the guru wealth

centrality	S1	S2	S3	S4
S1	1***			
S2	-0.453***	1***		
S3	-0.501***	0.399***	1***	
S4	-0.389***	0.202***	0.250***	1***

Table 2.6: Correlation matrix of traders trading net position. The first 4 traders, listed in descending order with respect to their centrality (with S1 to be the guru), are reported.

and that of the second most central trader, $S2$, (black solid line)[9]. As the reader can appreciate there are periods where the guru prevails over the system (ie. $W_{S1,t} - W_{S2,t} > 0$) and others where she is dominated by it. An intuition of how the minority game played by the hub provokes arbitrage is as follows. 72% of the time the guru follows the signal, which turns out to be correct 44.4% of the time (see Tab. 2.5). The signal, therefore, determines the hub action and, consequently, her trading net position, which is positively correlated (84%) with her wealth. On the one hand, the well-informed guru, who acts aggressively in the market and assumes the correct market position playing against other traders, over-performs the system and, consequently, exploits arbitrage in her favor. On the other hand, the badly-informed guru, equally vehement and in disagreement with the crowd, down-performs the market which exploits arbitrage to her detriment.

[9] S1 and S2 wealth at time t, $W_{S,t}$, is given by $W_{S,t} = C_{S,t} + A_{S,t}d_t$, where C and A is the amount of cash and stocks, respectively, and d the dividend. S2 is used as a proxy for the system due to the synchronization of the market orders of no-guru traders. However, results are robust also compering S1 wealth with the system's average wealth without the guru.

The effect of signal, trading net position and network configuration on traders wealth is better quantify via the following gravity model:

$$ln(W_{s,t}) = \alpha + \beta_0 ln(W_{s,t-1}) + \beta_1 \mathrm{p(d)}_{s,t} + \beta_2 ln(\mathrm{C}_{s,t}) + \varepsilon_{s,t}, \tag{2.5}$$

where W is the wealth of $S = 1...8$ traders, $p(d)_s$ the signal on the dividend value received by each agent and C the closeness among traders[10]. Specifically, this last variable measures the distance of each treader from the most central agent in the network (ie. the guru). We estimate Eq. 2.5 via an Arellano and Bond (1991) dynamic model using a two step GMM procedure with robust standard error. Two alternative model's specifications are considered: the case (a) includes the agent closeness, C, regardless of the correctness of the trading net position; the case (b) controls for the type of trading net position by inserting a dummy equal to 1 (0) when the agent is assuming the correct (wrong) market position, that is when the trading net position, η, is strictly positive (negative). Tab. 2.7 displays the estimated results from models (a) and (b) by considering the lagged dependent variable[11].

[10] C is calculated as the reciprocal of the sum of the length of the shortest paths between a player and all other subjects in the graph.

[11] The sample is made up of 338 observations, that is N=8 subjects play two different scenarios (T1 & T2), repeated 3 independent times over a time span of 7 periods

Variable	**Model (a)**	**Model (b)**
$\ln(W_{t-1})$	-0.105	-0.026
	(0.159)	(0.161)
p(d)	0.579 ***	0.257*
	(0.114)	(0.157)
ln(C)	-1.759	
	(1.292)	
$\ln(C) \mid \eta < 0$		-7.403***
		(2.293)
$\ln(C) \mid \eta > 0$		11.790***
		(3.186)
α	7.327***	7.273***
	(1.052)	(1.058)
N × T	288	288
AR1	[0.000]	[0.002]
AR2	[0.765]	[0.852]
Hansen	[0.003]	[0.559]

Table 2.7: Estimated results for Eq. 2.5.$\ln(C) \mid \eta < 0$ is the reference coefficient for the $\ln(C) \mid \eta > 0$ effect.

As can be seen, in both models the estimated coefficients associated to the signal, p(d), are positive and statistically significant, indicating the beneficial impact that the received information has on the players' wealth. The impact of the agents' position in the network, C, on the other hand, is not significant in model (a). This result is in line with what we have said about the guru wealth dynamics. Depending on the correctness/incorrectness of the hub market position, she can over-performs/down-performs with respect to the system. This obviously nullifies the overall effect of the market position on players' wealth. The specification made in model (b) mitigates this problem. As the reader can see, in fact, when the position is bound to the action (in)correctness, its effect clearly emerges. Specifically, when players take the correct position in the market, the centrality favors the wealth, as shown by the associated estimated coefficient equal to +11.79. This is not the case, however, in the opposite circumstance, where it can be seen that the centrality harms the players' wealth with a negative impact equal to 7.4.
It is now natural to wonder how this mechanism, linking the signal and the network position with the agent's wealth, affects price dynamics and, in

particular, the convergence between price and dividend. Firstly, we observe that the system is characterized by a strong dispersion of prices from the fundamental value, thus, reveling the efficient-market hypothesis denial. This is shown in the top panel of Fig. 2.4, where we display the price-dividend deviation (black dashed line). Now, to connect the price-dividend gap with the guru-system wealth discrepancy, we calculate the absolute value of the latter, which is proxy of arbitrage exploited to the guru's (dis)advantage, and correlate it with the former. We find a positive and significant correlation of 34.8%, indicating that the aggression of- or at the expense of- the guru, which impacts the wealth volatility gap, also pushes prices away from the fundamental value. Obviously, as the wealth dynamics is linked to the trading net position, the same is true for the price-dividend deviation. In this regard, we find a positive and significant correlation of 0.31 between the two variables. To sum up, the mechanism linking signal, wealth gap and price deviation is well summarized in diagram 2.5, where we display the time series of the guru wealth gap (as in Fig. 2.4) lined up in in ascending order (black solid line) with the respective value of the price-dividend deviation (red dashed line).

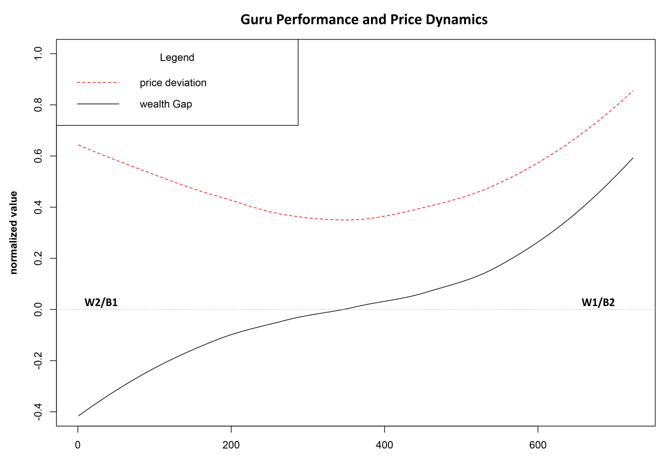


Figure. 2.5: Time series of the guru wealth gap (as in Fig. 2.4) ranked in ascending order (black solid line) with the respective value of the price-dividend deviation (red dashed line). W2(B1) refers to well (badly) informed-guru who does not follow (follows) the signal, thus assuming the wrong market position. W1(B2) refers to well (badly) informed-guru who follows (does not follow) the signal, thus taking the right market position.

Moving from the center to the left we notice how the guru, who does not perform the correct action (ie. W2-B1), sees his wealth decrease. However, as the system plays aggressively against her, the price moves away from the dividend. On the other hand, moving from the center to the right, the guru who performs the correct action (ie. W1-B2) is enriched at the expense of the system and, this time, it is the hub herself that moves the price away from the fundamental value.

2.4 Concluding remarks

Using the experimental data on a double action market, we have demonstrated the importance of the architecture defining the exchange relationships among traders on the prices' dynamics. At the aggregate level, we have observed that the trading network displays very distinct characteristics from a random graph, thus proving that interaction does not occur just via prices. The configuration of empirical exchanges, in fact, turned out to be highly centralized and compartmentalized in a few communities that impact on prices' volatility and price-dividend gap.
At a microscopic level our findings have suggested that traders behavior is the key element to comprehend the topology and the dynamics of the trading network. We have shown that the centrality of the empirical network is the result of the behavior of some agents who carry out a high number of transactions. These traders, defined gurus, play a minority game and are able, depending on the correctness/incorrectness of the received signal, to over-perform/down-perform the system. Moreover, the hub, regardless of her trading net position, with her impetus in buying and selling and her game dissociated from the crowd, is shown to be the engine of the price-dividend gap.

2.5 Appendix: the Experimental Instructions

Double Auction Treatment
Welcome to the experiment
This is an experiment on decision making in financial markets. The experiment is straightforward and the instructions are easy to understand. If you follow them carefully and make good decisions, you could earn a consider-

able amount of money, which will be paid to you in cash at the end of the experiment.

Experiment Overview

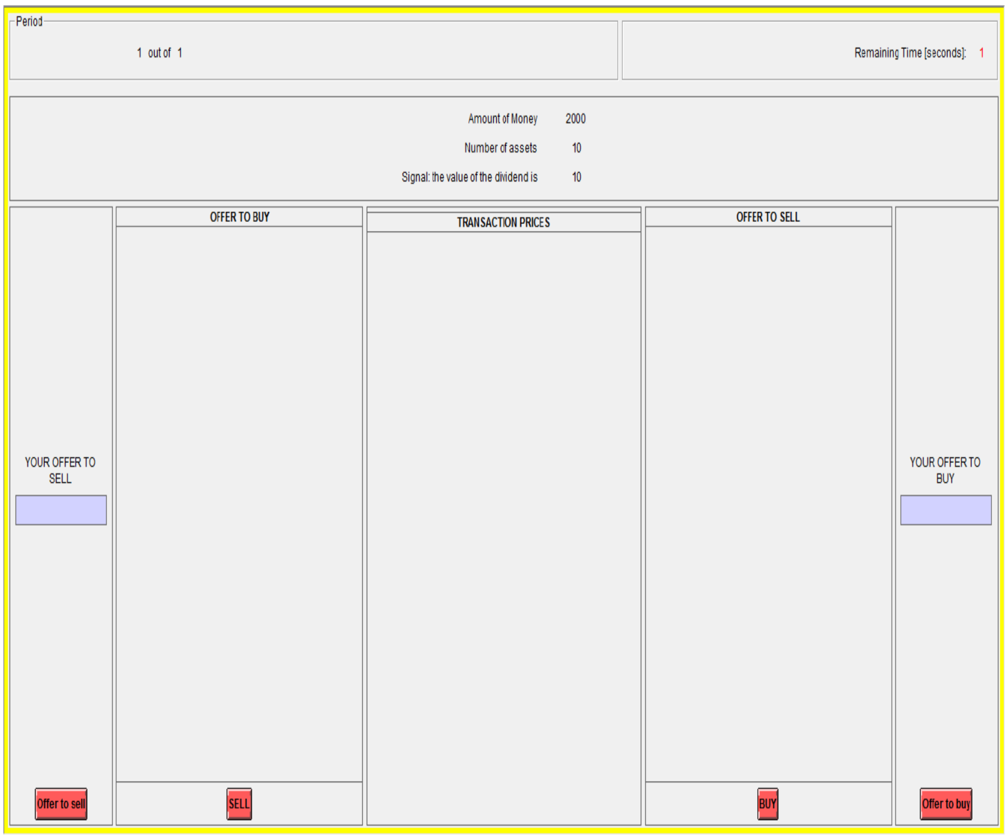
In this experiment you participate in a simple market. The market will take place over a sequence of 9 trading periods. You may think of each trading period as a "business or trading day". In this market a generic asset ("financial good") is being traded and you are free to buy or sell the asset. The money used in this experiment is "Experimental Currency Units" (ECU). Your cash payment at the end of the experiment will be in Euro. The conversion rate will be of 1 ECU to 0.013. In this experiment you make money either by trading the asset or from the dividend on the asset.

General Instructions

The market consists of 8 participants and 9 trading periods, of which 2 trial periods and 7 real periods. In the trial periods you will not be paid for your earnings. Only the real periods will account for your earnings. At the beginning of each period you will be endowed with 2000 ECU and 10 units of asset. At the end of each trading period, the asset will pay a dividend of either 10 or 20. At the beginning of each period, the dividend value will be randomly chosen by the experimenter and not revealed to the market participants. Then, with 50% chance the dividend will be 10 and with 50% chance the dividend will be 20. At the beginning of each period there are, in the market, 8 informative signals on the dividend value. Following a random rule, in each period, each subject will receive one of the 8 signals. There is a probability of [% OF CORRECT SIGNALS] that you will receive the correct signal, and a probability of [% OF INCORRECT SIGNALS] that you will receive the incorrect signal. For example, if the dividend value is 20, with [% OF CORRECT SIGNALS] chance you will receive a signal telling you that the dividend is going to be 20 at the of the period, and with [% OF INCORRECT SIGNALS] chance you will receive a signal telling you that the dividend will be 10 at the end of the period. Similarly, if the dividend value is 10, with [% OF CORRECT SIGNALS] chance you will receive a signal telling you that the dividend is going to be 10 at the of the period, and with [% OF INCORRECT SIGNALS] chance you will receive a signal telling you that the dividend will be 20 at the end of the period.

Buying and selling the asset

At the beginning of each trading period, the screen will show you your initial amount of money, the number of units of asset in portfolio and a signal about your information on the dividend. As reported in Figure 1, on the top left of the screen you will see the trading period in which you are trading. On the top right of the screen you will see how much time is left in the current trading period. In the center of the screen you will see your amount of money, the number of assets you own and your signal.



You can participate to the market in the following four ways:
1. Making an offer to sell the asset, by entering the price at which you are willing to sell.
To offer to sell a unit of the asset, enter the price at which you would like to sell in the box labeled "Your offer to sell" in the first column from the left of the screen, then click on the button "Offer to sell" on the bottom of the same column. The second column from right will show a list of offers to sell, each submitted by a different participant. The lowest offer to sell will be always placed on the bottom of the list. Your own offer will appear in blue.
2. Making an offer to buy the asset, by entering the price at which you are

willing to buy.
To offer to buy a unit of the asset, enter the price at which you would like to buy in the box labeled “Your offer to buy” in the first column from the right of the screen, then click on the button “Offer to buy” on the bottom of the same column. The second column from left will show a list of offers to buy, each submitted by a different participant. The highest offer to buy will be always placed on the bottom of the list. Your own offer will appear in blue.
3. Selling an asset by accepting an offer to buy.
You can select an offer to buy from the second column from the left by clicking on it. If you click the “sell” button at the bottom of this column, you will sell one unit of the asset at the selected price. You are not allowed to sell a unit of the asset to yourself. When you accept an offer to buy, it will disappear from the list. If you also previously submitted an offer to sell, it will disappear from the offers to sell because you have just sold a unit of your asset.
4. Buying an asset by accepting an offer to sell.
You can select an offer to sell from the second column from the right by clicking on it. If you click the “buy” button at the bottom of this column, you will purchase one unit of the asset at the selected price. You are not allowed to buy a unit of the asset from yourself. When you accept an offer to sell, it will disappear from the list. If you also previously submitted an offer to buy, it will disappear from the offers to buy because you have just bought a unit of your asset. You can only buy/sell one unit of the asset at a time. You can buy/sell several times in each trading period. When you buy an asset, the amount of your money will decrease by the price of purchase. You can only buy an asset if you have enough money to pay for it. When you sell an asset, the amount of your money will increase by the price of the sale. You can sell units of asset as long as you own them in portfolio. In the middle column of the screen, labeled “Transaction Prices”, you will see the prices at which the units of the asset have been traded in the current trading period. Any time you accept an offer to sell or buy, a new contract has been closed and the selected price will appear in the column “Transactions Prices”.

Your Earnings

At the end of each trading period your profit will be equal to your “Money before payment of dividends” minus “Initial Money” plus “Your total dividend”. At the end of the experiment, your final earnings will be equal to the sum of your profits in each of the 7 “real” trading periods (the trial periods do not count). The following scheme shows the composition of your earnings for each period:

Initial Money (2000 ECU) −
(Nr. of assets you bought x market price) +
(Nr. of assets you sold x market price)
= Money before payment of dividends

\-

Initial Money (2000 ECU)

\+

Dividend of the period x
Nr. of assets at the end of the period
= Your total dividend

=

Your earnings at the end of the period

Part II

The information flow in financial networks

Overview

In the second part of this project, I move from experimental to real market to study investors attitudes. Here, two empirical studies are proposed with Cryptocurrencies in the spotlight.
As the readers can note, the choice of such financial instrument is driven by at least two important reasons: i) their relevance in the international financial landscape, and ii) the plethora of behavioral factors inherent.
Indeed, there is no unique evidence about cryptocurrencies: some scholars remark their price volatility/instability, some others outline their high profitability. As it can be appreciated in the remainder of the work, it is really hard to reach a singular conclusion, since both of these characteristics are present depending on the period analyzed.
Here, investors' sentiments,beliefs and expectations are examined. The first preliminary project, that is a letter published on the *Journal of Behavioral and Experimental Finance (JBEF)*, considers the convergence of opinion during "media days", that is, days where the press media incidence of cryptocurrencies is higher and more positive.
Afterward, several factors are studied to predict and understand future Bitcoin price movement. Given the huge availability of ICT data, here I introduce different measures deriving from the Bitcoin world. In addition to the traditional internal factors driving cryptocurrencies, we include the information released by some network-based variants, such as: (i) cryptocurrencies connectivity, (ii) social and press media synchronization and (iii) the popular addresses activity, considering their on-chain Bitcoin supply movements. Results evidence the statistical significance of the measures adopted in explaining both price hikes and downfall at the extreme quantiles of the returns distribution, typical phenomena of a volatile instrument.
Here, I thank Professor Valerio Potì for joining us in this project.
Related Publications:

- Caferra, R. (2020). Good vibes only: The crypto-optimistic behavior. Journal of Behavioral and Experimental Finance, 28, 100407.

Chapter 3

Good Vibes Only: The Crypto-Optimistic Behavior

Abstract

This paper aims at investigating the relationship between news-driven sentiments and the convergence of behavior in cryptocurrencies market, contributing to the existing literature in the field. The novelty stands in the relation set between the tone of news and returns dispersion. The average daily sentiment score deriving from a worldwide online news dataset has been exploited as a proxy of market humor, in the attempt to identify how emotions spread by the press are related to traders' actions. By employing both Cross-sectional standard (CSSD) and absolute (CSAD) deviation, it is found that the rises and falls of optimism shape returns variability. Indeed, the paper evidences how an increase of news positivity is associated with a lower returns dispersion, evidencing the convergence of beliefs among investors.

3.1 Introduction

Cryptocurrencies can be considered as the present and future challenges for both scholars and financial analysts. Besides their real contribution and potential application to the economic and financial system, different studies addressed their efforts in detecting the driving factors influencing their price dynamics. The main aim of the current letter is to explain the potential convergence of evaluation linked to news-driven investors' sentiments.
Indeed, David Gerard (2018) stated that *"Bitcoin is less about technology than psychology"*, discussing how cryptos' market dynamics can be influenced by traders' humors and reactions. In this perspective, different papers investigated the performance of their market values, considering their price reaction to both positive and negative specific events (Feng et al.; 2018; Vidal-Tomás and Ibañez; 2018a;Al-Khazali et al.; 2018) and the generation of bubbles or explosive dynamics (Cheah and Fry; 2015; Bouri, Gupta and Roubaud; 2019). Additional insights about investors' sentiments and behavior can be offered by observing the herding behavior of these currencies. As widely known, herding refers to the imitation of the judgments of others while making decisions (Kumar and Goyal; 2015) leading to a synchronization of price co-movements of similar assets. Indeed, Christie and Huang (1995) suggested that in case of convergence of opinion, it can be observed a reduction of the variability of outcome, since beliefs converge to the prevailing market reaction. Historically, this pattern emerged during periods of financial turmoil- such as the 2008 crisis (see Humayun Kabir; 2018)- remarking the importance of studying how the herd instinct can driving asset prices in financial markets.
As discussed in Ballis and Drakos (2020), only few papers attempted to explain this phenomenon in cryptos' market. Indeed, in addition to the work offered by the authors, empirical evidences can be found in Bouri, Gupta and Roubaud (2019) and Vidal-Tomás et al. (2019), where the authors found that smallest cryptocurrencies are herding with the largest ones. As standard herding approach, different papers examine the relationship between the mean/variance relationship of returns (see Christie and Huang (1995) and Chiang and Zheng (2010) as pioneer studies). In these cases, herding happens if the variability of returns decreases for extremes (positive or negative) average values, since all the evaluations of assets head towards the same expectation. However, there are some other factors that might explain the convergency of behavior in cryptocurrencies market.

From here comes the need to further investigate such interesting pattern. The main idea is that media sentiments tone might shape investors humors, impacting price expectation. To clarify, investors might anchor Furnham and Boo (2011) their prediction to the information (sentiment) they receive (perceive). As stated in Song et al. (2017), media has a huge effect on financial market, and sometimes it drives significant market exercises. With regards to cryptocurrencies, Philippas et al. (2019) found that bitcoin prices are partially driven by media attention. These results have been also confirmed in the past by Kristoufek (2013) that examined the relationship between Bitcoin and search queries on Google Trends and Wikipedia. However, as discussed by the same author, a limitation of that work is the absence of a distinction between good/bad news. On this line a case study based on the individuation of some specific positive/negative events to test the semi-strong efficiency of bitcoins can be found in Vidal-Tomás and Ibañez (2018a), while Bouri, Gkillas and Gupta (2019) found a relation between news about US growth uncertainty and bitcoin price dynamics. However, more efforts can be done following this direction, as discussed in Gurdgiev and O'Loughlin (2020), where the same authors identified the need to enrich the discussion on the relation between news and bitcoin price. In particular, they stressed the importance of introducing sentiment scores on a continuous scale to fully reflect the intensity of investors reactions to news. The current work aims at covering this gap. Indeed, Song et al. (2017) evidenced how media articles can be categorized, on the basis of a lexicon-based approach, in positive and negative announcements, even detecting the positive/negative intensity of the information released Currently, literature lacks of paper analyzing the possible relation between sentiments dynamics generated by the worldwide online press on the convergence of investors' behavior in crypto market. Following Christie and Huang (1995) and Chiang and Zheng (2010), herding pattern is empirically investigated by analyzing the dynamics of cross-sectional standard deviation (CSSD) and absolute deviation (CSAD) of returns. Two main points are analyzed: i) the possible herding relation between returns variability and their average level, ii) a possible converge of opinion-i.e. reduction of returns variability- associated with the dynamic of the daily media tone. These and further aspects are discussed in the data and methodological section (Section 3.2). Empirical results are in section 3.3, while section 3.4 concludes.

3.2 Data and Methodology

For the purpose of this letter, 730 daily observations from the 01/01/2018 to the 01/01/2020 have been collected. Since several papers discussed the impact of media during particular explosive behavior Philippas et al. (2019) , the current work aims at investigating how cryptocurrencies behave during the "quiet after the storm", even if such period does not exclude interesting market fluctuations [1]. In other words, it is checked whether, during periods where no extreme events occur, it is possible to identify regularities in cryptocurrencies' price dynamics. To this extent, data have been collected moving from the period after the burst and the peak of the 2017 bubble and without including cryptos' behaviour during COVID-19 , since both of these periods consider particular and extreme events.
Data regarding daily cryptocurrencies prices have been sourced by Yahoo finance, sampling 13 cyptocurrencies: Bitcoin (BTC-USD), LiteCoin (LTC-USD), Ripple (XRP-USD), Ethereum (ETH-USD), Stellar (XLM-USD), Nxt (NXT-USD), Vertcoin (VTC-USD), Cardano (ADA-USD), Binance Coin BNB-USD), Thether (USDT-USD), EOS (EOS-USD), Zcash (ZEC-USD) and IOTA (MIOTA-USD). Returns ($r_{i,t}$) for each asset i at time t are calculated as the log differences of prices between t and t-1. Starting from the definition of financial returns proposed, we employ an equally weighted portfolio to calculate the average return at time t:

$$r_{m,t} = \frac{\sum_{i=1}^{N} r_{i,t}}{N} \tag{3.1}$$

where N is the number of cryptocurrencies, $r_{m,t}$ denotes the average market return and $r_{i,t}$ denotes each daily return.
ICT data regarding the media coverage of cryptocurrencies are sourced from the GDelt Project. As explained in the website GDelt Project (2020), this project is supported by Google and monitors the world's news all over the world. From here it is possible to download data regarding the Global Online News Coverage Dataset on the basis of some selected keywords. In particular, the keyword "cryptocurrency" has been queried. The output released offers the possibility to: (i) identify the daily media coverage of the selected topic, normalized by the all worldwide coverage monitored by GDELT and (ii)

[1] As mentioned in different authoritative blog of finance. See for instance Pedro Febrero; 2018.

the average emotional ”tone” (i.e. sentiment) of the news detected. In the latter case, an extreme negative (positive) score is assigned to each news in accordance to the negative (positive) of the tone of each article [2]. The results are averaged for the total daily news analyzed. Then, it can be possible to propose an average net daily sentiment (SE), considering both an unweighted metric (i.e. the index as it is) and a weighted measure based of the media incidence of cryptocurrency in a given day. In this case, the Normalized Media Incidence is proposed as a measure of the article containing the queried word, normalized for all the articles scraped by the software. In this way, it will be possible not only to consider the net positive/negative outcome of the lexicon-analysis, but also the media relevance of this tone in a specific day. This can be easily done by multiplying the average net daily sentiment by the normalized daily media coverage of the topic. A quick overview of both average returns and ICT data is included can be found in Table 3.1. It can be observed that both average returns and the average net daily sentiment exhibit a negative average value during the period analyzed.

Table 3.1: Descriptive statistics.

Variable	Mean	Standard Deviation	Minimum	Maximum
Average Returns	-0.0028	0.0431	-0.247	0.136
Average Net Daily Sentiment	-0.4184	0.597	-3.142	2.387
Normalized Media Incidence	0.104	0.041	0.030	0.400

The methodology proposed is based on the econometric approach firstly adopted in Christie and Huang (1995) and Chiang and Zheng (2010) to detect financial herding. Such methodology has been employed both in traditional assets market (see, for instance, Gleason et al.; 2004), both in cryptos' market (Vidal-Tomás et al.; 2019) to investigate this phenomenon. Firstly we introduce the methodology of Christie and Huang (1995). Here, returns dispersion is computed as the cross-sectional standard deviation (CSAD):

$$\mathrm{CSSD}_{m,t} = \sqrt{\frac{\sum_{i=1}^{N}(r_{i,t} - r_{m,t})^2}{N-1}} \tag{3.2}$$

In this case, herding is detected in the market if there is a low value of dispersion during periods of extreme market movements. Christie and Huang

[2]In this work, the details of the lexicon-based methodology are not discussed, since this has been already properly done by the GDelt Team.

(1995) investigate this effect considering the lower and upper tail of the distribution of market returns:

$$\text{CSSD}_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + \varepsilon_t \tag{3.3}$$

where D^U and D^L are dummies equal to 1 if market return on day t lies in the extreme upper tail and extreme lower tail (set at 5% in this case) respectively. In this case herding is observed for negative value of β^U and β^L coefficients, since the negative relation identifies a convergence of behavior in correspondence of extreme market movements. We extend this model by including the Average Daily Sentiment (SE_w) deriving from media coverage. As discussed in the data section, two versions of such variable are proposed, both unweighted ($w = 0$) and weighted ($w = 1$) for the percentage of media coverage in the specific day. Hence, the final model will be:

$$\text{CSSD}_{m,t} = \alpha + \beta^U D_t^U + \beta^L D_t^L + \beta^M \text{SE}_w + \varepsilon_t \tag{3.4}$$

On the other hand, Chiang and Zheng (2010) analyze herding through the cross-sectional absolute deviation of returns (CSAD) as a measure of return dispersion:

$$\text{CSAD}_{m,t} = \frac{\sum_{i=1}^{N} |r_{i,t} - r_{m,t}|}{N} \tag{3.5}$$

coming ahead with the following baseline econometric model to control for the relation between variability and average level of returns:

$$\text{CSAD}_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + \varepsilon_t \tag{3.6}$$

where $|r_{m,t}|$ is the absolute term and $r_{m,t}^2$ denotes the square of market returns. In this case, the extreme market movements are identified by the square of market returns, hence a negative value of β_3 indicates herding, that is a reduction of returns dispersion. Here again, the model is extended by considering the average net daily sentiment as before:

$$\text{CSAD}_{m,t} = \alpha + \beta_1 r_{m,t} + \beta_2 |r_{m,t}| + \beta_3 r_{m,t}^2 + \beta_4 \text{SE}_w + \varepsilon_t \tag{3.7}$$

With the two extensions proposed, we can detect the impact of news regardless of (i.e. controlling for) the level of returns.

3.3 Empirical results

Tables 3.2-3.3 report the results for both CSSD (tab. 3.2) and CSAD (tab. 3.3) specifications introduced in section 3.2. Baseline results - and then the relation between average returns and dispersion- in line with those of Vidal-Tomás et al. (2019), while some interesting insights emerge from the extended specification of the models. By observing the relationship between returns dispersion and their average level, and following the notion of herding introduced in the previous section it is possible to conclude that no herding exists. This can be attained since in table 3.2 both β^L and β^U are positive and statistically significant, contrary to the theoretical prediction. Additionally, in table 3.3 it can be observed that β_3 is not negative. However, both the CSSD and the CSAD approach confirm the existence of a negative relation between news tone and returns dispersion. In particular, such relation is less evident if one considers the unweighted average net tone, maybe it clearly emerges when the daily tone is weighted by the volume incidence of news[3]. In fact, by looking at β^M coefficient in table 3.2 it can be observed that the magnitude of the coefficient in the weighted version (w=1) is higher with respect to the unweighted one (w=0). Similarly, in table 3.3 the related coefficient (β_4) has a higher value for w=1. In all the cases the sign is negative, suggesting a reduction of dispersion associated with more optimistic news.

Table 3.2: Results from CSSD model speficifications with robust standard errors. (***), (**), (*) denotes that the coefficient is significant at the (1%), (5%), (10%) level. Baseline results refer to eq. 3.3, while the other two model refers to eq. 3.4.

Model	α	β^L	β^U	β^M	$\bar{R}^2$
baseline	0.027 (0.001)***	0.0216 (0.002)***	0.032 (0.004)***		0.191
w=0	0.0263 (0.000)***	0.0209 (0.002)***	0.031 (0.004)***	-0.002 (0.001)**	0.195
w=1	0.025 (0.000)***	0.012 (0.002)***	0.023 (0.004)***	-0.034 (0.008)***	0.212

[3]To validate the results found, additional attempts have been done considering SE as a dummy variable with value 1 in case of net positive sentiment and 0 vice versa. The related coefficient is -0.001 (p-value=0.06) and -0.001 (p-value=0.15) respectively for the CSAD and CSSD model.

Table 3.3: Results from CSAD model speficifications with robust standard errors.(***), (**), (*) denotes that the coefficient is significant at the (1%), (5%), (10%) level. Baseline results refer to eq. 3.6, while the other two model refers to eq. 3.7.

Model	α	β_1	β_2	β_3	β_4	$\bar{R}^2$
baseline	0.0129 (0.000)***	0.032 (0.015) **	0.235 (0.034)***	0.243 (0.277)		0.352
w=0	0.0127 (0.000)***	0.032 (0.015)**	0.233 (0.034)***	0.232 (0.278)	-0.001 (0.001)	0.353
w=1	0.0127 (0.000***	0.031 (0.015)**	0.231 (0.034)**	0.167 (0.288)	-0.017 (0.007)***	0.362

Results confirm that optimistic news are related to lower returns dispersion, highlighting a convergence of price expectation. As intuited in Philippas et al. (2019), media attention can be an important informative signal for the convergence of price expectations. Here, a clear empirical evidence of such relation has been provided. On the one hand, by looking at the relation between the level of returns and their dispersion, there is no evidence of herding. This result is perfectly in line with the baseline model of Vidal-Tomás et al. (2019). On the other hand, two major issues can be found when the effect of media is introduced.
Firstly, it can be observed that more optimistic (or less pessimistic) signals deriving from press news are associated with a reduction of returns dispersion (i.e. a convergence of beliefs). Additionally, such effect is amplified weighting for days when cryptocurrencies are most discussed. Indeed, an increase of the magnitude of the coefficient is observed when the average daily tone is weighed for the media relevance of bitcoin news of a specific day. Results found contribute to the identification of the key factors driving the price dynamics of cryptocurrency. As stated in Gurdgiev and O'Loughlin (2020), investors' sentiments have an important link with price formation and beliefs, since optimism leads to rising prices and convergence of expectations. As suggested by the same authors, a natural extension of their study is the investigation of the study of the tone used by press and their incidence might be crucial in defining investors' humor. To this extent, the current work covers this gap, showing how general media humor shapes markets' beliefs. This can be directly observable by considering the reduction of returns dispersion associated with the optimism spread by worldwide media coverage.

3.4 Conclusion

The current work investigates the relation between sentiments deriving from daily worldwide online news and returns dispersion, contributing to the existing literature on financial market and herding behavior in cryptocurrencies market. Drawing on Christie and Huang (1995) and Chiang and Zheng (2010), both Cross Sectional Standard Deviation (CSSD) and Cross Sectional Absolute Deviation (CSAD) of 13 cryptocurrencies returns have been employed to construct different model specifications. The time period have been selected in order to investigate the prevailing market dynamics after cryptos' burst of 2017. Results evidence that, looking at the mean/variance returns relation, there are no evidence of herding. However, it can be observed a decrease of the dispersion during days where wave of optimism are spread by media.

The relationship between news optimism and convergence of price dynamics offers important insights for investors, since it remarks how the evaluation of cryptocurrencies is volatile and anchored to behavioral factors and investors' humors. Therefore, this result offers interesting insights for future researches. For instance, it would be worthy to deeply discuss the causal linkage among news and price formation. To clarify, some limitations can be found in establishing the causal relationship, since it is not possible to establish the intra-day sequential order at which price changes and news are introduced. Hence, some future extensions might consider such aspects.

Chapter 4

Network ”in-formation” and Bitcoin price movement

abstract

This research revisits the Bitcoin pricing on the light of the information contained in network formation. In addition to the traditional internal factors driving cryptocurrencies, we include the information released by some network-based variants, such as: (i) cryptocurrencies connectivity, (ii) social and press media synchronization and (iii) the popular addresses activity, consindering their on-chain Bitcoin supply movements. We identify potential tail behavior employing a quantile-based approach. Results evidence the statistical significance of the measures adopted in explaining both price hike and downfall.

4.1 Introduction

Different studies discussed that cryptocurrencies price evolution is "internally driven by market participants"(Baek and Elbeck; 2015). From here, literature widely contributed in the identification of the crypto-related variables explaining price fluctuations. Summarizing (Jaquart et al.; 2021), one possible distinction might be among: (i) technical factors (e.g. past returns), (ii) blockchain factors (e.g. on-chain transactions), and (iii) interests-based measures (e.g. social media sentiments).
Recent developing in assets pricing found prominent the investigation of the formation of investors' expectation (Brunnermeier et al.; 2021). Indeed, the information released by several factors become crucial in explaining price behavior: the "anchoring effect" (see Furnham and Boo; 2011) of traders forecasting on the basis of the information (sentiment) they receive (perceive) and the related herding-like behavior (Kumar and Goyal; 2015) are all ingredients remarking how the convergence of beliefs to the prevailing market reaction might explain price dynamics. This scheme might fit the tail behavior of prices, i.e. the dynamics at lower/higher quantiles where agents might overeact in correspondence of extremely positive/negative circumstances.
The informational content of the past returns, the quantity traded and the social media influence have been still analyzed in the past across quantiles of returns distribution: (i) Chevapatrakul and Mascia (2019) studied investors over-reaction employing past returns, (ii) Balcilar et al. (2017) outlined the returns-predictivity of the quantity traded at the tail of the distribution, while (iii) Subramaniam and Chakraborty (2020) demonstrated how social media shaped investors' humors causing returns to fall (rise) further.
Despite these variables are representative of factors influencing traders' decision, they tell little or nothing about the evolving inter-relation in the underlying network they represent.
In our perspective, the network dynamics of the market factors determining the asset dynamics might reveal additional informational content for traders, which, in turn, will be further reflected in future prices. To this end, we propose a network-based variants to further improve the future price movement explanation. In particular, we consider:

- **Cryptocurrencies market connectivity** measure, that would represent the emerging asset dynamic conditional correlation network, i.e. the co-movements of returns across a representative set of altcoins;

- **social-press media syncronization**, considering the interaction among two representative actors of both popular consensus and authoritative dissemination of information, such as social media (e.g. Twitter) and official press (news media) about the theme of cryptocurrencies;

- the composition of the quantity transacted, considering the **weight of the popular addresses activity**, that are the actors influencing the circulating supply of bitcoin on-chain. Actually, even if-as stated in the blockchain website- the distinction is still not perfect, it might inferred that such movements derives from addresses that are prevalenty associated with exchanges platforms [1]. The increasing movement in exchanges platforms might be anticipatory of some subsequent speculative movements positively (negatively) affecting Bitcoin prices.

In this letter, we both (i) methodologically contribute to the application of networks theory and (ii) provide empirical evidence that the informational content of the added metrics further explain future price fluctuations.

4.2 Data and Hypothesis

4.2.1 Data and Methods

We download Bitcoin (BTC/USD) daily price index from www.coinmarketcap.com from 01/02/2018 to 31/12/2019 with a total amount of 699 observations. As anticipated, to construct the network we also employ the daily data of other 49 cryptocurrencies from the same website, and the rest of the network[2]. We also collect the daily blockchain on-chain transactions from www.blockchain.com. Here, it is possible to disentagle the volume considering the on-chain blocks of popular addresses, that, as discussed, are mostly

[1] Considering the list of the 100 most rich addresses https://bitinfocharts.com/top-100-richest-bitcoin-addresses.html. it is possible to observe that (i) the three richest adddress are exchanges platforms, and (ii) more than 95% of transactions derive from the platfoms.

[2] Augur, BitCNY, BitShares, Blackcoin, DigiByte, DigixDAO, DNotes, DogeCoin, DopeCoin, Emercoin, Ethereum, Expanse, Factom, Feathercoin, FirstBlood, FoldingCoin, GameCredits, GCRCoin, GoldCoin, Golem_Tokens, Gridcoin, Gulden, LBRY_Credits, Lisk, Litecoin, MonaCoin, NavCoin, NEM, NEO, NuBits, Nxt, Omni, Peercoin,Siacoin, SingularDTV, Stealth , Steem, Stellar, Stratis, SysCoi, Terracoin, Verge, Vertcoin, Viacoin, Waves, WhiteCoin, Zcash.

composed by exchanges platforms and the transactions made by the rest of the network. The number of tweets are available from `www.bitinfocharts.com`[3], while the world media incidence of the "cryptocurrency" theme have been sourced from the GDelt Project `https://www.gdeltproject.org/.` [4]. Before describing the whole variables, we discuss the construction of the network based metrics.

Network connectivity

Traditional asset correlation network are based on the construction of weighted link involving the correlation coefficients across the returns [5] of each pair of vertexes (i.e. assets), defining a threshold over which ties (i.e. correlation) turn significant, i.e. a link exist. The same approach have been preserved in cryptocurrencies market (see Vidal-Tomás; 2021). Anyway, as discussed in Lyócsa et al. (2012), such method, that is usually based on time windows to explore the evolution over time, is criticizable at least for two reasons: the arbitrariness of the rolling-window parameters selection and the empirical evidence of bias in the correlation coefficients when volatility increases. This is why, as suggested by the same authors we construct a Dynamic Correlation Netowork based on the daily dynamic conditional correlation (DCC) resulting from a GARCH model. Among the all the possible model specification, we opt for the construction of an DCC-AR(1)-EGARCH(1,1) model, since the asymmetric coefficient is on average positive (0.452) and statistically significant (average p-value=0.046).

Hence, at the end of the process, our daily (undirected) network is based on: (i) vertexes (i.e. the 50 cryptocurrencies) and (ii) weighted link based on the pairwise DCC. Following existing studies (Vidal-Tomás; 2021), we set a correlation threshold of 0.50 [6], above (below) which a link exists (does not exist) .

We consider a measure of network transitivity (NT) [7] to outline global connectivity among cryptocurrencies . The Transitivity (or clustering coefficient) measures the probability that the adjacent vertices of a vertex are connected (Csardi et al.; 2006). At graph level, a value closer to 0 indicate a disconnected graph, while approaching to 1 it indicates the full graph connection.

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[3]We impute the previous observation in case of missing data

[4] See Caferra (2020) for an utilization of the same dataset.

[5]Hereafter, returns are calculated as the log differences of prices

[6]We consider different higher thresholds. Materials available upon request.

[7]For robustness, we also consider the normalized network density obtaining similar results.

Media synchronization
On a similar vein, we consider the DCC over time of the two media measures introduced: the number of Tweets (TW) and the press incidence (PI)[8]. Here, as DCC increases, the new variable indicating the syncronization between the two sources (henceforth media syncronization-MS) will increase accordingly. This will capture how public (i.e. Tweets) and official press (prevalently formed by expert in the field) opinion about bitcoin would converge.
Popular addresses/Platforms incidence
In this case, we simply disentangle the total on-chain transactions (Q) considering the ratio between (the 100 most) popular addresses activity, that, as discussed before, is a proxy of exhange platforms on-chain movements, over the activities of other actors (the on-chain transactions of other addresses). We define as platform cohexistence rate (PCR) the resulting fractions.
Table 4.1 reports a descriptive overview of the variables constructed and employed.

Table 4.1: Descriptive Statistics.

Variable	Mean	Standard Deviation	Minimum	Maximum
Returns	-0.0003	0.037	-0.176	0.160
Transactions	275141.1	66668.96	135129	452646
Tweets	30035.3	16645.47	13294	109734
Media incidence	0.1017	0.037	0.030	0.400
Media synchronization	0.196	0.169	-0.25	0.58
Transitivity	0.779	0.045	0.642	0.871
PCR	0.047	0.020	0.018	0.245

Before proceeding with the discussion of the empirical results, we describe the quantile approach employed. In addition, following the main aim of the work, we outline the main expectations on the model coefficients on the basis of the presence/absence of the huge presence of popular traders.
To identify the predictive effects of the considered variables on the subsequent price dynamics, we build the following model:

$$q_\tau\left(r_t|\Omega\right) = \alpha_\tau + \beta_\tau r_{t-1} + \delta_\tau Q_{t-1} + \eta_\tau MI_{t-1} + \zeta_\tau NT_{t-1} + \theta_\tau MS_{t-1} + \lambda_\tau PCR_{t-1} \tag{4.1}$$

[8]we measure the DCC from the DCC-AR(1)-EGARCH(1,1) model based on first differences to ensure stationariety of both variables. Even in this case the asymmetric component is relevant.

Here, $q_\tau()$ is the quantile function conditioned to the $\tau \in (0,1)$ quantile, t is the time and Ω indicates the available information set. Returns (r_t) are calculated as the log differences of prices, and β_τ,δ_τ,η_τ,ζ_τ,θ_τ,λ_τ are the quantile coefficients associated to past returns r_{t-1}, the on-chain transactions Q_{t-1}, the media incidence (MI_{t-1}), Network transitivity NT_{t-1}, Media syncronization MS_{t-1} and popular addresses activity PCR_{t-1} measure.[9]. As it can be seen, the model involves for each traditional measure the correspondent network based variant, hence we do not include Tweets (TW) and press incidence (PI) jointly, but we insert them separately in two different model specifications [10]. In this case, we employ lagged independent variables both to model the causality relation (avoiding simoultaneity) and to avoid endogeneity (the bitcoin returns are included in the network construction).

4.2.2 Hypothesis set

The additional predictive power of network measures has been still suggested in Ho et al. (2020). However, this paper limits the analysis to the inclusion of these variables in machine learning methods, using conventional asset correlation network with rolling windows without providing details on the relatioship among these variables. To this end, our analysis contribute at least in two spheres: (i) providing a new network measures based on DCC, and (ii) defining not only the statistical relevance, but also the direction and the magnitude of the effect along the returns distribution.

Following the cited literature on the convergence of investors' belief, the convergence of both (i) market returns dynamics and social/press media attention would lead to a short-term future reinforcement of actual returns' dynamics. To wit, we expect that, at the tail of distribution, convergence of (or agreement about) positive (negative) expectations in correspondence of high (low) quantiles might lead to future positive (negative) returns increase. Specifically, similarly to Kristoufek (2013), we consider an increase of Tweets/press incidence/ media synchronization as an increase of positive (negative) feedback in correspondence of high (low) returns.

Considering the PCR measure, one can expect that the exacerbation of movement of a number of popular players/trading platforms would anticipate fu-

[9]We consider normalized measure for Q and TW, aligning on similar scale all the variables.

[10]We also ran the same quantile regression considering in separate specifications each regressor, preserving the same final results.

ture speculative movements. Even in this case, one can expect to observe further returns increase (decrease) in correspondence of higher (lower) tails of quantiles.
This will also enrich the debate on beliefs agreement and emerging price dynamics (He and Shi; 2012).

4.3 Results

Here we introduce the main results of the model. We conduct the quantile regression [11] moving from $\tau = 0.05$ to $\tau = 0.95$.[12]. To interpret the results, it is useful to note the following:

- A positive estimate of a coefficient implies that a positive variation of the given variable tends to be followed by an extension of the upper tail of the return distribution above the threshold τ. In a nutshell, considering the extreme values of the returns quantile distribution, a negative coefficient for extremely lower (higher) quantiles will mean that the increase of that variable causes a subsequent fall of returns.

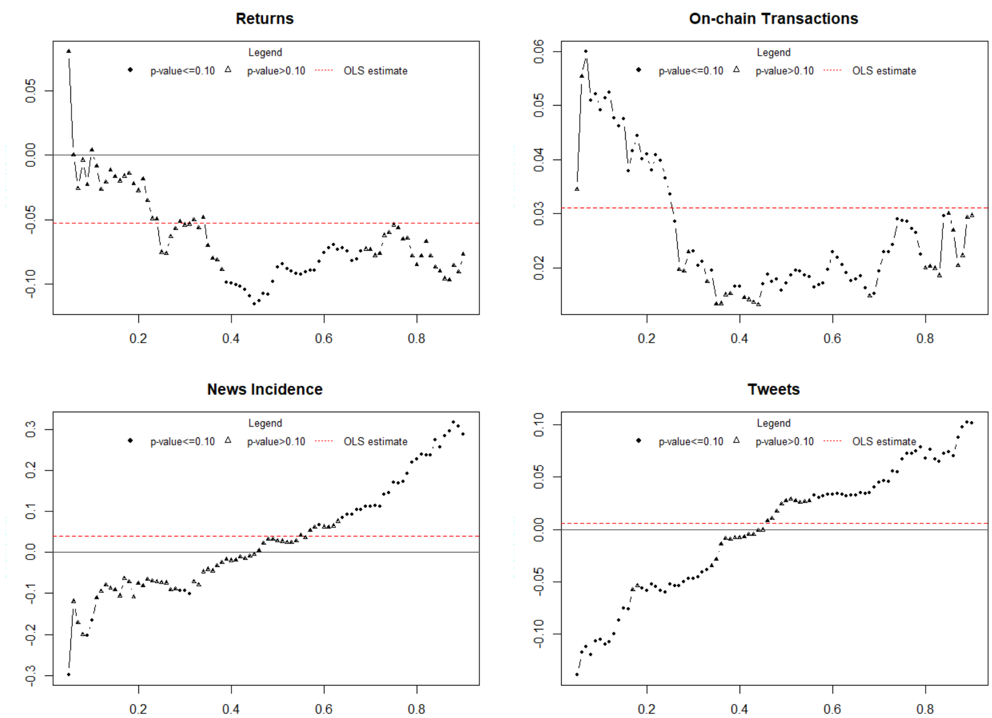
- Vice versa, a negative estimate of the coefficient implies that a positive variation of the given variable tends to be followed by a contraction of the upper tail of the return distribution above (below) τ. In a nutshell, considering the extreme values of the returns quantile distribution, a positive coefficient for extremely lower (higher) quantiles will mean that the increase of that variable causes a subsequent rise of returns.

In figures 4.1 and 4.2 there can be found respectively the results for the baseline coefficients and the network-based variants.

[11]Robust standard errors have been computed through the bootstrapping method.

[12] We report the results of the model where MI=TW, and separately, the results of MI when it is included substituting MI=PI. For the sake of space, we do not report the results related to the other variable coefficients when TW is replaced with MI since they are identical. However, they are available upon request.

Figure. 4.1: Coefficients (y-axis) of the baseline variables across quantiles (x-axis).



Let us summarize the graphical evidence of Fig.4.1:

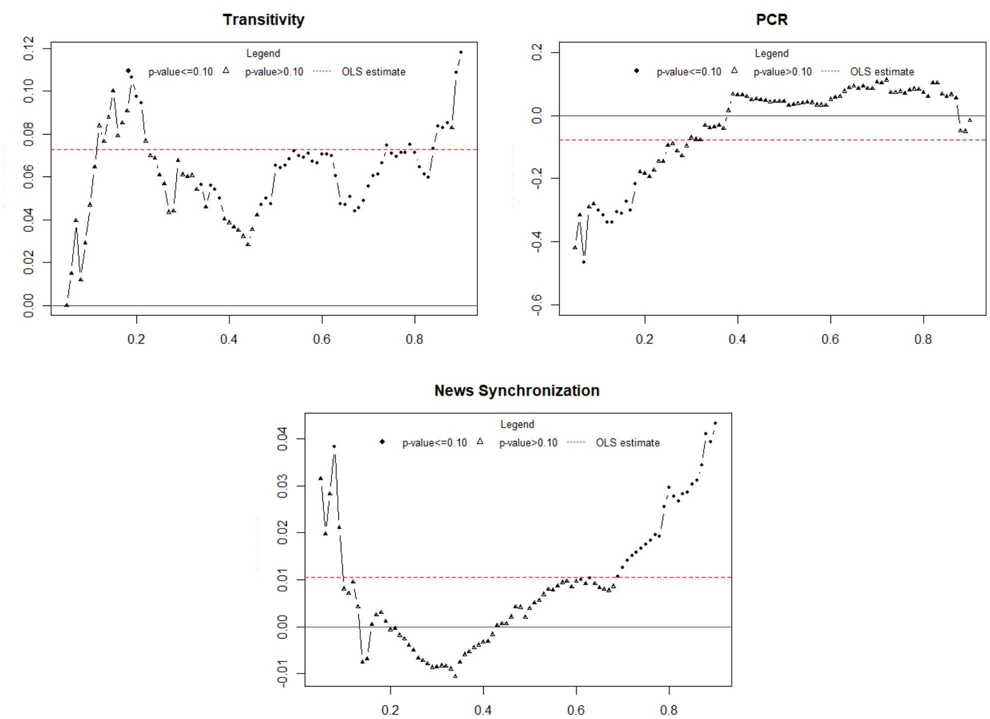
- the autoregressive relationship of returns exhibits general mean reversal confirmed by the OLS mean estimator (dashed red line) as in Chevapatrakul and Mascia (2019). Furthermore, it exhibits momentum on the downside, even if it is not statistically significant.

- On-chain transactions anticipate a general increase of returns for each quantile, as confirmed by the OLS mean estimator;

- In a similar vein of Subramaniam and Chakraborty (2020), the dynamics of News incidence and Tweets capture the non-linear behavior of returns. Despite the poor (and misleading) statistical significance of the OLS mean estimator, it is possible to observe that for lower(higher) quantile, the increase of such variables causes a further decrease (increase) of returns. This remark the volatility of this instrument and the speculative attacks of traders that sell-off cryptocurrencies during

”bad news” (an increase of media/social incidence when returns are lower) and increase their profits exchanging at higher prices during ”good news”(an increase of media/social incidence when returns are higher).

Figure. 4.2: Coefficients (y-axis) of the network-based variant variables across quantiles (x-axis).



The network measures in Fig. 4.2 reveal further interesting insights:

- The transitivity explains the convergence of beliefs causing returns to increase further, since it turns positive and statistically significant above the median (τ>0.5). This is consistent with herding theories. This attitude confirms and enriches the suggestion of Ho et al. (2020), shedding light on the existing relationship between the centrality measures and the Bitcoin price pattern.

- PCR turns negative and statistically significant in some intervals of lower quantiles, explaining how potential movements in trading platforms might sometimes anticipate a downfall of returns the day after.

- Media convergence (News synchronization) explains a further explosive behavior in correspondence of higher (above the median) returns. Interestingly, this network metrics explain how the coordination of beliefs causes price "pump" in the cryptocurrency market.

4.4 Conclusions

Based on the empirical results, we can draw the following conclusions:

I) returns are more predictable and exhibit momentum on the downside (consistent with several theories from the intermediary asset pricing literature), albeit in a manner that is not statistically significant

II) Regarding the volume of on-chain transactions Q, we can observe that (a) it always (i.e., across all quantiles of the return distribution) predicts higher returns and (b) it has a higher (positive) coefficient on the downside of the return distribution. Both observations are consistent with rational valuation of Bitcoin (which is a positive function of the cryptocurrency acceptance as a medium of exchange) but also with the alternative possibility that its price depends on herding and/or investors' attention since most of this volume is transactions with exchanges.

III) The fact that the network transitivity NT coefficients are statistically significant only past the median of the return distribution means that cryptocurrencies rise together. This is consistent with herding (and/or attention-driven market behaviour).

IV) The fact that the PCR coefficients are statistically significant only in negative parts of the domain of the return distribution means that Bitcoin crashes after flows towards exchanges occur. This is consistent with herding (and/or attention driven market behaviour) rather than rational valuation explanations.

V) The fact that the "media incidence" MI coefficients (whether for traditional media or social media/tweets) are statistically significant only in the tails of the return distribution means that, when Bitcoin rises and falls the most, this is preceded by high media attention. This is consistent both (a) with herding (and/or attention-driven market behavior) and (b) with the possibility that the rational valuation depends on measures of Bitcoin acceptance, which MI might proxy for.

VI) Regarding "media synchronization" MS (between traditional media and social media/tweets), we observe that the coefficients are positive to a statistically significant extent only in the tails of the return distribution. This means that, when Bitcoin rises, this is preceded by high media attention synchronization but, when it falls, the opposite is true. That is, media attention synchronization precedes price rises whereas media attention dissonance precedes prices falls. This too is more consistent with attention-driven market behaviour, rather than with rational valuation.

Fact (I), while of some interest, is not of help in identifying the possible role of attention-driven market behaviour. Facts (II)-(VI) can instead be of great help. We note that, while Fact (II) and Fact (V) admit both an explanation based on herding and attention-driven market behaviour and one based purely on rational valuation considerations, Fact (III), Fact (IV) and Fact (VI) offer support to the latter rather than the former explanation. These results and especially Fact (VI), offer support to theories that foresee that the convergence of the expectations of market operators is mediated by the activity of the media and in particular by the convergence of expectations in the media.

By employing a quantile approach based on network measures, we have been able to identify interesting Bitcoin tails behavior.

The first type of contribution is methodological, since we enrich the existing literature on the construction of the asset correlation network, basing our analysis on the daily dynamic conditional correlation as measure to identify the linkage and the closeness among each time series. This approach-that outperforms the other approaches based on rolling windows- seems to be promising, since it is able to properly explain price behavior.

The second type of contribution would be of extreme interest of experts, investors and scholars involved in the field. We provide empirical evidence that Bitcoin price movements are driven by the internal cryptocurrencies network architecture.

Future movements are anticipated by the convergence of expectations provided by the synchronization of the price dynamics (i.e. high transitivity) of the whole crypto ecosystem, the sentiments deriving from the increasing jointly consensus in both news and social world.

Additionally, the increasing on-chain amount of cryptocurrencies required by trading platforms (proxied by popular addresses) during bad times can be seen as "the days before the storm", anticipating subsequent price falls.

All in all, results evidence the statistical significance of the measures adopted in explaining both price hike and downfall, laying down the basis for further researches exploiting this approach.

Part III

The speed of silence and the beat of Bit: Hedging risk during financial turmoil

Overview

The journey into investors' minds and financial markets concludes with the analysis of the recent COVID-19 outbreak into the financial system.
The speed of silence -as the title suggests- refers to the rapid turn of the events related to the virus spread.
Indeed, few weeks after the first announcement of the Chinese COVID-19 case, its silent worldwide diffusion got overwhelmed. Suddenly, a deafening crack breaks the silence and the loud noise violently hits the health, economic and financial system.
The first work proposes examines the timing of the financial market collapse in the different Countries (China, South Korea, Israel, Russia, USA, Italy, Spain, Germany, France, England). Furthermore, an event study analyzes whether the different policies proposed (which find their long-run effectiveness, as reported in several cited studies) calm down investors' panic.
Here, the different beat (i.e. the different dynamics) of Bit(coin) and, more generally, cryptocurrencies, fascinated the whole financial world.
Indeed, the second and final paper revisits the role of Cryptocurrencies in the financial system. In the section before, we set out the volatility of the instruments, while here their hedging properties during financial turmoil are reported. Even if a financial contagion is observed during the pandemic announcement days in March, since both cryptocurrency and stock prices fell steeply, cryptocurrencies promptly rebounded, contrary to the persistent bear phase of stock markets.
Here, cryptocurrencies play the role of hedge when it is most needed, contrary to previous crisis (as the 2008-2011 one) where, as discussed in the letter, portfolio diversification was difficult to be obtained.
The published version of the paper can be found on *Finance Research Letters (FRL)*. I would like to thank my colleague and friend Dr David Vidal-Tomas for his contribution.
Related Publications:

- Caferra, R., & Vidal-Tomás, D. (2021). Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. Finance Research Letters, 101954.

Chapter 5

The day after tomorrow: financial repercussions of COVID-19 on the systemic risk

abstract

In this paper we study the financial repercussions of COVID-19 and the effect of anti-epidemic measures on financial markets. By using a composite dataset containing stock market indices of 10 countries characterized by heterogeneous levels of contagion, the daily COVID-19 cases and the 108 more restrictive measures implemented to limit the virus from the 31/12/2019 to the 13/03/2020, we examine the emergence of financial systemic risk, its speed of propagation and the effectiveness of the policies implemented to curb it. On the one hand, the spread of contagion and its transmission on financial markets is investigated via a lagged cross-correlation analysis. Our results show the emergence of systemic risk characterized by a high speed of diffusion. On the other hand, an augmented AR(1)-EGARCH(1,1) model is applied to examine the impact of anti-COVID-19 "policies" on financial markets. We show that, regardless of the level of contagion, the restrictive measures did not stop the virus-induced investors panic.

5.1 Introduction

"Epidemics and financial crises share certain general features, such as the potential to spread globally in an increasingly interconnected world, characterized by rapid mobility of people, commodities, information and capital. Disease outbreaks may also induce market turbulence, necessitating catastrophic risk management." (Peckham; 2013a).

The speed of globalization in spreading catastrophic events was suspected even in 1889 -during the "Asiatic Flu"- when, in approximately two months, the virus spread from Russia to America due to "modern transport infrastructure"[1]. Thirty years later, having the possibility to measure different features of a virus outbreak, given the huge availability of ICT data, we can offer a deeper explanation of the dynamics of the contagion and its repercussion in the economic context.

Generally speaking, it is well known that the spread of epidemics has strong repercussions on markets and exacerbates financial contagion (Peckham; 2013b) by generating a significant increase in prices co-movement due to systemic interconnection (see Pericoli and Sbracia; 2003 and Bargigli and Tedeschi; 2014b, for an extensive review). A branch of economic literature closely linked with complexity science identifies in the self-reinforcing interaction among market participants the channel to propagate/reduce financial frictions which translate into booms followed by busts (see, Grilli et al.; 2020b, for references on this topic). Typically, news, expectations and uncertainty about the future state of the world generate coordination phenomena or herding effects in traders' actions which affect stock market returns (see Wurgler and Baker; 2007 and Chen et al.; 2013). Different studies dealing with the emergence of financial contagion due to viruses spread, in fact, have found evidence of investors' overreaction, due to the arrival of news on virus outbreaks, able to destabilize financial markets (see, Donadelli et al.; 2016). In a similar vein, it has been shown that information on the health system resilience and the countries socio-economic stability has had a significant impact on stock markets both in the case of SARS in Asia and Ebola in Africa (Hanna and Huang; 2004; Giudice and Paltrinieri; 2017).

Pandemics are recurrent events in human history and a new pandemic was expected [2], what seriously questions if such a drastic phenomenon should

[1]https://en.wikipedia.org/wiki/1889_1890_pandemic

[2]https://www.newyorker.com/news/daily-comment/the-pandemic-isnt-a-black-swan-but-a-portent-of-a-more-fragile-global-system

be considered a "black swan event" (Taleb; 2007) or it should be included as a frequent episode in future risk management. Surely, it stresses the governments' preparedness to deal with (un)expected and potentially disastrous shocks. The recent vicissitudes due to the COVID-19 attack have reopened the debate on issues related to the systemic interconnectivity and on the measures to contain systemic risk. A rich and recent literature encouraged by the need to face the pandemic emergency has studied the virus socio-economic impact. Without wishing to be exhaustive, let us mention some papers dealing with the dynamics of the COVID-19 diffusion (Alos et al.; 2020; Kraemer et al.; 2020; Buscema et al.; 2020; Lee et al.; 2020)[3], its impact on financial markets (Albulescu; 2020; Ramelli and Wagner; 2020; Conlon and McGee; 2020; Corbet et al.; 2020; Akhtaruzzaman et al.; 2021; Caferra and Vidal-Tomás; 2021) and the measures/policies implemented to reduce its economic/financial spread (Gormsen and Koijen; 2020; McKibbin and Fernando; 2020; Kingsly and Henri; 2020; Baldwin and di Mauro; 2020; Collard et al.; 2020). In this paper, we intend to contribute to the last two lines of research. Specifically, we ask the following questions: was there a correlation between the COVID-19 spread and the financial markets collapse? How have financial markets responded to the measures implemented to curb the contagion? In order to answer these points we use several daily time series concerning closing values of 10 stock market indices, daily numbers of COVID-19 infections and data on the restrictive measures implemented to control the contagion. The analysis, running from the 31/12/2019 to the 13/03/2020, is conduced on a heterogenous sample of countries which, during the investigated time period, show different levels of infections. Specifically, we collect data from Italy, Spain, Germany, France, China, South Korea where there is a medium / high number of infected people, and from Israel, United States, Russia and United Kingdom, where few infections are registered. From a methodological point of view two approaches are adopted. On the one hand, to study the synchronization between market indices dynamics and number of infections, we utilize the cross correlation function. Although this technique is simple, the results are clear, highlighting the fast migration of the virus and its economic consequences. In line with other studies (see, for instance, Ramelli and Wagner; 2020), we show that the pandemic quickly turned into a financial crisis. Interestingly enough, this

[3] An interesting approach using network theory to describe viruses spread is proposed (Brockmann and Helbing; 2013).

is true not only for the highly infected areas but also for those COVID-19 free. This finding shows us once again that financial contagions are triggered both by real attack and "animal spirits" (see, for instance, Tedeschi et al.; 2012b). Moreover, the lagged cross correlation analysis allows us to grasp the speed of the infection transmission. We show that the virus just needs 15 days to spread from East to West. Furthermore, once in Europe, the speed of diffusion exponentially increases and the financial collapse happens the day after the pandemic arrive in Italy. On the other hand, to analyze how financial markets respond to the anti-COVID-19 measures, we implement an augmented AR(1)-EGARCH(1,1) model. This approach, based on the Efficient Market Hypothesis, is traditionally used to capture the impact of exogenous shocks on financial returns (Karafiath; 1988; Hansen and Lunde; 2005; Malik; 2011; Vidal-Tomás and Ibañez; 2018b; Zaremba et al.; 2020). It assumes that new public information is incorporated in prices motions and, consequently, these reflect the traders reaction (such as pessimism and optimism waves) following the announcement. As the reader can appreciate later on, our results show a general unstoppable pessimism that is not reversed by anti-Covid measures in the most affected countries' stock markets. On the contrary, the stock exchanges of less infected countries remain indifferent to the measures, showing not to believe in their preventive effect.

One year later, in 2021, different studies employed a retrospective analysis of the mitigatory effect of implemented policy measures (see Haug et al.; 2020). As stated by the authors, drastic measures have been the "nuclear option" for COVID-19: on the one hand, the short-term negative expectations have been reversed by the long run effectiveness of restrictions in containing the contagion, on the other hand, different collateral consequences might have took place on the socio-economic system. Here, we prove evidence of the investors behavior in the early-stage of the unstoppable virus outbreak, detecting if, even in the financial context, their short-term expectations have considered more the collateral effects (i.e. the sub-basement of the economic system) at the expense of the future benefits (i.e. the complete recovery of the system).

5.2 Data and descriptive analysis

The goal of this paper is to analyze the financial contagion generated by the COVID-19 spread and the effectiveness of the measures implemented to mitigate it. In this regard, three types of sources are used: **i)** the daily closing values of 10 stock market indices characterizing countries with different levels of contagion. These indices, downloadable from Thomson Reuters Eikon, are: the MIB (Italy), the Ibex35 (Spain), the DAX30 (Germany), the CAC40 (France), the FTSE100 (UK), the S&P500 (USA), the TA125 (Israel), the MOEX (Russia), the SHANGAI Composite (China) and the KOSPI (South Korea). All the selected countries, with the exception of Israel, United States, Russia and United Kingdom, where few infections are registered, report a medium / high number of infected people in the selected time window. The heterogeneity of the sample, and particularly the four counterfactual countries, allow us to understand if the financial contagion spreads regardless of the disease real attack, and the credibility of the preventive policies to contain it. **ii)** The daily COVID-19 cases downloadable from the European Centre for Disease Prevention and Control database[4]. **iii)** A dataset containing the 108 more restrictive measures implemented to control the contagion. These country-specific measures include travel restrictions, policy measures and National emergencies Acts. The dataset is built by merging the detailed time-line provided by Wikipedia with the GardaWorld.com website.[5]
The analyzed time window runs from the 31/12/2019 to the 13/03/2020. The start and end dates correspond, respectively, to the day on which China officially announces the existence of the outbreak COVID-19 and the day-after the characterization of this disease as "pandemic" by the World Health Organization. The end data (i.e. March 13) is set to capture only the "real" impact of the anti-COVID measures on financial markets and not the panic generated by ~~the~~ the World Health Organization announcement.

The time series of the stock index prices and returns are shown in Fig. (5.1). As expected, the Chinese financial market is the first to suffer from the impact of COVID-19. However, due to the closure of the Chinese stock market from 23/01/2020 to 03/02/2020 for the Lunar New Year holiday, the

[4]Data on the number of infected persons per day are available every week: https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide.

[5]The dataset is included in the Appendix, section (5.5).

drop in prices occurs after the onset of the disease (see point "a" in the figure). The shock wave takes about 15 days to hit the other markets and is particularly aggressive in Italy. In Fig. 5.2, we report the number of new daily cases of infections (blue bar) and the date when the measures to contain the contagion are implemented (dashed line).[6] As the reader can observe, most of the countries begin to apply massively anti-contagion measures only once the infection starts in their own territory. Two interesting exceptions are Russia and Israel where strong prevention measures are observed. On the other hand, the behavior of the United Kingdom is unusual. Here we observe some preventive measures, related to "flight routes suspensions", but any intensification of these measures when the infection appears on the national territory.

[6]It is worth mentioning that, later in time, some doubts arose on the accuracy of both i) early-stage daily cases data, since different (criticized) countries-specific detection methods were adopted (Iacobucci; 2020), and ii) the detection of number of deaths, since different problems arose in properly identifying the causality between COVID-19 and deaths on the light of other potential omitted variables/diseases (Brown; 2020;Woolf et al.; 2020). In this case, we do not enter the merit of the calculation method employed, and we limit ourselves in considering the high trust level that readers can have on the authoritative data source announcing virus contagion. We opt for daily cases as the raw proxy of virus diffusion and, consequently, as the early-warning indicator of potential stress of the health (and then economic) system. Furthermore, we cannot use the number of deaths since Russia and Israel did not record any case in the selected period.

Figure. 5.1: Normalized stock index prices and returns from 31/12/2019 to 13/03/2020.

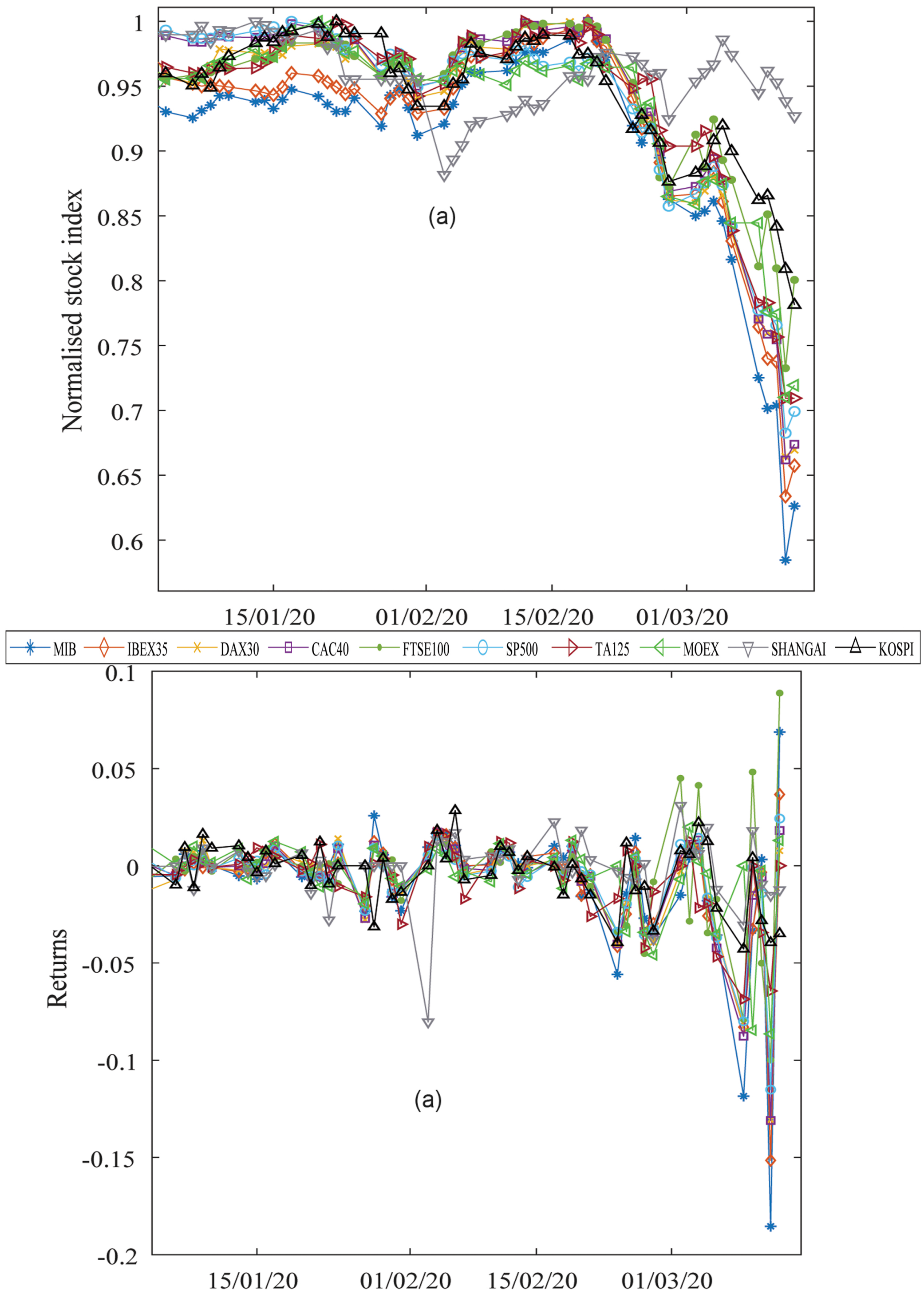
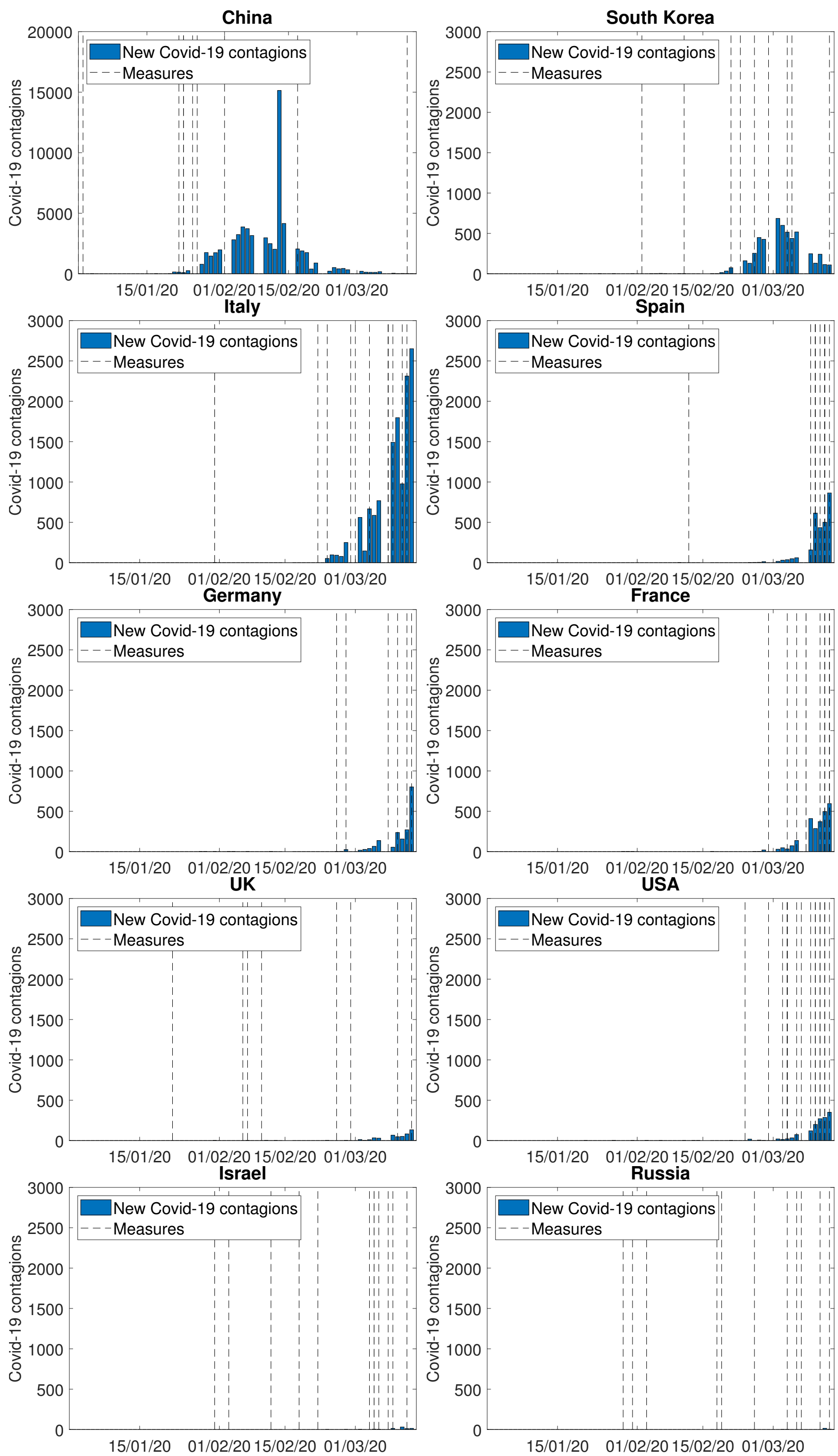


Figure. 5.2: Number of new daily infections (blue bar) and the date of anti-contagion measures (dashed line).



5.2.1 The spread of financial contagion

In this session, we study the spread of contagion and its transmission on financial markets. Considering China (Italy) as the worldwide (Western) trigger point, we analyze **i)** the cross-correlation between the number of new daily infections in China (Italy) and the lagged number of infection in the other countries and **ii)** the corresponding cross-correlation between the stock market indices (see Chatfield; 1994 and Shen and Zheng; 2009, for a similar approach). With this methodology, we do not aim at studying the causality between COVID-19 and market movement, but we would infer, considering each pairwise couple of countries: i) the cross-country propagation time of both virus and financial shock, considering the number of days (lags/leads) after which a similar situation occurs (i.e. where the highest correlation level is recorded), and ii) the synchronization of the two mentioned events, observing the alignment (meant as the difference of the correspondent number of days) between the peaks of correlation of COVID-19 cases and market indexes. This is meant as a preliminary and descriptive approach to figure out the worldwide situation at the dawn of COVID-19 outbreak.[7]Results are reported in Fig. 5.3. As the reader can observe, the correlations show similarities in the spread of the contagious and in the relation between the indices. Before the onset of the infection (i.e. up to lag 0), all prices time series were already slightly correlated. This fact reflects the well-known synchronization in the financial markets also known as globalization (see Saunders and Cornett; 2014 and Alfarano et al.; 2019). As we can see, the COVID-19 outbreak in China generates a “desynchronization” between the indexes series due to the Chinese market collapse. Obviously, also the correlation between the numbers of infections is negative in the first positive-lags –China, in fact, is the first country to be affected by the disease–. About 15 days after the outbreak of the COVID-19 in China, the infection spreads to other countries as shown by black bars in Fig. 5.3. It is in the few days following the spread of the pandemic that we re-observe a strong realignment between the financial series confirming the interconnection among markets and the onset of the systemic risk. In our highly globalized world, the cross-correlations evidence that only 15 days have been needed to spread the pandemic and just 20 days to bring down all markets. Obviously, considering Italy as the trigger point

[7]For the sake of soundess, we propose the same exercise using the growth rate of daily infections and the financial returns. Results preserve the same spirit of the description presented in the paper and can be found in the appendix.

and, therefore, considering the pandemic spread since its arrival in Europe, the whole process speeds up even further and, the "previous 15 days" become the "day after tomorrow", as shown in Fig. 5.4 where the highest correlations between the number of new daily infections in Italy and the lagged number of infection in other countries (black bars)[8], and between the MIB and the other stock indexes (white bars) are found at lags 1 and 2.

5.2.2 COVID-19 flood and disaster management

In this section, we analyze the financial markets reaction to policy measures implemented to deal with the virus spread. To this end we apply the augmented AR(1)-EGARCH(1,1) model (Karafiath; 1988; Hansen and Lunde; 2005; Malik; 2011), which is traditionally used to examine the effect of different shocks affecting financial markets, such as good or bad news, policy measures and calendar effects (Aharon and Qadan; 2019; Malik; 2011; Vidal-Tomás and Ibañez; 2018b; Zaremba et al.; 2020). The model specification is:

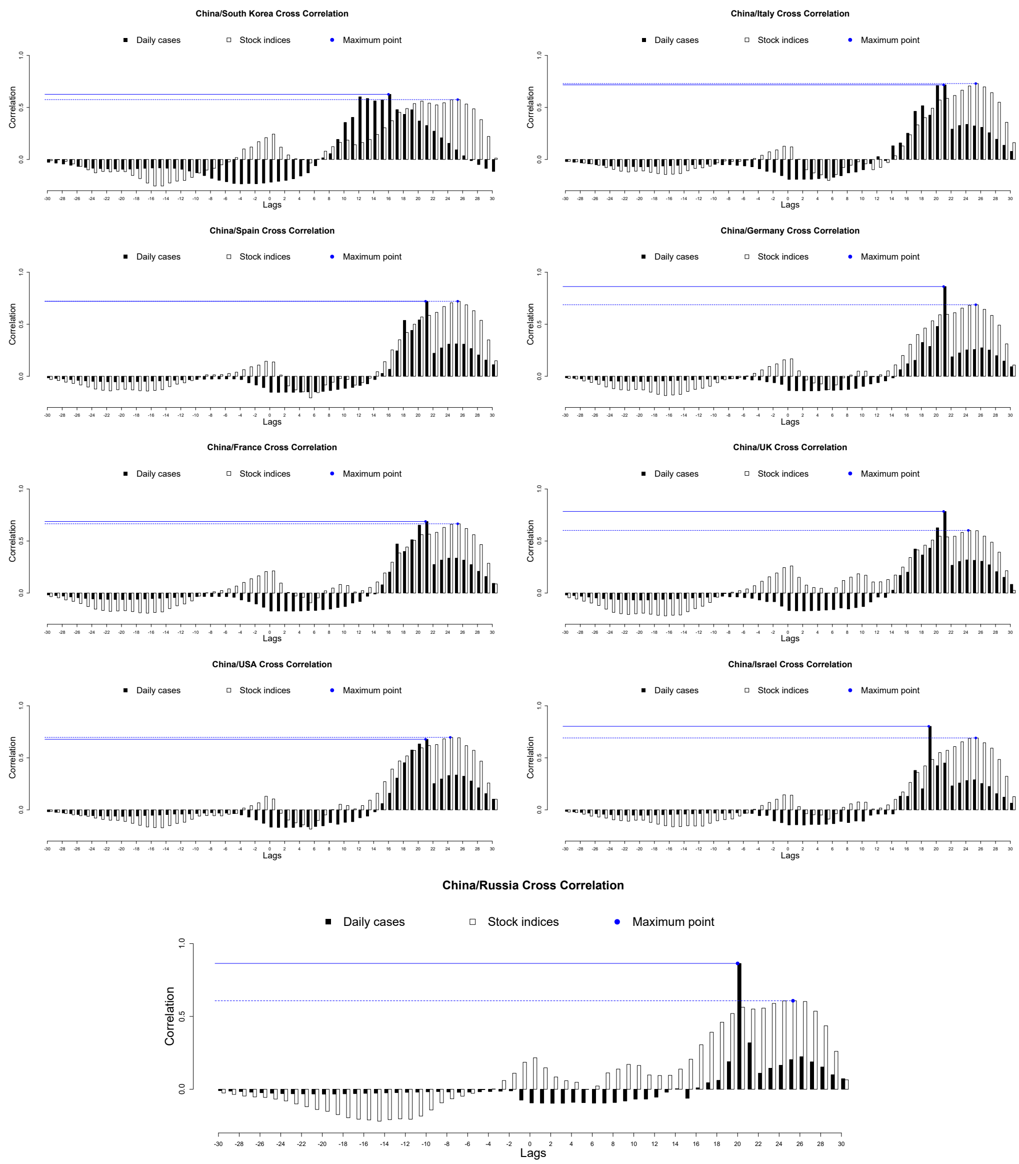
$$\begin{aligned} r_{i,t} = \mu + \beta_1 r_{i,t-1} + \beta_2 pm_{i,t} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} = h_{i,t} z_{i,t}, \quad z_{i,t} \sim i.i.d.N(0,1), \\ \log\left(h_{i,t}^2\right) = \omega + \alpha \left|\varepsilon_{i,t-1}/h_{i,t-1}\right| + \gamma\left(\varepsilon_{i,t-1}/h_{i,t-1}\right) + \rho \log\left(h_{i,t-1}^2\right), \end{aligned} \tag{5.1}$$

where $r_{i,t}$ denotes the return of the stock index i at day t, pm_t the dummy variable identifying security measures, $\varepsilon_{i,t}$ the error term, $z_{i,t}$ the white noise and $h_{i,t}^2$ the conditional variance given by the EGARCH model. Moreover, in relation to the conditional variance, α represents the magnitude of the variance shock, γ the sign effect and ρ the persistence of the shock volatility. Finally, the parameters β_1 and β_2 capture the market trend and the effect of the anti-COVID security measures, respectively.

In order to capture the immediate effect (i.e. the impact of each policy on the announcement day) and the gradual effect (i.e. the reaction including the rumors of the day before and the consequence of the day after) of the anti-COVID measures, we consider two measures of abnormal returns in the model 5.1. Considering the day of the announcement t, we include a dummy pm_t equal to 1 on the announcement day t (and 0 otherwise) to calculate the abnormal returns in that day (AR_0). In the other specification, pm_t is

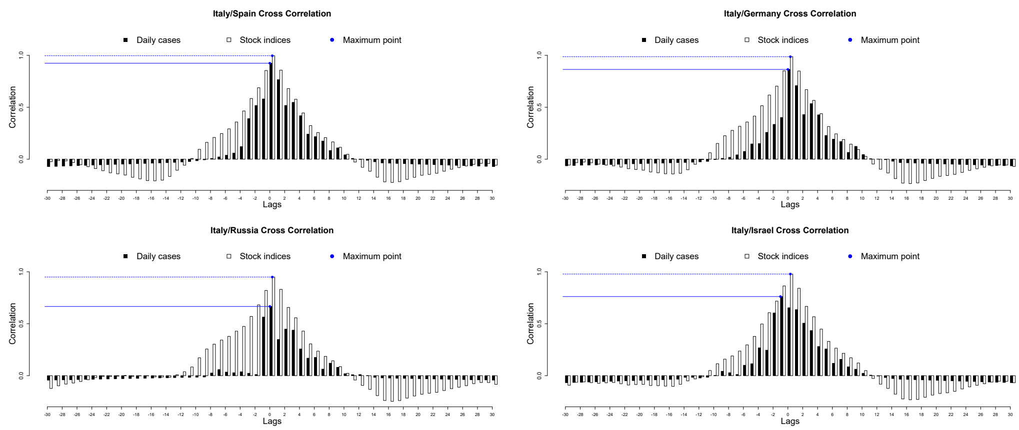
[8] Results on the correlations between other countries are omitted, but similar in spirit.

Figure. 5.3: Cross correlations with respect to Chinese values. Black bars represent the cross-correlation between the number of new daily infections; white bars shows the cross-correlation between stock indexes. The maximum value reached by the correlation of infections (indexes) is identified by a solid (dashed) blue line.



equal to $\frac{1}{3}$ on days $t-1$, t, and $t+1$ (and 0 otherwise), and we measure the cumulative abnormal returns on those days ($CAR_{(-1,1)}$).

Figure. 5.4: Cross correlations with respect to Italian values. Black bars represent the cross-correlation between the number of new daily infections; white bars shows the cross-correlation between stock indexes. The maximum value reached by the correlation of infections (indexes) is identified by a solid (dashed) blue line.



The pre-estimation test on the time series returns and post-estimation tests for the AR(1)-EGARCH(1,1) model are shown in Table 5.1. As the reader can observe, in the pre-estimation test, no ARCH effect emerges in Chinese (Shangai) and South Korean (KOSPI) indices, and therefore these two time series are removed from the sample.[9] As regards the post-estimation test, instead, we observe that all other indices are estimable with the chosen model. Interestingly enough, we also observe that most of the indices are characterized by a statistically significant presence of asymmetry (γ), which supports the choice of the EGARCH model as a good candidate to represent the dynamics of the conditional volatility (Hansen and Lunde; 2005).[10]

Table 5.1: P-values of pre- and post- Estimation tests.

Pre-estimation tests	MIB	IBEX35	DAX	CAC40	FTSE100	SP500	TA125	MOEX	SHANGAI	KOSPI
Arch(5)	0	0	0	0	0	0	0	0	0.98	0.15

Post-estimation tests	MIB	IBEX35	DAX	CAC40	FTSE100	SP500	TA125	MOEX	SHANGAI	KOSPI
Arch(5)	0.90	0.53	0.98	0.82	0.77	0.42	0.25	0.44	-	-
$Q^2(10)$	0.75	0.98	0.49	0.99	0.95	0.44	0.78	0.19	-	-

[9] At any rate, we include the results regarding Chinese (Shangai) and South Korean (KOSPI) indices in the Appendix, section (5.6).

[10] Results on the conditional variance are shown in the Appendix, section (5.6).

Let us now present the estimation of the AR(1)-EGARCH(1,1) model parameters, that is β_1 and β_2. Results are reported in Tab. 5.2, where the values of the parameters resulting from model estimation in the AR_0 and $CAR_{(-1,1)}$ specification are shown. Firstly, as expected, the β_1 parameter in the AR_0 specification is not statistically significant for all the stock returns except for the Russian one (i.e MOEX). This result on asset returns has been widely documented (Cont; 2001; Tedeschi et al.; 2009b) and is often cited as support for the "Efficient Market Hypothesis" (Fama; 1965b). By observing the lagged model specification (i.e $CAR_{(-1,1)}$), the estimated value of the β_1 parameter, while remaining in many cases not statistically significant, shows a general mean reversal dynamics.

On the other hand, as regards the estimated value of the parameter capturing the effect of anti-COVID measures on financial returns, β_2, we observe a clear separation between infected and (apparently) less infected countries, i.e Italy, Spain, Germany and France, vs United Kingdom, United State, Israel and Russia. In both model specifications we have a statistically significant negative effect of policies on the financial returns of those countries most affected by the pandemic. Moreover, interestingly enough, the value of the parameter estimated with the lagged model specification (i.e $CAR_{(-1,1)}$) always displays a statistically more negative impact than that estimated with the AR_0 one. This fact has a double interpretation. On the one hand, it suggests that the implemented measures are anticipated by the markets. On the other hand, the fact that poorly affected countries are statistically insensitive to anti-COVID policies strengthens the hypothesis of their perceived preventive uselessness.

Table 5.2: Estimates of the AR-EGARCH model (Eq. 5.1) analysing the effect of the measures on day t (AR_0), and analysing the effect of the measures on a window of 1 day $CAR_{(-1,1)}$.

AR(0)	SP500	FTSE100	DAX	CAC40	MIB	IBEX35	MOEX	TA125
β_1	-0.0012	0.0555	-0.0393	0.1741	0.2037	0.1265	-0.1315***	0.2016
	(0.1062)	(0.1308)	(0.0710)	(0.1147)	(0.1035)	(0.1288)	(0.0488)	(0.1258)
β_2	-0.0025	0.0024	-0.0174***	-0.0161***	-0.0244***	-0.0229**	-0.0048***	-0.0179
	(0.0064)	(0.0034)	(0.0045)	(0.0062)	(0.0072)	(0.0093)	(0.0016)	(0.0062)

CAR(-1,1)	SP500	FTSE100	DAX	CAC40	MIB	IBEX35	MOEX	TA125
β_1	-0.4734***	-0.2885***	-0.0244	-0.1591	-0.1881*	-0.2144	-0.0868	-0.3249**
	(0.0506)	(0.0793)	(0.0679)	(0.1316)	(0.0953)	(0.1380)	(0.0527)	(0.1628)
β_2	-0.0071	-0.0024	-0.0486***	-0.0738**	-0.1113***	-0.0327**	-0.0091	-0.0078
	(0.0078)	(0.0059)	(0.0073)	(0.0292)	(0.0190)	(0.0146)	(0.0034)	(0.0191)

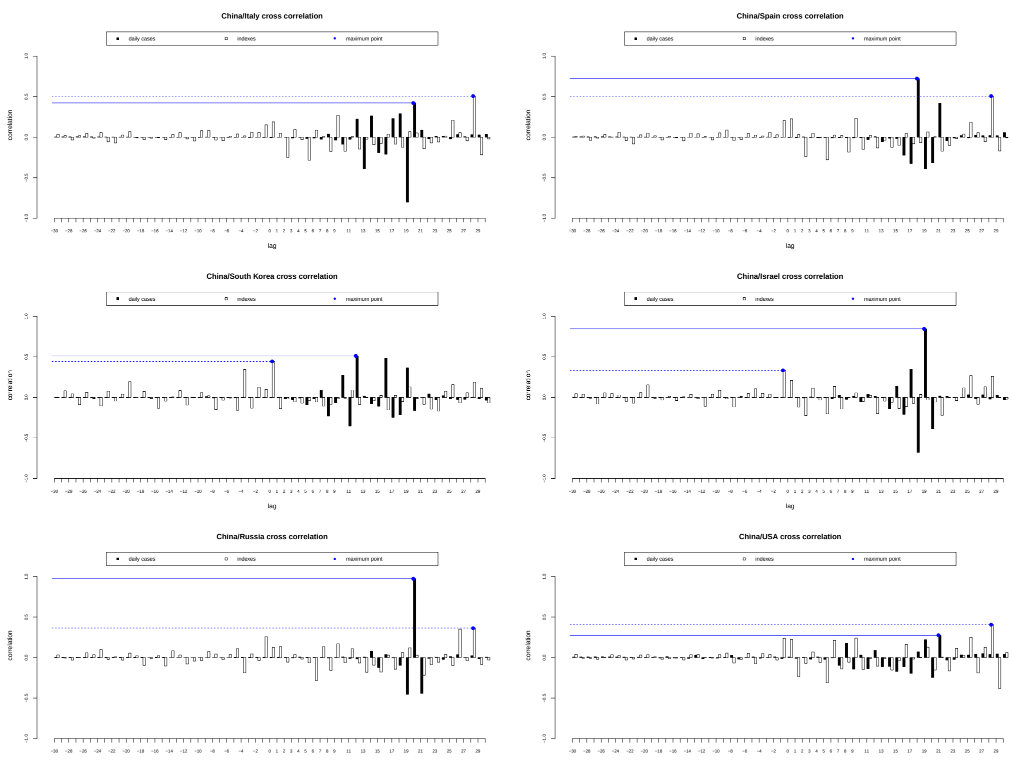
5.3 Concluding remarks

Our analysis has shown that the COVID-19 attack on financial markets brought back to light the well-known phenomenon of systemic risk. In fact, we have proven that the onset of the virus has caused a sudden and simultaneous fall in financial markets, possibly due to the strong interconnections among them. Whereby the pandemic has taken about 15 days to spread from eastern countries to western one, once in Europe, the contagion has hit almost all markets in unison. Moreover, our retrospective analysis shows how policy measures did not calm down investors panic. At least in the short run, the collateral components of such measures were predominant in shaping expectation. Although our results are still quite preliminary, they capture two interesting points. The first concerns the direction of the attack. While the 2009 crisis has spread from finance to the real sphere of the economy, the COVID-19 attack reversed this direction. This point, at first sight irrelevant, highlights the increasingly complex systemic interaction which dominates in modern socio-economic systems. The second key point is that, as in the previous crisis, long-term oriented policy measures can not lessen short-term financial pessimism.

Plausibly, the coordination failure of country-specific policy led to a delay in the containment of the initial contagion, since, as shown, most of the countries begun to apply massively anti-contagion measures only once the infection started in their own territory, without anticipating the virus intrusion. In the era of globalization, the pandemic outbreak is more likely to be a common necessary evil rather than an isolated country-specific problem. Once more the systemic risk has been faced in an uncoordinated and unidirectional way without applying the science of complexity, which recommends studying the socio-economic system starting with the coevolution of its sub-systems and not breaking it down into disjointed, non-communicating sub-spheres (see Tedeschi et al.; 2020a for further references). Once again, the past experience quickly fell into oblivion and Mr.Trichet' s words went unheard: "the key lesson we would draw from our experience is the danger of relying on a single tool, methodology or paradigm. Policy-makers need to have input from various theoretical perspectives and from a range of empirical approaches... we need to develop complementary tools to improve the robustness of our overall framework".

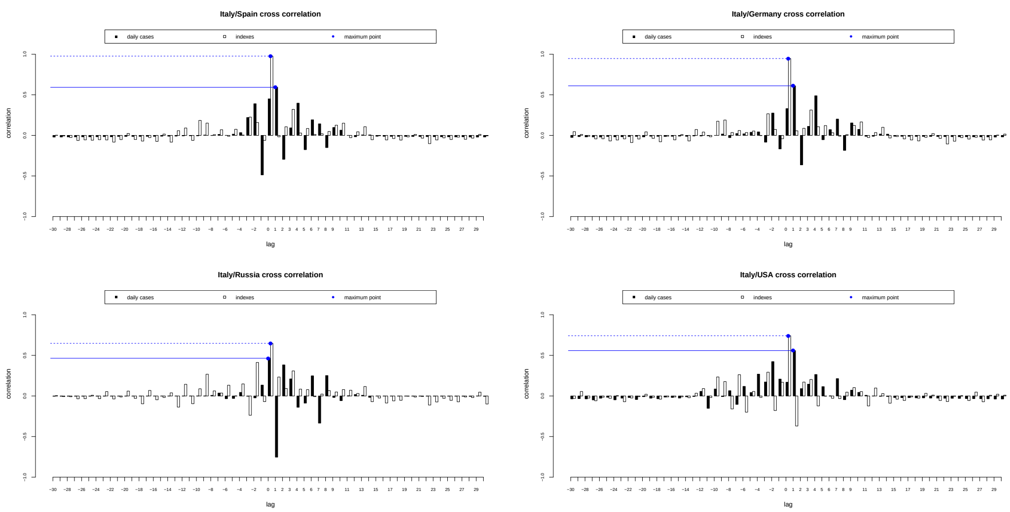
5.4 Appendix A1

Figure. 5.5: Cross correlations with respect to Chinese values. Black bars represent the cross-correlation between the growth rate of the number of new daily infections; white bars shows the cross-correlation between returns of the stock indexes. The maximum value reached by the correlation of infections (indexes) is identified by a solid (dashed) blue line.



The relevance of the economic interconnection and the systemic risk becomes more evident considering the chinese relatioship with Israel and South Korea. In these cases, the financial market collapse is synchronized (at t=0) with the Chinese stock market. It can be argued that the economies of these countries are highly interconnected and then, despite the delay of the cross-country spread of contagion, the financial repercussions are instantenous. In our highly globalized world, the cross-correlations evidence that only approximately 15-20 days have been needed to spread the pandemic and just 20 days to bring down all markets.

Figure. 5.6: Cross correlations with respect to Italian values. Black bars represent the cross-correlation between the growth rate of the number of new daily infections; white bars shows the cross-correlation between returns of the stock indexes. The maximum value reached by the correlation of infections (indexes) is identified by a solid (dashed) blue line.



5.5 Appendix A2

Table 5.3: Description of the events for each country.

China	Date	Event
1	31/12/2019	The two emergent notice letters from the Municipal Health Commission of Wuhan began to circulate on the Internet which were soon confirmed by Wuhan CDC who admitted that there were 27 cases of pneumonia of unknown cause on December 31.
2	01/01/2020	On January 1, 2020, the seafood market was closed down by Jianghan District's Health Agency and Administration for Market Regulation.
3	22/01/2020	Wuhan airport and railway stations are temporary closed.
4	23/01/2020	China: 2019-nCoV lockdown extended to Ezhou, Huanggang, Chibi and Zhijiang (Hubei province).
5	23/01/2020	The Beijing Culture and Tourism Bureau cancels all large-scale Lunar New Year celebrations in an effort to contain the growing spread of Wuhan coronavirus.
		On the same day, Chinese authorities enforce a partial lockdown of transport in and out of Wuhan. Authorities in the nearby cities of Huanggang and Ezhou Huanggang announce a series of similar measures.
6	25/01/2020	Travel restrictions were imposed on a further five cities in Hubei, taking the overall number of people affected to 56 million.
7	26/01/2020	The China Association of Travel Services reports that all tours, including international ones, will be suspended.
8	01/02/2020	Hubei's lockdown.
9	17/02/2020	Hubei province authorities issue new restrictions.
10	12/03/2020	Implementation of new restriction measures for travellers.

France	Date	Event
11	29/02/2020	Ban on gatherings of more than 5000 people.
12	04/03/2020	Haut-Rhin announces the ban on public gatherings in Bernwiller and Hésingue.
13	06/03/2020	New measures have been taken in the Haut-Rhin.
14	08/03/2020	Ban on gatherings of more than 1000 people.
15	08/03/2020	The prefects of Corsica and Corse-du-Sud announce a set of measures.
16	11/03/2020	The prefect of Hérault decided to close all educational establishments, all crèches and all structures welcoming children under the age of 15, in the territory of 16 municipalities to the north and east of Montpellier.
17	12/03/2020	Closure of schools and higher education.
18	12/03/2020	The European Central Bank announced an injection of 120,000 million euros in the 'euro zone' through the extra purchase of assets.
19	13/03/2020	Ban on gatherings of more than 100 people.
20	13/03/2020	Prohibition for ships carrying more than 100 passengers from calling or anchoring in inland and territorial waters.

Germany	Date	Event
21	26/02/2020	On 26 February, following the confirmation of multiple COVID-19 cases in North Rhine-Westphalia, Heinsberg initiated closure of schools, swimming pools, libraries and the town hall until 2 March.
22	28/02/2020	Heinsberg extended closure of daycare facilities and schools to 6 March. The officials imposed a 14-day home isolation for people who had had direct contacts with individuals in the current cases as well as people who showed flu symptoms.
		Lufthansa cut the number of short- and medium-haul flights by up to 25%, and removed multiple long-haul routes resulting in 23 long-haul aircraft being taken out of operation. On the same day, Germany enacted new health security measures to include regulations for air and sea travel, requiring passengers from China, South Korea, Japan, Italy and Iran to report their health status before entry. Train railway companies must report passengers with symptoms to authorities and the federal police would step up checks within 30 kilometres of the border.
23	08/03/2020	On 8 March, the German Health Minister recommended cancelling events with more than 1000 attendees for the time being.
24	10/03/2020	In reaction to a general ban on events with more than 1,000 participants put into immediate effect by several federal states, Germany's Ice Hockey league DEL announced that the 2019/2020 season would be cancelled immediately, and that the championship title would remain vacant this season. Several matches of the football leagues, including all Bundesliga matches of matchday 26, were announced to be played behind closed doors, a first in the 57-year history of the Bundesliga.
25	12/03/2020	The European Central Bank announced an injection of 120,000 million euros in the 'euro zone' through the extra purchase of assets.
26	13/03/2020	On 13 March, 14 of the 16 German federal states decided to close their schools and nurseries for the next few weeks. Germany's neighbours Czech Republic, Poland and Denmark closed their borders. The government decided to give financial support to artists, private cultural institutions and event companies that struggle in the crisis.

Table 5.4: Description of the events for each country.

Israel	Date	Event
27	31/01/2020	Israel suspend all flight from China.
28	03/02/2020	Entry restriction to non-resident.
29	12/02/2020	New travels restriction.
30	18/02/2020	Quarantine for Thailand, Hong Kong and Macao travelers.
31	22/02/2020	On 22 February, Israel instituted a 14-day home isolation rule for anyone who had been in South Korea or Japan. Israel also barred the entry of non-residents or citizens of Israel who were in South Korea during the 14 days prior to their arrival in Israel. The same directive was applied to those arriving from Japan starting 23 February.
32	04/03/2020	Implementation of new quarantine measures.
33	05/03/2020	West Bank authorities declare the state of emergency.
34	05/03/2020	Implementation of new quarantine measures.
35	06/03/2020	Betlemee placed in lockdown.
36	08/03/2020	Government orders mandatory self-quarantine for all travellers.
37	09/03/2020	On 9 March, Prime Minister Benjamin Netanyahu declared a mandatory quarantine for all people entering Israel, requiring all entrants to quarantine themselves for fourteen days upon entering the country.
38	12/03/2020	On 12 March, Israel announced that all universities and schools would close until after the Passover (spring) break.

Italy	Date	Event
39	31/01/2020	Air traffic suspended to and from China.
40	31/01/2020	On 31 January 2020, the Italian Council of Ministers appointed Angelo Borrelli, head of the Civil Protection, as Special Commissioner for the COVID-19 emergency.
41	22/02/2020	The government announced a new decree imposing the quarantine of more than 50,000 people from 11 different municipalities in Northern Italy. The Italian military and law enforcement agencies were instructed to secure and implement the lockdown.
42	24/02/2020	Multiple regions in Italy decided to close all schools and universities for two days to a week.
43	29/02/2020	Institutional closures extendend.
44	01/03/2020	On 1 March, the Council of Ministers approved a decree to organise the containment of the outbreak. In the decree, the Italian national territory was divided into three areas.
45	04/03/2020	The Italian government imposed the shutdown of all schools and universities nationwide for two weeks.
46	08/03/2020	Flight suspension from and to Milano Malpensa.
47	08/03/2020	In the night between 7 and 8 March, the government approved a decree to lock down Lombardy and fourteen other provinces in Veneto, Emilia-Romagna, Piedmont and Marche, involving more than 16 million people.
48	09/03/2020	Conte announced in a press conference that all measures previously applied only in the so-called ”red zones” had been extended to the whole country.
49	11/03/2020	The government allocated 25 billion euros for the emergency. In the evening, Conte announced a tightening of the lockdown, with all commercial and retail businesses except those providing essential services, like grocery stores and pharmacies, closed down.
50	12/03/2020	The European Central Bank announced an injection of 120,000 million euros in the ’euro zone’ through the extra purchase of assets.

Russia	Date	Event
51	29/01/2020	Officials close borders with China.
52	31/01/2020	On 31 January, Deputy Prime Minister Tatiana Golikova said Russia will restrict the entry of foreigners arriving from China, except for flights to Moscow Sheremetyevo Airport.
53	03/02/2020	State railway suspends trains to China.
54	18/02/2020	Aeroflot reduces flight operations to China and Hong Kong.
55	19/02/2020	Chinese citizens to be barred entry into Russia from February 20.
56	26/02/2020	Flights suspension from South Korea.
57	04/03/2020	On 4 March, Russia has temporarily banned the export of medical masks, gloves, bandages and protective suits.
58	06/03/2020	On 6 March, Moscow Mayor Sergei Sobyanin announced a “high alert regime”, ordering self-isolation for two weeks for Russians returning from China, South Korea, Iran, France, Germany, Italy and Spain. Rospotrebnadzor announced Russia has conducted 51,366 tests for the coronavirus nationwide.
59	07/03/2020	Aeroflot suspends flights to Hong Kong.
60	11/03/2020	Aeroflot announces more flight suspensions amid COVID-19 outbreak.
61	13/03/2020	Ministry of Education recommended regions to switch the educational process to distance learning if it is necessary. According to RBK, Moscow recommended that private schools go on a two-week vacation or switch to distance learning.

Table 5.5: Description of the events for each country.

South Korea	Date	Event
62	02/02/2020	South Korean officials announced that the country would ban the entry of foreigners who have recently visited China's Hubei province.
63	11/02/2020	Strict quarantine screening measures for travelers arriving from China, Hong Kong, and Macau.
64	21/02/2020	Government designates Daegu and Cheongdo as "special care zones".
65	23/02/2020	The Daegu Office of Education decided to postpone the start of every school in the region by one week.
66	26/02/2020	Several governments issue travel restrictions to and from South Korea due to the ongoing coronavirus outbreak.
67	29/02/2020	The government announced that it would supply 4.48 million masks in one day.
68	04/03/2020	South Korea announced a stimulus package of 11.7 trillion won (S$13.7 billion) on Wednesday (March 4) to cushion the impact of the largest outbreak of coronavirus outside China as efforts to contain the disease worsen supply disruptions and sap consumption.
69	05/03/2020	Ministry of Health announces new "special care zone" in Gyeongsan city (North Gyeongsang province).
70	13/03/2020	Daegu and Gyeongbuk are declared special disaster zones.

Spain	Date	Event
71	12/02/2020	Barcelona's Mobile World Congress was cancelled.
72	09/03/2020	Basque government announces the closing of all schools in the municipalities of Vitoria and Labastida.
73	09/03/2020	President of the regional government of Madrid, Isabel Díaz Ayuso, announces the cancellation of classes in the Autonomous community of Madrid at all educational levels due to the strong increase in cases in the region.
74	10/03/2020	The Government of Spain decreed the immediate cancellation of all direct flights from Italy to Spain until 25 March.
75	10/03/2020	Regional government of La Rioja announces the suspension of classes for a period of two weeks.
76	10/03/2020	The Constitutional Court suspends its activity for the following two days.
77	10/03/2020	Spanish Government suspends events with more than one thousand attendants in Madrid, La Rioja and Vitoria.
78	10/03/2020	The Valencian Government decides to postpone the Falles of Valencia for fifth time in its history and the Magdalena, in Castellón.
79	11/03/2020	Catalan government follows the steps of the Spanish government on the previous day and suspends events with more than one thousand attendants in the region.
80	12/03/2020	Catalan Government orders the confinement of the city of Igualada and the towns of Vilanova del Camí, Òdena and Santa Margarida de Montbui after Igualada Hospital became a contagion focus. This first measure in Spain will affect 70,000 people during 14 days.
81	12/03/2020	Nationwide closure of schools after all Autonomous Communities order it. More than 10 million students (1 million from university and 9 million from schools) ordered to stay at home for a period of two weeks.
82	12/03/2020	The European Central Bank announced an injection of 120,000 million euros in the 'euro zone' through the extra purchase of assets.
83	13/03/2020	Prime Minister of Spain Pedro Sánchez announces the declaration of the state of emergency in the nation for a period of 15 days, to become effective next day after the approval of the Council of Ministers.

UK	Date	Event
84	22/01/2020	Heathrow Airport received additional clinical support and tightened surveillance of the three direct flights that it receives from Wuhan every week; each were to be met by a Port Health team.
85	06/02/2020	Following confirmation of his result, the UK's CMOs expanded the number of countries where a history of previous travel associated with flu-like symptoms – such as fever, cough and difficulty breathing – in the previous 14 days would require self-isolation and calling NHS 111. These countries included China, Hong Kong, Japan, Macau, Malaysia, Republic of Korea, Singapore, Taiwan, Thailand.
86	07/02/2020	All flights between Manchester Airport (MAN) and mainland China suspended .
87	10/02/2020	The Secretary of State for Health and Social Care, Matt Hancock, announced the Health Protection (Coronavirus) Regulations 2020, to give public health professionals "strengthened powers" to keep affected people and those believed to be a possible risk of having the virus, in isolation.
88	26/02/2020	Containment measures implemented for passengers arriving from South Korea.
89	29/02/2020	British Airways to reduce flights to Italy, Singapore, and South Korea.
90	10/03/2020	British Airways temporarily cancels flights to/from Italy.
91	13/03/2020	Many sporting fixtures including the London Marathon, the Six Nations Wales vs Scotland fixture, and all Premier League and EFL football games were postponed and the 2020 United Kingdom local elections were postponed for a year.

Table 5.6: Description of the events for each country.

USA	Date	Event
92	24/02/2020	The Trump administration asked Congress for $2.5 billion in emergency funding to combat the outbreak.
93	29/02/2020	Travel restrictions imposed on Iran, Italy, and South Korea.
94	03/03/2020	Federal Reserve chairman Jerome Powell announced a 0.5 percentage point (50 basis point) interest rate cut in light of "evolving risks to economic activity" from the coronavirus.
95	04/03/2020	Los Angeles county (California state) confirmed six new cases of coronavirus disease (COVID-19) on Wednesday, March 4, prompting officials to declare a local emergency.
96	04/03/2020	Governor David Ige declared a state of emergency (Hawaii).
97	04/03/2020	The governor of California state, Gavin Newsom, declared a health emergency after the first coronavirus (COVID-19)-related death was confirmed in the state on Wednesday, March 4.
98	06/03/2020	Governor Eric Holcomb declared a public health emergency due to the first positive Indiana case.
99	07/03/2020	Cuomo declared a state of emergency in New York state.
100	09/03/2020	Proclamation of Disaster Emergency signed by Governor (Iowa).
101	10/03/2020	New York Governor Andrew Cuomo announced on Tuesday, March 10, that schools, houses of worship, and large gathering areas in New Rochelle (New York state) will be closed from Thursday, March 12.
102	10/03/2020	Governor Polis declared a state of disaster emergency.
103	10/03/2020	Governor Ned Lamont declared a public health emergency after two residents tested positive for coronavirus.
104	11/03/2020	Public health emergency announced by Governor Doug Ducey (Arizona).
105	11/03/2020	Governor Michelle Lujan Grisham declared a state of emergency (New Mexico).
106	12/03/2020	Governor John Carney declared a state of emergency following three more confirmed cases (Delaware).
107	12/03/2020	The Fed announced on March 12 that it would also expand its purchases of bonds and other measures valued at $1.5 trillion, to inject money into the banking system.
108	13/03/2020	On Friday, March 13, President Donald Trump declared a national emergency in the United States due to the ongoing outbreak of coronavirus disease.

5.6 Appendix A3

Table 5.7: Estimates of the AR-EGARCH model (Eq. 5.1) analysing the effect of the measures on day t (AR_0), and analysing the effect of the measures on a window of 1 day $CAR_{(-1,1)}$.

AR(0)	SP500	FTSE100	DAX	CAC40	MIB	IBEX35	MOEX	TA125	SHANGAI	KOSPI
β_1	-0.0012	0.0555	-0.0393	0.1741	0.2037	0.1265	-0.1315***	0.2016	-0.1266**	-0.0414
	(0.1062)	(0.1308)	(0.0710)	(0.1147)	(0.1035)	(0.1288)	(0.0488)	(0.1258)	(0.0549)	(0.3045)
β_2	-0.0025	0.0024	-0.0174***	-0.0161***	-0.0244***	-0.0229**	-0.0048***	-0.0179	-0.0137**	0.0064
	(0.0064)	(0.0034)	(0.0045)	(0.0062)	(0.0072)	(0.0093)	(0.0016)	(0.0062)	(0.0062)	(0.0090)
ω	-0.2139	-15.4389***	-12.3040***	-9.4553***	-7.3485***	-5.6756***	-16.6699***	-11.8822***	-10.5957***	-0.9827
	(0.1857)	(0.0003)	(0.9285)	(1.1273)	(0.7682)	(1.0943)	(0.5337)	(1.5178)	(2.3792)	(0.7550)
α	-0.8994***	1.5211***	1.2541***	1.6799***	1.8650***	1.7307***	-1.1026***	0.3047	-0.7231*	-0.8801
	(0.2609)	(0.2831)	(0.3455)	(0.3296)	(0.3446)	(0.3325)	(0.3455)	(0.2610)	(0.3877)	(0.3040)
γ	-1.1004***	-0.7731***	0.4791**	0.4934*	0.0159	0.6117**	-1.0647***	-0.4740*	-0.5837***	-0.6655
	(0.1610)	(0.2706)	(0.1875)	(0.2970)	(0.2188)	(0.2728)	(0.1964)	(0.2463)	(0.1646)	(0.2390)
ρ	0.9068***	-0.5983***	-0.4479***	-0.0289	0.2588***	0.4377***	-1.0368***	-0.3557**	-0.3198	0.8232
	(0.0000)	(0.0428)	(0.1200)	(0.1483)	(0.0992)	(0.1173)	(0.0504)	(0.1690)	(0.3059)	(0.1050)

CAR(-1,1)	SP500	FTSE100	DAX	CAC40	MIB	IBEX35	MOEX	TA125	SHANGAI	KOSPI
β_1	-0.4734***	-0.2885***	-0.0244	-0.1591	-0.1881*	0.2144	-0.0868	0.3249**	0.1810	-0.0379
	(0.0506)	(0.0793)	(0.0679)	(0.1316)	(0.0953)	(0.1380)	(0.0527)	(0.1628)	(0.1145)	(0.1444)
β_2	-0.0071	-0.0024	-0.0486***	-0.0738**	-0.1113***	-0.0327**	-0.0091	-0.0078	-0.0109	0.0054
	(0.0078)	(0.0059)	(0.0073)	(0.0292)	(0.0190)	(0.0146)	(0.0034)	(0.0191)	(0.0083)	(0.0094)
ω	-6.5039***	-12.7056***	-8.1197***	-9.4894***	-1.7784	-9.3971***	-15.6597***	0.1125	-0.5924***	-0.4077**
	(0.5244)	(0.5911)	(0.4579)	(1.9657)	(1.7405)	(1.2578)	(0.8055)	(2.2887)	(0.1512)	(0.1940)
α	1.7036***	1.1483***	2.5163***	1.3459***	0.7774**	1.5648***	-1.4357***	-0.2276	-0.9988***	-0.7399**
	(0.2132)	(0.2336)	(0.4081)	(0.3506)	(0.3878)	(0.3777)	(0.4683)	(0.6504)	(0.1138)	(0.3560)
γ	-0.9325***	-0.8445***	0.0036	0.3947	0.6960**	0.6520***	-1.1212***	-0.1800	-0.6851**	-0.5379**
	(0.2466)	(0.1672)	(0.2874)	(0.4474)	(0.3242)	(0.2300)	(0.2482)	(0.5977)	(0.3164)	(0.2440)
ρ	0.3889***	-0.3636***	0.2076***	-0.0668	0.8644***	-0.0635	-0.9553***	0.9841***	0.8504***	0.8968***
	(0.0645)	(0.0668)	(0.0634)	(0.2555)	(0.1973)	(0.1774)	(0.0833)	(0.1858)	(0.0000)	(0.0000)

Chapter 6

Who raised from the abyss: a comparison between Cryptocurrencies and Stock Market

Abstract

This research examines the behaviour of cryptocurrencies and stock markets during the COVID-19 pandemic through the wavelet coherence approach and Markov switching autoregressive model. Our results show a financial contagion in March, since both cryptocurrency and stock prices fell steeply. Despite this turn-down, cryptocurrencies promptly rebounded, while stock markets are trapped in the bear phase. In other words, we observe that the price dynamics during the pandemic depends on the type of the market. These findings are relevant for investors since some hedging properties can be found in the cryptocurrency response to such a drastic event.

6.1 Introduction

Cryptocurrencies have attracted the attention of many scholars and policymakers since the creation of the first digital currency, Bitcoin. Compared to the fiat currencies, this disruptive payment method does not require any bank intermediation, given that digital currencies are based on cryptographic technologies, i.e. they are decentralized in production and circulation. As a consequence, cryptocurrencies (i) cannot be controlled by any government or central bank, and (ii) are not connected with the real economy. Given these particular features, cryptocurrencies could be considered as perfect diversifiers during downturns or periods of high uncertainty, since public companies and fiat currencies are strictly connected with the state of the economy. For instance, public companies could suffer from a decrease in their stock prices due to multiple reasons that do not affect cryptocurrencies, such as poor management decisions, financial constraints, client loss and shifts in consumer preferences. In the same vein, the future of fiat currencies is related to their corresponding countries, thus they are vulnerable to any macroeconomic and political factor that destabilise the proper growth of the economy. However, the price evolution of cryptocurrencies is mainly connected with the behaviour of the traders and separated from any economic fundamental value, such as unemployment, production or consumption. This fact was demonstrated by (Baek and Elbeck; 2015), who contended that "Bitcoin market returns are mostly internally driven by market participants" (Baek and Elbeck; 2015, p. 33). The only connection of cryptocurrencies with the real economy is the fiat currency in which they are expressed.[1] This connection would be relevant if cryptocurrencies were related to central bank policies or other exchange rates.[2] Nevertheless, cryptocurrencies seem not to be correlated to international exchange rates (Baur et al.; 2018; Corbet et al.; 2018) and scholars are not able to find significant relations between the cryptocurrency behaviour and monetary policies (see Feng et al.; 2018; Vidal-Tomás

[1] For instance, BTC/USD (e.g., the Bitstamp exchange platform), BTC/JPY (e.g., the Zaif exchange platform) and BTC/KRW (e.g, the Bithumb exchange platform). Please, note here that USD, JPY and KRW refer to US dollar, Japanese yen and South Korean won, respectively. Investors can use different exchange platforms according to the fiat currency.

[2] For instance, this connection would be important if cryptocurrencies reacted to the devaluation or revaluation of any fiat currency.

and Ibañez; 2018b; Nguyen et al.; 2019; Lyócsa et al.; 2020).[3,4] Therefore, digital currencies are ideal candidates to reduce financial risks during periods of financial instability.
As highlighted by Goodell (2020), the ongoing COVID-19 pandemic represents a serious event affecting the worldwide economy.[5] In this unprecedented situation, scholars studied whether cryptocurrencies could be used as optimal instruments to diversify investors' portfolio.[6] More specifically, **?** showed that Bitcoin cannot be used as a safe-haven for the SP 500; and **?** observed an increase in the dynamic correlations between Bitcoin and traditional markets. Given these results, cryptocurrencies should not be considered as suitable alternatives for diversifying portfolios. However, given that cryptocurrencies are not related to the real economy by design, one question arises: Why cryptocurrencies should be affected by the COVID-19 pandemic in the same way as (or more than) the traditional stock markets? Publicly companies will suffer a decrease in stock prices due to the effect of the lock-downs and mobility restrictions on their future sales and profits. Nevertheless, cryptocurrencies could be only affected by the panic and fear of investors.

In the empirical section of this paper, we hypothesise that cryptocurrencies only suffered a short period of financial panic during the COVID-19 pandemic, whose effect disappeared faster than in the traditional stock markets due to the absence of a connection between digital currencies and the real economy. To support this hypothesis, we analyse the behaviour of Bitcoin and Ethereum, as main cryptocurrencies, and SP500 and Euro Stoxx 50, as main stock indices, focusing on the returns dynamics by means of the

[3] Considering the direct relationship between country-specific monetary policies and their fiat currencies, (Kurov and Stan; 2018), Bitcoin (e.g. BTC/USD) should be affected by the monetary policies of United States given that it is expressed in USD. However, and interestingly, scholars have not been able to observe this result. The absence of this logical relationship could be related to unknown Bitcoin properties that neutralise the effects of these policies. Therefore, scholars should address this point in future research in order to shed more light on this field.

[4] Roughly speaking, international exchange rates compare the economic strength between two economies (e.g., USD/EUR). However, in the case of cryptocurrencies, the exchange rate only expresses the value of the digital currencies in terms of an alternative fiat currency (e.g., BTC/USD). Hence, digital currencies are more similar to commodities (e.g., gold, silver, crude oil, or natural gas) than fiat currencies.

[5] See Yarovaya et al. (2020) for a recent review related to COVID-19 research.

[6] The following section briefly outlines key studies regarding this aspect, highlighting how cryptocurrencies could be potential alternative investments in a risk-sharing interconnected world.

wavelet coherence approach (Kang et al.; 2019, Sharif et al.; 2020 and Goodell and Goutte; 2020) and Markov switching autoregressive model (Krolzig; 2013). With these two methods, we study the (de)synchronization between cryptocurrencies and stock markets time series by comparing (i) their correlation in time-frequency domain and (ii) the transitions of their market regimes. Our contribution to the literature is twofold. On the one hand, the wavelet approach underlines that the main correlation between these assets is only found in the three first weeks of March, both at high and low frequencies (daily and monthly). On the other hand, the Markov switching autoregressive model highlights the robustness of cryptocurrencies in front of the pandemic due to their fast recovery, i.e. Bitcoin and Ethereum are most of the time found in a bull market. These results are relevant for scholars and investors since it demonstrates the absence of a relationship between cryptocurrencies and the real economy as long as the hedging properties of cryptocurrencies.

6.2 Literature review

Before moving to the empirical analysis, it is interesting to discuss how cryptocurrencies can be used in a global financial system that, even in the past, has shown its own flaws.

6.2.1 Hedging the equity risk during financial crises

The analysis of the correlation among different asset returns has traditionally been employed to define portfolio systematic risk (Chua et al.; 1990) and different investment diversification strategies due to the benefits of using uncorrelated financial instruments (Abanomey and Mathur; 1999). However, the international propagation of the financial crisis during the Great Recession underlined the difficulties of risk managers in an interconnected world. In particular, during this period, risk managers and investors could not benefit from the international diversification (Melvin and Taylor; 2009) since market crashes gave rise to high market correlations because of the loss aversion of traders (Tversky and Kahneman; 1986). Such drastic event exhibited the flaws of a global financial economy and the difficulties of describing properly a complex and interconnected system (Sinclair; 2010; Preis et al.; 2012). The best example of this global financial interconnectedness is found on the outburst of the United States sub-prime mortgage crisis -where it all began-, which could lead to the European sovereign debt crisis (Moro; 2014; Gruppe et al.; 2017; Wegener et al.; 2019). In other words, the collapse of the housing bubble in US could give rise to the collapse of the banking system in several Eurozone member states (Greece, Portugal, Ireland, Spain and Cyprus). Interestingly, in both cases, the macroeconomic conditions of *one area* affected the behaviour of *all the stock markets* with no exception, giving rise to a synchronised decrease in prices during the previous two crises (Vidal-Tomás and Alfarano; 2020).[7]

Within this framework, in an ever-evolving world, the risk of a new systemic collapse is always present and COVID-19 introduced an unprecedented crisis that immediately infected the entire economic and financial structure. During the previous crises, asset managers could not consider the role of cryptocurrencies in portfolio diversification, as their use in the international financial scenario was marginal due to the lack of knowledge about the cryptocurrency market. However, given the increasing number of cryptocurrency studies, the impact of the digital currencies on international finance is now far from being negligible. Indeed, the emergence of some hedging properties is still a recurrent object of research. For instance, Chan et al. (2019) found that Bitcoin is a strong hedge for several stock market indices using monthly data, while Pal and Mitra (2019) observed that gold provides investors with a better hedge against Bitcoin. Therefore, the COVID-19 pandemic is an important event that allows us to (i) shed some light on the strengths and weaknesses of cryptocurrencies and (ii) to analyse their ability to reduce losses when using as a diversifier in a synchronized international system.

6.3 Data

The data that has been used for this study is sourced from Yahoo Finance in daily frequency. In particular, to analyse the different behaviour of cryptocurrencies and stock indices during the spread of the pandemic, we use SP500,

[7] This international scenario underlines the concept *global financial village* proposed by Kenett et al. (2012).

Euro Stoxx 50[8], Bitcoin and Ethereum.[9] We consider the first two indices as proxies of the western financial markets' dynamics, namely, USA and Europe. Moreover, we analyse the exchange rate of Bitcoin and Ethereum as proxies of cryptocurrencies' behaviour since they are the largest cryptocurrencies of the market. In relation to the sample period, we are focused on the period 1/11/2019 – 01/06/2020, thus we can assess the evolution of these assets before and during the pandemic. Finally, for the empirical analysis of this letter, we compute returns as the log price difference.

In Table 6.1, we show the descriptive statistics of returns. As expected, the cryptocurrency market is characterised by a higher standard deviation, skewness and kurtosis, given its well-known explosive behaviour (Corbet et al.; 2019). However, we observe that the average return is lower in the stock markets than in the cryptocurrency market, which highlights the good performance of Bitcoin and Ethereum during this period compared to SP500 and Euro Stoxx 50.[10]

Table 6.1: Descriptive statistics.

Financial market	Mean	S.D.	Skewness	Kurtosis	Minimum	Maximum
Bitcoin	0.0001	0.0568	-3.9133	32.8238	-0.4647	0.1671
Ethereum	0.0013	0.0710	-3.3960	26.8767	-0.5507	0.1742
SP500	-0.0001	0.0269	-0.6737	6.0920	-0.1277	0.0897
Euro Stoxx 50	-0.0013	0.0238	-1.3798	8.2889	-0.1324	0.0883

To analyse properly the diverse price dynamics, we report in Fig. (6.1) the normalised price of each index, in which we divide the time series by

[8]We use the Euro Stoxx 50 index since (i) it is the most used in the literature (e.g., Brechmann and Czado; 2013; Chen et al.; 2018) and (ii) it represents the largest companies in the Eurozone. At any rate, using the Euro Stoxx index that includes 295 constituents, according to the official website (www.stoxx.com), we observe very similar results. Thus, we obtain consistent outcomes even when using an alternative index that represents large, mid and small capitalisation companies of the Eurozone (material upon request).

[9]With regard to the SP500 and Euro Stoxx 50 indices, we use adjusted prices in order to include the dividends that are paid to investors.

[10]Within the framework of the efficient market hypothesis proposed by Fama (1965b), returns include all the public and private information regarding the equity value and performance of the firms in the economy. Thus, the low average return in the stock markets represents the low expectations of the traders in the economy, since investors anticipate a decrease in firm sales and profits due to the government measures to face COVID-19.

the maximum price of the sample period. We observe on March 12th (grey vertical line) the minimum return in Bitcoin (-46.47%), Ethereum (-55.07%) and Euro Stoxx 50 (-13.24%), while SP500 suffered its second worst day with a return equal to -9.99% (see Table 6.1).[11] On this day, the financial panic was spread in most of the markets, probably, as a consequence of the insufficient measures taken by the European Central Bank (ECB hereafter) in response to the COVID-19 pandemic (Inman; 2020). Computing the average price before March 12th (dotted lines), we note that Bitcoin and Ethereum prices easily recovered from the financial panic period, while stock market prices continue to be affected by the restrictive measures adopted to tackle the health emergency, highlighting only a timid recovery. In other words, cryptocurrencies prices went up above their average price computed before March 12th (dotted lines) while, as can be observed in Fig. (6.1), stock markets are stuck below their average.

[11] In the case of SP500, the minimum return is found on March 14th (-12.77%).

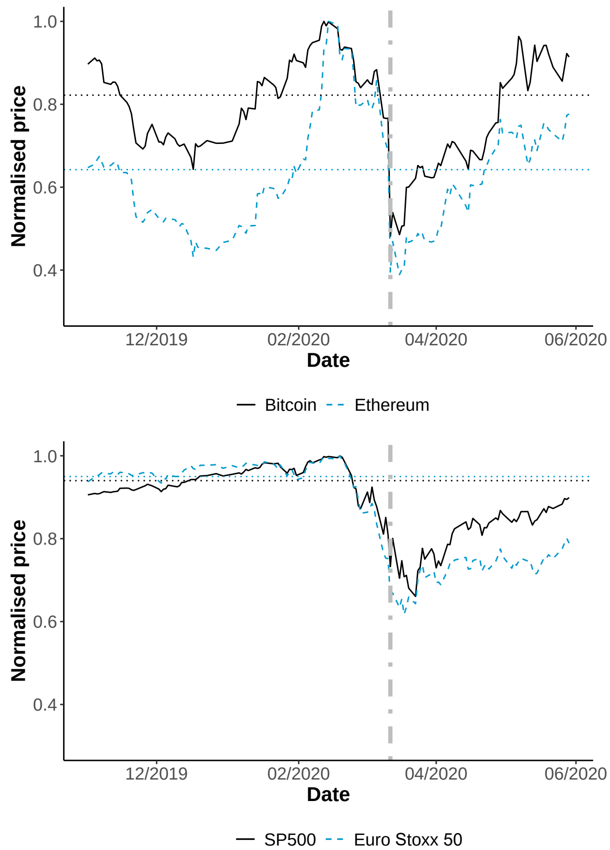


Figure. 6.1: Normalised price of cryptocurrencies (Bitcoin and Ethereum) on the left panel, and stock markets (SP500 and Euro Stoxx 50) on the right panel. The vertical grey line indicates the most negative day of the sample: March 12th. The dotted line refers to the average return computed before March 12th.

6.4 Methodology

As anticipated in the introduction, to analyse the behaviour of cryptocurrencies and stock markets we employ the wavelet coherence approach and the Markov switching autoregressive model.

6.4.1 Wavelet coherence approach

We use the wavelet coherence approach by means of the continuous wavelet transform, in order to analyse the co-movement between time series, both in time and frequency domain (see Kang et al.; 2019, Sharif et al.; 2020 and Goodell and Goutte; 2020).
According to Torrence and Compo (1998), the cross wavelet transform of two time-series x_t and y_t is defined by means of the continuous wavelet transform $W_n^x(u,s)$ and $W_n^y(u,s)$, as follows:

$$W_n^{x,y}(u,s) = W_n^x(u,s) * W_n^y(u,s) \tag{6.1}$$

where u is associated to the location, s to the scale and $*$ denotes the complex conjugate. This measure identifies areas in the time-frequency domain where prices show a high common power. In other words, it shows the local covariance between the time series at each scale.

Having computed the cross wavelet transform, the wavelet coherence, which captures the co-movement between two time series in the time-frequency domain, is defined as:

$$R^2(u,s) = \frac{|S(s^{-1}W^{xy}(u,s))|^2}{S(s^{-1}|W^x(u,s)|^2)S(s^{-1}|W^y(u,s)|^2)} \tag{6.2}$$

where S is a smoothing operator over time as well as scale, and $0 \leq R^2(u,s) \leq 1$ (Rua and Nunes; 2009). Values close to 0 indicate the absence of correlation, while values close to 1 indicates a high correlation. Nevertheless, unlike the standard correlation coefficient, the wavelet squared coherence is restricted to positive values. As a consequence, it is not possible to identify positive and negative co-movements properly. To overcome this issue, we employ the phase difference proposed by Torrence and Compo (1998) that allows us not only to distinguish between positive and negative co-movements but also to shed some light on the causal relationships between time series. Wavelet coherence phase difference is defined as:

$$\psi_{x,y}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W^{xy}(u,s))\}}{\Re\{S(s^{-1}W^{xy}(u,s))\}}\right) \tag{6.3}$$

where, $\Im$ and $\Re$ are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. In the figures that report the wavelet coherence analysis, arrows indicate phase differences, which underlines the synchronization between the two series. On the one hand, arrows pointing to the right (left) indicate time series that are in-phase (out of phase), i.e. they are positively (negatively) correlated. On the other hand, arrows pointing upward indicate that the first time series leads the second; whereas downward pointing arrows indicate that the second time series is leading the first.[12]

6.4.2 Markov switching autoregressive model

Following Krolzig (2013), we use the Markov switching autoregressive model of asset returns to examine the hidden regimes of each time series, which is defined as follows:

$$\begin{aligned} r_t = \mu\left(S_t\right) + \sum_{l=1}^{L} \phi_l(S_t) r_{t-l} + \sigma\left(S_t\right)\nu_t \\ \nu_t \sim \mathrm{NID}(0,1), S_t = 1,2 \end{aligned} \tag{6.4}$$

where the unobserved state is governed by a state variable S_t ($S_t = 1$ or $S_t = 2$) that denotes the corresponding regime: bull ($S_t = 1$) and bear[13] ($S_t = 2$) market; L is the number of lags; $\mu\left(S_t\right)$ and $\sigma\left(S_t\right)$ are the conditional mean and variance; and $v_t \sim i.i.d(0,1)$.[14] By maximizing the log likelihood, we estimate the transition probabilities: $P_{1,2}$ ($P_{2,1}$) denotes the transition from a bull (bear) market to a bear (bull) market, while $P_{1,1}$ ($P_{2,2}$) is the probability of staying in a bull (bear) market. Thus, the probability transition matrix can be written as follows:

$$P \equiv \left[\begin{array}{cc} P_{1,1} & P_{1,2} \\ P_{2,1} & P_{2,2} \end{array}\right]$$

Finally, for the purpose of this letter, we report the smoothed state probabilities (Kim et al.; 1999) that determines the transition between regimes.

[12] For the sake of space, and given the purpose of this study focused on co-movements between time series, we only report the wavelet coherence results, omitting the cross wavelet transform (material upon request).

[13] A bull phase is typically associated with rising prices, contrary to a bear phase that is associated to the decline or stalled period.

[14] For coherence with the methodology literature, we keep in both sections the nomenclature S to define the smoothing operator (wavelet coherence approach) and regime variable (Markov switching autoregressive model).

6.5 Empirical results

6.5.1 Wavelet coherence approach

Figs. (6.2) and (6.3) show the main results of the wavelet coherence analysis. The x-axis indicates the time domain component while the y-axis indicates the frequency component, from lower levels of scale, which refer to high frequency variations (i.e. daily fluctuations), up to higher levels of scale, which refer to low frequency variations (i.e. weekly or monthly fluctuations). The black contours identify regions with a coherence statistically significance at the 5% percentage level. The cone of influence, represented by the grey curve, shows the areas affected by edge effects. Finally, the degree of coherence is related to different colours: from blue (low coherence/co-movement) to red (high coherence/co-movement).

As can be observed in Fig. (6.2), we can easily identify two zones in which there is a significant high degree of positive co-movement between cryptocurrencies and stock markets, given the red areas and the arrows pointing to the right. On the one hand, at daily frequencies (scale: 0-4), the wavelet coherence analysis underlines a high co-movement during March. In particular, Bitcoin/Ethereum and SP500 are correlated from March 6th to March 18th while Bitcoin/Ethereum and Euro Stoxx 50 co-move from March 3th to March 16th. These co-movements highlight the highest level of uncertainty caused by the COVID-19 pandemic in Europe given the lock-down in Italy (March 9th) and Spain (March 14th) along with the official announcement of the pandemic (March 11th) and ECB measures (March 12th). However, the co-movement at high frequencies disappears from March 18th underlying the different effects of the COVID-19 on cryptocurrencies and stock markets at high frequencies. On the other hand, we can also observe a second region of high co-movement at low-frequencies (scale: 16-36) that lasts over time since February.[15] This second region supports the results observed by **?** and **?**, in which they highlight the relation between cryptocurrencies and stock markets. Nevertheless, if we compare Fig. (6.2) to Fig. (6.3), in which we report the internal relation of each type of market (i.e. Bitcoin-Ethereum and Euro

[15]In terms of causality, we observe that, at high frequencies, SP500 leads cryptocurrencies since arrows point downward highlighting a contagion from SP500 to cryptocurrencies. This result is less evident in the causal relations between cryptocurrencies and Euro Stoxx 50. On the other hand, at low frequencies, there is not a conclusive causal relation since Bitcoin and Ethereum lead SP500 while Euro Stoxx 50 slightly leads cryptocurrencies.

Stoxx 50-SP500), it is possible to note that, in Fig. (6.2), cryptocurrencies and stock markets are only related (over time) at lower frequencies while, in Fig. (6.3), Bitcoin-Ethereum and Euro Stoxx 50-SP500 are generally related regardless of the time-frequency domain. As we see in the next section, the fact that cryptocurrencies and stock markets are not related for all the time-frequency domain highlights, indeed, their different dynamics. As a consequence, they are not behaving in the same way during this unstable period.

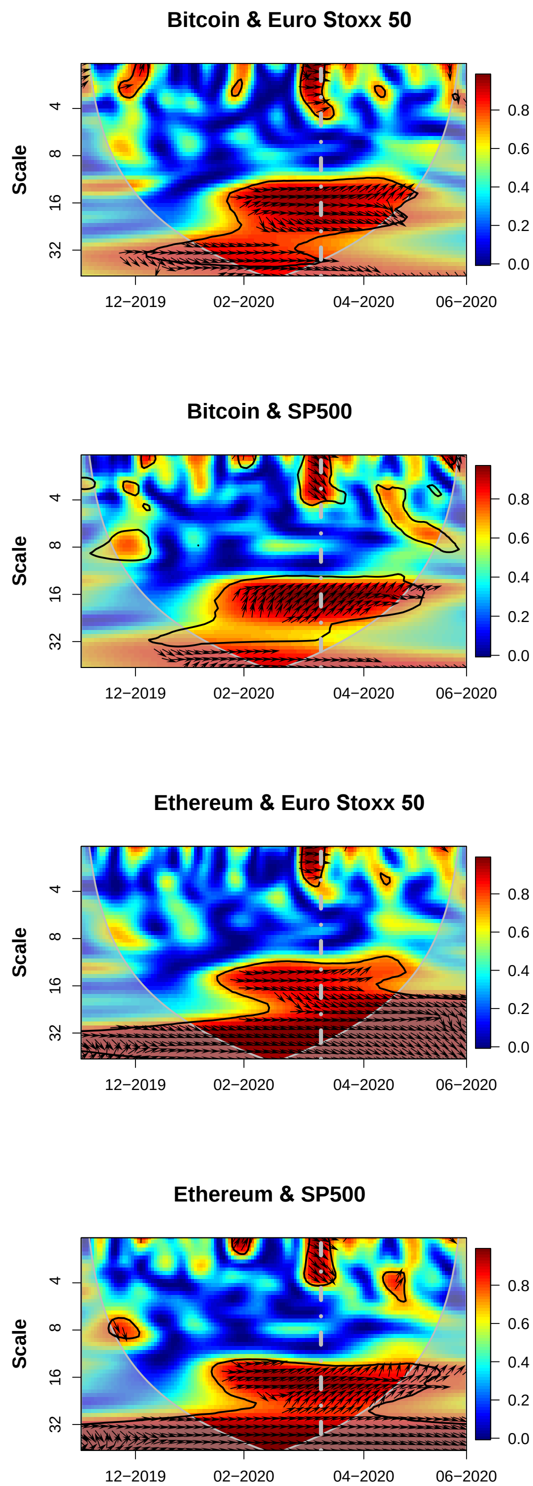


Figure. 6.2: Wavelet coherence between cryptocurrencies (Bitcoin and Ethereum) and stock markets (SP500 and Euro Stoxx 50). The vertical grey line indicates March 12th as a reference for the highest degree of financial panic.

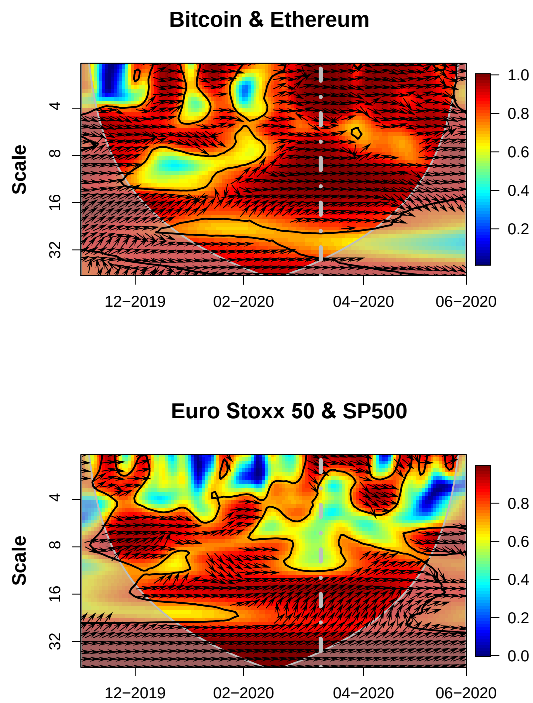


Figure. 6.3: Wavelet coherence between Bitcoin and Ethereum, on the left, and Euro Stoxx 50 and SP500, on the right. The vertical grey line indicates March 12th as a reference for the highest degree of financial panic.

6.5.2 Markov switching autoregressive model

In this section, we use the Markov switching autoregressive model introduced in Sec. (6.4.2). For the proper specification, we determine the optimum number of lags L by means of the Bayesian information criterion (BIC): lower BIC implies better fit. As can be observed in Table 6.2, the lower BIC is identified with one lag. The parameters estimated can be found in Table 6.3 while we report in Fig. (6.4) the smoothed transition probabilities from the Markov switching autoregressive model for each time series. The high degree of co-movement observed in Fig. (6.3) for Bitcoin-Ethereum and Euro Stoxx 50-SP500, regardless of the time-frequency domain, is supported by the Markov switching autoregressive model given that cryptocurrencies and stock prices have their own specific (and different) regime. In other words, the dynamics during the COVID-19 pandemic depends on the type of the market, i.e. cryptocurrencies or stocks.

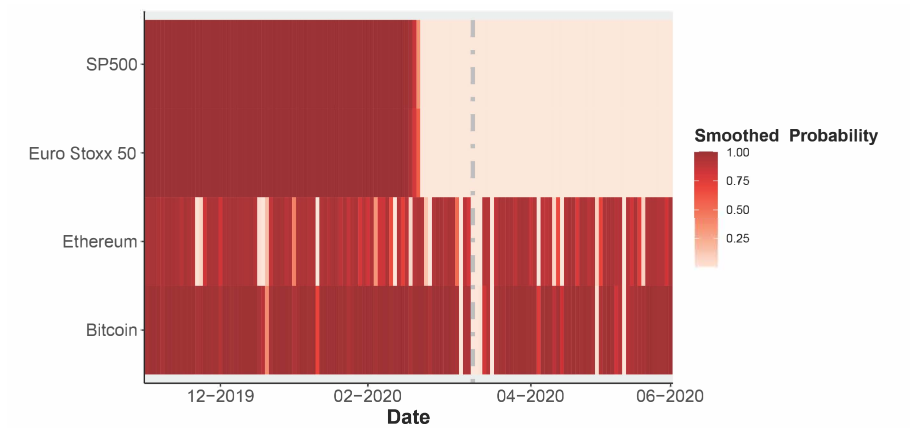


Figure. 6.4: Markov switching autoregressive model for each time series. The vertical grey line indicates March 12th as a reference for the highest degree of financial panic. A bull market is plotted as dark red (smoothed probability equal to 1) while a bear market is plotted as light red (smoothed probability equal to 0).

Focusing on the phase transitions, stock markets changed their state from a bull market to a bear market on February 20th. However, we identify generally a bull market in the case of Bitcoin and Ethereum, with the exception of the period March 9th - March 19th, in which there is a bear market with some rebounds.[16] In other words, in terms of market regimes, the COVID-19 pandemic only affected cryptocurrencies for 10 days while stock markets have been affected since February, i.e. cryptocurrencies perform better in front of the pandemic. This result is supported by Fig. (6.1), in which the simple normalised price already underlines the fast recovery of cryptocurrencies. Moreover, the period in which Bitcoin and Ethereum changed to a bear market, according to the phase transitions in Fig. (6.4) (March 9th - March 19th), is similar to the one observed in the wavelet coherence analysis (Fig. (6.2)), when Bitcoin and Ethereum are related to SP500 (March 6th - March 18th) and Euro Stoxx 50 (March 3th - March 16th) both at high and low frequencies. Therefore, to a greater or lesser extent, cryptocurrencies and stock prices are found in the same regime (Markov switching autoregressive model)

[16]Note that Ethereum seems to fluctuate more between the two regimes. However, this period is the longest bear market shared by both cryptocurrencies.

when they are related both at high and low frequencies (wavelet coherence). In other words, co-movement at low frequencies is not enough to state that cryptocurrencies cannot be used as a hedge since they are characterised by a different dynamics.

Table 6.2: Computation of the Bayesian Information Criterion for lags selection.

Lags	Bitcoin	Ethereum	SP500	Euro Stoxx 50
1	**-449.51**	**-392.29**	**-725.96**	**-691.58**
2	-439.62	-384.30	-715.22	-684.19
3	-432.89	-379.26	-716.38	-658.40
4	-425.28	-357.71	-660.09	-662.93

Table 6.3: Parameters of the Markov switching autoregressive model.

Parameters	Bitcoin	Ethereum	SP500	Euro Stoxx 50
$\mu\,(S_t = 1)$	0.00054	0.00538	0.00150	0.00069
	(0.00142)	(0.00150)	(0.00043)	(0.00046)
$\mu\,(S_t = 2)$	-0.00023	-0.00344	-0.00264	-0.00358
	(0.00316)	(0.01265)	(0.00230)	(0.00207)
$\phi_1(S_t = 1)$	0.04777	-0.04904	-0.03877	-0.06351
	(0.03502)	(0.02591)	(0.05412)	(0.03985)
$\phi_1(S_t = 2)$	-0.29065	-0.26599	-0.40504	-0.02549
	(0.16726)	(0.10913)	(0.05774)	(0.04138)
$\sigma\,(S_t = 1)$	0.00085	0.00062	0.00003	0.00006
	(0.00013)	(0.00014)	(0.00001)	(0.00001)
$\sigma\,(S_t = 2)$	0.02694	0.01843	0.00127	0.00111
	(0.01344)	(0.00548)	(0.00025)	(0.00019)
$P_{1,1}$	0.93169	0.80067	0.98541	0.98592
$P_{1,2}$	0.06831	0.19933	0.01459	0.01408
$P_{2,1}$	0.70842	0.64237	0.00000	0.00000
$P_{2,2}$	0.29158	0.35763	0.99999	0.99999

6.6 Conclusion

The ongoing COVID-19 pandemic generated a global stock market crash that began on February 20th 2020, affecting all the financial markets without exceptions due to its effects on the real economy. In this context, scholars studied whether cryptocurrencies could be used as a hedge during the pandemic. However, they observed that cryptocurrencies do not reduce financial risk. Given that by design cryptocurrencies should not be affected by the real economy, we revised the co-movement and hidden regimes of Bitcoin, Ethereum, SP 500 and Euro Stoxx 50 during the pandemic by means of the wavelet coherence approach and the Markov switching autoregressive model. Our analysis highlighted interesting results for investors and scholars.

First, the wavelet coherence approach showed that cryptocurrencies and stock markets co-move over time at low frequencies, however, there was only evidence of co-movement at high frequencies (i.e. daily fluctuations) during the main period of financial panic in March. Second, the Markov switching autoregressive model underlined the fast recovery of the cryptocurrencies in front of the COVID-19 pandemic since their bull market was only interrupted during March 9th - March 19th, while stock markets were found on a bear market since February 20th. In other words, COVID-19 only caused a short-term impact on cryptocurrency dynamics. Therefore, although cryptocurrencies and stock markets are correlated at some specific scales/periods, investors can diversify their portfolios since (i) the co-movement is not observed for all the frequency-time domain and (ii) they are found on different market phases during the pandemic.

Concluding Remarks

The experimental session of the thesis (i.e. part I) has proposed at least two interesting results.
Individually, the risk-propensity of traders and investors depends on the financial constraint of the shareholder/stakeholder groups on the behalf of which they are assuming risk. Different contract rules based on risk-sharing of gains and losses of fund managers might foster risk neutrality, avoiding gambling or extremely conservative investments.
In market context, traders' heterogeneity of expectation and then interaction is essential in explaining market inefficiency and volatility.
Moving from a stylized (i.e. experimental) to a market context (Part II), I found different factors coming from the complex financial architecture influencing investors' expectations. The role played by the synchronization of asset price movements, the media-related sentiments are, among others, crucial drivers shaping optimism/pessimism and particularly useful in explaining the tail behavior of financial returns.
Part III has exploited empirical real data, shifting the focus on the portfolio risk management during the period of financial turmoil. Considering the recent vicissitude of COVID-19, it was possible to observe a pandemic financial collapse in the first half of 2020. From here comes the need to understand how to diversify investment strategies, avoiding portfolio losses. Therefore, the last chapter has confirmed the different and outperforming dynamics of cryptocurrencies, discussing the disconnection with the real economy of this instrument.

Bibliography

Abanomey, W. S. and Mathur, I. (1999). The hedging benefits of commodity futures in international portfolio diversification, The Journal of Alternative Investments **2**(3): 51–62.

Aharon, D. Y. and Qadan, M. (2019). Bitcoin and the day-of-the-week effect, Finance Research Letters **31**.

Akhtaruzzaman, M., Boubaker, S. and Sensoy, A. (2021). Financial contagion during covid–19 crisis, Finance Research Letters **38**: 101604.

Al-Khazali, O., Elie, B., Roubaud, D. et al. (2018). The impact of positive and negative macroeconomic news surprises: Gold versus bitcoin, Economics Bulletin **38**(1): 373–382.

Albulescu, C. (2020). Coronavirus and financial volatility: 40 days of fasting and fear, arXiv preprint arXiv:2003.04005 .

Alfarano, S., Camacho, E. and Tedeschi, G. (2019). Alternative approaches for the reformulation of economics, J Econ Interact Coord **14**: 1–6.

Alfarno, S., Banal-Estanol, A., Camacho, E., Iori, G. and Kapar, B. (2019). Centralized vs decentralized markets in the laboratory: The role of connectivity.

Allen, F., Morris, S. and Shin, H. S. (2006). Beauty contests and iterated expectations in asset markets, The Review of Financial Studies **19**(3): 719–752.

Alos, E., Mancino, M. E., Merino, R. and Sanfelici, S. (2020). A fractional model for the covid-19 pandemic: Application to italian data, arXiv: 2008.00033 (q-bio) .

Andersen, S., Harrison, G. W., Lau, M. I. and Rutström, E. E. (2006). Elicitation using multiple price list formats, Experimental Economics **9**(4): 383–405.

Andersson, O., Holm, H. J., Tyran, J.-R. and Wengström, E. (2020). Risking other people's money: Experimental evidence on the role of incentives and personality traits, The Scandinavian Journal of Economics **122**(2): 648–674.

Andreoni, J. and Miller, J. (2002). Giving according to garp: An experimental test of the consistency of preferences for altruism, Econometrica **70**(2): 737–753.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations, The review of economic studies **58**(2): 277–297.

Attanasi, G., Centorrino, S. and Moscati, I. (2016). Over-the-counter markets vs. double auctions: A comparative experimental study, Journal of Behavioral and Experimental Economics **63**: 22–35.

Baek, C. and Elbeck, M. (2015). Bitcoins as an investment or speculative vehicle? a first look, Applied Economics Letters **22**(1): 30–34.

Baker, R. J., Laury, S. K. and Williams, A. W. (2008). Comparing small-group and individual behavior in lottery-choice experiments, Southern Economic Journal pp. 367–382.

Balcilar, M., Bouri, E., Gupta, R. and Roubaud, D. (2017). Can volume predict bitcoin returns and volatility? a quantiles-based approach, Economic Modelling **64**: 74–81.

Baldwin, R. and di Mauro, B. W. (2020). Mitigating the covid economic crisis: Act fast and do whatever it takes, VoxEu. org, CEPR .

Ballis, A. and Drakos, K. (2020). Testing for herding in the cryptocurrency market, Finance Research Letters **33**: 101210.

Banerjee, A. V. (1992). A simple model of herd behavior, The quarterly journal of economics **107**(3): 797–817.

Banerjee, A. V. (1993). The economics of rumours, The Review of Economic Studies **60**(2): 309–327.

Bargigli, L. and Tedeschi, G. (2014a). Interaction in agent-based economics: A survey on the network approach, Physica A: Statistical Mechanics and its Applications **399**: 1–15.

Bargigli, L. and Tedeschi, G. (2014b). Interaction in agent-based economics: a survey on the network approach, Phys. A **399**: 1–15.

Baum, C. F., Caglayan, M., Stephan, A. and Talavera, O. (2008). Uncertainty determinants of corporate liquidity, Economic Modelling **25**(5): 833–849.

Baur, D. G., Dimpfl, T. and Kuck, K. (2018). Bitcoin, gold and the us dollar–a replication and extension, Finance Research Letters **25**: 103–110.

Berardi, S. and Tedeschi, G. (2017). From banks' strategies to financial (in) stability, International Review of Economics & Finance **47**: 255–272.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades, Journal of political Economy **100**(5): 992–1026.

Bouri, E., Gkillas, K. and Gupta, R. (2019). Trade uncertainties and the hedging abilities of bitcoin, Economic Notes p. e12173.

Bouri, E., Gupta, R. and Roubaud, D. (2019). Herding behaviour in cryptocurrencies, Finance Research Letters **29**: 216–221.

Brechmann, E. C. and Czado, C. (2013). Risk management with high-dimensional vine copulas: An analysis of the euro stoxx 50, Statistics and Risk Modeling **30**(4): 307–342.

Brock, W. A. and Hommes, C. H. (1997). A rational route to randomness, Econometrica: Journal of the Econometric Society pp. 1059–1095.

Brock, W. A. and Hommes, C. H. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model, Journal of Economic dynamics and Control **22**(8-9): 1235–1274.

Brock, W. A., Hommes, C. H. et al. (1997). Models of compelxity in economics and finance, Technical report.

Brockmann, D. and Helbing, D. (2013). The hidden geometry of complex, network-driven contagion phenomena, Science **342**: 1337–1342.

Brown, R. B. (2020). Public health lessons learned from biases in coronavirus mortality overestimation, Disaster medicine and public health preparedness **14**(3): 364–371.

Brunnermeier, M., Farhi, E., Koijen, R. S., Krishnamurthy, A., Ludvigson, S. C., Lustig, H., Nagel, S. and Piazzesi, M. (2021). Perspectives on the future of asset pricing, The review of financial studies .

Buscema, P. M., Della Torre, F., Breda, M., Massini, G. and Grossi, E. (2020). Covid-19 in italy and extreme data mining, Physica A: Statistical Mechanics and its Applications **557**: 124991.

Caferra, R. (2020). Good vibes only: The crypto-optimistic behavior, Journal of Behavioral and Experimental Finance **28**: 100407.

Caferra, R. and Vidal-Tomás, D. (2021). Who raised from the abyss? a comparison between cryptocurrency and stock market dynamics during the covid-19 pandemic, Finance Research Letters p. 101954.

Caldarelli, G. (2007). Scale-free networks: complex webs in nature and technology, Oxford University Press.

Camerer, C. F. and Hogarth, R. M. (1999). The effects of financial incentives in experiments: A review and capital-labor-production framework, Journal of risk and uncertainty **19**(1): 7–42.

Carlé, T. A., Lahav, Y., Neugebauer, T. and Noussair, C. N. (2019). Heterogeneity of beliefs and trade in experimental asset markets, Journal of Financial and Quantitative Analysis **54**(1): 215–245.

Chakravarty, S., Harrison, G. W., Haruvy, E. E. and Rutström, E. E. (2011). Are you risk averse over other people's money?, Southern Economic Journal **77**(4): 901–913.

Challet, D., Marsili, M. and Zhang, Y.-C. (2005). Minority Games: Interacting Agents in Financial Markets (Oxford Finance Series), Oxford University Press, Inc.

Chan, W. H., Le, M. and Wu, Y. W. (2019). Holding bitcoin longer: The dynamic hedging abilities of bitcoin, The Quarterly Review of Economics and Finance **71**: 107–113.

Charness, G. and Sutter, M. (2012). Groups make better self-interested decisions, Journal of Economic Perspectives **26**(3): 157–76.

Chatfield, C. (1994). 3. random process models, Methods of Experimental Physics **28**: 63–92.

Cheah, E.-T. and Fry, J. (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin, Economics Letters **130**: 32–36.

Chen, L., Lu, H. and Yang, L. (2013). Investor sentiment, disagreement, and the breadth—return relationship, Management Science **59**: 1076–1091.

Chen, Y., Mantegna, R. N., Pantelous, A. A. and Zuev, K. M. (2018). A dynamic analysis of s&p 500, ftse 100 and euro stoxx 50 indices under different exchange rates, PloS one **13**(3): e0194067.

Chevapatrakul, T. and Mascia, D. V. (2019). Detecting overreaction in the bitcoin market: A quantile autoregression approach, Finance Research Letters **30**: 371–377.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets, Journal of Banking & Finance **34**(8): 1911–1921.

Chiarella, C., Iori, G. and Perelló, J. (2009). The impact of heterogeneous trading rules on the limit order book and order flows, Journal of Economic Dynamics and Control **33**(3): 525–537.

Christie, W. G. and Huang, R. D. (1995). Following the pied piper: Do individual returns herd around the market?, Financial Analysts Journal **51**(4): 31–37.

Chua, J. H., Sick, G. and Woodward, R. S. (1990). Diversifying with gold stocks, Financial Analysts Journal **46**(4): 76–79.

Cipriani, M., De Filippis, R., Guarino, A. and Kendall, R. (2020). Trading by professional traders: An experiment, FRB of New York Staff Report (939).

Cirillo, P., Tedeschi, G. and Gallegati, M. (2012). The boulogne fish market: the social structure and the role of loyalty, Applied Economics Letters **19**(11): 1075–1079.

Clauset, A., Shalizi, C. R. and Newman, M. E. (2009). Power-law distributions in empirical data, SIAM review **51**(4): 661–703.

Collard, F., Hellwing, C., Assenza, T., Kankanamge, S., Dupaigne, M., Werquin, N. and Feve, P. (2020). The hammer and the dance: equilibrium and optimal policy during a pandemic crisis, CEPR, Discussion Paper **N. DP14731, 2020**.

Coller, M. and Williams, M. B. (1999). Eliciting individual discount rates, Experimental Economics **2**(2): 107–127.

Conlon, T. and McGee, R. (2020). Safe haven or risky hazard? bitcoin during the covid-19 bear market, Finance Research Letters .

Cont, R. (2001). Empirical properties of asset returns: stylized facts and statistical issues, Quantitative Finance **1**(2): 223–236.

Corbet, S., Larkin, C. and Lucey, B. (2020). The contagion effects of the covid-19 pandemic: Evidence from gold and cryptocurrencies, Finance Research Letters .

Corbet, S., Lucey, B., Urquhart, A. and Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis, International Review of Financial Analysis **62**: 182–199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets, Economics Letters **165**: 28–34.

Csardi, G., Nepusz, T. et al. (2006). The igraph software package for complex network research, InterJournal, complex systems **1695**(5): 1–9.

Donadelli, M., Kizys, R. and Riedel, M. (2016). Dangerous infectious diseases: Bad news for main street, good news for wall street?, Journal of Financial Markets **35**.

Eckel, C. C. and Grossman, P. J. (1996). Altruism in anonymous dictator games, Games and economic behavior **16**(2): 181–191.

Erdős, P. and Rényi, A. (1959). On random graphs i.(pdf) publ, Math **6**: 290–297.

Fama, E. F. (1965a). The behavior of stock-market prices, The journal of Business **38**(1): 34–105.

Fama, E. F. (1965b). The behavior of stock-market prices, The journal of Business **38**(1): 34–105.

Fehr-Duda, H., De Gennaro, M. and Schubert, R. (2006). Gender, financial risk, and probability weights, Theory and decision **60**(2): 283–313.

Feng, W., Wang, Y. and Zhang, Z. (2018). Informed trading in the bitcoin market, Finance Research Letters **26**: 63–70.

Ferri, G. and Morone, A. (2014). The effect of rating agencies on herd behaviour, Journal of Economic Interaction and Coordination **9**(1): 107–127.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments, Experimental economics **10**(2): 171–178.

Fischer, G. (2013). Contract structure, risk-sharing, and investment choice, Econometrica **81**(3): 883–939.

Furnham, A. and Boo, H. C. (2011). A literature review of the anchoring effect, The journal of socio-economics **40**(1): 35–42.

Galla, T. and Zhang, Y.-C. (2009). Minority games, evolving capitals and replicator dynamics, Journal of Statistical Mechanics: Theory and Experiment **2009**(11): P11012.

Ghosal, V. and Loungani, P. (2000). The differential impact of uncertainty on investment in small and large businesses, Review of Economics and Statistics **82**(2): 338–343.

Giudice, A. and Paltrinieri, A. (2017). The impact of the arab spring and the ebola outbreak on african equity mutual fund investor decisions, Research in International Business and Finance **41**.

Gleason, K. C., Mathur, I. and Peterson, M. A. (2004). Analysis of intraday herding behavior among the sector etfs, Journal of empirical Finance **11**(5): 681–694.

Goodell, J. W. (2020). Covid-19 and finance: Agendas for future research, Finance Research Letters .

Goodell, J. W. and Goutte, S. (2020). Co-movement of covid-19 and bitcoin: Evidence from wavelet coherence analysis, Finance Research Letters .

Gormsen, N. J. and Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations, University of Chicago, Becker Friedman Institute for Economics Working Paper (2020-22).

Grilli, R. and Tedeschi, G. (2016). Modeling financial markets in an agent-based framework, Economics with Heterogeneous Interacting Agents, Springer, pp. 103–155.

Grilli, R., Tedeschi, G. and Gallegati, M. (2014). Bank interlinkages and macroeconomic stability, International Review of Economics & Finance **34**: 72–88.

Grilli, R., Tedeschi, G. and Gallegati, M. (2015). Markets connectivity and financial contagion, Journal of Economic Interaction and Coordination **10**(2): 287–304.

Grilli, R., Tedeschi, G. and Gallegati, M. (2020a). Business fluctuations in a behavioral switching model: Gridlock effects and credit crunch phenomena in financial networks, Journal of Economic Dynamics and Control **114**: 103863.

Grilli, R., Tedeschi, G. and Gallegati, M. (2020b). Business fluctuations in a behavioral switching model: Gridlock effects and credit crunch phenomena in financial networks, Journal of Economic Dynamics & Control **114**.

Grossman, S. J. and Stiglitz, J. E. (1976). Information and competitive price systems, The American Economic Review **66**(2): 246–253.

Gruppe, M., Basse, T., Friedrich, M. and Lange, C. (2017). Interest rate convergence, sovereign credit risk and the european debt crisis: a survey, The Journal of Risk Finance **18**: 432–442.

Guala, F. and Mittone, L. (2005). Experiments in economics: External validity and the robustness of phenomena, Journal of Economic Methodology **12**(4): 495–515.

Guiso, L. and Paiella, M. (2008). Risk aversion, wealth, and background risk, Journal of the European Economic association **6**(6): 1109–1150.

Gurdgiev, C. and O'Loughlin, D. (2020). Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty, Journal of Behavioral and Experimental Finance **25**: 100271.

Halim, E., Riyanto, Y. E. and Roy, N. (2019). Costly information acquisition, social networks, and asset prices: Experimental evidence, The Journal of Finance **74**(4): 1975–2010.

Hanna, D. and Huang, Y. (2004). The impact of sars on asian economies, Asian Economic Papers **3**(1): 102–112.

Hansen, P. R. and Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a garch (1, 1)?, Journal of applied econometrics **20**(7): 873–889.

Harris, M. and Raviv, A. (1993). Differences of opinion make a horse race, The Review of Financial Studies **6**(3): 473–506.

Harrison, G. W. (1994). Expected utility theory and the experimentalists, pp. 43–73.

Harrison, G. W., Lau, M. I., Rutström, E. E. and Tarazona-Gómez, M. (2013). Preferences over social risk, Oxford Economic Papers **65**(1): 25–46.

Hart, O. and Holmström, B. (1987). The theory of contracts, Advances in economic theory: Fifth world congress, Vol. 1, Cambridge University Press Cambridge.

Haug, N., Geyrhofer, L., Londei, A., Dervic, E., Desvars-Larrive, A., Loreto, V., Pinior, B., Thurner, S. and Klimek, P. (2020). Ranking the effectiveness of worldwide covid-19 government interventions, Nature human behaviour **4**(12): 1303–1312.

He, X.-Z. and Shi, L. (2012). Disagreement, correlation and asset prices, Economics Letters **116**(3): 512–515.

Hey, J. D. and Morone, A. (2004). Do markets drive out lemmings—or vice versa?, Economica **71**(284): 637–659.

Ho, K.-H., Chiu, W.-H. and Li, C. (2020). A short-term cryptocurrency price movement prediction using centrality measures, 2020 International Conference on Data Mining Workshops (ICDMW), IEEE, pp. 369–376.

Holt, C. A. and Laury, S. K. (2002). Risk aversion and incentive effects, American economic review **92**(5): 1644–1655.

Hommes, C. H. (2006). Heterogeneous agent models in economics and finance, Handbook of computational economics **2**: 1109–1186.

Humayun Kabir, M. (2018). Did investors herd during the financial crisis? evidence from the us financial industry, International Review of Finance **18**(1): 59–90.

Iacobucci, G. (2020). Covid-19: Lack of capacity led to halting of community testing in march, admits deputy chief medical officer.

Inman, P. (2020). Christine lagarde under fire for ecb coronavirus response, The Guardian . 29 January.

Jaquart, P., Dann, D. and Weinhardt, C. (2021). Short-term bitcoin market prediction via machine learning, The Journal of Finance and Data Science **7**: 45–66.

Kang, S. H., McIver, R. P. and Hernandez, J. A. (2019). Co-movements between bitcoin and gold: A wavelet coherence analysis, Physica A: Statistical Mechanics and its Applications **536**: 120888.

Karafiath, I. (1988). Using dummy variables in the event methodology, Financial Review **23**(3): 351–357.

Karlan, D., Goldberg, N. et al. (2011). Microfinance evaluation strategies: Notes on methodology and findings, The handbook of microfinance pp. 17–58.

Kenett, D. Y., Raddant, M., Lux, T. and Ben-Jacob, E. (2012). Evolvement of uniformity and volatility in the stressed global financial village, PloS one **7**(2): e31144.

Kim, C.-J., Nelson, C. R. et al. (1999). State-space models with regime switching: classical and gibbs-sampling approaches with applications, MIT Press Books **1**.

King, R. R., Smith, V. L., Williams, A. W. and Van Boening, M. (1993). The robustness of bubbles and crashes in experimental stock markets, Nonlinear dynamics and evolutionary economics pp. 183–200.

Kingsly, K. and Henri, K. (2020). Central banks respond to covid-19 to stave off a financial crisis, they need for targeted fiscal measures should not be understated, They Need for Targeted Fiscal Measures Should not Be Understated (March 27, 2020) .

Kirman, A. (1991). Epidemics of opinion and speculative bubbles in financial matkets, Money and financial markets chap **17**.

Kirman, A. (1993). Ants, rationality, and recruitment, The Quarterly Journal of Economics **108**(1): 137–156.

Kirman, A. (2010). Complex economics: individual and collective rationality, Routledge.

Kirman, A. P. and Vriend, N. J. (2000). Learning to be loyal. a study of the marseille fish market, Interaction and Market structure, Springer, pp. 33–56.

Kirman, A. P. and Vriend, N. J. (2001). Evolving market structure: An ace model of price dispersion and loyalty, Journal of Economic Dynamics and Control **25**(3-4): 459–502.

Kraemer, M. U. G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D. M., du Plessis, L., Faria, N. R., Li, R., Hanage, W. P., Brownstein, J. S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O. G. and Scarpino, S. (2020). The effect of human mobility and control measures on the covid-19 epidemic in china, Science **368**: 493–497.

Kranton, R., Pease, M., Sanders, S. and Huettel, S. (2020). Deconstructing bias in social preferences reveals groupy and not-groupy behavior, Proceedings of the National Academy of Sciences **117**(35): 21185–21193.

Kristoufek, L. (2013). Bitcoin meets google trends and wikipedia: Quantifying the relationship between phenomena of the internet era, Scientific reports **3**(1): 1–7.

Krolzig, H.-M. (2013). Markov-switching vector autoregressions: Modelling, statistical inference, and application to business cycle analysis, Vol. 454, Springer Science & Business Media.

Kumar, S. and Goyal, N. (2015). Behavioural biases in investment decision making–a systematic literature review, Qualitative Research in financial markets .

Kurov, A. and Stan, R. (2018). Monetary policy uncertainty and the market reaction to macroeconomic news, Journal of Banking & Finance **86**: 127–142.

Lane, T. (2016). Discrimination in the laboratory: A meta-analysis of economics experiments, European Economic Review **90**: 375–402.

LeBaron, B. (2006). Agent-based computational finance, Handbook of computational economics **2**: 1187–1233.

Lee, K.-B., Han, S. and Jeong, Y. (2020). Covid-19, flattening the curve, and benford's law, Physica A: Statistical Mechanics and its Applications **559**: 125090.

Lei, V. and Vesely, F. (2010). In-group versus out-group trust: The impact of income inequality, Southern Economic Journal **76**(4): 1049–1063.

Lux, T. and Marchesi, M. (2000). Volatility clustering in financial markets: a microsimulation of interacting agents, International journal of theoretical and applied finance **3**(04): 675–702.

Lyócsa, Š., Molnár, P., Plíhal, T. and Širaňová, M. (2020). Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin, Journal of Economic Dynamics and Control **119**: 103980.

Lyócsa, Š., Vỳrost, T. and Baumöhl, E. (2012). Stock market networks: The dynamic conditional correlation approach, Physica A: Statistical Mechanics and its Applications **391**(16): 4147–4158.

Malik, F. (2011). Estimating the impact of good news on stock market volatility, Applied Financial Economics **21**(8): 545–554.

Masclet, D., Colombier, N., Denant-Boemont, L. and Loheac, Y. (2009). Group and individual risk preferences: A lottery-choice experiment with self-employed and salaried workers, Journal of Economic Behavior & Organization **70**(3): 470–484.

Mata, R., Josef, A. K., Samanez-Larkin, G. R. and Hertwig, R. (2011). Age differences in risky choice: a meta-analysis, Annals of the New York Academy of Sciences **1235**: 18.

Maxfield, S., Shapiro, M., Gupta, V. and Hass, S. (2010). Gender and risk: women, risk taking and risk aversion, Gender in Management: An International Journal .

McKibbin, W. J. and Fernando, R. (2020). The global macroeconomic impacts of covid-19: Seven scenarios.

Melvin, M. and Taylor, M. P. (2009). The global financial crisis: Causes, threats and opportunities. introduction and overview, Journal of International Money and Finance **28**(8): 1243–1245.

Moro, B. (2014). Lessons from the european economic and financial great crisis: A survey, European Journal of Political Economy **34**: S9–S24.

Morone, A., Nuzzo, S. and Temerario, T. (2021). Decision process and preferences over risk under the "endogenous decision rule": results from a group experiment, Economics and Business Letters **10**(2): 107–115.

Morris, S. and Shin, H. S. (2002). Social value of public information, american economic review **92**(5): 1521–1534.

Newman, M. (2010). Networks: An introduction oxford univ.

Newman, M. E. (2003). The structure and function of complex networks, SIAM review **45**(2): 167–256.

Nguyen, T. V. H., Nguyen, B. T., Nguyen, K. S. and Pham, H. (2019). Asymmetric monetary policy effects on cryptocurrency markets, Research in International Business and Finance **48**: 335–339.

North, D. C. (1991). Institutions, Journal of economic perspectives **5**(1): 97–112.

Pal, D. and Mitra, S. K. (2019). Hedging bitcoin with other financial assets, Finance Research Letters **30**: 30–36.

Panchenko, V., Gerasymchuk, S. and Pavlov, O. V. (2013). Asset price dynamics with heterogeneous beliefs and local network interactions, Journal of Economic Dynamics and Control **37**(12): 2623–2642.

Peckham, R. (2013a). Contagion: epidemiological models and financial crises, Journal of Public Health **36**(1): 13–17.

Peckham, R. (2013b). Economies of contagion: financial crisis and pandemic, Economy and Society **42**(2): 226–248.

Pericoli, M. and Sbracia, M. (2003). A primer on financial contagion, Journal of Economic Surveys **17**: 571–608.

Philippas, D., Rjiba, H., Guesmi, K. and Goutte, S. (2019). Media attention and bitcoin prices, Finance Research Letters **30**: 37–43.

Preis, T., Kenett, D. Y., Stanley, H. E., Helbing, D. and Ben-Jacob, E. (2012). Quantifying the behavior of stock correlations under market stress, Scientific reports **2**: 752.

Prosser, T. (2005). Regulatory contracts and stakeholder regulation, Annals of Public and Cooperative Economics **76**(1): 35–57.

Ramelli, S. and Wagner, A. F. (2020). Feverish stock price reactions to covid-19.

Rockenbach, B., Sadrieh, A. and Mathauschek, B. (2007). Teams take the better risks, Journal of Economic Behavior & Organization **63**(3): 412–422.

Rohde, I. M. and Rohde, K. I. (2011). Risk attitudes in a social context, Journal of Risk and Uncertainty **43**(3): 205–225.

Rua, A. and Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis, Journal of Empirical Finance **16**(4): 632–639.

Ruiz-Buforn, A., Camacho-Cuena, E., Morone, A. and Alfarano, S. (2021). Overweighting of public information in financial markets: A lesson from the lab, Journal of Banking & Finance p. 106298.

Samuelson, P. A. (1937). A note on measurement of utility, The review of economic studies **4**(2): 155–161.

Saunders, A. and Cornett, M. (2014). Financial markets and institutions: A modern perspective, McGraw-Hill/Irwin .

Sharif, A., Aloui, C. and Yarovaya, L. (2020). Covid-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the us economy: Fresh evidence from the wavelet-based approach, International Review of Financial Analysis .

Shen, J. and Zheng, B. (2009). Cross-correlation in financial dynamics, EPL (Europhysics Letters) **86**(4): 48005.

Shupp, R. S. and Williams, A. W. (2008). Risk preference differentials of small groups and individuals, The Economic Journal **118**(525): 258–283.

Sinclair, T. J. (2010). Round up the usual suspects: Blame and the subprime crisis, New Political Economy **15**(1): 91–107.

Smith, V. L., Suchanek, G. L. and Williams, A. W. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets, Econometrica: Journal of the Econometric Society pp. 1119–1151.

Smith, V. L., Williams, A. W., Bratton, W. K. and Vannoni, M. G. (1982). Competitive market institutions: Double auctions vs. sealed bid-offer auctions, The American Economic Review **72**(1): 58–77.

Song, Q., Almahdi, S. and Yang, S. Y. (2017). Entropy based measure sentiment analysis in the financial market, pp. 1–5.

Spicka, J. (2020). Socio-demographic drivers of the risk-taking propensity of micro farmers: Evidence from the czech republic, Journal of Entrepreneurship in Emerging Economies .

Steiger, S. and Pelster, M. (2020). Social interactions and asset pricing bubbles, Journal of Economic Behavior & Organization **179**: 503–522.

Stiglitz, J. E. (1990). Peer monitoring and credit markets, The world bank economic review **4**(3): 351–366.

Stiglitz, J. E. (2004). Comments in P. Milgrom, Putting auction theory to work, Cambridge University Press.

Subramaniam, S. and Chakraborty, M. (2020). Investor attention and cryptocurrency returns: Evidence from quantile causality approach, Journal of Behavioral Finance **21**(1): 103–115.

Taleb, N. N. (2007). The black swan: The impact of the highly improbable.

Tedeschi, G., Caccioli, F. and Recchioni, M. (2020a). Taming financial systemic risk: models, instruments and early warning indicators, J Econ Interact Coord **15**: 1–7.

Tedeschi, G., Caccioli, F. and Recchioni, M. C. (2020b). Taming financial systemic risk: models, instruments and early warning indicators.

Tedeschi, G., Iori, G. and Gallegati, M. (2009a). The role of communication and imitation in limit order markets, The European Physical Journal B **71**(4): 489–497.

Tedeschi, G., Iori, G. and Gallegati, M. (2009b). The role of communication and imitation in limit order markets, Eur. Phys. J. B **71**: 489.

Tedeschi, G., Iori, G. and Gallegati, M. (2012a). Herding effects in order driven markets: The rise and fall of gurus, Journal of Economic Behavior & Organization **81**(1): 82–96.

Tedeschi, G., Iori, G. and Gallegati, M. (2012b). Herding effects in order driven markets: the rise and fall of gurus, J. Econ. Behav. Organ. **81**: 82–96.

David Gerard (2018). Bitcoin is less about technology than psychology. Interview released on the 02-Feb-2018 https://davidgerard.co.uk/blockchain/2018/02/02/bitcoin-is-less-about-technology-than-psychology.

GDelt Project (2020). Gdelt: The global database of events, language, and tone. Online Access on August 2020, https://www.gdeltproject.org/about.html.

Pedro Febrero (2018). Bitcoin opinion: This is the quiet before the storm. CCN 13-10-2018, https://finance.yahoo.com/news/bitcoin-opinion-quiet-storm-140026457.html.

Torrence, C. and Compo, G. P. (1998). A practical guide to wavelet analysis, Bulletin of the American Meteorological society **79**(1): 61–78.

Tversky, A. and Kahneman, D. (1986). Rational choice and the framing of decisions, Journal of business pp. S251–S278.

Vidal-Tomás, D. (2021). Transitions in the cryptocurrency market during the covid-19 pandemic: A network analysis, Finance Research Letters p. 101981.

Vidal-Tomás, D. and Alfarano, S. (2020). An agent-based early warning indicator for financial market instability, Journal of Economic Interaction and Coordination **15**(1): 49–87.

Vidal-Tomás, D. and Ibañez, A. (2018a). Semi-strong efficiency of bitcoin, Finance Research Letters **27**: 259–265.

Vidal-Tomás, D. and Ibañez, A. (2018b). Semi-strong efficiency of bitcoin, Finance Research Letters **27**: 259–265.

Vidal-Tomás, D., Ibáñez, A. M. and Farinós, J. E. (2019). Herding in the cryptocurrency market: Cssd and csad approaches, Finance Research Letters **30**: 181–186.

Von Neumann, J. and Morgenstern, O. (1947). Theory of games and economic behavior, 2nd rev.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses, Econometrica: Journal of the Econometric Society pp. 307–333.

Wang, Z., Liu, S. and Yang, H. (2019). The influence of social network structure on stock price disclosure, Physica A: Statistical Mechanics and its Applications **533**: 122064.

Wegener, C., Kruse, R. and Basse, T. (2019). The walking debt crisis, Journal of Economic Behavior & Organization **157**: 382–402.

Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F. and Rose, J. (2020). Bubbles and financial professionals, The Review of Financial Studies **33**(6): 2659–2696.

Woolf, S. H., Chapman, D. A., Sabo, R. T., Weinberger, D. M. and Hill, L. (2020). Excess deaths from covid-19 and other causes, march-april 2020, Jama **324**(5): 510–513.

Wurgler, J. and Baker, M. (2007). Investor sentiment in the stock market, Journal of Economic Perspectives **21**: 129–152.

Yamamoto, R. and Lebaron, B. (2010). Order-splitting and long-memory in an order-driven market, The European Physical Journal B **73**(1): 51–57.

Yarovaya, L., Brzeszczynski, J., Goodell, J. W., Lucey, B. M. and Lau, C. K. (2020). Rethinking financial contagion: Information transmission mechanism during the covid-19 pandemic., Available at SSRN 3602973 .

Zaremba, A., Kizys, R., Aharon, D. Y. and Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe, Finance Research Letters p. 101597.

Zhang, J. and Casari, M. (2012). How groups reach agreement in risky choices: an experiment, Economic Inquiry **50**(2): 502–515.