New Advances in Behavioural Finance

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Edited by

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CHAPTER 1

INTRODUCTION

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Behavioral Finance is the study of the influence of psychology on the behavior of investors and other financial decision-makers. It also seeks to explain how these decisions are reflected on corporations and financial markets.

Throughout its development over the past three decades, the new knowledge generated by Behavioral Finance about financial markets has been huge. For example, today we know that financial markets are inhabited by investors who do not diversify their portfolios as much as they should (French and Poterba, 1991; Barber and Odean, 2000), who trade excessively (Barber and Odean, 2001, 2002) and who often exhibit herding behaviors (Barber *et al.*, 2009; Li *et al.*, 2017). In addition, investors are often mistaken and these mistakes impact stock prices (Cooper *et al.*, 2001; Rashes, 2001).

We are now aware that stock returns are predictable, exhibiting some persistent patterns. For example, the momentum effect according to which stocks with higher returns in the recent past continue to outperform while past losers tend to have lower returns in the near future, is a pervasive feature of stock markets (Jegadeesh and Titman, 1993; Fama and French, 2012; Asness *et al.*, 2013). In addition, we know that the momentum effect tends to be stronger amongst the most traded stocks (Lee and Swaminathan, 2000) and in the stocks with information that is more difficult to process (Zhang, 2006). This effect seems to be explained by cultural factors (Chui *et al.*, 2010), among others. A number of theoretical behavioral models connect the behavioral features observed in individual decision-making with the patterns of predictability found in empirical studies on financial market prices (Barberis *et al*., 1998; Daniel *et al*., 1998; Hong and Stein, 1999).

We also know more about the decision making-process of professional investors, commonly known as arbitrageurs, like mutual fund managers and pension fund managers. These institutional investors are becoming increasingly important in modern financial markets and are generally understood to perform the task of correcting the mispricing errors made by other investors. In fact, it is well established that the stocks held by these informed investors tend to have more efficient prices (Nagel, 2005; Phalippou, 2008). However, it has also been found that institutional investors suffer from significant limitations in their quest against pricing errors (Shleifer and Vishny, 1997) and that, in some circumstances, they can even contribute to increase the inefficiency of financial markets (Nagel and Brunnermeier, 2004; Griffin *et al*., 2011).

The battle between Behavioral Finance and Neoclassical Finance has left some important "casualties" in the neoclassical side. For example, today, after the pioneering results by Lo and MacKinlay (1988) and Jegadeesh (1990), no self-respecting scholar still argues that returns in stock markets can be best described by a “random walk” in all circumstances. In addition, the standard equilibrium model of pre-behavioral finance, the Capital Asset Pricing Model, was also discredited for lack of empirical support and was replaced by models that reflect the different investment styles available to investors such as the three-factor model of Fama and French (Fama and French, 1993) and the Carhart's four-factor model (Carhart, 1997), for example.

This book gathers contributions in several areas of Behavioral Finance and is divided into three parts. Part I is devoted to the financial decisions made by individuals in different contexts: in a TV contest (chapter 2), in a laboratory experiment (chapter 3) and in international stock markets (chapter 4). The analysis of how decisions are made in different environments is one of the distinct features of Behavioral Finance, contributing to increase the robustness of its conclusions. In chapter 2, Lobão studies the players' decisions in the Portuguese version of the TV show “The Price is Right”, reporting significant deviations from the optimization rules assumed by axiomatic rationality. The results indicate that the normative logic of choice is descriptively false, corroborating the perspective of Tversky and Kahneman (1986), among others. If individuals are shown not to be able to maximize their expected utility in a decision environment where rules are relatively simple and clear, it is plausible to admit that in contexts of greater ambiguity and complexity and where learning is a difficult process (e.g., in financial markets) the decisions will deviate even further from the predictions of axiomatic rationality.

In chapter 3, Goulart, Costa Jr., Andrade and Santos examine the disposition effect in a laboratory experiment. The disposition effect can be defined as the tendency to hold on to losing stocks for too long while selling winning stocks too early. This effect impacts most investors (Barber *et al.*, 2007) and may contribute to the momentum pattern mentioned above (Grinblatt and Han, 2005). The main result of the study is that there is a significant increase in the disposition effect when the financial performance of individual decision-makers is to be made public. These findings suggest that social incentives may be important in the financial markets and go in the same direction as other studies that conclude that social interaction induces stock market participation and trading (e.g., Hong *et al.*, 2004).

In chapter 4, Lobão e Maio analyze the effects of national culture on herding formation in international stock markets. It is now well established that national culture plays an important role in the decisions that take place in financial markets (e.g., Beugelsdijk and Frijns, 2010; de Jong and Semenov, 2006). The evidence shown in the chapter indicate that investors deciding in more masculine cultures and in cultures characterized by a higher power distance tend to be less prone to herd. The main implication of these results is that culture is an important omitted variable in studies that examine cross-country differences in financial decision-making.

Part II of the book includes studies on how market prices are formed. In chapter 5, Lobão and Almeida explore the possibility of predicting large and sudden negative returns (i.e., price crashes) in a sample of large European stocks. This topic is of great importance as crashes can cause substantial losses in investors' portfolios. The authors conclude that the usefulness of the indicators to identify the stocks more prone to crash critically depends on the notion of crash under consideration. Despite this, some characteristics such as the stock's past return, its volatility, its size, and the relationship between market capitalization and book value make it possible to build strategies that allow to improve the risk-return relationship of the investors' portfolio.

In chapter 6, Lobão and Brito study the stock price reaction to earnings announcements made by a group of European firms with large capitalization. Existing empirical evidence suggests that stock markets typically underreact to earnings information, creating the so-called post-earnings announcement drift (PEAD) (Bernard and Thomas, 1989). Lobão and Brito find only slight signs of PEAD, which illustrates the importance of considering the decisions of informed investors in the formation of prices. The results obtained by Lobão and Brito show that if the stocks are traded in markets with better information conditions - typically the case of the most liquid stocks such as those included in the sample - price inefficiencies are expected to be less significant as a result of the performance of those sophisticated investors. This indicates that the existence of a significant PEAD may result from an inefficient incorporation of information into prices, which is usually attributable to an environment inhabited essentially by uninformed investors and where significant barriers to arbitrage play an important role (Mendenhall, 2004; Chung and Hrazdil, 2011).

The following two chapters address the distribution of market prices. In an efficient market, prices are expected to be uniformly distributed. However, the literature on the topic concludes that asset prices tend to be less frequent at certain price levels (case in which such price levels are understood to be considered as a psychological barrier) or tend to be more frequent at certain price levels (what is usually called price clustering). In Chapter 7, Fonseca, Lobão and Pacheco examine for the first time the existence of psychological barriers in round numbers in the markets of American Depository Receipts (ADRs) and Exchange Traded Funds (ETFs). Several studies have concluded that prices exhibit important barriers in round numbers in asset classes such as single stocks and stock indices (e.g., Lobão and Pereira, 2017; Lobão and Couto, 2019), derivatives (Schwartz *et al*., 2004) and cryptocurrencies (Fonseca *et al*., 2019). In contrast to this empirical evidence, the authors found significant signs of psychological barriers in only two ETFs and one ADR, among the 12 assets under scrutiny (six ADRs and six ETFs). Research on psychological barriers in these two markets is still in its infancy; in the future it would be of interest to identify the determinants of psychological barriers and to understand the impact of arbitrage forces on the phenomenon.

In chapter 8, Lobão and Pinto explore the tendency of prices in the Nord Pool Electricity Market to accumulate around specific values. The main conclusion is that hourly prices in eleven of the 21 bidding zones under analysis cluster in a statistically significant way. The results suggest that the prices in the that market are not uniformly distributed and therefore cannot be adequately described by a “random walk”.

The next two chapters focus on the impact of sentiment on stock markets. One of the main results of Behavioral Finance is that investor sentiment significantly influences stock prices. When the sentiment is more positive (negative), markets tend to become overpriced (underpriced), so future returns tend to be lower (higher) (Baker and Wurgler, 2007; Baker *et al*., 2012). In chapter 9, Paule-Vianez and Orden-Cruz investigate the impact of public fear associated with the COVID-19 pandemic on the stock markets of Portugal and Spain. The authors show that investor sentiment has negatively affected the returns of the Iberian markets, especially in the Portuguese stock market.

In chapter 10, Sena, Tasa and Ugurlub study the long-term impact of four events (the terrorist attacks that occurred in 11 September 2001 and in London in 2005, the Brexit referendum of 2016 and the US presidential election of 2016) in the stock markets of 20 countries. The main result is that events of political nature (the Brexit referendum and the US presidential election) had a greater effect in the long run. More specifically, the Brexit referendum caused the greatest long-term impact as it negatively and significantly affected long-term returns in 17 of the 20 countries under scrutiny.

The last part of the book is concerned with financial literacy, illustrating the potential for convergence between this field of study and Behavioral Finance. In fact, it is necessary to understand how individuals use the financial information at their disposal in order to design literacy programs that will allow them to overcome the errors that usually affect their judgment. In chapter 11, Ribeiro, Madaleno, Botelho and Lobão show, on the basis of data collected in an online survey, that there is a low correlation between the levels of financial literacy and digital literacy. This finding suggests that it is key that literacy programs consider the skills of using digital tools by the individuals to whom these programs are directed.

In chapter 12, Ribeiro, Madaleno, Botelho and Lobão analyze the determinants of financial and digital literacy. Their main result is that male individuals, with lower levels of risk aversion and with higher levels of education and income tend to present higher levels of financial literacy and digital financial literacy. In addition, older individuals tend to exhibit a lower level of digital financial literacy. These results are potentially useful for promoters of financial literacy and digital literacy programs.

In summary, we believe that the chapters of this book present a rich and updated view of the paths taken by Behavioral Finance in the last decades. It is likely that the tendency of cross-disciplinary integration that we have been witnessing will continue as scientific disciplines other than psychology, such as sociology or neuroscience, can help to understand how financial decisions are made. The body of work included in this book can be a stimulus for further investigation in that direction.

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PART I:

FINANCIAL DECISION-MAKING

CHAPTER 2

RATIONALITY IN THE FIELD: EVIDENCE FROM A TV SHOW

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Abstract

We test the rationality of choices made by the contestants in the Portuguese version of the TV show “The Price is Right”. Using data of 327 bidding contests that took place in the episodes aired between August 1990 and April 2015, we document that in general players used the informational advantage provided by sequential nature of the game to their profit. However, the last player is shown to depart significantly from the optimal strategy. Overall, our results suggest that the rules of axiomatic rationality are not a suitable starting point for a descriptive theory of how individuals decide.

Key-words: rationality, TV show, learning, Portugal

1. Introduction

Although choices under risk are fundamental in every branch of finance, empirical testing of the theories of rational choice has proven to be difficult. Given the criticism against experimental studies (e.g., Rabin, 2006), the rationality of choice of such different agents as professional athletes (Pope and Schweitzer, 2011), casino players (Croson and Sundali, 2006) and online bettors (Lobão and Rolla, 2015) has been assessed in their natural environment. In addition, TV game shows have proved to be a great laboratory to study economic decision-making as the rules of the games are better defined than in real life and the stakes are usually much more substantial than those in experimental studies. Consequently, researchers have analyzed the behaviour of contestants in TV game shows, for example "Cash Cab" (Bliss *et al*., 2012), "Come Dine with Me" (Schüller *et al*., 2014), "Deal or No Deal" (Blavatskyy and Pogrebna, 2010; Baltussen *et al*., 2016), "Divided" (van Dolder *et al*., 2015), "Friend or Foe?" (Oberholzer-Gee et al., 2010), "Jeoparty" (Jetter and Walker, 2017) and "The Price is Right" (Bennett and Hickman, 1993; Berk *et al*., 1996; Tenorio and Cason, 2002; Lobão, 2020).

This chapter adds to this literature. The bidding game contest, which occurred on the Portuguese version of the TV show "The Price is Right", is the focus of our study. In each auction, four contestants sequentially guess the retail price of an item worth about 50 euros. The bidder whose guess is closest to the retail price without exceeding it wins the prize and plays in subsequent games for more expensive prizes.

In this chapter we explore the ability of individuals to adopt the optimal strategy in the bidding game. Our results indicate that, in general, players take advantage of the sequential nature of the bidding game. However, there are significant departures from optimal behaviour since the fourth player only bids optimally in less than 27% of the rounds.

The remainder of this chapter develops as follows. In section 2, we describe the game show in greater detail. Section 3 describes the optimal strategy to be adopted by the participants of the bidding game and, in particular, by the fourth bidder. Section 4 presents the sample considered in the empirical study. In section 5 we discuss our empirical findings. Section 6 concludes the chapter.

2. Description of the game

RTP, the Portuguese public broadcasting television, has been airing "The Price is Right" for more than three decades now. The show lasts 50 minutes and includes a bidding game. The rules of this bidding game are simple. At the start of each episode, four audience members are called from the audience to come down and compete in the bidding game. The contestants are then presented with a commercially-sold item on display, accompanied by a short description. The four players participate in a sequential auction, from left to right on the screen in the first round, on the retail price of the item so that the guesses of the previous bidders are known at the time each contestant makes his decision. A bidder must round his bid to the nearest euro and cannot submit the same bid as a previous contestant. Verbal advice from the audience is allowed. The winner of the auction, who bids closest to the actual retail price without going over, gains the item and the opportunity to play for more valuable prizes later in the program. If all four bids exceed the actual price, the game is replayed in the same bidding order. If a bidder bids the exact price, a 50 euros bonus is awarded to the winner. The winner, who leaves the bidding podium to compete individually in other games, does not make any payment in exchange for receiving the item. After each bidding game, a new contestant is selected from the audience to replace the previous winner in the contestants' row. A new prize is revealed and bidding proceeds with the new contestant bidding first with the sequence continuing left to right. Thus, unless the first bidder wins, the bidding order changes in the next auction. Overall, the sequential bid auction occurs three times over the course of a show. It is possible, therefore, that one or more players participate in all three games without ever winning.

3. The optimal strategy

Given the sequential nature of the auction, the fourth bidder has two important advantages over her competitors. First, the fourth bidder can learn the values of her opponents' bids and then adjust the estimated value based on this information. Second, the fourth bidder has the opportunity to maximize her probability of winning by placing a cut-off bid, that is, bidding exactly one euro above a competitor. Since this strategy effectively slashes that competitor's probability of winning to zero (unless that bidder has guessed the exact value of the item), the ability to submit a cut-off bid is a strategic advantage of bidding last. In his analysis of the game, Berk *et al*. (1996) show the fourth contestant should always bid either one euro, the lowest existing bid plus one euro (L+1), the middle existing bid plus one euro (M+1), or the highest existing bid plus one euro (H+1). Furthermore, Berk *et al*. (1996) conclude that when players follow a rational strategy (i) the fourth bidder must win at least as often as the third bidder and the third bidder must win at least as often as either the first or second bidders, (ii) the first and second bidders together cannot win more than 4/9 of the time, (iii) the fourth bidder should win at least 1/3 of the time, , and (iv) that players should bid in descending order at least 1/8 (= 12.5%) of the time.

4. The sample

One hundred and thirteen shows of the Portuguese version of "The Price is Right", aired between August 1990 and April 2015, were viewed and the results were manually transcribed. The bids, the order of the bids, the retail value of the prize and the gender of each bidder were recorded. The ordering of rounds within each show was also preserved and the rounds (in number of 9) in which all the bids exceeded the price of the prize were excluded from the sample (since there were no winners). In all, the dataset included 327 bidding contests and a total of 1,308 bids.

The statistical description of the retail prices of the prizes under dispute are presented in table 1.

Table 1 – Retail prices of the prizes under dispute in the bidding game (in euros)

Mean	Median	Maximum	Minimum	Stand. deviation
51.23	45.00	99.00	21.00	21.44

The retail prices varied from 21 euros to 99 euros being the average retail price of 51.23 euros.

5. Empirical results

5.1. Bidding rounds

We begin by examining the winning percentage of each of the bidders in table 2.

Table 2 – Winning percentage and overbidding according to the bidding order

Contestant	No. of wins	Winning percentage	Percent of bids that exceed the actual retail price	Average bid (in euros)
1	67	20.49%	19.57%	39.03
2	73	22.32%	25.08%	41.64
3	89	27.22%	19.88%	40.92
4	98	29.97%	23.55%	41.20

Table 2 shows that the bidding order seems to be relevant to the probability of winning the bidding game. The first bidder won less often than the second bidder, the second bidder won less often than the third bidder and the fourth bidder won the most often. This confirms the proposition (i) presented above and suggests that each bidder use the informational advantage of learning the values of her opponents' bids to adjust the estimated value based on this information. A Chi-square test rejects the hypothesis that the winning percentage is the same across the four bidders at better than the 10% level (p-value=0.05831).

The first and second bidders won together 42.81% of the rounds, that is, they won less than 4/9 (about 44.44%) of the rounds thus confirming the proposition (ii) stated above.

Regarding proposition (iii), Table 2 shows that the fourth bidder won slightly less than 1/3 of the rounds (29.97%). There were no significant differences in the average bid presented by each of the four bidders. Overall, considering the results presented here we cannot reject the hypothesis that the contestants had rational expectations. Regarding the results presented by Berk *et al.* (1996) in the US, there is only one difference that should be mentioned. Contrary to what happened in Portugal, the fourth bidder in the US game won the bidding contest in more than 1/3 of the rounds (39.5%).

Proposition (iv) predicts that if contestants bid rationally, the first bid should be highest and the rest should follow in descending order. Table 3 shows the bidding-order frequency observed in our sample.

Table 3 shows that the strictly descending order (1234) was observed only in 3.06% of the rounds. The most prevalent pattern is the strictly ascending order (4321) which was observed in about 11% of the auctions. The hypothesis that the bidding orders occur equally often is strongly rejected by a Chi-square test at better than the 1% level. Therefore, the proposition (iv) is rejected. These results mirror the evidence collected in the US by Berk *et al.* (1996).

Although the results in table 2 are consistent with the presence of rational expectations in the participants of the bidding game, the results in table 3 indicate that the players do not typically follow the optimal strategy. The apparent conflict between these two sets of results suggests that it is important to understand the features of the strategy adopted by the players, and in particular by the fourth bidder.

Table 3 - Bidding-order frequency

Bidding order (descending)	Frequency
1234	3.06%
1243	3.36%
1324	2.75%
1342	2.45%
1423	3.06%
1432	2.45%
2134	3.98%
2143	5.50%
2314	3.98%
2341	2.75%
2413	3.36%
2431	6.73%
3124	2.45%
3142	3.06%
3214	5.50%
3241	4.59%
3412	3.67%
3421	4.59%
4123	3.98%
4132	4.28%
4213	4.28%
4231	3.67%
4312	5.50%
4321	11.01%

5.2. The strategy of the fourth bidder

As mentioned before, the fourth contestant should always bid either one euro, the lowest existing bid plus one euro (L+1), the middle existing bid plus one euro (M+1), or the highest existing bid plus one euro (H+1). Table 4 presents data regarding the behaviour of the fourth bidder.

Table 4 – Strategies adopted by the fourth bidder

	No. of observations	Percentage of total	Winning percentage
Optimal strategy	88	26.91%	50.00%
Sub-optimal strategy	239	73.09%	22.59%

In our sample there were only 88 bids (26.91% of the total bids) of the fourth bidder that were consistent with an optimal strategy. Of these, in half of the cases the fourth bidder won the round. However, about three quarters of the bids (73.09%) depart from the optimal strategy. In this case, the percentage of rounds won was substantially lower (only 22.59%). Since the first group of bidders performed significantly better (z stat=4.79; p<0.01), it is surprising that only 26.91% of the fourth bidders adopted the optimal strategy. In two different US samples, Bennett and Hickman (1993) and Berk *et al*. (1996) show that the fourth bidder adopts optimal strategies 45.39% and 43.52% of the time, respectively. Thus, in our sample the frequency of the optimal strategy is even lower.

Table 5 shows the three types of optimal strategies and their rate of success.

Table 5 – Optimal strategies adopted by the fourth bidder

	No. of observations	Percentage of optimal bids	Winning percentage
1 euro	0	0.00%	-
L+1	21	23.86%	23.81%
M+1	25	28.41%	32.00%
H+1	42	47.73%	73.81%

H+1, that is, the strategy of bidding the highest existing bid plus one euro is the most frequent of the optimal strategies (representing 47.73% of the total of optimal bids) and is also the strategy that performs best since it won 73.81% of the rounds where it was used.

The high rate of success of the H+1 strategy suggests that the first three bidders present a systematic downward bias when estimating the price of the prize. To test this hypothesis, we compare the average bid of the first three bidders with the actual retail price. Table 6 presents the results.

Table 6 – The average of the three first bids and the price of the prize

	No. of observations	Percentage of total
Average bid > retail price	75	22.94%
Average bid < retail price	247	75.54%
Average bid = retail price	5	1.53%

Table 6 shows that in 75.54% of the rounds, the first three bidders presented a systematic downward bias when estimating the price of the item. Only in 22.94% of the auctions the average of the first three bids exceeded the price of the item. The difference in these frequencies is statistically significant at the 1% level. This means that for the fourth bidder it would be advantageous to adopt the simple strategy of bidding one euro above the highest existing bid. In fact, when we compare the overall rate of success of the fourth bidder (29.95% in table 2) with the rate of success that the fourth bidders would have obtained had they adopted a H+1 strategy in all the rounds (44.95%), we conclude that the two proportions are significantly different (z stat=3.96; $p<0.01$). This indicates that the H+1 strategy outperforms the observed choices of the fourth bidders. These results are in line with those presented by Bennett and Hickman (1993) and Berk *et al*. (1996) for US samples.

Bennett and Hickman (1993) suggest that the fourth bidder can adopt a second-best strategy in alternative to the H+1 strategy. Given the advantage held by the fourth bidder in a sequential game, a second-best outcome of the fourth bidder is to avoid cutting-off the first bidder. In fact, if the first bidder wins, the fourth bidder will keep his advantageous position as we will repeat as the fourth bidder in the following round. Thus, one should expect first bidders to be cut-off less often than either the second and third bidders (unless of course the first bidder was the one that made the highest bid). In our sample, first bidders were cut-off twelve times in which the fourth contestant was not following the H+1 strategy. In similar circumstances, second and third bidders were cut-off fourteen and twenty times, respectively. Thus, following the hypothesis suggested by Bennett and Hickman (1993), it seemed that fourth bidders were not as likely to cut-off the first bidder as either of the other two contestants.

5.3. Learning

In order to assess whether the fourth bidder learns in the show as each day's rounds proceed, we refer to a logit regression in which we regress the optimal bids (bidding L+1, M+1 or H+1) to round numbers and some control variables. The dependent variable is defined as a binary variable equal to one if the fourth bid was either L+1, M+1 or H+1, and equal to zero otherwise. ROUND is the round number of the respective show that day and that varies in our sample from 1 to 4, since there were four bidding rounds in the days where all the contestants overbid. Our control variables are GENDER, which is the gender of the fourth bidder (1 for male and 0 for female) and PRIZE, which is the retail price of the item under dispute. The control variables take into account the possibility that the behaviour of the fourth bidder may vary depending on its gender and on the price of the prize.

Table 7 shows the estimated coefficients in the logit regressions.

Table 7 – Logit regressions regarding the learning hypothesis

Const.	ROUND	GENDER	PRIZE	Adj. R-square
-0.728** (0.018)	−0.135 (0.345)	-	-	-0.008
−0.971*** (0.004)	−0.153 (0.287)	0.468* (0.070)	-	-0.004
−0.757 (0.104)	−0.161 (0.266)	0.471* (0.069)	−0.003 (0.507)	-0.008

Notes: The dependent variable is defined as a binary variable that equals unity if the fourth bid was either L+1, M+1 or H+1, and equals zero otherwise. ROUND is the round number of the respective show that day; GENDER stands for the gender of the fourth bidder and equals unity if the fourth bidder is male and zero if the fourth bidder is a female; PRIZE represents the retail price of the item under dispute in euros. Robust p-values in parenthesis. *, ** and *** represent significance at the 10%, 5% and 1% levels respectively.

The results do not confirm the hypothesis that fourth bidders learn to cut-off other contestants as the show proceeds. In fact, the sign of the coefficient on ROUND is always negative but the coefficients are not statistically significant at the conventional levels. This result goes against the findings of Bennett and Hickman (1993), Berk *et al*. (1996), Tenorio and Cason (2002) and Healy and Noussair (2004) that conclude that more experienced players tend to behave more in line with what would be optimal than inexperienced individuals. The coefficient of GENDER is positive and statistically significant at the 0.1 level, which means that male players are more likely to cut-off previous bidders. The retail price of the prize does not seem to be relevant in the decision to adopt an optimal behaviour, thus corroborating the result obtained by Tenorio and Cason (2002).

The higher propensity of men to adopt aggressive behaviours in the bidding game (cutting-off other contestants) is consistent with the evidence that suggests that men are less risk averse in the context of decisions with financial implications, including betting decisions. For example, Bruce and Johnson (1994) find greater risk propensity amongst male bettors and higher levels of bettor confidence in their choices. Lower risk-taking by women was also found in financial markets (Barber and Odean, 2001) and corporate finance (Faccio *et al.*, 2016). The difference in behaviour between the two genders may be due to the style of information processing, as suggested by Graham *et al*. (2002).

The outcome of adopting aggressive behaviours seems to depend on the context in which the decision takes place. In our research and in other studies related to betting decisions (e.g., Bruce and Johnson, 1994), the adoption of more aggressive behaviour favors male decision-makers who thus tend to perform better. However, in the context of financial markets and corporate finance, the higher risk aversion of women has been found to make them to perform significantly better than men (Barber and Odean, 2001; Faccio et al., 2016).

6. Conclusion

The basic tenet of traditional finance is rational behaviour which means that an individual is assumed to be always rational in decision-making, acting within his own self-interest. People are expected to maximize their expected utility. In this chapter, we tested these assumptions recurring to the decisions of subjects in the bidding game of the Portuguese version of the TV game show “The Price is Right”.

Our evidence shows that, in general, players take advantage of the sequential nature of the bidding game. Bidders seem to adjust their estimates considering the information provided by the contestants that bided previously. This informational advantage leads the first bidder to win less often than the second bidder, the second bidder to win less often than the third bidder and the fourth bidder to win most of the time. However, there are significant departures from optimal behaviour and the strategic advantage of the fourth player does not seem to be well understood. In fact, the fourth bidder only bids optimally in about 27% of the rounds. Had the fourth bidder played optimally he would have won about 45% of the time instead of 30% of the time as it was observed in our sample. Moreover, there seems not be any significant learning effects and men were found to adopt optimal strategies more often than women.

Tverky and Kahneman (1979, 1986) have shown that subjects in many cases violate the tenets of rationality. Our results illustrate a deviation from those rules and suggest that the rules of axiomatic rationality are not a suitable starting point for a descriptive theory of how individuals decide.

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CHAPTER 3

HEDGING AGAINST EMBARRASSMENT

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Abstract

This chapter assesses the extent to which the expected disclosure to peers of an individual investor's financial performance influences his/her stock-trading decisions. In a lab experiment, participants trade in incentivized stock market simulations, knowing that their financial performance will be either made public or kept private. The results show a significant increase in the disposition effect when financial performance is to be made public, resulting from a spike in the realization of gains. We conclude by suggesting that this phenomenon may be due to individuals' strategic attempt to hedge against the embarrassment of ending the trading session at the bottom of the performance ranking.

Key-words: Disposition effect; Behavioral finance; Lab experiments; Self-conscious emotions.

1. Introduction

In a Wall Street asset management company, a regular meeting is conducted in order to evaluate the financial performance of its various fund managers. During the meeting, managers who had the worst performance over the past months are asked to come forward and explain to colleagues and to senior managers why they failed to achieve a good performance. An experienced fund manager, John, is concerned about being among the worst performers, which will force him to come forward in the next meeting. To minimize the risk of this unpleasant experience, John wonders about adopting an investment strategy that could avoid putting him in the bottom group.

The previous scenario illustrates the potential influence of social comparisons and, in particular, the role played by the disclosure of an individual investor's financial performance in determining investment decisions. Recent evidence suggests that, in fact, social comparisons play a major role in the way individuals make investment decisions (Linde and Sonnemans 2012). In the previously described "fund manager" example, two questions arise: if John knows that his performance will be revealed to his peers at a later point in time, will he behave differently in the trading sessions relative to a scenario in which his performance is expected to remain private? If so, how would the expected disclosure of his performance impact his investment decisions?

In this chapter we assess a yet unexplored route in the field: *whether*, and if so, *how* the expected disclosure to peers (vs. privacy) of individual investors' financial performance influences one of the most prevalent anomalies in behavioral finance, the disposition effect—that is, investors' higher propensity to sell the stocks that have increased (vs. decreased) in value relative to the purchase price (Odean 1998, Shefrin and Statman 1985, Weber and Camerer 1998).

The expected disclosure of investment outcomes can be of relevance to both individual and professional investors. Professional traders and asset managers, for example, have their respective performances made public in various setting, such as bonus payments and the disclosure of managed-funds' performance. In fact, internal public disclosure of employees' performances is often used for the incentive purposes (Endlich, 2000; Derman, 2004). In his biography, *My Life as a Quant*, the famous physicist and later financial expert Emanuel Derman describes how annual bonus payment used to work during his time as an employee at the investment bank Goldman Sachs. At that time, the payroll system was unable to cut a check for more than $100,000 US dollars. If an employee's year-end bonus was, for example, $1,000,000, then he would receive ten checks, each one sealed in its own envelope, with the whole bundle neatly stacked and secured by a rubber band. "Thus, although bonus amounts were private, and you were encouraged to keep them that way, you could guess the order of magnitude of someone's bonus by the thickness of their deck of checks. Even a mini-bundle of two checks was instantaneously distinguishable from one. Some traders received a fat stack and some of them flaunted it. One well-paid young trader had a habit of taking his bundle and silently riffling through it, meticulously counting the envelopes one at a time in full view of his colleagues." (Derman, 2004 p. 185).

To test whether and how the expected disclosure to peers (vs. privacy) of individual investors' financial performance influences the disposition effect (hereafter DE), we conducted a lab experiment in which undergraduate students participated in a simulated trading session. Participants were either told that their performance in the simulation would be made public (vs. kept private). They then played the simulation, revealed, or did not, their performances to others, and were paid according to their final earnings. The findings show that participants made different financial decisions in the stock market simulation when they expected their performance to be made public compared to the situation in which they expected their performance to be kept private. Precisely, the disposition effect increased significantly in the public condition, primarily driven by an increase in people's propensity to sell stocks that had increased in value relative to the purchase price.

Although we do not provide direct evidence for the underlying process, we speculate that the spike in the realization of gains observed in the public condition may at least in part result from people's attempt to avoid the embarrassment of finishing the trading session at the bottom of the performance ranking. That is, investors derive explicit disutility from ending in the bottom group when having to disclosure his or her financial performance to peers, which contrasts to the notion of a rational investor who only derives utility over final wealth. Our evidence suggests that the spike in the realization of gains is the channel through which this process occurs. Put simply, selling gains may be seen as a good/safe strategy for someone who wants to avoid the bottom investors' performance rank.

The rest of the chapter is organized as follows. In Section 2, we discuss the related research. In Section 3, we detail the lab experiment whereas in

Section 4 we build a theoretical argument to understand and explain the results from our experiment. Section 5 provides a general discussion along with robustness checks and section 6 concludes.

2. Related Research

The DE represents one of the classic anomalies in behavioral finance (Shefrin and Statman 1985; Barberis and Thaler 2003). People are more prone to sell assets that have increased in value relative to the purchase price than those that have decreased in relation to the same reference point. Although it is difficult to explain from a rational standpoint, this phenomenon has been observed in conventional stocks markets (Ferris, Haugen, and Makhija 1988, Frazzini 2006, Lakonishok and Seymour 1986, Odean 1998), e-trading (Lee, Park, Lee, and Wyer 2008), and behavioral and neuroeconomic laboratories (Frydman et al. 2014, Weber and Camerer 1998).

Analyses at the individual level show that investor expertise tends to reduce the DE (Calvet, Campbell, and Sodini, 2009; Dhar and Zhu 2006, Feng and Seasholes 2005). Nonetheless, the DE has, in general, been shown to be prevalent across markets and cultures. The phenomenon has been observed in Australia (Brown et al. 2006), Finland (Grinblatt and Keloharju 2001), Japan (Bremer and Kato 1996), and Taiwan (Barber, Lee, Liu and Odean, 2008), among other countries. We rely on this well-documented effect to address a yet unexplored research avenue in financial decision-making: the extent to which investors' decisions, and consequently, the DE, vary when they are aware that their financial performances will be made public (vs. kept private).

Whether consciously or not, an individual will naturally attempt to influence how others perceive him. These self-presentation or impression management concerns and tactics have been shown to impact people's feelings, thoughts, judgments, and decision-making (Goffman 1959, Jones and Pittman 1982, Schlenker 1980). Consumers, for instance, feel more embarrassed when buying condoms next to strangers than alone (Dahl, Manchanda, and Argo 2001), and choose to purchase a greater variety of goods in public than in private because they expect the variety to be more valued by others (Ratner and Kahn 2002).

There is also evidence suggesting that at least some institutional investors use impression management strategies when it comes time to disclose their financial performance to their clients. For instance, Lakonishok et al.

(1991) showed that pension funds—particularly smaller ones, at the end of the fourth quarter—are disproportionally more likely to have their poorly-performing holdings sold, to dispose of what the client would likely see as a 'bad bet' (see also: Musto, 1999). Similarly, Hertzberg, Liberti, and Paravisini (2010) showed that loan officers are more likely to self-report bad news at times when it is expected to have a lower impact on their career prospects (see also Hertzberg, Liberti, and Paravisini 2011). In those cases, however, the "window dressing" strategies are often explained by sheer financial reasons (e.g., to avoid losing a client, or avoid losing a job), rather than psychological ones, such as the potential embarrassment or pride one may feel as a result of public exposure of performance. Moreover, none of these strategies focuses on their respective overall impacts on the DE.

We argue that self-presentation to peers should impact the individual investors' decision-making in a stock market simulation setting. There are a few reasons to believe so.

First, the expected publicity of performance outcomes tends to impact one's decisions. For instance, McManus and Rao (2015) show that, when observed by others, participants in a lab experiment distort their behavior and avoid displaying intellectual ability and ambition traits. Instead of projecting themselves as "high types", they opt for choices associated with "low-type" ability when observed by a social audience, despite evidence that the underlying trait was privately considered to be desirable. Ashraf, Bandiera and Lee (2014) find evidence that, in a health work training program in Zambia, employer recognition and social visibility increase performance while social comparison reduces it, especially for low-ability trainees. The socialization of results is also found to have an impact on employee motivation (Marino and Ozbas, 2014).

Further, investors tend to believe that skills, rather than sheer luck, determine financial performance in the stock market (Barber and Odean, 1999). Therefore, it is reasonable to expect that the pride felt over a successful investment decision or the embarrassment of a failed one in front of peers will have an anticipatory impact on people´s decisions in stock-market settings. There is evidence in the literature to support this intuition (Bault, Coricelli and Rustichini, 2008). For instance, the DE is increased when traders have access to a social network due to negative peer reinforcement and amplification of loss aversion (Heimer, 2016). Our findings are consistent with those reported in Heimer (2016). Our study, however, differs in important aspects with respect to Heimer's. In his case the investor endogenously chooses whether to tell others about his performance, whereas in our case we sidestep the endogeneity issue as the participants in the lab experiment are exogenously forced to disclosure his or her performance in the public condition.

We lean on this literature to conduct a lab experiment in order to study the impact of publicity of an individual investor's financial performance on DE. The next section details the experiment.

3. Lab Experiment

This experiment tests the extent to which anticipated disclosure of financial performance to peers impacts the DE in a stock market simulation. Given that relative to a private setting, anticipated disclosure to peers further highlights the social costs and benefits of future pride or embarrassment, respectively, we expect the DE to vary between the private vs. public settings. This is in line with existing results in the literature on the effects of publicity of results (Bault, Coricelli and Rustichini, 2008).

3.1 Experiment Methodology

Sample and Design. Sixty-three students participated in a one-hour experiment. The experiment employed a two (financial performance: public vs. private; between) by two (realization: gains vs. losses; within) by two (predetermined market trend: A vs. B) mixed design. The predetermined market trend factor served as a replicate.

Procedure. Each experimental session took place in a behavioral laboratory. Before the simulation started, all participants were informed that they would be playing a stock market simulation and that their individual performances would determine their final payment. They were given specific instructions about the simulation and were told that they would be paid in cash at the end of the session. Participants were either told that their performance in the simulation would be made public or told that their performance would be kept private. Participants then played the simulation and revealed, or did not, their performances to others, and were paid according to their final earnings.

Stock Market Simulation. A 30-period stock market simulation was developed for the experiment. At the start of the simulation, each participant was given 10,000 monetary units, which they were told was the equivalent of 10 Brazilian Reais (approximately $5 USD at the exchange rate prevailing at the time). They used this sum for their stock buying and selling trades during the simulation. After the simulation was complete, each participant exchanged their final balance (cash balance plus the value of the portfolio) in monetary units for the equivalent amount in Reais.

In each trading period, which lasted up to three minutes, they were allowed to buy and sell one, or several, of the six stocks available in the market (Note: a similar procedure was applied in Weber and Camerer, 1998)

In the first four rounds, the participants simply observed the stock trends to obtain some initial information about the market. From the fifth round on, they were allowed to trade. To assess the scope of the effects, two different market trends were generated and randomly assigned to the participants in each condition. They were paid based on their ending total assets (cash balance plus the value of the portfolio, at the end of the 30th period), which indicates their respective financial performance.

Participants were given information on the price variations of the six stocks, modeled on the six stocks with the highest number of trades (during an unspecified period) on the São Paulo Stock Exchange. Participants were randomly assigned to either one of the two market trends considered in the experiment: positive or negative trend. Each market trend dataset contained different securities, but the criterion of choice for collecting the price series was always the highest number of trades. The main feature of the positive market trend is that the equally-weighted portfolio invested in the six assets belonging to that trend has a positive average return. Similarly, in the negative market trend the equally-weighted portfolio invested in the six assets belonging to that trend has a negative average return. We depict in Figures 1 and 2 the price series of each of the six stocks (A to F) of the positive and negative market trends, respectively. No information is given as to which of the two market trends the participant is trading on.

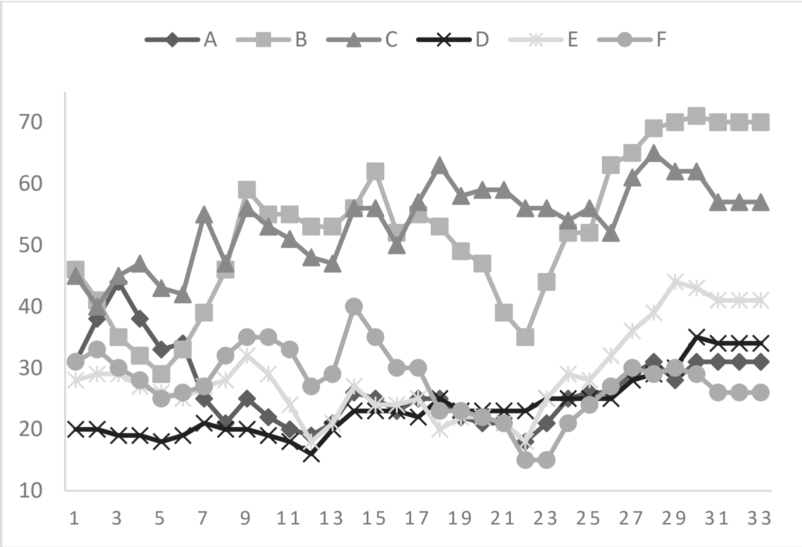

Figure 1: Price series of the six stocks (A to F) in the *positive* market trend

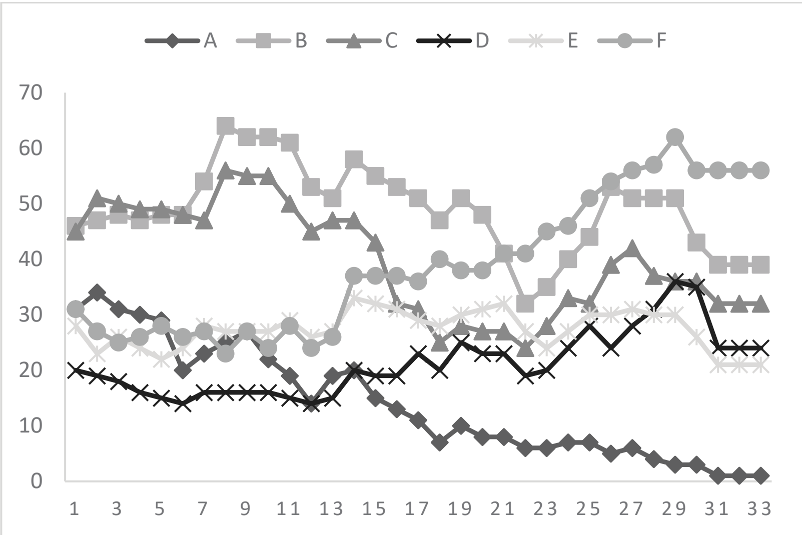

Figure 2: Price series of the six stocks (A to F) in the *negative* market trend

The simulation design employed in this study has certain peculiarities, which are described below:

a) the design includes a larger number of trading periods than were used by Weber and Camerer (1998), whilst allowing a shorter period of time for participants to trade. In Weber and Camerer's experiments the average time taken by each student was 2 hours. In contrast, the maximum duration of the experiments described in this study was 60 minutes.
b) the low number of shares used by Weber and Camerer (1998) was maintained (at six shares). The prices of these shares were generated on the basis of historical data on shares that were part of the Ibovespa index during a past period, when the market was following either a rising or falling trend.
c) no additional information is provided beyond the current prices of each stock and their previous prices.
f) the computerized simulation offers the option to save a final output file containing a report listing all the buy and sell trades made by each participant during the simulation. This report enables calculation of returns and of risks incurred, in addition to analyses of the effects under investigation in this study.
g) the simulation conducted by Weber and Camerer (1998) lasted 14 periods and offered 6 shares to trade, but it is assumed that these numbers were limited by the fact that the simulation was not implemented with the aid of a computer. Since our simulations are computerized, we chose to simulate up to 30 periods. See below a screenshot of the stock market simulation's interface (Figure 3).

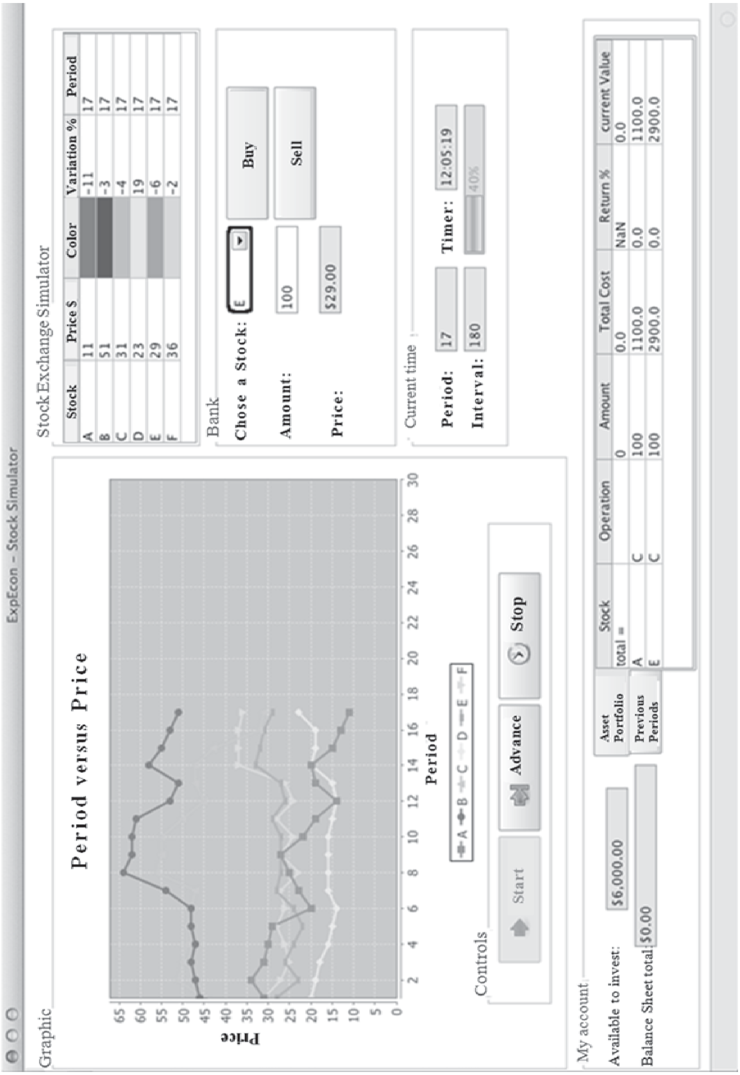

Figure 3: Main Screen (ExpEcon)

Public vs. Private Manipulation. All of the participants were informed both verbally and on the instruction sheet that they should write down their total assets (cash balance plus the value of the portfolio, at the end of the 30th period) on a sheet of paper located next to the computer, and that they would be paid accordingly. The participants in the "public" condition were told that at the end of the experimental session, they should come to the white board and write down their full name and total assets. The participants in the "private" condition were asked to put the sheet of paper with the reported earnings into an envelope. The experimenter would then pick up the envelope from each participant, privately insert the corresponding payments, and then hand them back to the participants. It was conveyed to them that their performance would be kept completely private.

Dependent Variable(s). The presence and size of the DE was computed following Odean's (1998) procedure. First, for each period, the stocks were classified into four categories: "realized gains" ("losses") for the stocks that were sold after having increased (decreased) in value relative to the purchase price, and "paper gains" ("losses") for the stocks that were not sold after having increased (decreased) in value relative to the same. The totals of winning and losing stocks sold and held in each period was tallied, and the proportion of gains and losses realized was computed:

$$PGR_i = \frac{N_{rg}^i}{N_{rg}^i + N_{pg}^i},\ PLR_i = \frac{N_{rl}^i}{N_{rl}^i + N_{pl}^i}$$

where N_{rg}^i (N_{rl}^i) is the number of trades by investor i with a realized gain (loss) and N_{pg}^i (N_{pl}^i) is the amount of the paper gain (loss) for investor i.

The disposition effect coefficient (DC) of investor i is then

$$DC_i = PGR_i - PLR_i,$$

where $-1 \leq DC_i \leq 1$. A positive DC_i value indicates that a larger proportion of gains was realized, compared with the proportion of losses realized, in which case investor i displays the DE.

Note that the above analyses can be conducted at either the individual or aggregate level (Odean 1998, Shefrin and Statman 1985, Weber and Camerer 1998). At the individual level, the proportion of gains and losses realized *by each participant* is computed and then averaged across participants. At the market level, the proportion of realized gains and losses is based on the total sum of realized gains and losses, along with paper gains and losses, of all participants in a given market or setting. Both analyses were conducted and reported. Note that, whereas the individual level of analysis generates four proportional averages, with the unit of analysis being the participant (hence, a relatively small sample size), aggregate analysis generates four actual proportions, with the unit of analysis being the transactions (hence, a much larger sample size). T tests were used in individual analysis, whereas z tests for comparing proportions were used in the market level analysis.

3.2 Results

Tables 1 and 2 show the results from the Individual and Aggregate level of analysis.

Table 1 – Descriptive statistics for *individual* DCs

	Total	Public	Private
Sample size	63	33	30
PGRi mean	0.2295	0.2832	0.1704
PLR_i mean	0.1634	0.1683	0.1580
DC_i mean	0.0661	0.1149	0.0124
DC_i median	0.0752	0.1017	0.0213
DC_i max	0.6028	0.6028	0.3015
DC_i min	-0.6022	-0.6022	-0.4643
DC_i std. dev.	0.2100	0.2363	0.1643
t test for mean DC_i= 0 *(p-value – two tailed)*	2.4976^{***} *(0.0063)*	2.7944^{***} *(0.0026)*	0.4118 *(0.3402)*

Individual level (two samples, unequal variance)
(1) The test to verify PGR (private) ≠ PGR (public) is t = 3.16, p-value = 0.002
(2) PPR (private) ≠ PPR (public), t = 0.23, p-value = 0.816
(3) DC (public) >DC (private), t =2.02, p-value (one-tailed) =0.024
(4) * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 – Descriptive statistics for *aggregate* DCs			
	Total	Public	Private
Sample size	63	33	30
Realized gains (RG)	600	383	217
Realized losses(*RL*)	360	214	146
Paper gains (*PG*)	2291	1084	1207
Paper losses (*PL*)	2486	1303	1183
PGR=*RG*/(*RG*+*PG*)	0.2075	0.2611	0.1524
PLR=*RL*/(*RL*+*PL*)	0.1265	0.1411	0.1099
DC =PGR - PLR	0.0810	0.1200	0.0425
Std. Error (*PGR-PLR*)	0.0098	0.0145	0.0128
Z stat. (*p-value*)	8.2842*** *(0.0000)*	3.3182*** *(0.0005)*	8.2544*** *(0.0000)*

Aggregate level

(1) one-tailed tests: Null hypothesis: DC ≤ 0; Alternative hypothesis: DC> 0;

(2) Comparing the proportion of *gains realized* (PGR) between Public and Private:

Public: 383/1467(=0.2611) vs.Private: 217/1424 (=0.1524), Z=7.20 ***

(3) Comparing the proportion of *losses realized* (PLR) between Public and Private:

Public: 214/1517 (=0.1411) vs.Private: 146/1329 (=0.1099), Z= 2.50 **

(4) Test to verify if DC (public) ≥ DC(private)

a) Using SE of total sample: Z =(0.1200-0.0425)/0.0098=7.91***

b) Using SE of two subsample:

$Z = (0.1200-0.0425)/(0.0145^2+0.0128^2)^{1/2}=3.997$***

(5) * significant at 10%; ** significant at 5%; *** significant at 1%

Individual level of analysis. The market trend (A vs. B) did not impact the type of realization (gain vs. loss) and/or the anticipated disclosure of the participant's performance (private vs. public). The two market trends conditions were then collapsed. In general, the participants demonstrated a significant DE. They were more prone to sell the stocks that had increased in value relative to the purchase price than they were those that had decreased in value relative to the same. However, this primary effect on the participants' selling decisions was qualified by a significant interaction between the type of realization (gains vs. losses) and the anticipated disclosure of performance (public vs. private). When it was made explicitly clear to the participants that their financial performance would be kept private, the participants were only slightly more prone to realize gains than they were to realize losses.

However, when the participants knew that they would be required to approach the whiteboard and write their name and financial performance—the "public" condition—they realized gains much more frequently than losses. A comparison within the type of realization shows that the impact of the public or private designation on the increased DE was driven by the changes in the realization of gains. There was no significant difference between the PLRs when the private and public groups were compared. However, the participants were more prone to realize their gains when they knew that their performance would be made public as opposed to kept private. Figure 4 shows the differences between PLR and PGR for the individual and aggregate level of analysis.

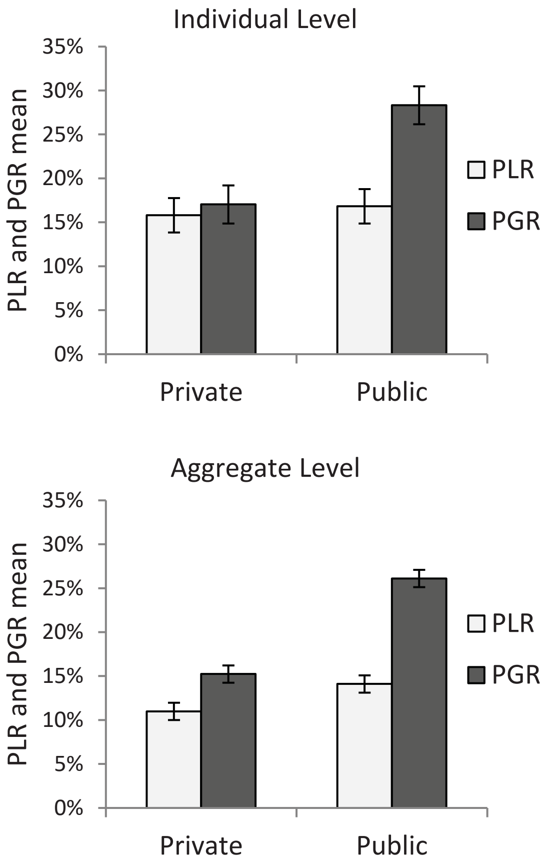

Figure 4: Differences between PLR and PGR

Aggregate level of analysis. In general, the pattern of results at the aggregate level of analysis mirror those obtained with the individual level, although some small differences were also observed. Firstly, the DE was perceptible, in that the winning stocks were sold much more frequently than losing ones. Contrary to the individual level, the winning stocks were sold more frequently than the losing stocks within both the public and private groups.

However, confirming the interaction observed at the individual level, the DE in the public condition was positive and significantly larger than that of the private condition. A comparison between the types of realization showed that the participants were more prone to realize gains under the public than the private setting. Despite this, the same trend was also observed for losses, albeit to a lesser extent.

3.3 Discussion of Results

The results of the experiment show that the participants made different financial decisions in the stock market simulation when they expected their performance to be made public compared to the situation in which they expected their performance to be kept private. Whether from individual or aggregate-level analysis, two conclusions can be drawn. First, there is an increase in the DE under the public setting compared with the private. Furthermore, the effect is primarily driven by an increase in people's propensity to sell stocks that have increased in value relative to the purchase price. Why might this be the case?

4. Hedging Against Embarrassment

We speculate that the spike in the realization of gains observed in the public condition of the experiment represents people's attempt to avoid the embarrassment of finishing the trading session at the bottom of the performance ranking (i.e., among the low performers on the white board). We argue that everything else being equal, our participants are more likely to hold to the goal of avoiding embarrassment than that of achieving pride.

Empirical evidence from related areas provide support for the assumption that bad is stronger than good (Baumeister, Bratslavsky, Finkenauer and Vohs, 2001; Rozin and Royzman, 2001). Negative emotions are more frequent than positive ones (Averill 1980); negative events wear off more slowly than positive ones (Brickman, Coates, and Janoff-Bulman 1978); financial losses hurt in a degree greater than that in which gains of the same magnitude bring pleasure (Kahneman and Tversky 1984). Therefore, it is possible that, for most people, the embarrassment of a failed performance will loom larger than the pride of a successful one. Recent evidence supports the notion that people are relatively sensitive about the 'bottom' of the ranking and try hard to avoid it, which has been labeled 'last-place aversion' (Kuziemko, Buell, Reich and Norton, 2014).

Further, we suspect that participants are likely to hold the belief that selling gains represents a reasonable strategy for the avoidance of a poor performance. Because the purchase price is a strong reference point from which to judge the relative performance of the portfolio, the realization of gains allows people to, if only subjectively, form a financial cushion to compensate for current and/or future losses. In addition, selling gains can give the impression that one is moving up the ladder, or, at least, avoiding its bottom. Thus, in the case of a "public" setting, being extra risk-averse in terms of gains may be the result of an attempt to avoid the embarrassment of ending the trading session among the lowest-ranked investors on the financial performance ranking.

5. General Discussion

When people anticipate revealing their financial performance (i.e., earnings), they display a stronger DC (disposition coefficient), driven primarily by a higher tendency to sell the stocks that have increased in value relative to the purchase price. This phenomenon may result from people's strategic attempt to hedge against the embarrassment of ending the trading session among the poor performers.

5.1 DE on Returns

If participants attempted to realize gains more frequently than losses to hedge against embarrassment, testing for whether or not the strategy was generally successful is merited. In other words, did those who display stronger DEs show, on average, a better financial performance in the simulation? A regression analysis with the participants in the "public" setting indicates that larger DCs do not improve financial performance. If anything, the correlation coefficient points to the contrary ($\beta = -0.1729$ (0.3623), $t\ (28) = -0.47$, $p = .637$). These results resonate with previous findings in the literature, which demonstrate that the DE does not enhance financial performance and often has a damaging effect on returns (Odean 1998; Weber and Camerer 1998).

5.2 Turnover, Cushion and other strategies

A series of multiple regressions (Table 3) assessed the association between the DC and additional variables.

Table 3 – Regression analysis for control variables

DC	Interc.	1=Publ. 0=Priv.	Volat.	Cushion	Turnover	Stocks Mean Quantity	Trans.
Model 1	-0.0104	0.1289**					
0.0688	*(0.0426)*	*(0.0581)*					
Model 2	0.0741	0.1450**	-0.0221				
0.0755	*(0.0836)*	*(0.0595)*	*(0.0188)*				
Model 3	0.0576	0.1449**	-0.0214	0.0262			
0.0580	*(0.1099)*	*(0.0601)*	*(0.0193)*	*(0.1121)*			
Model 4	0.1428	0.1580**	-0.0202	-0.0642	-0.5916		
0.0688	*(0.1286)*	*(0.0606)*	*(0.0192)*	*(0.1328)*	*(0.4709)*		
Model 5	0.1604	0.1589**	-0.0209	-0.0712	-0.6246	-0.0028	
0.0495	*(0.2616)*	*(0.0623)*	*(0.0214)*	*(0.1613)*	*(0.6391)*	*(0.0374)*	
Model 6	0.1455	0.1695**	-0.0215	-0.0726	-0.5155	0.0064	-0.0005
0.0372	*(0.2644)*	*(0.0649)*	*(0.0216)*	*(0.1624)*	*(0.6669)*	*(0.0405)*	*(0.0009)*

(1) The table presents the coefficient, and in parentheses the robust standard error. In bold, the adjusted R^2.

(2) $DCi = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + u_i$

Where X_{1i}= 1 is the binary variable for participants in "public" setting and X_{1i} = 0 for the private setting; X_{2i} is the average standard deviation of the assets comprising the portfolio of each participant in the simulation period. This average is weighted by the percentage share of each asset in the portfolio of the participant, and the standard deviation of each asset is calculated based on price fluctuations, i.e., as rounds are played, the data set used to calculate the standard deviation of the asset increases (Volatility); X_{3i} is the average percentage of his total assets that the participant keeps in cash each period as a proportion of total equity (Cushion); X_{4i} is the average percentage of investment assets traded in relation to total assets (investments plus cash) per period (Turnover). For example: a participant who has a total of 10,000 monetary units (investments plus cash balance) who trades 5,000 monetary units has a turnover of 50%; X_{5i} is the average number of stocks held in portfolio, varying between 0 and 6, which is the total number of options in the simulation (Stocks Mean Quantity); X_{6i} is the total number of buy and sell per participant (Trans.).

(3) The total sample includes 63 participants. When the volatility variable is included, the number of participants drops to 54. Nine participants are excluded due to data capture error in the simulation software. A similar procedure was adopted in Dhar and Zhu (2006).

(4) White's (1980) regression correction was employed: heteroskedasticity-consistent standard errors.

(5) * significant at 10%; ** Significant at 5%; ***Significant at 1%

Apart from public and private setting, no other explanatory variable showed significant results. Some findings suggest that Turnover (defined as the average percentage of investment assets traded in relation to total assets - investments plus cash balance - per period) is associated with overconfidence or the DE, and that, in general, it causes poorer financial performance (Barber and Odean, 2000; Statman, Thorley and Vorkink, 2006).

We assume that a possible strategy to avoid the embarrassment of being among worst performers would be that of making fewer transactions; in theory, the risk of losing transactions would be lower thusly. However, a simple regression with all participants in the "public" setting indicates that the turnover variable has no explanatory power for the DE (β = -0.2955 (0.6124), t (28) = -0.48 | p = 0.63). Furthermore, the effect is found to be the opposite of that originally expected, that is, the greater the DE in the "public" setting, the lower the turnover.

As to the private setting, the direction of the correlation is similar; however, there is an explanatory power in the Turnover variable: β = -0.8111 (0.4398), t (24) = -1.84 | p=0.078. The significance of the Turnover variable corroborates the results found by Barber and Odean (2001) and Statman et al. (2006).

A consideration of the fact that relatively few sales of losing positions took place may explain part of this contradictory movement between turnover and DE. The tendency toward holding losing positions for longer confirms the decrease in turnover, simultaneously increasing the DE.

According to Table 3, the “financial cushion" strategy of holding onto cash provided by realized gains was not significant. Consequently, it is observed that the control variables, in general, showed no great explanatory power for variations the DE.

5.3 Conclusion

Financial performances are often expected to be made public. In this chapter, we show that whether the performance is expected to become public or kept private has a systematic impact on financial decision making. In a lab experiment, we show a significant increase in the disposition effect when financial performance is to be made public. This increase results essentially from a spike in the realization of gains. We speculate that people are selling gains in a strategic attempt to hedge against the embarrassment of ending the trading session at the bottom of the performance rank. Future research should assess the robustness of the phenomenon and the role of the proposed psychological mechanism. We hope that these findings will provide further insights into the role of social incentives in individual financial decision-making.

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CHAPTER 4

HERDING AROUND THE WORLD: DO CULTURAL DIFFERENCES INFLUENCE INVESTORS' BEHAVIOR?

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Abstract

In the last few years, culture has been found to play an important role in economic decisions. In this chapter we explore the impact of cultural differences on the investors' decision to imitate the actions of others (i.e., herding behavior). We establish a theoretical relationship between Hofstede's cultural dimensions and the herding behavior among investors. Moreover, we test that relationship in a sample covering 39 countries in the period 2001-2013. The results suggest that cultural dimensions influence the investors' imitative behavior since investors deciding on more masculine cultures and on cultures characterized by a higher power distance tend to be less prone to herd. The results for individualism, uncertainty avoidance and long-term orientation were found to be statistically non-significant at

conventional levels. Collectively, the results highlight the importance of some features of the cultural environment on financial decision-making.

Key-words: herding behavior; culture; Hofstede's cultural dimensions; stock markets; cross-country analysis.

1. Introduction

The increasing awareness of the impact that investors' behavior have on stock prices has led scholars during the last decades to consider factors such as psychological biases and social interactions to explain financial decisions. There are several studies that show the importance of the social component in financial decisions. The main conclusion is that the interest in participating in financial markets is largely stimulated by other investors and is related to the number of peers that also participate (Hong *et al.*, 2004). Moreover, word-of-mouth plays a pivotal role in the decision to invest in stock markets (Hong *et al.*, 2005).

Hofstede (2001) defines culture as a collective programming of the mind that is manifested in our values and norms and reflected in our actions. According to the author, culture may be understood as a "software of the mind" that is stable over time. This implies the existence of a societal value system shared by dominant groups and the existence of institutions (e.g., family, school and law), where certain behaviors are encouraged and entail people to consistently behave the same way when facing similar situations. Since investors take into account others' opinion, it is relevant to analyze herding because this collective behavior may lead prices to deviate from fundamentals (Christie and Huang, 1995). Furthermore, it is important to notice that investors' behavior and their social interactions are also dependent on the country they live in because they have different cultural backgrounds that impact their view of reality. Although cultural finance is a recent field of research, it is possible to find several empirical contributions in the literature where cultural variables are found to shed light on financial decision-making. These contributions focus on such diverse topics as investors' trading strategies (Chui *et al.*, 2010), corporate mergers and acquisitions (Ferris *et al.*, 2013), and decisions regarding international asset allocation (Beugelsdijk and Frijns, 2010; Anderson *et al.*, 2011).

However, studies that explain herding through cultural differences among countries are very scarce. We add to this strand of the literature, exploring the impact of cultural differences on the investors' decision to herd. This chapter contains two main contributions. Firstly, there is a contribution in the field of Behavioral Finance as we establish a theoretical relationship between the various cultural dimensions defined by Hofstede (2001) and the herding behavior among investors. Secondly, there is an empirical contribution to the extent that we examine the impact of culture in the investors' herding behavior. We analyze 39 countries in the period 2001-2013 using the measure of herding proposed by Chang *et al*. (2000) and applying Hofstede's five cultural dimensions (2001). Our empirical results indicate that investors acting in societies with higher levels of masculinity and greater power distance tend to be less prone to herd. These results carry relevant implications both for researchers on the topic and for financial markets regulators.

The chapter is structured as follows. In section 2 we present a selective literature review concerning herding and culture. We proceed in section 3 with the formulation of hypothesis and the description of the data and methodology used in the empirical study. The results are discussed in section 4. Section 5 concludes the chapter.

2. Literature Review

2.1. Herding

Herding is a phenomenon that has been widely investigated in the last decades. It has been seen as a behavior capable of increasing volatility and destabilizing financial markets (e.g., Kremer and Neutz, 2013). Herding can be defined as investors' mutual imitation, which implies individuals to suppress their own beliefs and ignore their private information to follow other investors' actions.

According to Devenow and Welch (1996), herd behavior can be classified as irrational or rational. The irrational view consists in investors following one another blindly, being their decisions mostly based in psychological factors. The rational view has to do with the expectation of an investor to reap informational payoffs (Banerjee, 1992) and with reputational concerns (Scharfstein and Stein, 1990), mainly due to the existence of a principal-agent relationship.

Since herd behavior consists in an increased correlation in investors' decisions, even if there is theoretical grounding to justify this behavior, to prove it empirically is a difficult task. This happens because when investors trade in the same direction one does not know whether they are imitating each other intentionally or whether they are just reacting to the same piece of information. Nevertheless, it is possible to find several empirical studies about this topic contemplating different periods, geographies and measures of herding. An important stream in the literature analyzes the herding in the market as a whole. For example, Christie and Huang (1995) studied the US stock market to conclude that herding levels declined during periods of higher price volatility. These results were later confirmed by Caparrelli *et al.* (2004) for the Italian market. Most authors conclude that imitative tendencies tend to be exacerbated during bear market periods (e.g., Yao *et al*., 2014; Gong and Dai, 2017) contributing to an increase in price volatility (e.g., Blasco *et al*., 2012).

Another set of studies focus on the herding among mutual funds. Most authors conclude that the level of herding among these agents is modest (e.g., Grinblatt *et al*., 1995; Wermers, 1999). Despite this, there seem to be important exceptions: for example, Lobão and Serra (2007) report a level of herding among Portuguese mutual funds 4 to 5 times higher than that observed in the US. There are studies for the US and Taiwan stock markets that suggest that herding tends to be more pronounced in low-capitalization stocks (Wermers, 1999; Hsieh, 2013), although there are also contradictory results in this respect for European markets (Lobão and Serra, 2007; Kremer and Neutz, 2013). In general, the herding among mutual funds seems to have a significant effect on prices (Zheng *et al*., 2015) contributing to speed up its adjustment process (Hsieh, 2013).

Although there is still no consensus about the prevalence of herd behavior around the world, the phenomenon seems to be more significant in less mature markets. This may be related to the fact that the development of the mutual funds in less developed countries is still recent, which implies that managers in charge of those funds tend to be more inexperienced and tend to be more prone to follow other investors' decisions.

2.2. Culture and Finance

Although culture may seem a concept difficult to quantify, there have been over the years some attempts to measure it through a dimensionality approach, based on large-scale surveys. The dimensions most widely used in empirical studies are the ones of Schwartz (1994) and Hofstede (2001). In this study we will apply Hofstede's five dimensions. This choice is motivated by the extensive support that this theoretical framework has been gathered and by the indications that there is a significant convergence between the dimensions proposed by other authors and Hofstede's dimensions (Soares *et al*., 2007).

It is important to understand the five cultural dimensions that according to Hofstede (2001) describe a country's culture. The first dimension opposes individualism to collectivism, reflecting the degree of reinforcement of individual or collective achievements and interpersonal relationships. In individualistic societies, people tend to be more autonomous, independent, give more weight to their individual opinion, value differences of opinion and focus on their own attributes and abilities. On the other hand, collectivism implies individuals to be more dependent on the group and group opinions usually prevail to personal opinions. The second dimension confronts masculinity and femininity and is related to the social role that is attributed to each gender. Men are usually associated with values such as firmness, competitiveness and toughness, so they tend to be more autonomous and ambitious. Women, on the contrary, are usually associated with values such as protection, generosity and concern with human relations, so they tend to be more cooperative and solidary. The third dimension contrasts countries with high and low uncertainty avoidance, referring to the extent to which people are uncomfortable with ambiguous situations. Countries characterized with high uncertainty avoidance enjoy predictability, so they tend to have stricter rules and safety measures. The fourth dimension compares countries with high and low power distance. This has to do with the degree of acceptance of an unequal power distribution within a society by those who have less power. Countries characterized by high power distance tend to be more obedient and respectful of an authority, being more dependent and having less own initiative. Finally, the fifth dimension confronts long-term orientation with short-term orientation. Long-term oriented countries value thrift, stability and perseverance towards future outcomes, while short-term oriented countries give more weight to immediate results.

These five cultural dimensions are been found to be useful to understand the decisions made by investors and corporate managers. For example, Chui *et al.* (2010) related individualism to the momentum phenomenon, realizing that investors from individualistic countries produce higher momentum profits. Ferris *et al.* (2013) applied Hofstede's dimensions to mergers and acquisitions and concluded that CEOs from countries characterized by higher individualism, lower uncertainty avoidance and lower long-term orientation tend to underestimate the risk underlying mergers and to overestimate synergy gains. Also, Mihet (2012) and Li *et al*. (2013) noticed that managers from countries with higher individualism, lower uncertainty avoidance and lower power distance tend to be more prone to make high-risk decisions. Beugelsdijk and Frijns (2010) and Anderson *et al.* (2011) concluded that agents in countries with higher individualism invest more in foreign markets and agents in long-term oriented countries tend to hold more diversified portfolios. More recently, Dodd *et al.* (2013) showed that firms from developed countries cross-list in markets with greater cultural similarities measured by Hofstede's cultural dimensions and Ahern *et al.* (2015) found that three key dimensions of national culture (trust, hierarchy, and individualism) affect merger volume and synergy gains.

The empirical literature regarding the influence of culture on herding among investors is rather limited, especially when it comes to market-wide studies. In a study of 47 countries around the world, Zhan (2013) concludes that less individualistic nations tended to exhibit a higher number of synchronized stock price movements, which he attributes to the presence of herding behavior. Zheng (2015) analyses the impact of cultural variables on the volatility patterns of fifteen stock markets. The main conclusion is that countries with lower power distance, higher masculinity and higher uncertainty avoidance are more prone to transit from low volatility states to high volatility states, which the author relates to the presence of heightened herding behavior in the market. Beckmann, Menkhoff and Sutto (2008) examined the behavior of 1025 asset managers operating in the US, Germany, Japan and Thailand with the help of a questionnaire survey. They found clear evidence that more individualistic countries have asset managers that show less herding. In a related paper, Zouaoui *et al.* (2011) used the measure of individualism developed by Hofstede (2001) to identify those national stock markets that were expected to be more affected by herd-like behavior and by episodes of crisis led by sentiment.

3. Hypothesis, Data and Methodology

3.1. Hypothesis

In the existing literature, individualism seems to be associated with overconfidence and self-attribution biases (e.g., Chui *et al.*, 2010). In fact, individualism encourages independent action and individual choices (Li *et al.*, 2013), which leads individuals to have more confidence in their own abilities, overestimating the precision of their predictions and being more tolerant to risk (e.g. Barber and Odean, 2009; Ferris *et al.*, 2013). On the contrary, in collectivistic cultures investors give less importance to their private information and rely more in others' opinion (Chui *et al.*, 2010).

Therefore, the hypothesis we formulate regarding individualism is the following:

H1: Individualistic countries tend to exhibit less herding.

Current studies show that masculinity is usually associated with overconfidence and risk-taking behavior (e.g., Beckmann and Menkhoff, 2008). Barber and Odean (2001) found that overconfident investors tend to trade more. Studying a US sample, those authors showed that men in their sample have traded more 45% than women. Moreover, Anderson *et al.* (2011) concluded that masculinity leads to a stronger international portfolio diversification since male investors tend to believe they possess superior information than others. This leads us to formulate the following hypothesis:

H2: Masculine countries tend to exhibit less herding.

Furthermore, existing studies that test the influence of uncertainty avoidance in financial decisions suggest a positive association between that cultural dimension and risk-aversion (e.g., Nguyen and Truong, 2013). According to Beugelsdijks and Frinjs (2010) and Anderson *et al.* (2011), investors from countries with higher uncertainty avoidance tend to exhibit a stronger home bias because they prefer to hold safer and familiar investments. On the other hand, Hofstede (2001) states that uncertainty avoidance captures a propensity people have to follow the same set of rules, which may denote the tendency to track others' decisions. Considering this, we formulate the following hypothesis:

H3: Countries with high uncertainty avoidance tend to exhibit more herding.

According to Hofstede (2001), in countries that exhibit a high power distance people tend to be more dependent and have less own initiative, which is consistent with the presence of higher levels of herding. Moreover, Mihet (2012) noticed that in countries characterized by low power distance, values that encourage competition and that hinder herding like trust and equality, are of importance. Therefore, we posit the following:

H4: Countries with high power distance tend to exhibit more herding.

Finally, when it comes to long-term orientation, it is well established that mutual funds managers that are evaluated on a short-term basis (e.g., every quarter) have incentives to follow their peers as this may help maintaining their reputation (Scharfstein and Stein, 1990). Furthermore, Shiller (2000) argues that short-term investors tend to join the bandwagon (i.e, they herd) and enter or exit the market ignoring such crucial factors such as the intrinsic value of the assets they are trading. Considering these contributions we posit that:

H5: Countries with short-term orientation tend to exhibit more herding.

3.2. Data

We use daily data for 39 countries for the period 2001-2013.[1] The stock market indices representing each one of the national markets were collected from Datastream Global Equity Indices and the World Bank, being all the variables measured in local currency. In this study we use the logarithm of returns.

As for the cultural dimensions, data was obtained from Hofstede (2010) and Hofstede's website (www.geerthofstede.nl). Each of the five Hofstede's cultural dimensions (individualism, masculinity, uncertainty avoidance, power distance and long-term orientation) assumes a value between 0 and 100 in each of the 39 countries of the sample. When the value is closer to zero, the country scores lower on that dimension and when the value is closer to 100, the country scores higher on that dimension. The value that a country obtains for each dimension is the one to be applicable during the entire sample period, since the cultural dimensions are time-invariant.

3.3. Methodology

a) Measure of herding

We apply in our work the measure proposed by Chang *et al.* (2000) that captures herding through the cross-sectional dispersion of asset returns (CSAD), as specified below:

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[1] The countries included in the sample are the following: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Indonesia, Ireland, Israel, Italy, Japan, Korea, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Portugal, Romania, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, the US and the UK.

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}|$$

where N is the number of firms, $R_{i,t}$ is the observed return of firm i at time t and $R_{m,t}$ is the cross-sectional average stock of N returns in the portfolio at time t.

According to this measure, a low dispersion would indicate that individual returns do not diverge considerably from the overall market return, pointing to the presence of herding. The rationale is that in the presence of herding investors suppress their own opinions in favor of the market consensus. Then this makes individual returns to cluster around the market return.

Since the measure of Chang *et al*. (2000) focuses on tendencies that are observable in the market as a whole, it adopts a market wide approach. For this reason, in our study we also capture the existence of herd behavior in the market as a whole, without concerns to the class of investor (e.g., individual investors, institutional investors, etc.) that causes it.

b) Control variables

Since our objective is to test the additional power of cultural variables to explain the herd behavior, it is necessary to consider as control variables the main determinants of herding that are usually found in the literature. Table 1 shows the factors that, according to the existing studies, are expected to influence the intensity of herding behavior in financial markets.

Table 1 – Determinants of herding according to the existing literature

Determinants of herding	Variable	Relevant literature
Book-to-market ratio	$\frac{Book\ value\ of\ balance\ sheet}{Market\ capitalizarion}$	Lakonishok *et al*. (1994); Blasco, *et al*. (2009)
Price volatility	$\frac{\sum_{i=1}^{n} R_{it}^{2}}{n}$	Chang *et al*. (2000); Lobão and Serra (2007); Chui *et al*. (2010)
Firm size	$\frac{\sum_{i=1}^{n} Share\ price_{i,t} * Number\ of\ common\ shar}{Number\ of\ firms}$	Wermers (1999); Sias (2004)
Turnover	$\frac{Total\ value\ of\ shares\ traded}{Average\ market\ capitalization}$	Wang (1998); Suominem (2001); Christoffersen and Tang (2010)
Bull and bear markets	Algorithm proposed by Bry and Boschan (1971)	Bry and Boschan (1971); Chauvert and Potter (2000)
Extreme market movements	Dummy – 5% lower tail and 5% upper tail of returns' distribution	Christie and Huang (1995); Chang *et al*. (2000)
Market capitalization to GDP ratio	$\frac{Market\ Capitalization}{GDP}$	Beugelsdijks and Frijns (2010); Nguyen and Truong (2013)
GDP per capita	$\frac{GDP}{Population}$	

The book-to-market ratio can be seen as a proxy for risk and as such it can be responsible for cross-section variability. For example, Lakonishok *et al.* (1994) noticed that a higher book-to-market ratio was related to investors' underreaction, since they tend to lower their expectations by extrapolating past prices to the future. In the field of herding, Blasco *et al.* (2009), in a study of the Spanish market, concluded that a lower book-to-market ratio leaded to a higher level of imitation.

Volatility can be used as a proxy for information uncertainty, making information more ambiguous and less reliable, which leads investors to seek information in other agents' signals (Chui *et al*., 2011). Overall, in the literature, volatility tends to be related with higher levels of herding since correlations tend to rise in periods of high volatility. Nevertheless, Lobão and Serra (2007) found a negative relationship between volatility and level of herding while studying the Portuguese market. According to the authors, higher volatility can be considered a proxy for new and unexpected information, thus reflecting more information, leading to a lower level of herding.

The size of firms influence herd behavior since is associated with the information flows that companies produce. Wermers (1999) claimed that herding is more prone to occur in small stocks, since they provide less information thus forcing investors to decide in an ambiguous environment.

Turnover can be seen as a synonym of better quality information. This is the perspective supported by Suominem (2001), for example. However, Wang (1998) argued that turnover may be seen as a proxy for investors' consensus in the market. Empirically, Christoffersen and Tang (2010) supported the first view when analysing the US market, thus concluding that herding tends to be higher when turnover is lower.

Investors can react differently when facing a rising or falling market. Several authors have confirmed this conjecture empirically (e.g., Siganos and Chelley-Steeley, 2006). Moreover, Chang *et al*. (2000), in an analysis of five developed markets, conclude that herding tended to be significantly stronger during bear markets. We define bull and bear market periods using the measure proposed by Bry and Boschan (1971). The algorithm is based on the identification of potential peaks and troughs, i.e. points higher or lower than a window of surrounding points, and on the length of the cycles between those points. We used a window of 6 months to identify the peaks and troughs and eliminated cycles with duration less than 15 months.

The asymmetric behavior may be intensified in the presence of extreme market conditions. Therefore, we take into account the possible asymmetry between the upside and downside of the market extreme conditions, considering as a control variable the fact that the returns are located on the 5% lower tail or in the 5% upper tail of the returns' distribution.

Market capitalization to GDP ratio can be viewed as a proxy for economic and institutional development, as well as a proxy for a country's liquidity (e.g., Beugelsdijks and Frijns, 2010; Nguyen and Truong, 2013). This implies a positive association with stock market development, which would attract more investors to the market.

Finally, GDP tends to be related with institutional quality and financial development, implying that in a country with higher GDP per capita investors should exhibit a lower level of herding.

c) Model specification

In our model, the dependent variable is the cross-sectional absolute deviation (CSAD) proposed by Chang *et al.* (2000). To analyze whether culture may have an impact on herd behavior, we include as explanatory variables the five cultural dimensions defined by Hofstede (2001) and control herding for the abovementioned determinants.

Our regression is thus specified as follows:

$$CSAD_{i,t} = \beta_1 + \beta_2{*}BTM_{i,t} + \beta_3{*}VOL_{i,t} + \beta_4{*}SIZE_{i,t} + \beta_5{*}TURN_{i,t} + \beta_{6*}EXTREME\_UP_{i,t} + +\beta_{7*}EXTREME\_DOWN_{i,t} + \beta_{8*}BULL\_BEAR_{i,t} + \beta_{9*}MC/GDP_{i,t} + \beta_{10*}GDPpc_{i,t} + \beta_{11*}IND_i + \beta_{12*}MAS_i + \beta_{13*}UA_i + \beta_{14*}PD_i + \beta_{15*}LTO_i + \varepsilon_{i,t}$$

where

$CSAD_{i,t}$ = cross-sectional absolute deviation of individual returns to market returns in country *i* at moment *t*,

$BTM_{i,t}$ = book-to-market ratio in country *i* at moment *t*,

$VOL_{i,t}$ = daily volatility in country *i* at moment *t*,

$SIZE_{i,t}$ = average size of firms expressed by the market capitalization, in country *i* at moment *t*,

$TURN_{i,t}$ = the turnover rate of the market in country *i* at moment *t*, EXTREME_UP$_{i,t}$ = the dummy variable, with a value of 1 if the returns lie on the 5% upper tail of the returns' distribution in country i at moment t and 0 otherwise,

EXTREME_DOWN$_{i,t}$ = the dummy variable, with a value of 1 if the returns lie on the 5% lower tail of returns' distribution in country i at moment t and 0 otherwise,

BULL_BEAR$_{i,t}$ = the dummy variable, with a value of 1 if the market is in an upward trend and 0 otherwise,

MC/GPD$_{i,t}$ = the market capitalization relative to gross domestic product in country i at moment t,

GDPpc$_{i,t}$ = the gross domestic product per capita in country i at moment t,

IND$_i$, MAS$_i$, UA$_i$, PD$_i$ and LTO$_i$ = levels of individualism, masculinity, uncertainty avoidance, power distance and long-term orientation, respectively, of country i.

To estimate the model we use panel data, applying the EGLS method with cross-section random effects (since we have time-invariant variables) and White period correction to control for heteroskedasticity. To assess the possibility of multicollinearity of the dependent variables, one of the major issues in panel data analysis, we computed the variance inflation factors recurring to a Tikhonov regularization procedure (ridge regression) having found no such problem.

4. Empirical results and discussion

Table 2 contains the results obtained with the application of the model.

Table 2 shows the results of the regression of herding on cultural factors and control variables. Daily cross-sectional absolute dispersions of returns are regressed on Hofstede's cultural dimensions, (Individualism – IND, masculinity – MAS, uncertainty avoidance – UA, power distance – PD and long-term orientation – LTO) and a set of control variables (book-to-market ratio – BTM, volatility – VOL, size of the firms – SIZE, turnover rate – TURN, market capitalization related to GDP – MC/GDP, gross domestic product per capita – GDPpc and dummies expressing extreme up and down movements – EXTREME_UP and EXTREME_DOWN – as well as market trend – BULL_BEAR). The model is estimated using Panel EGLS with cross-country random effects and White Period (PCSE) consistent estimates of standard errors and covariance are used to compute t-statistics. F_1 (F-statistic test) is used to test the hypothesis that all the estimated slope coefficients, except the coefficients of cultural dimensions, are jointly equal to zero, while F_2 is used to test the hypothesis that all the estimated slope coefficients are jointly equal to zero. The *p*-values are in parenthesis. A positive sign in the coefficient means that the variable has a positive impact in the dispersion of returns, which means that it has a negative impact on herding. *, ** and *** represent significance at the 10%, 5% and 1% levels respectively.

Table 2 – Results for the determinants of herding and cultural dimensions

Dependent variable: CSAD

Method: Panel EGLS (cross-section random effects)

Periods included: 3.392

Total panel (unbalanced) observations: 130.661

	Variable	Coefficient	Std. Error	t-statistic	Prob.
Control variables	C	0.284887	0.100592	2.83	0.0046
	BTM	0.103345***	0.012202	8.47	0.0000
	VOL	0.017374***	0.002532	6.86	0.0000
	SIZE	0.000001***	0.000000	-2.59	0.0095
	TURN	0.128775**	0.056666	2.27	0.0231
	MC/GDP	-0.000219*	0.000132	-1.66	0.0973
	GDPpc	0.000004**	0.000001	2.15	0.0312
	EXTREME_UP	0.485705***	0.024428	19.88	0.0000
	EXTREME_DOWN	0.411216***	0.023331	17.63	0.0000
	BULL_BEAR	-0.004424	0.009148	-0.48	0.6287
Cultural variables	IND	0.001157	0.000788	1.47	0.1422
	MAS	0.001863*	0.001015	1.84	0.0664
	UA	-0.001017	0.000672	-1.51	0.1298
	PD	0.001815*	0.001060	1.71	0.0869
	LTO	0.000307	0.000910	0.34	0.7356

Adjusted $R^2 = 0.382610$
F_1= 177.14 (0.00)
F_2= 207.87 (0.00)

a) Control variables

Our results show that all control variables except the one representing market trends is statistically significant at a 10% level.

From the results obtained, we can observe that book-to-market ratio, volatility, turnover, GDP per capita and both dummies reflecting extreme market movements, reveal a positive relationship with CSAD, meaning that an increase in those variables (or the evidence of the situation to which the dummies refer) will cause a decrease in the level of herding. On the other hand, size and market capitalization to GDP exhibit a negative relationship with CSAD, thus evidencing that an increase in these variables leads to an increase in the level of herding.

Regarding the book-to-market ratio, the results are consistent with Lakonishok *et al.* (1994) and Blasco *et al.* (2009), supporting the vision that investors are uninformed and so, they herd more when the indicator is lower. Firms that present a lower book-to-market ratio tend to show worse financial indicators (for example, a lower volume of sales or a higher price-earnings ratio). In these circumstances, uninformed investors tend to be attracted, as a group, to firms that show better financial indicators, disregarding the fact that they may be paying too much for those shares (Lakonishok *et al*., 1994). This may justify a higher level of herding when firms have lower book-to-market ratios.

In what concerns volatility, our results go in the same direction as the ones found in Lobão and Serra (2007), meaning that volatility is probably associated with the arrival of unexpected public information.

The coefficient of size is also positive and statistically significant which supports the assertion that smaller firms may be more susceptible to herding due to lack of information.

Our findings also show that a higher turnover is associated with lower levels of herding. This may happen because low turnover is associated with poorer information and a higher turnover reflects higher differences of opinion among investors with respect to a stock’s intrinsic value.

For the extreme movements, we found, against our expectations, that herding is less likely to occur under these extreme situations. However, these results are consistent with Hwang and Salmon (2004), who consider herding to be more intense in quiet periods, and that investors during periods of crisis tend to be more analytical and to look more attentively to fundamentals.

Regarding market capitalization to GDP, our results show that a higher ratio would lead to more herding. This may be related to the fact that more developed stock markets are more liquid and attract more investors to trade. Then, if there are more opportunities to trade stocks in the market, investors are more able to pursue herding strategies in that market. On the other hand, the result obtained may be capturing spurious herding instead of "pure" herd behavior. In fact, in more developed stock markets, information quality is better and investors may trade in the same direction just because they had access to the same piece of information.

Our results for GDP per capita are in consonance with Anderson *et al.* (2011), showing that tends to exist less herding in countries characterized by a higher GDP per capita. This result is consistent with the view that institutional development plays an important role in the development of financial markets. In fact, it is plausible to admit that the development of market institutions like regulators and producers of information (e.g., credit agencies and financial analysts) may provide investors with better and cheaper information, which may make herding relatively less attractive.

The results related to bull and bear markets obtained are not statistically significant, which suggest that herd behavior is not significantly influenced by the market trend.

b) Cultural dimensions

The results obtained allow us to conclude that culture may in fact play a significant role in financial decision-making and, in particular, on herd behavior. In fact, our findings show that masculinity and power distance have a statistically significant explanatory power for this phenomenon at the 10% significance level.

Regarding masculinity, the results for this dimension are in tune with the predictions from previous literature that suggest that herding tends to be less significant in more masculine cultures, *ceteris paribus*. The results also confirm our second hypothesis (H2). Thus, the evidence is consistent with the view that men tend to be more self-confident and ambitious, which leads them to trust their own abilities and to adopt risk-taking behaviors. Our evidence is also consistent with the results found by Barber and Odean (2001), who have established a significant relationship between gender and trading.

As for power distance, our results seem to support the idea suggested by Mihet (2012) that low power distance is closely related to values such as trust, equality and cooperation. The explanation may lie in the link between power distance and institutions quality. It is plausible to admit that high power distant countries usually have institutions protecting the existing level of welfare, which includes a stronger protection of shareholders. Therefore, these countries tend to have higher institutional quality which is associated with a more abundant flow of information (Chui *et al.*, 2010). These conditions favor a decrease in the levels of herding.

Individualism, uncertainty avoidance and long-term orientation are cultural dimensions that were found to be not statistically significant. This means that the first, the third and the fifth hypothesis that were posited in section 3.1. do not find support in the results of our empirical study.

Overall, our findings suggest that some cultural dimensions have an impact in investors' decision-making and should be considered when one wants to understand the behavior of investors in financial markets. Specifically, we reached the conclusion that masculinity and power distance influence negatively the existence of herding in the market.

5. Conclusion

Financial investors do not decide in isolation. On the contrary, they interact with each other, and that social interaction may lead them to adopt a different decision from the one they would choose if they were deciding on their own. Also, culture permeates virtually every aspect of people's decisions, including financial decisions.

Considering this, we explored in this chapter the influence that culture may exert on investors' decisions to imitate the actions of others (i.e., herding behavior). We established a theoretical relationship between the various cultural dimensions defined by Hofstede (2001) and the herding behavior among investors. Then we tested those relationships in a sample of 39 countries using those cultural dimensions and the measure of herding proposed by Chang *et al.* (2000).

The results suggest that some dimensions of culture have the ability to influence investor's imitative behavior. Countries characterized by a higher level of masculinity and power distance are less prone to herd behavior. The results for individualism, uncertainty avoidance and long-term orientation were not statistically significant at conventional levels. Collectively, these results highlight the importance of considering some features of the cultural environment when predicting how investors in a specific market will behave.

The results presented in this study are also relevant in the perspective of the regulator of financial markets. In fact, one important implication is that regulators should act more attentively in countries where the culture propitiate a higher level of herding. This is the case of countries characterized by a more masculine culture (the cases of Japan, Hungary and Austria, for example), where the levels of power distance are more significant (the cases of Malaysia, the Philippines and Romania, for example) or where the two cultural traits reach, in aggregate, a higher level (the cases of the Philippines, Malaysia and Mexico, for example). In countries with these characteristics, the authorities should be more severe in the application of regulatory measures that aim to reduce the harmful effects of herding in the formation of prices.

Our study presents some limitations. First, the measure of herding we employed may be affected by spurious herding, since it does not distinguish changes in returns' dispersion driven by sentiment from those driven by prices adjusting to the coming of new information to the market. Furthermore, that indicator of herding may be affected by factors that are not directly related to the phenomenon such as informational inefficiencies. Secondly, we assume that the herding observed in one country is influenced by cultural dimensions that affect investors from that country. The fact that a relevant portion of the investments made in a country may come from investors that are located in another country may limit the implication of our results as well as the results of several of the studies in the field of cultural finance. Finally, although Hofstede's dimensions are widely used due to their clarity and simplicity, there are criticisms made to these dimensions. For example, Kirkman *et al*. (2006) argue that something as complex as culture cannot be reduced to just five dimensions.

The current chapter represents a first attempt to investigate the impact of culture of herding. However, much remains to be known about this topic. For example, it would be interesting to have studies including other cultural dimensions such as those suggested by Schwartz (1994) and GLOBE Project (2004) and considering different herding measures (e.g., Christie and Huang, 1995; Hwang and Salmon, 2004) not only for the market as a whole but also for specific industries. Further avenues of research on the relationship between culture and herding may include the examination of the impact of factors such as the informational efficiency of the markets, the presence of institutional investors, the volatility of the macroeconomic environment and the level of investors' financial literacy.

Cultural finance is a fertile field of research and much of the influence of cultural variables on financial decision-making is yet to be discovered. We hope that our study will help to motivate future research on this subject.

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Part II:

Asset Pricing

CHAPTER 5

PREDICTING STOCK PRICE CRASHES: EVIDENCE FROM EUROPE

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Abstract

This chapter explores the factors that explain the crash of individual securities on European equity markets in the period 2003-2016. Our multivariate analysis shows that the results vary according to the adopted crash measure. In addition, it was found that variables that capture the stock's past return, its volatility, its size, and the relationship between market capitalization and book value (market-to-book ratio) are the main predictors of the crash risk. A strategy based on these variables would allow the investor to create a portfolio with a better performance measured by the Sharpe ratio. Although the strategy was successful in providing higher risk-adjusted returns, it was not able to reduce the incidence of stock price crashes. Our results can be of interest to investors that want to manage the likelihood of crashes in their portfolios.

Key-words: stock markets, crashes, Europe

1. Introduction

Asset price crashes are probably the most challenging event for the portfolio manager. The factors that explain the crashes of the stock markets at an aggregate level have been the subject of abundant studies over the last few decades, particularly after the so-called technological bubble, formed in the second half of the 1990s (Shiller, 2005; Lybeck, 2011). However, the firm-specific factors that explain the probability of witnessing a crash on a single stock have been a scarcely studied topic, particularly in European markets.

One of the main difficulties in studying this theme lies in the definition of "crash". Different authors consider different concepts of "crash". For example, Ak *et al*. (2016) define a crash as a "large and abrupt negative stock return relative to the distribution of returns leading up to the crash.". Other authors, like Habib and Hasan (2017, p. 391) for example, consider that a crash can be defined as "the likelihood of observing extreme negative values in the distribution of firm-specific returns".

Our study explores the reasons behind the crash of individual securities on the European equity markets in the period 2003-2016 considering several measures of crash. Our results allowed us to identify a set of crash predictors, with a high level of statistical significance. We show that these indicators can be used to build a portfolio with the best performance measured by the Sharpe ratio.

The remainder of this chapter is structured as follows. In section 2, we review the relevant literature on the topic. Section 3 describes the data and methodology adopted in the empirical study. Section 4 presents our empirical findings. In section 5 we explore the investment implications of our results. Section 6 concludes the chapter.

2. Literature review

The literature review is divided into two sections. Firstly, we present the main theories for stock price crashes and then we discuss the factors that, so far, are believed to impact the likelihood of stock price crashes to happen.

2.1. Stock Price Crash Theories

Jin and Myers (2006) presented one of the most influential theories on stock price crashes. According to the authors, managers tend to withhold bad news from the public by engaging in more opaque reporting systems. Opaqueness, in turn, has both positive and negative effects for corporate insiders. On the positive side, it allows managers to capture more cash flow than they might if investors had all the information. On the other side, once the bulk of bad news is too much to hide, insiders give up and tend to release it all at once, resulting in large negative returns for the stock price. As Kothari *et al*. (2009) have noted, this accumulation of bad news leads to an asymmetric distribution of stock price returns whereas in a scenario where managers release information as it comes, a regular flow of good and bad news regarding the company is expected, leading up to less skewed returns distributions. Because the less the public knows about the company, the more insiders can take advantage of the company's resources in their own benefit, managers have incentives to keep information from being released to the general public.

Some other contributions build up on this agency-theory framework and help understand the exact nature of this opacity. For example, Benmelech *et al*. (2010) show that managers whose compensation is indexed to stock performance tend to engage in negative NPV (net present value) projects to hide the absence of opportunities that the firm may be facing (providing there are no positive NPV projects available) in order to make it seems that the company has a lot of growing opportunities even though it is, indeed, destroying value. In the same line, Bleck and Liu (2007) conclude that the existence of historic cost accounting does not allow outsiders to easily access current information about current projects hence reducing market transparency by increasing firm opacity. This leads to more pronounced asset price crashes.

Hong and Stein (2003) present another theory on stock price crashes. The authors attribute price crashes to the difference of opinion between investors. When investors have heterogeneous expectations and there are market frictions such as short-selling restrictions, some bearish investors cannot reflect into the prices their negative expectations. Thus, their information is kept outside of the market which leads to an overvaluation of stock prices. In this scenario, if for some reason (for example, a piece of new negative information comes out) a portion of bullish investors decides to exit the market, a bearish investor can become the marginal buyer in the market. In these circumstances' prices will start reflecting the opinion of those bearish investors thus leading to a sudden price decrease, i.e., a crash.

Cao *et al*. (2002) develop a theory on the same vein. In a context where investors face fixed setup trading costs, they need to verify their information by assessing other informed investors' trades in order to believe that they can recoup those these costs. This need for validation holds investors from trading which diminishes market participation and produces an information-blockage between those agents and the stock market. This market produces return distributions that exhibit the negative skewness associated to stock price crashes.

Finally, Campbell and Hentschel (1992) propose a model where stock returns' volatility is the source of stock price crash risk. An increase in stock market volatility leads investors to require a higher risk premium which pressure stock prices downward. Volatility feedback in stock returns can explain part of the return's negative skewness.

2.2. Stock Price Crash Determinants

The factors that are found in the literature to influence the likelihood of having a stock price crash can be classified into i) capital market factors, ii) company factors, iii) management factors and iv) other factors.

2.2.1. Capital market factors

Chen *et al*. (2001) use data from the US stock markets to conclude that past trading volume, past positive returns and firm size are positively associated with the stock price crash risk. However, the influence of the two last factors was put into question by Harvey and Siddique (2000).

More recently, Ak *et al*. (2016) conclude that more volatile stocks are more prone to crash

and Chang *et al*. (2017) found that higher stock liquidity is also related to a higher stock price crash risk. Managers of highly liquid firms tend to withhold bad news from the public because, due to its higher liquidity on the market, investors would promptly sell their stocks.

According to Callen and Fang (2015b), stock price crash risk is positively influenced by the existence of a high short-interest. However, even though short-sellers are believed to be able to predict negative returns, the variables the authors use measure short-interest are also related to other potential predictors of stock price crashes such as poor earnings quality (Desai *et al*., 2006) or financial misconduct (Karpoff and Lou, 2010).

2.2.2. Company factors

Hutton *et al*. (2009) show that firms that present more opaque financial reporting, measured through discretionary accruals, have a higher crash risk. This result was later corroborated by Zhu (2016) and Kim *et al*. (2019) that conclude that accruals and opaque financial reports are often used to hide bad news from outsiders. These conclusions go in line with the theoretical framework of Jin and Myers (2006) presented above. Moreover, there is a positive relation between practices of earnings management and a heightened probability of a stock price crash in the following year (Francis *et al*., 2016).

Kim *et al*. (2011) find that tax avoidance is related to stock price crashes at a firm-level. The authors, however, conclude that this effect is mitigated when companies are more widely followed by analysts and better monitored by external agents.

On the other hand, conservative accounting practices tend to be negatively related to stock price crash risk (Kim and Zhang, 2016). This follows from the fact that conservatism has the effect of decreasing information asymmetry in the market thus avoiding negative surprises to investors (LaFond and Watts, 2008).

Finally, Kim *et al*. (2014) show that firms that have higher corporate social responsibility ratings tend to have lower stock price crash risk.

2.2.3. Management factors

Since management is a crucial factor in firm performance, it is important to understand how it can influence stock price crashes. Kim *et al*. (2016) concludes that overconfident CEOs tend to overestimate projects' returns and to disregard negative feedback regarding their actions, which leads to a higher crash likelihood. Also, more confident CEOs tend to present less conservative financial statements which, as mentioned above, is positively related to stock price crashes (Ahmed and Duellman, 2013).

Demographic factors are also found to influence the probability of having a stock price crash. The existence of younger CEOs in the firm signal a higher crash probability (Andreou *et al*., 2016a).

Regarding CFOs' equity incentives, Kim *et al*. (2011) conclude that there is a significantly positive relation between CFOs' stock options and stock price crash risk. More recently, Bao *et al*. (2018) conclude that stock price crash increases after a firm voluntarily incorporates clawback provisions in CEOs' compensation contracts. This type of incentive may lead managers to withhold bad news from the public in order to maximize their possible returns.

Finally, board size is also found to be a predictor of stock price crashes. Empirically, a higher number of members in the board of a company results in fewer stock price crashes (Andreou *et al*., 2016b).

2.2.4. Other factors

There are a set of other factors that are found to influence stock price crash likelihood. For example, religion has been suggested as a predictor for stock price crash as Callen and Fang (2015a) conclude that companies with headquarters located in counties with higher levels of religiosity present a lower stock price crash risk. The presence of institutional investors monitoring the firm has been associated with a lower stock price crash risk (Callen and Fang, 2013). Companies where insiders have a higher proportion of ownership tend to have fewer future crashes (Andreou *et al*., 2016b). Analysts' expectations may also perform an important role in this topic. As shown by Ak *et al*. (2016), companies about which sell-side analysts have very optimistic prospects on future sales and net margin tend to have a higher crash risk propensity.

3. Data and methodology

Our sample comprises all the companies included in STOXX ® Europe 600 index from January 2003 until July 2016. The index includes companies from 17 different countries across Europe with small to large market capitalization companies.

As in previous literature (e.g., Chen *et al*, 2001; Ak *et al*., 2016), we divide our analysis in 6-month periods. Therefore, our sample includes 28 periods (semesters), with a total of 16,801 data points. All the data was retrieved from Thomson Reuters DataStream.

In order to understand what impacts the stock price crash likelihood in our sample, we perform a series of cross-sectional regressions. Since there is not a consensus about the variables that best capture the likelihood of having a crash (Habib *et al*., 2018) we consider as dependent variables four different measures of crash risk at the level of the individual stock: *DUVOL*, *NCSKEW*, *CRASH* and *MIN.RET*.

The “down-to-up volatility” (*DUVOL*) is computed as the logarithm of the ratio between the magnitude of the standard deviation observed in the days with returns below the period mean (“down” days) to the standard deviation observed in the days with returns above the period mean (“up” days). Higher values on this indicator represent a more left-skewed distribution and thus, a higher crash probability.

$$DUVOL_{i,t} = log\left\{(n_u - 1)\sum_{DOWN} R_{i,t}^2 \middle/ \left[(n_d - 1)\sum_{DOWN} R_{i,t}^2\right]\right\}$$

where $R_{i,t}$ denotes the sequence of demeaned daily stock returns to stock *i* during period t , and n_u and n_d are the number of up and down days, respectively.

The “negative coefficient of skewness” (*NCSKEW*) compares the shape of the left (negative) tail of the distribution of returns with the shape of the right (positive) tail. Higher values of this indicator indicate a longer left tail meaning that the stock is more prone to crash than another one with a smaller left tail.

$$NCSKEW_{i,t} = -\frac{n(n-1)^{\frac{3}{2}}\sum R_{i,t}^3}{(n-1)(n-2)\left(\sum R_{i,t}^2\right)^{\frac{3}{2}}}$$

where $R_{i,t}$ denotes the sequence of demeaned daily stock returns to stock *i* during period *t* and *n* is the number of daily stock returns in the period.

The third dependent variable (*CRASH*) considered in our study was firstly proposed by Ak *et al*. (2016) and takes the negative ratio of the minimum daily return over the period to the sample standard deviation of returns for the previous period.

$$CRASH_{i,t} = \frac{-Min\left(R_{i,t}\right)}{\sqrt{\sum R_{i,t-1}^2/(n-1)}}$$

where $R_{i,t}$ represents the sequence of demeaned daily stock returns to stock *i* during period *t* and *n* is the number of daily stock returns in the period.

Finally, we also use the negative of the minimum daily return of the period (*MIN.RET*) as a dependent variable in the regression. Note that in all the measures a larger positive value indicates a higher likelihood of having a stock price crash.

Chen *et al*. (2001) recurred to *DUVOL* and *NCSKEW* whereas Ak *et al*. (2016) used *NCSKEW*, *CRASH* and *MIN.RET* in their study. The variable *DUVOL* was also applied by Kim *et al*. (2011, 2019). There are some differences in these four measures. It is noteworthy that whereas *CRASH* and *MIN.RET* focus on the left side of the return's distribution, *DUVOL* or *NCSKEW* consider the overall distribution. Given its importance in the literature on stock price crashes, *DUVOL* will be our main variable of interest.

Table 2 presents the descriptive statistics of the crash measures described above.

Table 2: Descriptive statistics on the dependent variables

		DUVOL	NCSKEW	CRASH	MIN.RET
Obs.	Valid	16,793	16,801	16,751	16,800
	Missing	8	0	50	1
Mean		-0.144	0.015	3.682	2.50%
Median		-0.131	-0.033	2.938	1.90%
Std. Deviation		0.507	1.253	2.876	2.49%
Maximum		6.160	10.171	90.757	66.50%
Percentiles	5	-0.779	-1.556	1.520	0.90%
	95	0.522	1.898	8.169	6.00%

CRASH presents a mean value of 3.682 which means that the minimum daily return over a 6-month period averaged 3.682 standard deviations. The negative sign in the mean of *DUVOL* indicates that the stock returns in our sample present a positive skewness. The mean of the minimum daily returns over a 6-month period was -2.50% and the lowest return over a 6-month period was -66.50%.

Our independent variables include several factors already established in the literature as important determinants of stock price crashes. To avoid the look-ahead bias, the data regarding every independent variable is taken before the period in consideration. That is, to explain the stock price crash on period *t+1*, we use data that would be available to the investor in the previous period, *t*.

Following Callen and Fang (2015b), we use detrended turnover (*DTURNOVER*) as a measure for trading volume, which can be considered as a proxy for investors disagreement. Turnover is measured as the average monthly traded volume divided by the average monthly shares outstanding in the previous 6 months. To detrend the variable, we subtract the previous 6 months' turnover value.

As in Chen *et al.* (2001), past stock return (*PAST_RETURN*) is defined as the cumulative return of the company stock during the previous 6-month period. This return is measured as the log change in the return index of the stock and is then market-adjusted by the contemporaneous STOXX® Europe 600 cumulative return.

The market-to-book ratio (*MTB*) is the market capitalization divided by the latest available book value of equity provided by the database on the last day of the previous 6-month period (Ak *et al*., 2016).

Analyst coverage (*COVERAGE*) is measured as the logarithm of 1 plus the number of analysts following the company at the beginning of the period under analysis. The number of analysts following each company is measured by the number of earnings per share forecasts for the next year before the considered period. These data were collected in the I/B/E/S database.

We use the measure of scaled accruals proposed by Bhattacharya *et al*. (2003) to proxy for opacity (*OPACITY*). According to these authors, higher values of scaled accruals suggest higher earnings aggressiveness which can be thought of as an opacity measure.

In order to measure liquidity (*ILLIQUIDITY*), we compute the ratio between the bid-ask spread and price, as suggested by Huberman and Halka (2001).

Corporate social responsibility (*CSR*) was measured using a variant of the indicator suggested by Kim *et al*. (2014). ASSET4 Environmental, Social and Corporate Governance Data, through Thomson Reuters DataStream, provides an equal weighted average score to assess how well the company acts in areas such as environmental, social and corporate governance. The higher the value, the better the company performs in the respective area being that 100 is the maximum value. We use this measure as a percentage of the maximum value.

Forecasted sales growth (*SGROW*) is measured as in Ak *et al.* (2016). On the day before the beginning of each 6-month period, we collected the mean estimate for company sales for the following year (*FY1*) and for the year after (*FY2*) on I/B/E/S database. The variable considered is the ratio between *FY2* estimate and *FY1*, minus unity. Forecasted net margin growth (*NMGROW*) is measured as the forecasted net margin two years from the starting date minus the forecasted net margin one year after the starting period date.

Size (*SIZE*) is the logarithm of the market capitalization of the company on the day before the starting period and leverage (*LEVERAGE*) is measured as the ratio on total liabilities to total assets on the preceding day of period start.

Returns' volatility (*SIGMA*) is measured by the sample standard deviation of the daily logarithmic returns on the previous 6 months before the period starting date.

Finally, we include $DUVOL_{t-1}$, that is, the value of the variable *DUVOL* in the previous 6-month period as a control variable.

Table 3 shows the descriptive statistics of the independent variables that we have just described.

Table 3: Descriptive statistics on the independent variables

				Percentiles		
	Obs.	Mean	Std. Deviation	25	50	75
DTURNOVER	16,417	0.0011	0.0473	-0.0126	0.0004	0.0133
PAST_RETURN	16,753	0.0019	0.0888	-0.0398	0.0063	0.0508
MTB	16,290	2.8494	45.8424	1.2300	2.0300	3.3600
COVERAGE	16,654	1.2033	0.2682	1.1139	1.2553	1.3802
ILLIQUIDITY	16,720	0.0030	0.0045	0.0010	0.0017	0.0032
OPACITY	12,597	-0.0415	0.0941	-0.0737	-0.0400	-0.0088
CSR	15,247	0.7055	0.2701	0.5485	0.8248	0.9169
SGROW	16,416	0.0605	0.1435	0.0272	0.0496	0.0785
NMGROW	16,367	0.0020	4.2483	0.0008	0.0045	0.0108
SIZE	16,800	3.8360	0.5724	3.4052	3.7516	4.2163
LEVERAGE	16,611	0.6488	0.2333	0.5075	0.6409	0.7976
SIGMA	16,753	0.0085	0.0045	0.0056	0.0073	0.0099
DUVOL t-1	16,751	-0.1327	0.4172	-0.3621	-0.1301	0.1001

4. Empirical results

Table 4 shows the estimated coefficients in the linear regressions of crash variables measured over the subsequent 6-month period on crash forecasting variables.

Table 4: Regressions of crash variables on crash forecasting variables

	Panel A	**Panel B**	**Panel C**	**Panel D**
	Dependent variable = DUVOL	Dependent variable = NCSKEW	Dependent variable = CRASH	Dependent variable = MIN.RET
DTURNOVER (+)	0.020** (2.057)	0.018* (1.936)	-0.004 (-0.384)	0.008 (0.854)
PAST_RETURN (+)	0.076*** (7.298)	0.030*** (2.848)	-0.067*** (-6.519)	-0.080*** (-8.193)
MTB (+)	0.028*** (3.013)	0.045*** (4.808)	0.097*** (10.459)	0.131*** (14.867)
COVERAGE (+)	0.027** (2.401)	0.026** (2.329)	-0.004 (-0.354)	-0.028*** (-2.672)
ILLIQUIDITY (-)	-0.019* (-1.901)	0.013 (1.256)	-0.044*** (-4.435)	-0.003 (-0.292)
OPACITY (+)	-0.013 (-1.380)	-0.009 (-0.928)	-0.006 (-0.651)	-0.017* (-1.914)
CSR (-)	-0.003 (-0.291)	-0.001 (-0.097)	-0.003 (-0.335)	-0.027*** (-2.809)
SGROW (+)	0.024** (2.496)	0.018* (1.877)	0.041*** (4.287)	0.063*** (7.039)
NMGROW (+)	0.005 (0.555)	0.009 (0.923)	0.006 (0.672)	0.006 (0.696)
SIZE (+)	0.045*** (4.112)	0.013 (1.153)	-0.021* (-1.911)	-0.048*** (-4.601)
LEVERAGE (-)	-0.016* (-1.689)	-0.025*** (-2.614)	-0.002 (-0.261)	0.004 (0.420)
SIGMA (-)	-0.059*** (-5.944)	-0.012 (-1.226)	-0.139*** (-14.166)	0.288*** (31.094)
$DUVOL_{t-1}$ (+)	0.041*** (4.077)	0.038*** (3.789)	0.002 (0.175)	-0.004 (-0.404)
Adjusted R^2	0.018	0.005	0.033	0.134

Notes: *DTURNOVER* is the monthly average value of the traded volume divided by the number of shares outstanding in the previous 6-month period detrended by the same measure observed in the previous 6 months. *PAST_RETURN* is the cumulative return of the stock during the previous 6-month period. *MTB* is the inverse of the market-to-book value on the last day of the previous 6-month period. *COVERAGE* is the log of unity plus the number of analysts following the company at the beginning of the period under analysis. *OPACITY* is the scaled accruals. *ILLIQUIDITY* is the average bid-ask spread scaled by the stock price. *CSR* is the score provided by ASSET4. *SGROW* is the ratio of the sales forecast for the next year divided by the sales forecast for the present year minus unity. *NMGROW* is the forecasted change in margin for the next year. *SIZE* is the logarithm of the market capitalization at the beginning of the respective period. *LEVERAGE* is the ratio of total liabilities to total assets. *SIGMA* is the sample standard deviation of returns in the previous period. $DUVOL_{t-1}$ is the variable *DUVOL* in the previous period. t-statistics in parenthesis. Intercept not shown. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.

In panel A, we can observe that the coefficients related to the variables *DTURNOVER*, *PAST_RETURN*, *MTB*, *ILLIQUIDITY*, *SGROW*, *SIZE*, *SIGMA* and $DUVOL_{t-1}$ have the expected sign and are statistically significant at the level of 5%. These results corroborate the evidence presented by Chen *et al*., (2001) and Callen and Fan (2013, 2015b). The variable *LEVERAGE* is also statistically significant, but only at the level of 10%. When the dependent variable is *NCSKEW*, the results remain fairly consistent with the previous regression. The statistically significant variables at the 5% level are now *PAST RETURN*, *MTB*, *COVERAGE*, *LEVERAGE* and $DUVOL_{t-1}$. *SGROW* is also statistically significant but only at the 10% level. In panel C, that is, in the regression that has *CRASH* as the dependent variable, the only variables that present a coefficient with the expected sign and are statistically significant at the conventional levels are *MTB*, *ILLIQUIDITY*, *SGROW* and *SIGMA*. Regarding the last regression, in panel D, the only coefficients that fulfil these conditions relate to the variables *MTB*, *CSR* and *SGROW*. The remaining variables are either not significant at conventional levels of significance or have a sign that is contrary to expectations. Overall, the results show that the determinants of crash risk seem to depend critically on the way that risk is measured.

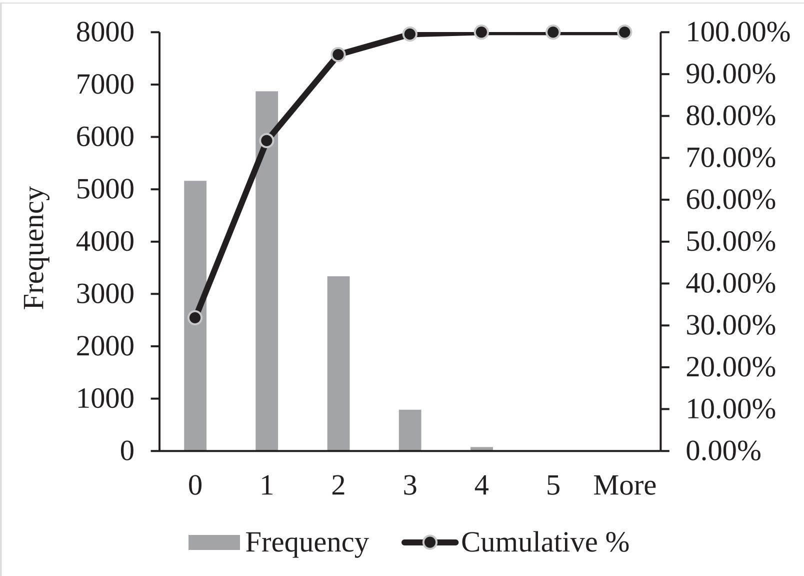
5. Investment implications

5.1. Strategy

Having determined the key predictors of crash risk, we next investigate whether we could have used those predictors to achieve a better risk-adjusted result and to reduce the incidence of high crash-prone stocks in the portfolio. In order to test that we will apply a set of investment rules based on the results obtained in the previous section. Following the framework proposed by Ak *et al*. (2016), we start by identifying the most significant crash predictors. Given the importance of the variable *DUVOL* in the literature on stock price crashes, we select the five most significant variables in panel A of table 4 as the key predictors of crash risk: *PAST_RETURN*, *SIGMA*, *SIZE*, $DUVOL_{t-1}$ and *MTB*. Next, we rank stocks on each of the five predictors of crashes at the beginning of each semester. Then, we select the top 20% of stocks most likely to crash based in each variable. In order to do that, we choose the top 20% of stocks ranked on *PAST_RETURN*, *SIZE*, $DUVOL_{t-1}$ and *MTB* and the bottom 20% ranked on *SIGMA*. Hence, if a stock belongs to one of these groups, we classify it has having one crash-flag. Thus, a stock can have between 0 and 5 crash-flags being that, the more crash-flags a stock has, the more crash-prone it is.

Figure 1 shows the frequency of crash flags during a period of 28 semesters.

Figure 1: Frequency of crash flags



Notes: the figure shows the frequency analysis for the observations with 0, 1, 2, 3,4 or 5 crash-flags. On the left Y-axis, it is represented the frequency of each observation by number of crash-flags. The right Y-axis, indicates the cumulative percentage of the number of crash flags.

There is a high percentage of observations with zero or one crash flags (32% and 42%, respectively); only about 26% of the stocks in the sample have two or more crash flags.

Table 5 presents the equal-weighted mean value of various crash risk measures for the six-month period following the classification of firms into different crash risk groupings, according to the number of crash flags.

Table 5: Mean value of crash measures for the following six-month period according to the number of crash flags

Crash Flags	N. Obs.	DUVOL	NCSKEW	CRASH	MIN.RET
0	31.786%	-0.167	-0.042	3.581	-2.741%
1	42.309%	-0.139	0.029	3.672	-2.470%
2	20.554%	-0.126	0.059	3.797	-2.225%
3	4.865%	-0.084	0.082	3.865	-2.088%
4	0.474%	-0.082	0.236	4.051	-1.824%
5	0.012%	0.066	0.148	4.162	-1.850%

Table 5 shows that the value of the variables *DUVOL* and *CRASH* increases monotonically in each of the groups of stocks as the number of crash flags increases. However, in the case of the crash predictor *NCSKEW* the mean value of the variable is higher in the group of stocks with four crash flags than in the group of stocks with five crash flags. This result, however, is not very significant since there are only two stocks in our sample with five crash flags. In the case of the *MIN.RET* variable, one would expect the absolute value of the variable to decrease as the number of crash flags increases. And this happens with the exception, again, of the groups of stocks with four and five crash flags. In additional analyses (not reported) we could verify that this is due to the choice of the *SIGMA* variable as predictor of crash risk.

To assess whether our predictive variables can provide some useful guidance to portfolio's management activities, we start by organizing, all the stocks according to the number of crash-flags at the beginning of each 6-month period. Thus, we create two distinct equal-weighted portfolios: a "high-crash-risk" portfolio that gathers stocks with more than two crash flags, and a "low-crash-risk" portfolio that comprises the stocks with less than three cash flags. Once the portfolios are built, we assume that the they will remain unchanged over the following 6 months. Then, at the beginning of the next period, the portfolios are rebalanced in order to accommodate the changes of the predictors.

5.2. Results

Figure 2 depicts the performance of the high-crash-risk portfolio, the low-crash-risk portfolio and the STOXX600 index

Figure 2: Portfolio value of the high-crash-risk portfolio, the low-crash-risk portfolio and the STOXX600 index

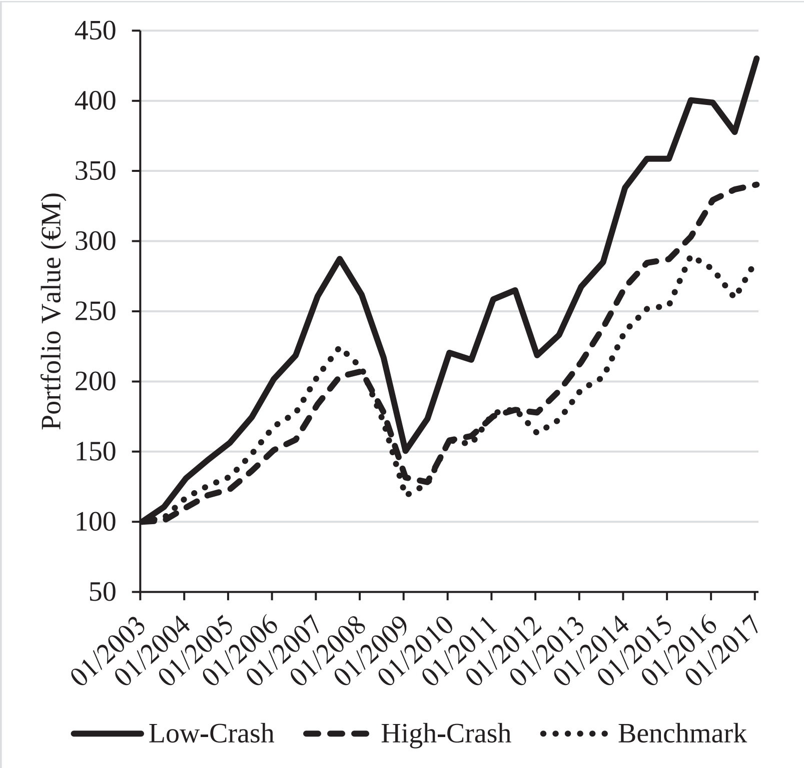


Figure 2 shows that the selection methodology of the low-crash portfolio provided higher returns than both the high-crash-portfolio and the benchmark. More specifically, 100M€ invested in each portfolio, rebalanced at the beginning of each semester ignoring transaction costs, would result in approximately 430€M had we invested in the low-crash portfolio, 340€M had we in the high-crash portfolio and 287€M had we invested in the benchmark.

Table 6 shows the performance of the high-crash-risk portfolio and of the low-crash-risk portfolio considering the parameters of risk and return.

Table 6: Performance of portfolios built following a crash flag strategy

	Low-crash-risk portfolio	High-crash-risk portfolio
Excess return	12.06%	8.51%
Volatility	20.78%	17.06%
Sharpe Ratio	0.5804	0.4986
Vs. STOXX600 index:		
Beta	1.135	0.734
Alpha	5.12%	4.84%
Tracking Error	6.78%	10.82%

Notes: the excess return was calculated as the average annualized return for each period subtracted by the corresponding 3-month UK bill as risk-free rate. Volatility is measured as the annualized value of the daily standard deviation of the portfolio returns. Sharpe ratio is the ratio between the two previous measures.

Besides achieving a higher return, the low-crash-risk portfolio based on the crash flag strategy described above yielded a better risk-adjusted performance measured by the Sharpe ratio. Both the overall risk and the systematic risk of the low-crash-risk portfolio are higher but it seems that they are more than compensated by a higher return. The lower tracking error of the low-crash-risk portfolio indicates that it follows more closely the benchmark.

Overall, it is fair to conclude that even though *DUVOL* is a widely used measure in the stock price crash literature, using it as a basis for a strategy like that described in this chapter in the context of the European markets, does not seem to be effective at avoiding stock price crashes. Nevertheless, the strategy would allow investor to improve the risk-adjusted performance of their portfolio.

6. Conclusion

Stock price crashes are one of the most important events from the portfolio manager's perspective as they can imply significant losses. For this reason, it is essential to try to identify in advance the securities that are most likely to crash.

In this chapter we examined the determinants of the stock price crash at the level of individual stocks in a sample of European securities covering the period 2003-2016. Our multivariate analysis shows that the results vary according to the adopted crash measure. In addition, it was found that variables that capture the stock's past return, its volatility, its size, and the relationship between market capitalization and book value (market-to-book ratio) are the main predictors of the crash risk. A strategy based on these variables would allow the investor to create a portfolio with a better performance measured by the Sharpe ratio. Although the strategy was successful in providing higher risk-adjusted returns, it was not able to reduce the incidence of stock price crashes.

There is much to be investigated regarding the crash risk in European stock markets. Further avenues for research may include repeating the tests for a larger sample and studying the importance of the Great Financial Crisis in the patterns of predictability of crashes.

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CHAPTER 6

TESTING THE POST-EARNINGS ANNOUNCEMENT DRIFT IN A SAMPLE OF LARGE EUROPEAN STOCKS

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Abstract

This chapter analyzes the stock prices responses to annual and interim earnings announcements made by a sample of European firms included in the EURO STOXX 50 index, with the purpose of determining if the disclosure of such information is efficiently incorporated into stock prices. Our results suggest that earnings announcements convey useful information for the determination of stock prices and that investors are able to anticipate the nature of the earnings surprise (positive or negative surprise) as prices reflect some of the content of the announcements before the formal disclosures. A substantial impact is observed in the event day and in the following day, not only on returns but also on trading volume. Although there are signs of a post-earnings announcement drift in the case of the good news stocks, we think that the size of the phenomenon is not sufficient to

create a profitable trading rule. Overall, our results are illustrative of the power of arbitrage in the case of the stocks with greater visibility in the European context.

Key-words: post earnings announcement drift, large stocks, Europe, arbitrage

1. Introduction

The post-earnings announcement drift (PEAD) is the empirical finding that after earnings are announced, estimated abnormal returns continue to drift up for "good news" and down for "bad news". This phenomenon is widely considered to be a challenge to the semi-strong version of the efficient market hypothesis. The revision of expectations regarding future earnings implies that investors' expectations regarding such earnings are less than perfectly accurate. The PEAD is usually attributed to some form of underreaction to the information contained in the earnings disclosure. Alternative explanations based on risk or research design flaws have been rejected (Bernard and Thomas, 1989).

The PEAD was firstly described by Ball and Brown (1968) and a number of authors have subsequently corroborated their results for the US market (Bernard and Thomas, 1989, 1990; Chan *et al*., 1998). However, the evidence regarding the PEAD in European stock markets is still relatively scarce.

In this chapter we fill this gap by measuring the stock prices responses to annual and interim earnings announcements made by a sample of large European firms. We recurred to the notions of abnormal return and abnormal trading volume at the time of the disclosure to quantify the degree of market surprise.

Our results indicate that earnings announcements convey useful information for the determination of stock prices and that investors are able to anticipate the nature of the earnings surprise, i.e., whether it is a positive or negative surprise. A substantial impact is observed in the event day and in the following day, not only on returns but also on trading volume. Although there are signs of a post-earnings announcement drift in the case of the good news stocks, in general our results are consistent with the semi-strong form of market efficiency.

The remainder of this chapter is organized as follows: section 2 presents the literature review and section 3 addresses the methodological aspects, namely the data used in the study and the methods followed in the empirical study. The fourth section discusses the empirical results and the last section concludes the chapter.

2. Literature Review

Ball and Brown (1968) detected the PEAD over the period 1957-1965 in a sample of 261 US firms. Foster *et al*. (1984) corroborate the results presented Ball and Brown (1968) finding that over the 60 trading days after an earnings disclosure, a long position in stocks with highly positive unexpected earnings, combined with a short position in stocks with highly negative unexpected earnings, produces an annualized abnormal return of 25%.

Frost and Pownall (1994) compared the strength of the post-earnings drift in fourteen different countries, including the US and the UK. They concluded that the stock price response to earnings announcements is significantly greater in the US than in the UK. They attribute the differences in the intensity of the effect to microstructure factors, mainly related to market liquidity. Hew *et al*. (1996) document that the PEAD exists in the UK but only for the earnings announcements of small firms.

The studies concerning the prevalence of the PEAD in Continental European stock markets are relatively scarce. This lack of studies has been attributed to the fact that Continental European accounting practices have been designed primarily for users other than investors and also because the market of investment analysts is relatively less developed (Pellicer and Rees, 1999). Kallunki (1996) reports a significant delay in the stock market's reaction to the Finnish firm's earnings especially in the case of negative information. Considering 139 annual announcements for 52 Polish firms, Jermakowicz and Tomaszewski (1998) provide evidence of a significant association between stock returns and annual earnings. Pellicer and Rees (1999) examined the Spanish stock market during the period 1991-1995 to conclude that a trading strategy based on earnings disclosures would produce abnormal returns in a context of higher volatility. They attribute these results to the neglect of value-relevant information by unsophisticated investors. Sponholtz (2008) investigated the reaction to earnings disclosures in Denmark, finding significant positive abnormal returns in the days of the announcements. van On the other hand, Huffel *et al*. (2009) did not find any systematic PEAD to semi-annual announcements in the Belgian stock market. More recently, Gerard (2012) report a positive association between earnings surprises and future abnormal returns in a sample of European companies over the period 1997-2010. The author concludes that information uncertainties play an important role in determining the premiums earned by PEAD strategies. We add to this literature be scrutinizing the reaction of a sample of large European stocks to earnings announcements in the period after the global financial crisis.

In our study we also examine the trading volume around earnings disclosures. Beaver (1968) found a dramatic volume reaction to the announcement of earnings which is suggestive that investors do look directly at reported earnings and do not use other variables to the exclusion of reported earnings. Bamber (1987) concludes that the duration of volume adjustment to earnings disclosures is an increasing function of unexpected earnings magnitude. Landsman and Maydew (2001) corroborate these results in a more recent US sample. We contribute to this literature by examining the reaction of trading volume to the disclosure of earnings on a large sample of European stocks.

3. Data and Methodology

3.1. Data

Our sample includes all the stocks listed for more than one year in the EURO STOXX 50 index over the sample period, that is, from August 15, 2012 to December 31, 2017. Due to lack of data, the following three stocks were an exception to this rule, being excluded from the final sample: Osram Licht, Intesa Sanpaolo and Unilever. To avoid survivorship bias, we made sure that all the stocks eventually delisted during the sample period were included in our study provided that they had been listed for more than one year. The final sample includes 51 European stocks.

All European companies included in the EURO STOXX 50 index must report their financial information according to the IFRS (International Financial Reporting Standards). We focus on annual and interim earnings reports (quarterly and half-year reports) since firms disclose earnings at regular intervals. Data regarding earnings announcement's dates, fiscal year-end reports and interim reports, which includes quarterly, half-year and yearly reports, are needed to conduct the empirical study. This information, together with data concerning stock turnover, historical prices and earnings announcement dates was obtained from Thomson Reuters Datastream.

Over our sample period, we considered a total of 944 earnings announcement. Table 1 provides data on the different types of news events that were collected.

Table 1 - Earnings Announcements: description by frequency

Earnings Announcements	Annual earnings	Half-Yearly earnings	Quarterly earnings	Total
Number of announcements Frequency	153 16.21%	99 10.49%	692 73.30%	944 100%

Following the criteria suggested by MacKinlay (1997), we divided the announcements sample into three categories: good news, bad news and no news. Table 2 describes the frequency of each one of the news event categories in our sample.

Table 2 - Earnings Announcements Description by News Outcome

Earnings Announcements	Good News	No News	Bad News	Total
Number of announcements Frequency	480 50.85%	5 0.53%	459 48.62%	944 100%

3.2. Methodology

In this study we recur to the event studies methodology to examine the impact of the event (in the case, the announcement of earnings) on the event date (day zero) that is, on the day when the earnings were disclosed, and in the days that surround the event date. Therefore, the methodology is based on the construction of an event window to assess the price changes before and after an earnings announcement, as well as the calculation of abnormal returns. We consider an event window of 41 days, which includes 20 days before the event, the event day, and 20 days after the earnings disclosure. In addition, we analyse the evolution in the trading volume to assess whether this variable presented significant differences in the period around the event date. We follow MacKinlay (1997) in the analysis of abnormal returns and Beaver (1968) in the examination of trading volume.

Regarding the price returns analysis, we use the market model to measure the expected (normal) performance of the assets under scrutiny, considering the EURO STOXX 50 index as the proxy of the market portfolio. The market model defines the relationship between the normal return of a certain security i and the return of the market portfolio R_{mt}, as follows:

$$\mathbf{R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}}$$

where:

R_{it} is the normal return of a security i in the period t,
β_i and α_i are the market model parameters,
R_{mt} is the return of the market portfolio in the period t, and
ε_{it} is the zero mean disturbance term.

Consequently, the abnormal returns can be defined as follows:

$$\mathbf{AR_{it} = R_{it} - E(R_{it})}$$

where:

AR_{it} is the abnormal return of a security i in the period t,
$E(R_{it}) = \widehat{\alpha_i} + \widehat{\beta_i} R_{mt}$, which are the expected returns of a security i in the period t, and
$\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated market model parameters.

In this event study, the estimation window is [-140, -21], that is, to estimate the parameters of the market model we use the observations comprised in the period that begins 140 days before the event date and that ends 21 days before the event date. Ordinary least squares (OLS) are used for the estimation procedure.

Under the null hypothesis (H_0) that the event has no impact on the evolution of stock price returns, the distribution of the sample abnormal return of a given observation in the event window is assumed to be:

$$\mathbf{AR_{it} \sim N\left(0, \sigma^2(AR_{it})\right)}$$

where:

$$\mathbf{\sigma^2(AR_{it}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}\left[\frac{1 + (R_{mt} - \widehat{u_m})^2}{\hat{\sigma}^2_m}\right]}$$

where:

L is the estimation window,
σ_m^2 is the variance of the market returns during the estimation window,
$\hat{u}_m$ is the mean of the market returns, during the estimation window, that is, $\frac{1}{L_1}\sum_{t=\,t_0+1}^{t_1} R_{mt}$, and
$\sigma_{\varepsilon_i}^2$ is the disturbance variance of a given security i, being $\frac{1}{L-2}\sum_{t=t_0+1}^{t_1}(R_i - \hat{\alpha}_i - \hat{\beta}_i R_{mt})^2$.

As the length of the estimation window (L) increases, $\frac{1}{L_1}\left[\frac{1+(R_{mt}-\widehat{u_m})^2}{\hat{\sigma}_m^2}\right]$ approaches zero as the sampling error of the parameters approach zero and the variance of the abnormal return is then given by:

$$\sigma^2(AR_{it}) = \sigma_{\varepsilon_i}^2$$

The abnormal return observations must be aggregated in order to draw inferences for the event of interest (MacKinlay, 1997). Considering the aggregation through time, we compute the Cumulative Abnormal Return (CAR_i). The (CAR_i) from $t_1$to t_2, where $t_1 \leq t_2$, can be defined as the sum of all abnormal returns for the considered time period:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

The distribution of the CAR_i under the null hypothesis that the event has no impact on the evolution of the returns is defined as follows:

$$CAR_i(t_1, t_2) \sim N(0, \sigma_{\varepsilon_i}^2(t_1, t_2))$$

where:

$$\sigma_i^2(t_1, t_2) = (t_2 - t_1 + 1)\sigma_{\varepsilon_i}^2$$

Considering the aggregation of abnormal returns across assets, we use the average abnormal returns ($\overline{AR}$). Considering N events and assuming that there is no overlapping of event windows for the included assets, we estimate the aggregate abnormal returns as follows:

$$\overline{\mathrm{AR}_{\mathrm{t}}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{AR}_{\mathrm{it}}$$

The variance of $\overline{AR}$ is defined as:

$$\mathrm{Var}\,(\overline{\mathrm{AR}_{\mathrm{t}}}) = \frac{1}{\mathrm{N}^2} \sum_{\mathrm{i}=1}^{\mathrm{N}} \sigma_{\varepsilon_{\mathrm{i}}}^2$$

Analogously, the cumulative abnormal return and its variance for any interval in the event windows can be defined as:

$$\overline{\mathrm{CAR}}(\mathrm{t}_1, \mathrm{t}_2) = \sum_{\mathrm{t}=\mathrm{t}_1}^{\mathrm{t}_2} \overline{\mathrm{AR}_{\mathrm{t}}}$$

$$\mathrm{Var}\big(\overline{\mathrm{CAR}}(\mathrm{t}_1, \mathrm{t}_2)\big) = \sum_{\mathrm{t}=\mathrm{t}_1}^{\mathrm{t}_2} \mathrm{Var}(\overline{\mathrm{AR}_{\mathrm{t}}})$$

The null hypothesis (H_0) of the event having no impact on stock price returns can be tested using:

$$\theta_1 = \frac{\overline{\mathrm{AR}_{\mathrm{t}}}}{\mathrm{Var}(\overline{\mathrm{AR}_{\mathrm{t}}})^{\frac{1}{2}}} \sim \mathrm{N}(0{,}1)$$

After testing the impact of the earnings announcements, through the calculation of the abnormal returns, on the security prices it is also important to measure the effect of the news events on the trading volume.

In addition, the analysis to obtain the abnormal trading volume is carried out, also using the market model. Thus, according to Beaver (1968), the abnormal trading volume can be defined as follows:

$$AV_{it} = V_{it} - E(V_{it})$$

where:

V_{it} is the actual trading volume of a certain security *i* in the period *t*, and $E(V_{it}) = \widehat{\alpha}_i + \widehat{\beta}_i V_{mt}$ is the expected trading volume of a given security *i* in the period *t*, computed using the market model.

The actual trading volume can be computed as follows:

$$V_{it} = \frac{number\ of\ shares\ of\ firm\ i\ traded\ in\ day\ t}{number\ of\ shares\ outstanding\ for\ firm\ i\ in\ day\ t}$$

Thus, the abnormal trading volume is defined as:

$$AV_{it} = V_{it} - \hat{\alpha}_i - \hat{\beta}_i V_{mt}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated model parameters.

Analogously, given N events, the average abnormal trading volume $\overline{(AV_t)}$ for the period *t* can be defined as:

$$\overline{AV_t} = \frac{1}{N}\sum_{i=1}^{N} AV_{it}$$

The inferences regarding the impact of the event of interest on the trading volume can be made using:

$$\theta_2 = \frac{\overline{AV_t}}{Var(\overline{AV_t})^{\frac{1}{2}}} \sim N(0,1)$$

where the variables have the same meaning defined above.

4. Empirical results

4.1. Stock price returns analysis

Considering that α_{it} was not statistically significant at a 5% significance level for the stocks included in the sample, we decided to adopt the following model for the analysis of the abnormal returns:

$$R_{it} = \beta_i R_{mt} + \varepsilon_{it}$$

Table 3 presents the descriptive statistics of the market model estimation.

Table 3 – Descriptive Statistics for the Market Model Estimation: abnormal returns

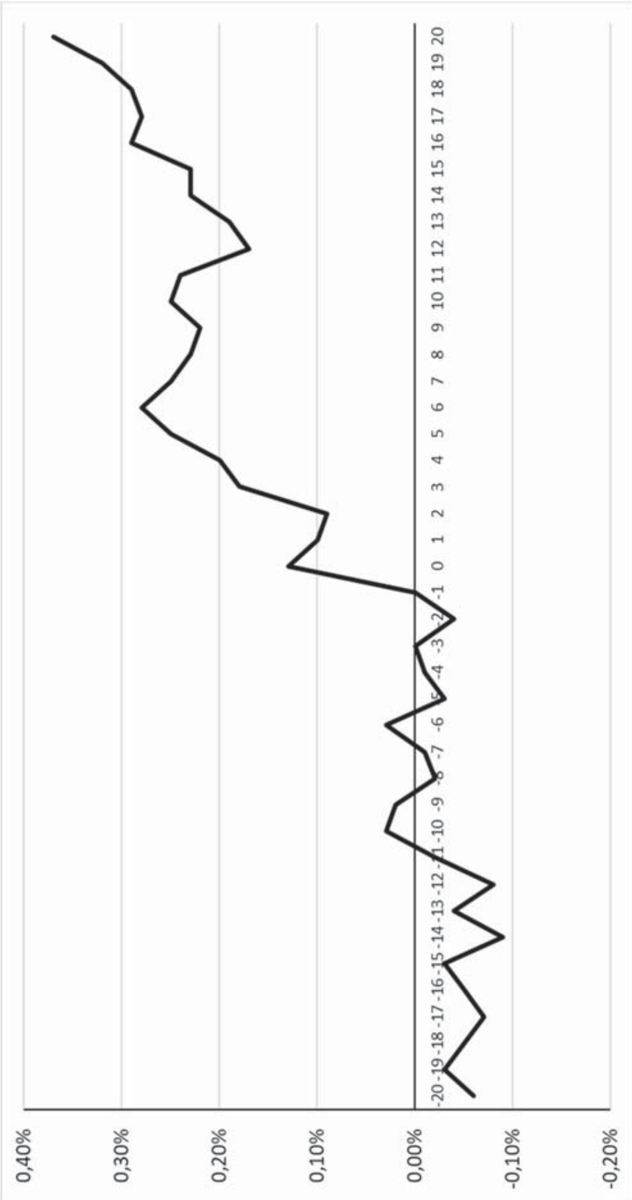
	Mean	Standard Deviation
Daily stock returns (R_{it})	0.04%	1.70%
R-squared (R^2)	0.4868	0.2006
Beta (β_{it})	0.9697	0.3419

The average R^2 obtained during the data analysis implies that only 48.68% of the daily stock returns are explained by the EURO STOXX 50 index. Subsequently, we determined the daily abnormal returns for every stock and event period as well as the cumulative abnormal returns. Figure 1 presents the cumulative average abnormal returns for all 944 earnings announcements in the 41-day event window.

The positive cumulative average abnormal returns observed after the earnings announcements indicate that investors consider this piece of information to be a positive signal for the shareholder value.

Table 4 presents the average abnormal returns, the cumulative average abnormal returns and the corresponding estimated statistics for each event day.

Figure 1 – All earnings announcements - cumulative average abnormal returns



Source: Authors' elaboration

Table 4 – Average abnormal returns and cumulative average abnormal returns

Event Day	$\overline{AR}$	θ_1	$\overline{CAR}$
-20	-0.06%	**-2.7843***	-0.06%
-19	0.03%	1.3408	-0.03%
-18	-0.02%	**-9.5499***	-0.05%
-17	-0.02%	**-7.8997***	-0.07%
-16	0.02%	1.1525	-0.05%
-15	0.02%	1.1860	-0.03%
-14	-0.06%	**-2.6830***	-0.09%
-13	0.05%	1.5134	-0.04%
-12	-0.04%	**-3.5719***	-0.08%
-11	0.06%	1.5531	-0.02%
-10	0.05%	1.4897	0.03%
-9	-0.01%	**-3.0806***	0.02%
-8	-0.04%	**-3.2739***	-0.02%
-7	0.01%	0.9695	-0.01%
-6	0.04%	1.4675	0.03%
-5	-0.06%	**-2.8054***	-0.03%
-4	0.02%	1.1667	-0.01%
-3	0.01%	**18.5163***	0.00%
-2	-0.04%	**-3.5132***	-0.04%
-1	0.04%	1.3849	0.00%
0	0.13%	1.7795	0.13%
+1	-0.03%	**-3.9526***	0.10%
+2	-0.01%	**-13.8889***	0.09%
+3	0.09%	1.7058	0.18%
+4	0.02%	1.2212	0.20%
+5	0.05%	1.5066	0.25%
+6	0.03%	1.3311	0.28%
+7	-0.03%	**-4.2503***	0.25%
+8	-0.02%	**-43.2213***	0.23%
+9	-0.01%	**-7.4108***	0.22%
+10	0.03%	**7.3980***	0.25%
+11	-0.01%	**-4.6211***	0.24%
+12	-0.07%	**-2.6070***	0.17%
+13	0.02%	1.2217	0.19%
+14	0.04%	1.4735	0.23%
+15	0.00%	-0.0257	0.23%

+16	0.06%	1.5795	0.29%
+17	-0.01%	**-8.9392***	0.28%
+18	0.01%	0.8461	0.29%
+19	0.03%	1.3661	0.32%
+20	0.05%	1.4895	0.37%

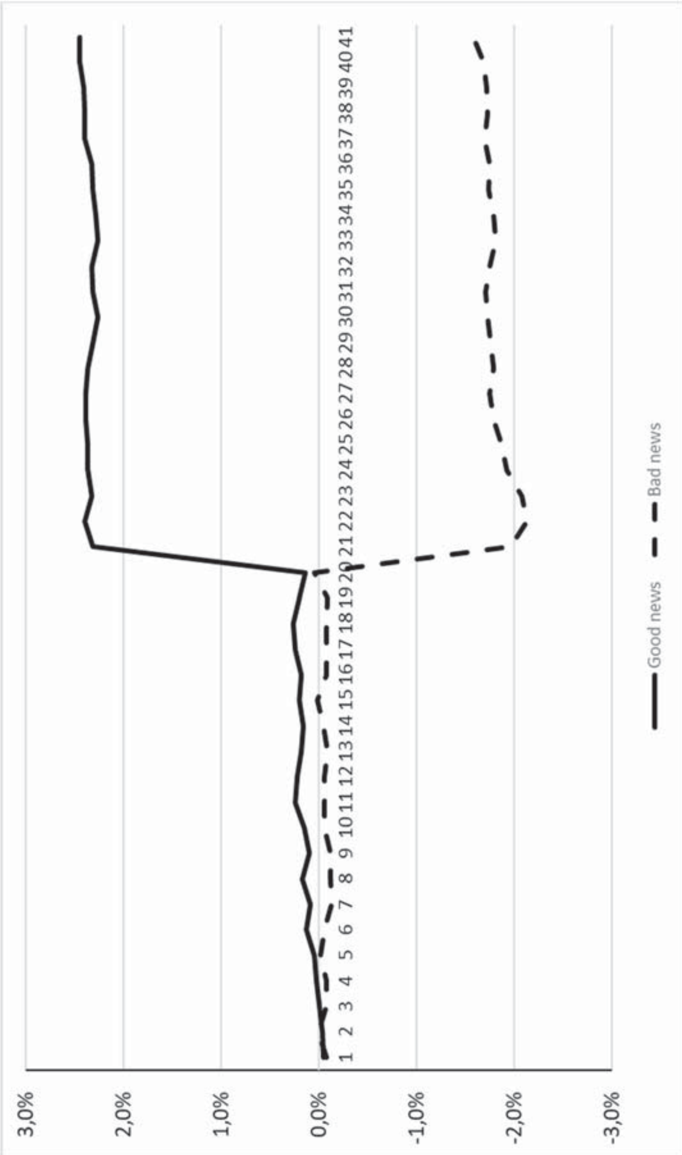
* Parameters statistically significant at a 1% significance level.

These results comprise every earnings announcement in our sample, be it good news, bad news or no relevant news. The evidence indicates the existence of a statistically significant negative average abnormal return in the two days that follow the event day, leading us to conclude that the null hypothesis that the event has no impact on stock returns is reject with a 1% confidence level. It is also noteworthy that the average abnormal return in the event day (day 0), although positive, it is not statistically different from zero at the conventional levels of statistical significance. All in all, we can conclude that these results imply that European stocks reacted negatively to the earnings disclosure, right after the formal announcement.

We also computed the same statistics considering the good and bad news categorization. As mentioned before, the final sample for the event study analysis consisted of 480 good news stocks, 459 bad news stock and five stocks with no news. Due to the small number of events related to no news and the relative irrelevance of these results to the debate about market efficiency we decided not to comment these events in the following analysis.

Figure 2 presents a visual illustration of the cumulative average abnormal returns in the event window for the good news stocks and for the bad news stocks, respectively.

Figure 2 – Good and bad news announcements - cumulative average abnormal returns



Source: Authors' elaboration

It is clearly observable in Figure 2 that earnings disclosures do have a great value relevance, as both the curves present steep shifts in the event date.

Tables 5 and 6 provide the results of the average abnormal returns and cumulative average abnormal returns.

Table 5 - Average abnormal returns and cumulative average abnormal returns: good news stocks

Event Day	$\overline{AR}$	θ_1	$\overline{CAR}$
-20	- 0.04%	-1.2107	-0..04%
-19	0.01%	-0.5991	-0..03%
-18	0.03%	**34.3781***	0..00%
-17	0.03%	-1.0525	0..03%
-16	0.02%	-0.7153	0..05%
-15	0.08%	**3.0031***	0..13%
-14	- 0.04%	-1.2308	0..09%
-13	0.08%	**3.0668***	0..17%
-12	- 0.07%	-1.4267	0..10%
-11	0.05%	**4.7654***	0..15%
-10	0.09%	**2.8776***	0..24%
-9	- 0.02%	-0.7139	0..22%
-8	- 0.04%	-1.2094	0..18%
-7	- 0.02%	-0.7961	0..16%
-6	0.04%	**9.3805***	0..20%
-5	- 0.02%	-0.8595	0..18%
-4	0.06%	**3.7621***	0..24%
-3	0.03%	**18.1460***	0..27%
-2	- 0.07%	-1.4286	0..20%
-1	- 0.06%	-1.3518	0..14%
0	2.17%	**2.0258***	2..31%

+1	0.09%	**2.8269***	2..40%
+2	-0.07%	-1.4448	2..33%
+3	0.04%	**7.1508***	2..37%
+4	0.00%	0.3440	2..37%
+5	0.02%	**2.3973***	2..39%
+6	0.00%	0.1715	2..39%
+7	-0.02%	-0.8872	2..37%
+8	-0.06%	-1.3582	2..31%
+9	-0.05%	-1.2687	2..26%
+10	0.05%	**5.0294***	2..31%
+11	0.02%	**3.2527***	2..33%
+12	-0.07%	-1.4427	2..26%
+13	0.02%	**9.4521***	2..28%
+14	0.04%	**5.4975***	2..32%
+15	0.01%	0.9214	2..33%
+16	0.07%	**3.2358***	2..40%
+17	0.00%	0.0758	2..40%
+18	0.01%	1.0481	2..41%
+19	0.04%	**8.3800***	2..45%
+20	0.00%	0.2402	2..45%

* Parameters statistically significant at a 1% significance level

Table 6 - Average abnormal returns and cumulative average abnormal returns: bad news stocks

Event Day	$\overline{AR}$	θ_1	$\overline{CAR}$
-20	-0.07%	**-10.3079***	-0.07%
-19	0.08%	1.1666	0.01%
-18	-0.08%	**-7.4109***	-0.07%
-17	-0.01%	-0.6334	-0.08%
-16	0.07%	1.0789	-0.01%
-15	-0.04%	**-6.0421***	-0.05%
-14	-0.08%	**-7.1314***	-0.13%
-13	0.01%	0.4161	-0.12%

-12	0.00%	-0.0141	-0.12%
-11	0.07%	1.0972	-0.05%
-10	0.00%	0.1568	-0.05%
-9	0.00%	**-7.6900***	-0.05%
-8	-0.04%	**-4.6893***	-0.09%
-7	0.05%	0.9759	-0.04%
-6	0.06%	0.9884	0.02%
-5	-0.09%	**-5.4162***	-0.07%
-4	-0.01%	-0.5088	-0.08%
-3	0.00%	0.0324	-0.08%
-2	-0.01%	-0.2570	-0.09%
-1	0.14%	1.4091	0.05%
0	-2.01%	**-2.0583***	-1.96%
+1	-0.16%	**-3.0791***	-2.12%
+2	0.05%	0.9109	-2.07%
+3	0.15%	1.4552	-1.92%
+4	0.05%	0.9077	-1.87%
+5	0.08%	1.1645	-1.79%
+6	0.05%	0.9767	-1.74%
+7	-0.04%	**-4.0222***	-1.78%
+8	0.03%	0.7512	-1.75%
+9	0.03%	0.6652	-1.72%
+10	0.02%	0.5560	-1.70%
+11	-0.04%	**-4.5591***	-1.74%
+12	-0.07%	**-13.9321***	-1.81%
+13	0.03%	0.7010	-1.78%
+14	0.05%	0.8990	-1.73%
+15	-0.01%	-0.2242	-1.74%
+16	0.05%	0.9121	-1.69%
+17	-0.03%	-1.8032	-1.72%
+18	0.01%	0.3099	-1.71%
+19	0.03%	0.7059	-1.68%
+20	0.10%	1.2584	-1.58%

* Parameters statistically significant at a 1% significance level

The results presented in Tables 5 and 6 confirm the significant abnormal returns (at 1% significance level) on the event date and also on day +1. This means that the null hypothesis that the average abnormal returns in day 0 and day +1 are equal to zero is strongly rejected for both good and bad news stocks. Therefore, the information contained in earnings disclosures has a significant impact on returns. The significant average abnormal return in the day after the event day is consistent with an adjustment of the investors' portfolio. Moreover, the PEAD anomaly seems to be present but only among the good news stocks, as the average abnormal returns for those stocks are positive in fifteen of the twenty days subsequent to the event day. In nine of those fifteen event days, the average abnormal return is statistically different from zero and the cumulative average abnormal return increases from 2.31% in the event day to 2.45% in day +20. On the other hand, the panorama of bad news stocks is significantly different. These stocks experience statistically significant negative abnormal returns on the event day and on day +1. However, in the following days the average abnormal returns tend to be positive, although not statistically significant at the conventional levels of significance. So, they seem to exhibit a slight positive drift and the cumulative average abnormal return increases from -1.96% in the event day to -1.58% in day +20. This implies that the market may actually overreact to the negative earnings surprises on the event day and day +1, after which a price correction takes place. An analogous behavior is not observable with the good news stock as the positive drift among them suggests an underreaction to the earnings disclosure.

It is also noteworthy that both groups of stocks experience statistically significant average abnormal returns before the event date. In the case of the good news stocks, those average abnormal returns are significantly positive in eight of the trading days that precede the event date; in the case of the bad news stocks, the average abnormal returns are significantly negative in seven of the days that antecede the event day. This suggests that investors seem to have correctly anticipated the news beforehand. According to MacKinlay (1997), it is possible that the market may acquire information about the earnings before their formal announcement and that that may be reflected in the pre-event returns, as in the sample of this study. For example, analysts' forecasts and press releases may convey valuable information to investors about the upcoming earnings announcements. However, in spite of that, our results show that the market could not anticipate all the information since, as we have seen, the investors react greatly to the earnings disclosures.

4.2. Trading volume analysis

To examine the trading volume reaction over the event window and following the methodology proposed by Beaver's (1968), we firstly estimated the market model to determine the expected trading volume. Table 7 presents the descriptive statistics for the estimation.

Table 7 – Descriptive Statistics for the Market Model Estimation (Abnormal Trading Volume)

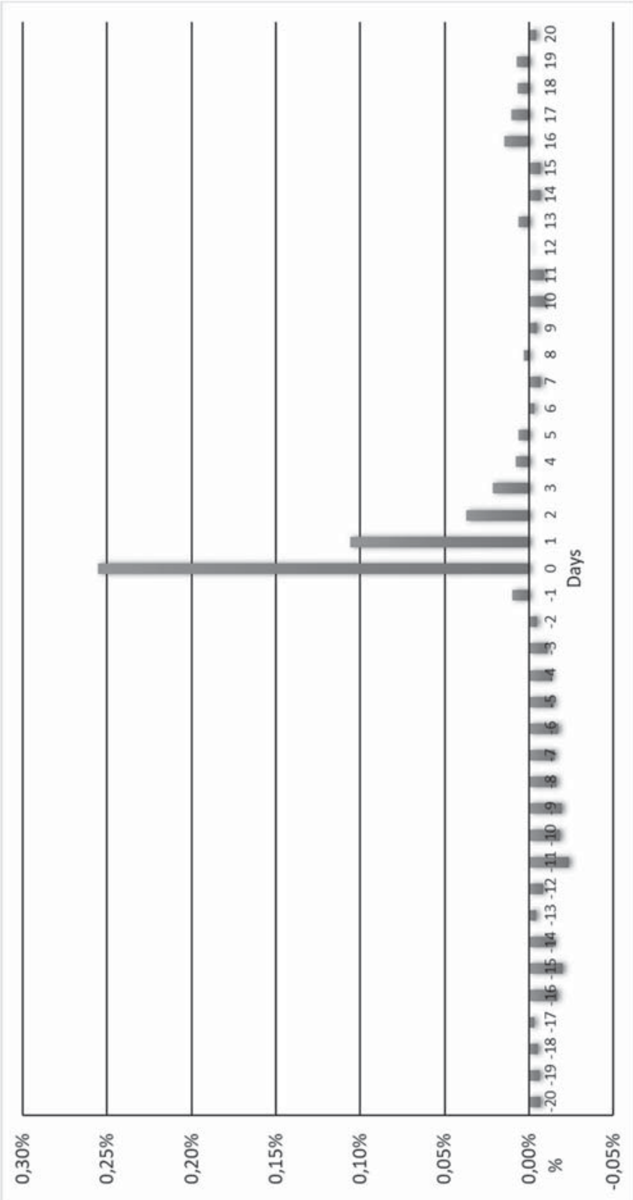
	Mean	Standard Deviation
Daily Trading Volume (R_{it})	0.38%	0.31%
R-squared (R^2)	0.4106	0.1979
Beta (β_{it})	0.8930	0.5914
Alpha (α_{it})	0.0003	0.0016

The average R-squared obtained for the trading volume market model estimation (0.4106) is inferior to that obtained for the stock price market model (0.4868). This suggests that it is less reliable to estimate the trading volume based on the EURO STOXX 50 index recorded trading volume. The average β_{it} is also lower in comparison to that obtained for the stock price market model (0.9697). This indicates that the evolution of stock trading volume can be explained to a lesser degree by the EURO STOXX 50 index trading volume variations.

Then, we computed the average abnormal trading volume for each day of the event window. Figure 3 depicts the results.

Figure 3 and Table 8 show an excess of activity in the announcement day and in the following day with a positive and statistically significant (at a level of 1%) abnormal trading volume in those two moments. There was no significant increase in the trading volume before the announcement day. The return to the average trading volume is shown to be very fast as on day +2 we can no longer observe a statistically significant average abnormal trading volume.

Figure 3 – Average abnormal trading volume results



Source: Authors' elaboration

Table 8 – Average abnormal trading volume results

Event Day	$\overline{AVOL}$	θ_2
-20	-0.01%	-0.1758
-19	-0.01%	-0.1699
-18	-0.01%	-0.1322
-17	0.00%	-0.0826
-16	-0.02%	-0.4364
-15	-0.02%	-0.5028
-14	-0.01%	-0.3718
-13	0.00%	-0.1085
-12	-0.01%	-0.2102
-11	-0.02%	-0.5965
-10	-0.02%	-0.4567
-9	-0.02%	-0.4788
-8	-0.02%	-0.4004
-7	-0.02%	-0.3713
-6	-0.02%	-0.4227
-5	-0.01%	-0.3576
-4	-0.01%	-0.3210
-3	-0.01%	-0.2714
-2	0.00%	-0.1193
-1	0.01%	0.2431
0	0.26%	**6.1232***
+1	0.11%	**2.5290***
+2	0.04%	0.8808
+3	0.02%	0.5112
+4	0.01%	0.1856
+5	0.01%	0.1492
+6	0.00%	-0.0762
+7	-0.01%	-0.1564
+8	0.00%	0.0683
+9	0.00%	-0.1105
+10	-0.01%	-0.2308
+11	-0.01%	-0.2045
+12	0.00%	-0.0122
+13	0.01%	0.1450
+14	-0.01%	-0.1579
+15	-0.01%	-0.1573
+16	0.01%	0.3361

+17	0.01%	0.2373
+18	0.01%	0.1503
+19	0.01%	0.1577
+20	0.00%	-0.1021

* Parameters statistically significant at a 1% significance level

5. Conclusion

In this chapter we analyzed the stock prices responses to annual and interim earnings announcements made by a sample of European firms included in the EURO STOXX 50 index, with the purpose of determining if the disclosure of such information is efficiently incorporated into stock prices. Our results suggest that earnings announcements convey useful information for the determination of stock prices and that investors are able to anticipate the nature of the earnings surprise (positive or negative surprise) as prices reflect some of the content of the announcements before the formal disclosures. A substantial impact is observed in the event day and in the following day, not only on returns but also on trading volume.

Although there are signs of a post-earnings announcement drift in the case of the good news stocks, we think that the size of the phenomenon is not sufficient to create a profitable trading rule. The modest level of PEAD found in our sample is consistent with the findings of Hou *et al.* (2009) that suggest that the effect tends to be stronger in low volume stocks. Thus, the evidence referring to a sample of large European stocks is consistent with the semi-strong form of market efficiency.

Our results can also be interpreted in the context of the process of arbitrage. In theory, it would be expected that our sample, as it includes highly liquid securities, followed by a large number of financial analysts, and with great visibility, would show less significant signs of PEAD. These characteristics of the securities included in our sample favor the role of arbitrageurs in mitigating market anomalies, including the PEAD. This result has been confirmed empirically by several authors. For example, Mendenhall (2004) shows that the magnitude of the PEAD is negatively related to measures of arbitrage risk while Francis *et al*. (2007) conclude that the PEAD is stronger when the uncertainty of information available to investors is more significant. In this sense, the empirical evidence collected in our study illustrates the power of arbitrage in the universe of stocks that enjoy a more complete information market.

Several factors such as the level of sophistication of investors, the quality of financial reporting or even national cultures have been found to impact the intensity of the PEAD (Hirshleifer *et al*., 2008; Hung *et al*., 2015; Dou *et al*., 2016). Future avenues of research could involve studying whether these factors influence the results obtained in our sample.

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CHAPTER 7

PSYCHOLOGICAL BARRIERS IN THE MARKETS FOR ADRS AND ETFS

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Abstract

In this chapter we study for the first time the existence of psychological barriers at round numbers in the markets for ADRs and ETFs. We perform uniformity tests, barrier hump tests, barrier proximity tests and conditional effects tests to a sample comprised by the daily closing quotes of six of the most liquid assets in each of those two markets. Overall, we found evidence of the existence of psychological barriers in only two of the ETFs under study: Brazil and Germany ETFs. Regarding ADRs, we report strong signs of barriers for Vale and inconclusive results for the remaining assets.

Key-words: Psychological barriers; American Depositary Receipts; Exchange-Traded Funds.

1. Introduction

Psychological Barriers are currently one of the most important topics of research in the field of Behavioral Finance, with several empirical studies published since the 1990's on a variety of financial assets, such as stock indices, single stocks, bonds, derivatives and gold, among others. However, there is a lack of studies regarding the existence of psychological barriers in the ADRs and ETFs markets. This gap in the literature is surprising given the economic importance of these markets. For example, data from the Investment Company Institute shows that in 2018, almost 2,000 ETFs were listed in the US for assets worth the staggering figure of 3.4 trillion USD. Also, according to the Bank of New York Mellon, the combined trading value of listed depositary receipts on US exchanges in that same year reached the value of 4.2 trillion USD.

In this chapter we examine for the first time the existence of psychological barriers in the markets for ADRs and ETFs. Our sample includes six of the most liquid assets in each of those two markets. We test for uniformity in the trailing digits of the daily closing prices and use regression and GARCH models to assess the differential impact of being above or below a possible barrier.

The results evidence the existence of psychological barriers in only three of the assets under scrutiny, being one ADR (Vale On 1:1) and two ETFs (MSCI Brazil and Horizons Capital Dax Germany). Overall, we find our results to be consistent with the efficient market paradigm presented by Fama (1970).

The remainder of this chapter is organized as follows: section 2 presents the literature review and section 3 addresses the methodological aspects, namely the data used in the study and the various methodological steps.

The fourth section discusses the empirical results and the last section concludes the chapter.

2. Literature review

2.1. Possible causes of psychological barriers

Psychological barriers can be seen as limits to arbitrage provoked by mental biases. Mitchell (2001) pointed out that a psychological barrier can be viewed as an impediment to an individual's mental outlook, that is, an obstacle created by the mind, barring advance or preventing access. The decisional bias of anchoring, that is, the tendency exhibited by most people to make estimates by starting from an initial value and then adjust, most of the times insufficiently (Tversky and Kahneman, 1974), can be at the root of psychological barriers. Westerhoff (2003) used anchoring to develop a model that produces persistently misaligned exchange rates which move within the limits of a fluctuation band. These limits function as support and resistance levels, that is, as psychological barriers.

Aspiration levels, a concept of psychological theory which was introduced to economic theory by Simon (1955) alongside the notion that the economic agent might not pursue the optimal solution but actually settle for a satisfactory solution, can also be one of the causes of psychological barriers. Sonnemans (2006) noted that some investors, when buying a stock, already have an idea for what price they will be able to sell the stock in the future. Additionally, some financial analysts also use target prices for individual stocks and these are also typically round numbers (Sonnemans, 2006), which will lead to many limit sell offers being posted at round whole numbers.

Psychological barriers can be provoked by odd pricing as well. According to Sonnemans (2006, p. 1938), “odd pricing is the tendency of consumers to consider an odd price like 19.95 as significantly lower than the round price of 20.00”. This tendency could be originated by the limited amount of memory that people have, which leads them to attach more significance to the first digits of a price as they contain more significant information than the last digits (Brenner and Brenner, 1982). Odd pricing is very common in consumer goods, with a number of studies (e.g., Holdershaw *et al.*, 1997; Folkertsma, 2002) showing that prices tend to have 9 as the last significant digit.

Finally, psychological barriers could be caused by the fact that option exercise prices are usually round numbers (Dorfleitner and Klein, 2009). Delta hedgers are frequently most active when the price of the underlying is close to the exercise price – in other words, when the option is at the money – so, purely technical reasons can also cause additional trading activity in the underlying asset.

2.2. Previous empirical studies

The first empirical studies on psychological barriers were performed in the early 1990's and focused mainly on stock indices. In this section, for brevity reasons, we highlight those studies about psychological barriers in stock indices and single stocks, putting aside other studies applied to bonds, derivatives, commodities or cryptocurrencies (some examples are, respectively, Burke, 2001; Schwartz *et al.*, 2004; Agarwal and Lucey, 2007; Fonseca *et al*., 2019).

Donaldson and Kim (1993) tested whether DJIA's movements around key reference points exhibited psychological barriers during the period 1974-1990, finding that those movements were indeed restrained by support and resistance levels at multiples of 100. After breaking through a 100-level, the DJIA moved by more than otherwise warranted. Ley and Varian (1994) also studied the DJIA, with a wider time interval (1952-1993), and confirmed the non-uniformity of the distribution but added that there is no predictive power on the daily closing prices resulting from psychological barriers.

Koedijk and Stork (1994) tested the existence of psychological barriers in five major stock markets (from Belgium, Germany, Japan, the US and the UK) between 1980 and 1992. Their results corroborated the conclusions from the previous studies: psychological barriers are real, but they do not imply predictability of stock returns.

Cyree *et al.* (1999) extended the analysis to six foreign stock indices, alongside the DJIA and the S&P 500, and controlled for the separate and potentially offsetting effects of crossing barriers from below and above. Their findings support the existence of psychological barriers and show that these effects are particularly pronounced when the barrier is approached from below.

Bahng (2003) conducted the first study about this topic on Asian stock markets, using the daily prices of seven indices. The Taiwanese index and the Indonesian index exhibited some signs of psychological barriers.

Dorfleitner and Klein (2009) focused on European stock indices, namely the German DAX 30, the French CAC 40, the British FTSE 50 and the Euro-zone related DJ EURO STOXX 50. They found only fragile traces of psychological barriers in all indices at the 1000s barrier level and also indications of barriers at the 100-barrier level, except in the CAC 40.

Shawn and Kalaichelvan (2012) tested the existence of psychological barriers in five European stock indices. They only found evidence for barriers in the main Switzerland stock index at the 1000 level.

More recently, Woodhouse *et al.* (2016) found evidence of psychological barriers at the 100 level in the NASDAQ and Lobão and Pereira (2017) analyzed the main Southern European stock markets (Greece, Italy, Portugal and Spain) to conclude that only the Iberian markets exhibited strong indication of barriers. Finally, Lobão and Fernandes (2018) found no consistent psychological barriers in individual stock prices near round numbers in the markets of Taiwan, Brazil and South Africa.

3. Data and methodology

3.1. Data

The sample considered in the study includes six of the most liquid ADRs and six of the most liquid ETFs. The ADRs included in our sample were Alibaba 1:1, Nokia 1:10, Novartis 1:1, Royal Dutch Shell 1:2, Vale On 1:1 and Teva Pharmaceuticals 1:1 and the ETFs considered were iShares MSCI Brazil, Horizons Capital Dax Germany, iShares MSCI Japan, iShares MSCI South Africa, iShares Russell 1000 and SPDR S&P 500. We collected the daily closing quotes for each asset for the period between January 1, 2008 and December 31, 2017. The exceptions were Alibaba ADR and the Germany ETF since the first trading day of these two assets occurred after January 1, 2008. Thus, for those assets the start date of the data is the first trading day. All the data were collected from Thomson Reuters Datastream.

Table 1 presents the descriptive statistics of the assets included in the sample with the denomination which will be used from now on for each asset. The table shows that in the period under analysis ADRs and ETFs provided mean returns close to zero.

Table 1 – Descriptive statistics

Market	Asset	Start Date	End Date	N	Return Series				Level Series	
					Mean	Std Dev	Skewness	Kurtosis	Min.	Max.
ADR	Alibaba	Sep 19, 2014	Dec 31, 2017	856	0.0711	1.9133	0.2348	3.7718	57.39	191.19
	Nokia	Jan 1, 2008		2609	-0.0809	2.9127	-0.3293	9.5049	1.69	38.39
	Novartis			2609	0.0167	1.2673	-0.0999	5.2864	33.96	106.12
	Shell			2609	-0.0075	1.8483	-0.0199	9.2449	36.96	87.92
	Teva			2609	-0.0344	1.9461	-1.6565	30.6603	11.23	72.00
	Vale			2609	-0.0377	3.3276	-0.1251	6.1480	2.15	43.91
ETF	Brazil	Jan 1, 2008		2609	-0.0265	2.4367	-0.3770	10.6983	17.33	100.47
	Germany	Oct 23, 2014		832	0.0270	1.1844	-0.8977	9.5630	21.46	31.91
	Japan	Jan 1, 2008		2609	0.0046	1.4031	0.2532	13.4178	27.48	60.62
	South Africa			2609	0.0028	2.2778	-0.2685	11.2820	25.87	76.87
	US: Russell 1000			2609	0.0239	1.2423	-0.3469	10.4627	37.06	149.93
	US: S&P 500			2609	0.0231	1.2601	-0.0879	14.9512	68.11	268.20

3.2. Methodology

3.2.1. Definition of barriers

Following Brock *et al.* (1992), we use the so-called band technique to define a barrier as an interval between two numbers at the same distance from the number which constitutes the actual barrier. The main reason for this technique is the idea that market players will become more active at a certain level before the price touches a round number. The barrier level l is defined as the number of zeros that a barrier has and the barrier levels $l = -1$ and $l = -2$ refer to the 0.1-level and 0.01-level barriers, respectively (Dorfleitner and Klein, 2009). We define as potential barriers the multiples of 0.01, 0.1, 1, 10, 100 and 1000 and define intervals with an absolute length of 2%, 5% and 10% to the corresponding barriers, thus considering the following restriction bands:

Barrier level $l = 3$ (1000s): 980-1020; 950-1050; 900-1100
Barrier level $l = 2$ (100s): 98-102; 95-105; 90-110
Barrier level $l = 1$ (10s): 9.8-10.2; 9.5-10.5; 9.0-11.0
Barrier level $l = 0$ (1s): 0.98-1.02; 0.95-1.05; 0.90-1.10
Barrier level $l = -1$ (0.1s): 0.098-0.102; 0.095-0.105; 0.090-0.110
Barrier level $l = -2$ (0.01s): 0.0098-0.0102; 0.0095-0.0105; 0.0090-0.0110.

For each asset, we then examine the barrier levels which are susceptible of constituting psychological barriers.

3.2.2. M-values

De Ceuster *et al.* (1998) argue that one should consider the possibility of barriers at the levels …, 10, 20, …, 100, 200, …, 1000, 2000, …, i.e. generally at:

$$k\ X\ 10^{l}, k = 1, 2, \dots, 9; l = \dots, -1, 0, 1, \dots \quad (3.1)$$

and also at the levels …, 10, 11, …, 100, 110, …, 1000, 1100, …, i.e. generally at:

$$k\ X\ 10^{l}, k = 10, 11, \dots, 99; l = \dots, -1, 0, 1, \dots \quad (3.2)$$

The M-values we use in our study are defined according to these barriers.

$$M_k = \left[P_t * \frac{100}{k}\right] mod\ 100,\ \ k = 0.01, 0.1, 1, 10, 100, 1000 \quad (3.3)$$

where $\left[P_t * \frac{100}{k}\right]$ is the integer part of $P_t * \frac{100}{k}$ and $mod\, 100$ is the reduction modulo of 100.

Illustrating this with a purely theoretical quote of 1234.56789, the M0.01 is 78, the M0.1 is 67, the M1 is 56, the M10 is 45, the M100 is 34 and the M1000 is 23.

3.2.3. Uniformity test

After defining the M-values, the next step is to examine if they follow a uniform distribution, through the uniformity test introduced by Ley and Varian (1994), which consists of a Kolmogorov-Smirnov Z-statistic test where we will be testing H0: uniform distribution against H1: non-uniform distribution. In the presence of psychological barriers, it is expected to reject the null hypothesis. However, it is important to underline that this rejection does not by itself confirm the existence of such barriers.

3.2.4. Barrier tests

Following the literature on price barriers (e.g., Aggarwal and Lucey, 2007), we perform two barrier tests, a barrier proximity test and a barrier hump test. The purpose of these tests is to assess if the series observations on or near a barrier occur less frequently than what would be predicted by a uniform distribution.

A barrier proximity test examines the frequency of M-values in the proximity of potential barriers, applying the following equation:

$$f(M) = \alpha + \beta D + \varepsilon, \qquad M = 00{,}01, \dots, 99 \qquad (3.4)$$

where $f(M)$ is defined as the frequency with which a quote closes with its last two digits in cell M, minus 1 percentage point, and D is a dummy variable which takes the value 1 if the price of the asset is at the potential barrier and 0 elsewhere. Besides the strict dummy, which takes the value 1 if M=00 and takes the value 0 otherwise, we will study three dummies for each potential barrier level:

D_{98-02} = 1 if M ≥ 98 or M ≤ 02, = 0 otherwise

D_{95-05} = 1 if M ≥ 95 or M ≤ 05, = 0 otherwise

D_{90-10} = 1 if M ≥ 90 or M ≤ 10, = 0 otherwise.

The β coefficients are expected to be negative and statistically significant in the presence of psychological barriers.

The barrier hump test examines the entire shape of the distribution of M-values and is broader than the barrier proximity test as it does not focus solely on the proximity of the potential barriers. We implement this test using the following equation, which was introduced by Bertola and Caballero (1992):

$$f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon, \qquad M = 00{,}01, \dots, 99 \quad (3.5)$$

where $f(M)$ is once again defined as the frequency with which a quote closed with its last two digits in cell M, minus 1 percentage point, and the independent variables are the M-value and its square.

In the presence of psychological barriers, the M-values are expected to follow a hump-shape distribution, which will be reflected in Eq. (3.5) through negative and statistically significant δ, whereas under the null hypothesis of no barriers, δ should be zero and the M-values should follow a uniform distribution.

3.2.5. Conditional effects test

The final test of our methodology was introduced by Cyree *et al.* (1999) and is designed to detect changes in the conditional mean and variance of the distribution of returns during the sub-periods before and after crossing a barrier, either from above or below. We use a 5-day window before and after crossing a barrier.

In order to identify if a barrier is crossed in an upward or downward movement and examine the difference in returns between the 5-day periods before and after the barrier is crossed, we will use four dummy variables: UB for the 5-day period before prices cross a barrier on an upward movement, UA for the 5-day period after prices cross a barrier on an upward movement, DB for the 5-day period before prices cross a barrier on a downward movement and DA for the 5-day period after prices cross a barrier on a downward movement. Each of these dummies will take the value 1 on the identified days and the value 0 elsewhere. Taking into account, as stated by Cyree *et al.* (1999), that the distributional shifts implied by psychological barriers invalidate the basic assumptions of OLS, we will then regress the following equations using a GARCH (1,1) model:

$$R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t \quad (3.6)$$

$$\varepsilon_t \sim N(0, V_t) \quad (3.7)$$

$$V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t \quad (3.8)$$

In the absence of barriers, it is expected that the coefficients of the indicator variables will take the value zero both in the mean and variance equations, whereas any coefficient significantly different from zero (either positive or negative) will indicate the presence of psychological barriers.

The four null hypotheses to be tested using a Wald test are the following:

H1: There is no significant difference in the conditional mean return before and after an upwards crossing of a barrier;

H2: There is no significant difference in the conditional mean return before and after a downwards crossing of a barrier;

H3: There is no significant difference in the conditional variance before and after an upwards crossing of a barrier;

H4: There is no significant difference in the conditional variance before and after a downwards crossing of a barrier.

4. Empirical results

4.1. Uniformity test

Table 2 shows the results of the uniformity tests for each financial asset, using a Kolmogorov-Smirnov Z-test which studies the distribution of the M-values for a total of 12 financial assets and 28 potential barriers. Overall, the financial assets exhibit signs of psychological barriers, as there are statistically significant evidence at a 5 percent significance level that M-values do not follow a uniform distribution for, at least, one barrier level for all the 12 assets and for, at least, two barrier levels for 8 of the 12 assets under study (the exceptions are the Shell and Vale ADRs and the Germany and South Africa ETFs).

Table 2 – Uniformity test results

			M1	M10	M100
ADR	Alibaba	Z Stat.	2.640853	0.916470	10.43078
		p-value	0.0000***	0.3704	0.0000***
	Nokia	Z Stat.	1.962082	9.355578	--
		p-value	0.0009***	0.0000***	--
	Novartis	Z Stat.	1.205620	2.498224	18.51664
		p-value	0.1093	0.0000***	0.0000***
	Shell	Z Stat.	1.948468	1.264737	--
		p-value	0.0010***	0.0816*	--
	Teva	Z Stat.	1.822424	1.809143	--
		p-value	0.0026***	0.0029***	--
	Vale	Z Stat.	1.295465	4.072440	--
		p-value	0.0697*	0.0000***	--
ETF	Brazil	Z Stat.	1.659428	2.532433	--
		p-value	0.0081***	0.0000***	--
	Germany	Z Stat.	0.827227	4.759643	--
		p-value	0.5005	0.0000***	--
	Japan	Z Stat.	3.402057	6.867324	--
		p-value	0.0000***	0.0000***	--
	South Africa	Z Stat.	1.292552	2.480497	--
		p-value	0.0708*	0.0000***	--
	US: Russell 1000	Z Stat.	1.625609	1.629835	5.100530
		p-value	0.0101**	0.0099***	0.0000***
	US: S&P 500	Z Stat.	1.150749	3.205473	10.35219
		p-value	0.1415	0.0000***	0.0000***

Table 2 presents the results of a Kolmogorov-Smirnov test for uniformity. Z-stat stands for the value of the test statistic; p-value shows the marginal significance of this statistic. H0: uniformity; H1: non-uniformity. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

The Nokia and Teva ADRs, the Brazil, Japan and Russel 1000 ETFs reject uniformity at a 5 percent significance level for every potential barrier level. The results of this test do not show any significant differences between the two types of financial assets under study.

4.2. Barrier tests

4.2.1. Barrier proximity test

Tables 3 to 6 contain the results of the barrier proximity tests performed on the selected ADRs and ETFs. As previously mentioned, in the presence of a psychological barrier it is expected that β is negative and significant, which means that there is a lower frequency on the M-values around round numbers.

Table 3 – Barrier proximity test results for the strict dummy

	M1			M10			M100		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
ADR									
Alibaba	2.6480	0.0000***	0.3834	-0.1841	0.6267	0.0024	0.2879	0.7885	0.0007
Nokia	0.0739	0.7611	0.0009	-0.3906	0.5317	0.0040	--	--	--
Novartis	0.1901	0.3544	0.0088	-0.0809	0.7601	0.0010	-0.4681	0.6683	0.0019
Shell	0.6547	0.0023***	0.0908	0.2288	0.2976	0.0110	--	--	--
Teva	0.8870	0.0002***	0.1294	0.7708	0.0020***	0.0936	--	--	--
Vale	0.1127	0.5408	0.0038	0.2675	0.3547	0.0087	--	--	--
ETF									
Brazil	0.3062	0.1440	0.0217	-0.0422	0.8589	0.0003	--	--	--
Germany	-0.1603	0.7100	0.0014	-0.7673	0.2279	0.0148	--	--	--
Japan	2.3969	0.0891*	0.0292	0.2288	0.5432	0.0038	--	--	--
South Africa	-0.0035	0.9853	0.0001	-0.1971	0.3305	0.0097	--	--	--
US: Russell 1000	-0.0035	0.9852	0.0001	-0.2745	0.1403	0.0221	-0.2358	0.7345	0.0012
US: S&P 500	0.0739	0.6800	0.0017	0.3062	0.1506	0.0210	0.3062	0.6148	0.0026

Table 3 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of M-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M=00 and 0 otherwise (see section 3.2.4. for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 4 – Barrier proximity test results for the 98-02 dummy

	M1			M10			M100		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
ADR									
Alibaba	0.4722	0.0153**	0.0585	-0.0935	0.5886	0.0030	0.3492	0.4755	0.0052
Nokia	0.0286	0.7965	0.0007	-0.5039	0.0751*	0.0320	--	--	--
Novartis	-0.0682	0.4672	0.0054	0.0771	0.5237	0.0042	-0.2780	0.5772	0.0032
Shell	0.0851	0.3959	0.0074	0.0367	0.7150	0.0014	--	--	--
Teva	0.3514	0.0016***	0.0974	0.4321	0.0001***	0.1412	--	--	--
Vale	0.1174	0.1610	0.0199	-0.0198	0.8812	0.0002	--	--	--
ETF									
Brazil	0.0206	0.8306	0.0005	-0.1327	0.2188	0.0154	--	--	--
Germany	0.1872	0.3403	0.0093	-0.8755	0.0021***	0.0925	--	--	--
Japan	-0.0843	0.8965	0.0002	0.4967	0.0031***	0.0855	--	--	--
South Africa	0.0125	0.8852	0.0002	0.0286	0.7572	0.0010	--	--	--
US: Russell 1000	0.0690	0.4209	0.0066	-0.1085	0.2022	0.0165	-0.3667	0.2464	0.0137
US: S&P 500	0.0609	0.4563	0.0057	0.0044	0.9638	0.0001	-0.0198	0.9433	0.0001

Table 4 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, and *D* is a dummy variable that takes the value 1 if M≥98 or M≤02 and 0 otherwise (see section 3.2.4. for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 5 – Barrier proximity test results for the 95-05 dummy

	M1			M10			M100		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
ADR									
Alibaba	0.2129	0.1199	0.0245	-0.0496	0.6801	0.0017	0.5828	0.0854*	0.0299
Nokia	0.0274	0.7227	0.0013	-0.6342	0.0010***	0.1044	--	--	--
Novartis	-0.0235	0.7199	0.0013	-0.0235	0.7807	0.0008	-0.3680	0.2884	0.0115
Shell	0.0353	0.6140	0.0026	0.0040	0.9550	0.0001	--	--	--
Teva	0.1958	0.0122**	0.0623	0.4033	0.0000***	0.2535	--	--	--
Vale	0.0666	0.2545	0.0132	-0.1487	0.1041	0.0267	--	--	--
ETF									
Brazil	0.0588	0.3796	0.0079	-0.1331	0.0755*	0.0319	--	--	--
Germany	0.1532	0.2622	0.0128	-0.8167	0.0000***	0.1658	--	--	--
Japan	0.0392	0.9309	0.0001	0.3524	0.0026***	0.0888	--	--	--
South Africa	-0.0509	0.3983	0.0073	0.0392	0.5435	0.0038	--	--	--
US: Russell 1000	0.0509	0.3935	0.0074	-0.0078	0.8959	0.0002	-0.3484	0.1128	0.0255
US: S&P 500	0.0783	0.1676	0.0193	0.0431	0.5264	0.0041	0.0979	0.6128	0.0026

Table 5 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of M-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥95 or M≤05 and 0 otherwise (see section 3.2.4. for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 6 – Barrier proximity test results for the 90-10 dummy

	M1			M10			M100		
	β	p-value	R^2	β	p-value	R^2	β	p-value	R^2
ADR									
Alibaba	0.1848	0.0783*	0.0313	-0.0194	0.8336	0.0005	0.4242	0.1033	0.0268
Nokia	-0.0044	0.9414	0.0001	-0.7599	0.0000***	0.2539	--	--	--
Novartis	-0.0506	0.3129	0.0104	-0.1314	0.0401**	0.0423	-0.5288	0.0454**	0.0402
Shell	0.0141	0.7928	0.0007	-0.0113	0.8337	0.0005	--	--	--
Teva	0.1273	0.0348**	0.0447	0.3283	0.0000***	0.2847	--	--	--
Vale	0.0442	0.3258	0.0099	-0.1869	0.0071***	0.0715	--	--	--
ETF									
Brazil	0.0511	0.3199	0.0101	-0.1453	0.0108**	0.0644	--	--	--
Germany	0.0745	0.4789	0.0051	-0.5776	0.0001***	0.1405	--	--	--
Japan	-0.0783	0.8214	0.0005	0.2498	0.0056***	0.0756	--	--	--
South Africa	-0.0113	0.8073	0.0006	0.0673	0.1730	0.0189	--	--	--
US: Russell 1000	0.0072	0.8757	0.0003	0.0164	0.7193	0.0013	-0.2885	0.0870*	0.0296
US: S&P 500	0.0210	0.6308	0.0024	0.0395	0.4493	0.0059	0.4854	0.0008***	0.1092

Table 6 shows the results of a barrier proximity test using the regression $f(M) = \alpha + \beta D + \varepsilon$, where the dependent variable is the frequency of appearance of M-values, minus 1 percentage point, and D is a dummy variable that takes the value 1 if M≥90 or M≤10 and 0 otherwise (see section 3.2.4. for further details). H0: β=0; H1: β<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Regarding the ADRs, we observe that considering a barrier in the exact zero modulo point (Table 3), none of the selected assets present negative and significant estimates for β for any barrier level; we find some negative β estimates, namely for Alibaba, Nokia and Novartis, but all of them have p-values over 10% and it is not possible to reject uniformity at the conventional significance levels. When we consider a barrier in the 98-02 interval (Table 4), the findings are almost the same, the only exception being Nokia, which presents a negative estimate for β for the 10-level barrier, now significant at a 10 percent significance level. Assuming a barrier in the 95-05 interval (Table 5), once again the only negative and significant estimate for β is that of Nokia for the 10-level barrier, which is now significant at a 1 percent level. Finally, for the 90-10 interval barrier (Table 6), we find negative and significant β estimates for Nokia at the 10-level barrier – significant at a 1 percent level – for Novartis at the 10 and 100-level potential barriers – both significant at a 5 percent level – and for Vale at the 10-level barrier – significant at a 1 percent level.

Summing up, we cannot reject the no-barrier hypothesis for Alibaba, Shell and Teva at any potential barrier level, whereas we find some signs of the existence of psychological barriers for Nokia around the 10-level round numbers, Novartis around the 10-level and 100-level round numbers and Vale around the 10-level round numbers.

As for the ETFs, Table 3 shows that none of them have negative and significant β estimates for any barrier level if we consider a barrier in the exact zero modulo point. Assuming a 98-02 interval barrier (Table 4), the Germany ETF is the only one which seems to reject the no-barrier hypothesis, for the 10-level barrier, with a negative estimate for β that is significant at 1 percent significance level. Widening the interval to 95-05 (Table 5), we find negative and significant β estimates for Brazil and Germany, both at the 10-level barrier, statistically significant at 10 percent and 1 percent level, respectively. Finally, assuming a barrier in the 90-10 interval (Table 6), we find three negative and significant β estimates: Brazil at the 10-level barrier, significant at a 5 percent level; Germany at the 10-level barrier, significant at a 1 percent level; and Russell 1000 at the 100-level barrier, significant at a 10 percent level.

Overall, concerning the ETFS, we cannot reject the no-barrier hypothesis for Japan, South Africa and S&P 500 for any potential barrier level; on the other hand, we find some signs of the existence of psychological barriers for Brazil and Germany around the 10-level round numbers and Russell 1000 around the 100-level round numbers.

4.2.2. Barrier hump test

The barrier proximity test examines the entire shape of the distribution of M-values. As explained in Section 3.2.4, in the presence of barriers δ is expected to be negative and significant. Tables 7 and 8 show the results of these tests on the selected ADRs and ETFs, respectively.

In the case of the ADRs, we find evidence of a hump-shape distribution of M-values for Nokia, Novartis and Vale at the 10-level barrier, as well as for Novartis at the 100-level barrier. These are precisely the four potential barriers that presented negative and significant β estimates – therefore suggesting the presence of psychological barriers – in the barrier proximity test. We find only one other estimate which is negative but not significant at any confidence level: Alibaba at the 10-level barrier; all the other δ estimates are positive.

As for the ETFs, we only find evidence that M-values follow a hump-shape distribution for Brazil and Germany, both at the 10-level barrier. Therefore, from the trio of potential barriers which presented signs of the existence of psychological barriers around round numbers we drop the Russell 1000 at the 100-level barrier, which actually presents a negative estimate but with a p-value higher than all the confidence levels used in our study; the same happens with Japan and South Africa at the 1-level barrier and Russell 1000 at the 10-level barrier.

In general, the results of these tests seem to be consistent with the evidence produced by the barrier proximity test. We have found consistent signs of psychological barriers around round numbers for three of the six selected ADRs – Nokia, Novartis and Vale –, as well as for two of the six selected ETFs – Brazil and Germany.

Table 7 – Barrier hump test results for the selected ADRs

	M1			M10			M100		
	δ	p-value	R^2	δ	p-value	R^2	δ	p-value	R^2
Alibaba	0.000138	0.0153**	0.065869	-1.54E-05	0.7618	0.000974	0.000575	0.0000***	0.333027
Nokia	4.59E-05	0.1560	0.026924	-0.000575	0.0000***	0.575686	--	--	--
Novartis	3.27E-06	0.9052	0.011650	-9.73E-05	0.0039***	0.138839	0.000425	0.0009***	0.276687
Shell	1.17E-05	0.6919	0.001627	-5.59E-06	0.8494	0.008225	--	--	--
Teva	6.74E-05	0.0421**	0.043547	0.000187	0.0000***	0.375537	--	--	--
Vale	3.32E-05	0.1783	0.018617	-0.000160	0.0000***	0.188277	--	--	--

Table 7 shows the results of a barrier hump test using the regression $f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon$,, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, regressed to the said M-values and the respective squares. (see section 3.2.4. for further details). H0: δ=0; H1: δ<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 8 – Barrier hump test results for ETFs

	M1			M10			M100		
	δ	p-value	R^2	δ	p-value	R^2	δ	p-value	R^2
Brazil	3.02E-05	0.2834	0.0172	-0.000136	0.0000***	0.1910	--	--	--
Germany	5.37E-05	0.3520	0.0090	-0.000454	0.0000***	0.3485	--	--	--
Japan	-3.26E-05	0.8639	0.0029	0.000169	0.0000***	0.3816	--	--	--
South Africa	-1.64E-06	0.9483	0.0154	1.57E-05	0.5538	0.0566	--	--	--
US: Russell 1000	7.26E-06	0.7731	0.0059	-4.03E-05	0.1048	0.0359	-8.10E-05	0.3837	0.0111
US: S&P 500	7.37E-06	0.7591	0.0030	2.41E-05	0.3865	0.0651	0.0003	0.0001***	0.4016

Table 8 shows the results of a barrier hump test using the regression $f(M) = \alpha + \gamma M + \delta M^2 + \varepsilon$,, where the dependent variable is the frequency of appearance of *M*-values, minus 1 percentage point, regressed to the said M-values and the respective squares. (see section 3.2.4. for further details). H0: δ=0; H1: δ<0. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

4.3 Conditional effects test

Tables 9-11 present the results of the conditional effects test, where we examine the behavior of the selected financial assets' prices in the 5-day period before and after crossing a barrier from below (thus constituting a potential resistance level), and also in the 5-day period before and after crossing a barrier from above (thus constituting a potential support level).

We perform this test for one potential barrier level only for each asset, chosen as the most likely to constitute an actual barrier level, according to the results from the previous tests. Therefore, regarding ADRs, the conditional effects test is applied to the 10-level barrier for Nokia, Shell, Teva and Vale and to the 100-level barrier for Alibaba and Novartis; concerning ETFs, it is applied to the 10-level barrier for Brazil, Germany, Japan and South Africa and to the 100-level barrier for Russell 1000 and S&P 500.

The results of the mean return equation are shown in Table 9. The mean return after crossing a barrier from below is positive for all the 12 financial assets – and significant at a 5 percent level for all of them except the Russell 1000 ETF. Before crossing a barrier in such movement, the mean is positive for all assets except for the Russell 1000 ETF but only significant at a 5 percent level for five of the assets: the Shell, Vale and Teva ADRs; Brazil and South Africa ETFs. Still concerning the upward movements, the results show that the magnitude of returns is significantly higher after crossing a barrier for all assets, with the exception of the Russell 1000 ETF.

As for the crossings from above, the mean return is negative for all assets after crossing a barrier in such movement – significant at a 5 percent level for all assets but the Novartis ADR, the Russell 1000 and S&P 500 ETFs – and also negative before crossing the barrier for all assets – but only significant at a 5 percent level for seven of them: the Alibaba, Shell, Teva and Vale ADRs and the Brazil, Germany and South Africa ETFs. The magnitude of returns is higher in the 5-day period after crossing a barrier for all assets except for the Russell 1000 and S&P 500 ETFs. Overall, the results presented in Table 10 show no significant differences between the two categories of financial assets.

Table 10 shows the results of the variance equation. In the presence of psychological barriers, we should find positive variance indicators before crossing a barrier – suggesting that the market is more turbulent in this period – and negative indicators after crossing a barrier – indicating that the market is quieter in this period.

Table 9 – Conditional effects test results – Return equation

			C	UB	UA	DB	DA
ADR	Alibaba	Coef.	0.0983	0.0547	1.6299	-0.8418	-1.6034
		p-value	0.1476	0.8073	0.0017***	0.0000***	0.0170**
	Nokia	Coef.	-0.0382	0.7351	0.9095	-0.2340	-1.5297
		p-value	0.3395	0.0710*	0.0150**	0.6312	0.0005***
	Novartis	Coef.	0.0354	0.4736	0.7088	-0.2643	-0.4854
		p-value	0.0995*	0.1015	0.0028***	0.3876	0.0736*
	Shell	Coef.	0.0450	0.3777	0.7132	-0.5026	-0.8579
		p-value	0.0929*	0.0000***	0.0000***	0.0000***	0.0000***
	Teva	Coef.	0.0097	0.3458	0.7450	-0.4300	-0.7015
		p-value	0.7643	0.0148**	0.0000***	0.0119**	0.0000***
	Vale	Coef.	-0.0072	0.6160	1.0205	-0.5886	-1.2353
		p-value	0.8868	0.0127**	0.0000***	0.0074***	0.0000***

ETF	Brazil	Coef.	0.0256	0.3690	0.8655	-0.5792	-1.0529
		p-value	0.4792	0.0053***	0.0000***	0.0001***	0.0000***
	Germany	Coef.	0.0502	0.1783	0.3197	-0.2531	-0.5785
		p-value	0.2540	0.0811*	0.0000***	0.0061***	0.0000***
	Japan	Coef.	0.0350	0.1263	0.3577	-0.1362	-0.4280
		p-value	0.0739*	0.1701	0.0000***	0.2949	0.0000***
	South Africa	Coef.	0.0281	0.2752	0.6303	-0.2667	-0.9081
		p-value	0.4588	0.0112**	0.0000***	0.0140**	0.0000***
	US: Russell 1000	Coef.	0.0673	-0.0848	0.2738	-0.2571	-0.1503
		p-value	0.0000***	0.9112	0.2005	0.3713	0.8607
	US: S&P 500	Coef.	0.0581	0.1697	0.2047	-0.1207	-0.0500
		p-value	0.0001***	0.4191	0.0002***	0.6231	0.7796

Table 9 shows the results of the mean equation of a GARCH estimation of the form $R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t$; $\varepsilon_t \sim N(0, V_t)$; $V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. UB, UA, DB and DA are dummy variables. UB takes the value 1 in the 5 days before crossing a barrier from below; UA takes the value 1 in the 5 days after crossing a barrier from below; DB takes the value 1 in the 5 days before crossing a barrier from above; DA takes the value 1 in the 5 days after crossing a barrier from above. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Table 10 – Conditional effects test results – Variance equation

			C	RESID(-1)^2	GARCH(-1)	UB	UA	DB	DA
ADR	Alibaba	Coef.	0.7553	0.0478	0.7358	-0.5385	1.0928	-0.9632	1.4206
		p-value	0.0055***	0.0151**	0.0000***	0.0628*	0.2258	0.0000***	0.1180
	Nokia	Coef.	0.7941	0.1264	0.7865	-1.0685	-0.9180	1.3644	0.7502
		p-value	0.0000***	0.0000***	0.0000***	0.0271**	0.0118**	0.0131**	0.2654
	Novartis	Coef.	0.0226	0.0397	0.9435	0.0741	-0.1783	0.2536	-0.0883
		p-value	0.0000***	0.0000***	0.0000***	0.6242	0.2170	0.1491	0.6097
	Shell	Coef.	0.0191	0.0558	0.9301	-0.0643	0.0134	0.3454	-0.1418
		p-value	0.0000***	0.0000***	0.0000***	0.0636*	0.6760	0.0000***	0.0120**
	Teva	Coef.	0.0102	0.0149	0.9796	0.1429	-0.1622	1.1689	-1.0615
		p-value	0.0013***	0.0000***	0.0000***	0.0002***	0.0000***	0.0000***	0.0000***
	Vale	Coef.	0.0510	0.0498	0.9429	-0.2275	-0.2453	0.4373	0.2057
		p-value	0.0037***	0.0000***	0.0000***	0.1604	0.1044	0.0431**	0.3239

ETF	Brazil	Coef.	0.0438	0.0715	0.9088	0.0408	-0.1109	0.3923	0.1985
		p-value	0.0000***	0.0000***	0.0000***	0.6909	0.2017	0.0002***	0.1374
	Germany	Coef.	0.0347	0.0492	0.8869	0.0924	-0.1267	0.1250	0.1274
		p-value	0.0015***	0.0000***	0.0000***	0.0035***	0.0000***	0.0018***	0.0107**
	Japan	Coef.	0.0135	0.0918	0.9012	-0.0089	-0.0565	0.1886	-0.0459
		p-value	0.0000***	0.0000***	0.0000***	0.7387	0.0948*	0.0000***	0.2944
	South Africa	Coef.	0.0695	0.0821	0.8968	-0.1016	-0.1285	0.1148	0.2549
		p-value	0.0001***	0.0000***	0.0000***	0.1055	0.0288**	0.1286	0.0005***
	US: Russell 1000	Coef.	0.0605	0.2516	0.7133	0.7572	-0.1788	0.1784	-0.7377
		p-value	0.0000***	0.0000***	0.0000***	0.4250	0.0000***	0.4187	0.4391
	US: S&P 500	Coef.	0.0161	0.1081	0.8764	-0.0501	-0.0477	0.3230	-0.0954
		p-value	0.0000***	0.0000***	0.0000***	0.1595	0.0495**	0.0239**	0.3952

Table 10 shows the results of the variance equation of a GARCH estimation of the form $R_t = \beta_1 + \beta_2 UB_t + \beta_3 UA_t + \beta_4 DB_t + \beta_5 DA_t + \varepsilon_t$; $\varepsilon_t \sim N(0, V_t)$; $V_t = \alpha_1 + \alpha_2 UB_t + \alpha_3 UA_t + \alpha_4 DB_t + \alpha_5 DA_t + \alpha_6 V_{t-1} + \alpha_7 \varepsilon_{t-1}^2 + \eta_t$. UB, UA, DB and DA are dummy variables. UB takes the value 1 in the 5 days before crossing a barrier from below; UA takes the value 1 in the 5 days after crossing a barrier from below; DB takes the value 1 in the 5 days before crossing a barrier from above; DA takes the value 1 in the 5 days after crossing a barrier from above. V_{t-1} refers to the moving average parameter and ε_{t-1}^2 stands for the GARCH parameter. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Regarding upward movements, we find positive variance indicators before crossing a barrier for five of the twelve financial assets (two ADRs and three ETFs) and negative indicators after crossing a barrier for nine assets (four ADRs and five ETFs). As for downward movements, we find positive indicators before crossing barriers for eleven assets (five ADRs and six ETFs) and negative indicators after crossing barriers for six assets (three ADRs and three ETFs).

Finally, Table 11 exhibits the results of the Wald test to the hypotheses listed in Section 3.2.5. We find significant changes in the conditional mean returns after crossing a barrier in an upwards movement for three ADRs and two ETFs (Alibaba, Shell and Teva; Brazil and South Africa), while for downwards movements we observe that changes in the conditional mean returns for two ADRs and three ETFs (Shell and Vale; Brazil, Germany and South Africa). As for differences in the conditional variance, we observe significant results for the Teva ADR and the Germany ETF – concerning upwards movements and regarding downwards movements we find significant differences for three ADRs and one ETF, namely: Alibaba, Shell and Teva; Japan.

Table 11 – Conditional effects test results

			H1	H2	H3	H4
ADR	Alibaba	Chi-square	7.9877	1.2574	2.7057	5.8591
		p-value	0.0047***	0.2621	0.1000	0.0155**
	Nokia	Chi-square	0.1073	3.6186	0.0417	0.3461
		p-value	0.7432	0.0571*	0.8381	0.5563
	Novartis	Chi-square	0.5189	0.2791	0.8422	1.1637
		p-value	0.4713	0.5973	0.3588	0.2807
	Shell	Chi-square	7.8901	5.5832	1.5729	20.3956
		p-value	0.0050***	0.0181**	0.2098	0.0000***
	Teva	Chi-square	5.6925	1.3536	17.547	705.7751
		p-value	0.0170**	0.2446	0.0000***	0.0000***
	Vale	Chi-square	1.7849	4.4885	0.0035	0.3152
		p-value	0.1815	0.0341**	0.9530	0.5745

ETF	Brazil	Chi-square	6.9414	5.3912	0.7334	0.7552
		p-value	0.0084***	0.0202**	0.3918	0.3848
	Germany	Chi-square	1.3130	5.7049	15.891	0.0009
		p-value	0.2518	0.0169**	0.0001***	0.9758
	Japan	Chi-square	3.7495	3.3155	0.7474	9.9656
		p-value	0.0528*	0.0686*	0.3873	0.0016***
	South Africa	Chi-square	6.9718	17.115	0.0634	1.1055
		p-value	0.0083***	0.0000***	0.8012	0.2931
	US: Russell 1000	Chi-square	0.2044	0.0141	0.9788	0.8648
		p-value	0.6512	0.9056	0.3225	0.3524
	US: S&P 500	Chi-square	0.0259	0.0530	0.0016	2.9682
		p-value	0.8720	0.8180	0.9679	0.0849*

Table 11 shows the results of a Wald test to four hypotheses. H1: There is no significant difference in the conditional mean return before and after an upwards crossing of a barrier; H2: There is no significant difference in the conditional mean return before and after a downwards crossing of a barrier; H3: There is no significant difference in the conditional variance before and after an upwards crossing of a barrier; H4: There is no significant difference in the conditional variance before and after a downwards crossing of a barrier. Significance at the 10%, 5% and 1% levels are denoted respectively *, ** and ***.

Overall, the evidence suggests that returns and volatility tend to increase after crossing a barrier from below and tend to decrease after crossing a barrier from above which is in line with the equilibrium models that posit a positive relationship between risk and return. The GARCH term is positive and significant at a 1 percent level for every asset, indicating significant GARCH effects. Again, we do not find significant differences between ADRs and ETFs. Finally, analyzing the results of the Wald test, we observe significant signs of the existence of psychological barriers in the Alibaba, Shell, Teva and Vale ADRs, and in the Brazil, Germany, Japan and South Africa ETFs.

5. Conclusion

In this chapter we conducted the first study on psychological barriers in two of the currently most dynamic financial markets, the ADRs and ETFs markets.

We considered a sample of six of the most liquid assets in each of those two markets. Overall, after analyzing the range of each asset's quotes and defining all potential psychological barriers, we found evidence of the existence of psychological barriers in only two of the ETFs under study: Brazil and Germany ETFs. Regarding ADRs, we evidence strong signs of barriers for Vale and inconclusive results for the remaining assets. In spite of that, barrier tests show some indications of psychological barriers for Nokia and Novartis, while the conditional effects test shows stronger signs of barriers for Alibaba, Teva and Shell.

In spite of that evidence, our results are globally consistent with the efficient market paradigm since one of the chief features of an efficient capital market is that prices should not exhibit any particular patterns (Fama, 1970). The signs of psychological barriers evidenced by our results are rather limited, with the majority of the considered assets presenting a behavior tipically associated to price efficiency.

Our study presents several limitations which may lead to future research on this topic. For instance: studies with broader samples could lead to stronger results; it could be fruitful to analyze the prevalence of psychological barriers in different time periods according to the price trend prevailing in the market at the time; and it would be interesting to investigate the relationship between the features of ADRs and ETFs (in terms of liquidity, volatility, etc.) and the prevalence of psychological barriers.

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CHAPTER 8

PRICE CLUSTERING IN THE NORD POOL ELECTRICITY MARKET

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Abstract

Price clustering can be defined as the tendency for prices to accumulate around specific values. In this chapter we test the hypothesis of price clustering in the 21 bidding areas of Nord Pool Electricity Market. Our sample includes the hourly prices observed in the year 2019. The results show the presence of statistically significant price clustering in eleven of the 21 bidding areas under scrutiny. Out of the more than 160,000 prices, the final digit 0 appears 11.94% of the time, higher than the expected 10% if the prices were uniformly distributed. Our evidence is difficult to reconcile with the idea that prices follow a random walk, one of the basic tenets of the efficient market hypothesis.

Key-words: Nord Pool; price clustering; electricity market; market efficiency.

1. Introduction

Price clustering can be defined as the tendency for the price of an asset (stocks, commodities, currencies and others) to stick around some specific set of values, most often round numbers such as whole digits (XX.00) or half digits (XX.50). One can also observe a more specific type of clustering, namely numbers with the right digit equal to zero (XX.X0) or five (XX.X5) for example.

The standard explanations for price clustering are offered by the price resolution hypothesis (Ball *et al.*, 1985), the negotiation hypothesis (Harris, 1991), the attraction hypothesis (Goodhart and Curcio, 1991) and the collusion hypothesis (Christie and Schultz, 1994). The price resolution hypothesis suggests that price clustering results from the achievement of the optimal level of price resolution, i.e., the desired degree of price accuracy. A coarser price resolution due to the lack of information possessed by the market agent about the underlying value of the security induces traders to submit orders at round-numbered prices. The negotiation hypothesis is based on the idea that price clustering occurs because traders, when trying to reduce the costs of negotiating, use a restricted set of prices to specify the terms of their trades. According to the attraction hypothesis, price clustering results from a natural attraction for some numbers over others, whereas the proponents of the collusion hypothesis suggest that prices cluster due to the collusion of market makers, who try to avoid odd eight quotes to enable wider spreads and thus higher profit margins per transaction. Overall, there is an agreement that price clustering is caused by human bias, haziness and bounded rationality (Mitchell, 2001).

Evidence in favour of the existence of price clustering is very extensive, and studies have been made for several types of assets. Apart from the studies regarding the US stock market (Christie *et al.*, 1994; Harris, 1991), research has also been done regarding other developed stock markets (Hu *et al.*, 2017; Lobão and Pereira, 2017; Lobão *et al*., 2019), emerging stock markets (Lobão and Fernandes, 2018; Lobão *et al*., 2020), the foreign exchange market (Sopranzetti and Datar, 2002), real estate (Palmon *et al*., 2004), commodities (Ball *et al*., 1985; Cummins *et al*., 2015), derivatives (Narayan *et al*., 2011; Palao and Pardo, 2012), cryptocurrencies (Urquhart, 2017; Fonseca *et al*., 2019), and utility markets such as the Australian water market (Brooks *et al*., 2013).

In this chapter we test the hypothesis of price clustering in the Nord Pool electricity market. Thus, we contribute to the literature on this financial phenomenon, which is still rather scarce regarding the utility's markets in general, and almost non-existent concerning electricity markets such as Nord Pool.

Nord Pool is Europe's leading power market and offers trading, clearing, settlement and associated services in both day-ahead and intraday markets across nine European countries (Nord Pool, 2019) with 380 companies from 20 countries trading in the Nordic, Baltic, Germany and United Kingdom markets. Besides the electricity physical market – Nord Pool Spot – investors can trade derivatives related to the Nord Pool power market via external markets (namely through NASDAQ OMX Commodities Europe). Thus, this exchange not only connects the production of electricity with the distributors of electricity in several European countries, but also allows investors to follow diverse strategies with exposure to the electricity market by using instruments such as derivatives.

The evidence collected in the current study supports the existence of price clustering in several bidding areas. Out of the more than 160,000 hourly prices, the final digit 0 appears 11.94% of the time, higher than the expected 10% if the prices were uniformly distributed.

The existence of clustering in Nord Pool prices can have a significant impact on the stakeholders, namely investors. As stated by Sopranzetti and Datar (2002), the existence of price clustering can have two major consequences: (1) on the valuation of derivatives instruments, as traditional models assume that the underlying assets show a uniform distribution of prices; (2) on investors and other stakeholders whose risk hedging and portfolio management strategies depend on this electricity market.

Understanding the statistical properties of the prices formed in the electricity market is essential not only to strengthen the scientific research, but also to the development of new models that better represent the dynamics of a security.

The structure of this chapter is as follows. The second section reviews the literature on the topic of price clustering and on the structure of the Nord Pool market. The third section presents the data and the methodology that will be applied in the empirical study. The fourth section analyses the empirical results. The fifth section concludes the chapter.

2. Literature Review

2.1. The Nord Pool electricity market

The creation of Nord Pool started way back in 1991, when the Norwegian parliament decided to deregulate the market for the trading of electrical energy. Today, Nord Pool offers the day-ahead power trading and a continuous intraday trading of power products with physical delivery. The introduction of online trading platforms (both for the day-ahead and intraday markets) happened in 2015 with markets that allow the trading of energy for every hour and every day of the year.

To better understand how Nord Pool system is built, we must first distinguish the two phases that compose every power market, from its producer to its end-user (individuals or companies). In the initial phase, the producers of energy are responsible to generate electricity through a source of energy (such as wind power, hydropower, nuclear reactions or condensing plants), that later provide to a supplier who redirects this power to the final consumer via the distribution grid. At this second stage, the distributor company interacts with the final consumer, to which are applied the traditional costs such as distribution fees and taxes specific to each situation. It is important to notice that this transaction of power is not perfect and faces challenges such as ramping (i.e. change in power flow/generation from one-time unit to the following) and losses of energy along the distribution grid (inevitably leading to a difference between the volume sold by a bidding area and the volume received by another).

In practice, the main difference from Nord Pool to the traditional energy market is that, instead of having a small set of monopolistic companies that dominate the vertical chain – producing and distributing electricity to the final consumer – the initial stage previously described is made through a decentralized exchange, with both producers and suppliers vulnerable to changes in the supply and demand, and with the counterparty risk covered by Nord Pool who acts as a clearing house that guarantees the settlement of the contracts and delivery of power. This way, even though energy providers can set their desired price to the final consumer (which can choose among several available energy providers), all of them buy the electrical energy via Nord Pool or directly from a producer.

The Nord Pool Spot allows for the physical delivery of power, both on an intraday or a day-ahead basis. Other financial markets are also connected to the Nord Pool Spot market, such as the NASDAQ OMX Commodities

Europe market. In the NASDAQ OMX Commodities Europe market institutional and individual investors can trade several derivative instruments such as futures and options, for hedging strategies and speculative investments. Regarding the Nord Pool Spot market, we can further divide it into two sub-markets – the day-ahead market or Elspot market, and the intraday market or Elbas market.

2.2. Price dynamics in the Nord Pool market

Despite the differences and the special characteristics of energy, Nord Pool establishes prices using the process known as marginal price setting, also used by other energy markets. As electricity cannot be stored and must be delivered at the precise moment the final consumer needs it, demand presents high levels of inelasticity. To the supply side, the production of electricity is also more demanding than other types of energy and commodities since it implies high levels of variable costs (depending on the source of energy used). These characteristics justify the usefulness of Nord Pool as a system that establishes the equilibrium between supply and demand, since only by facing the cost of producing one MW/h with the price the customer is willing to pay for the final MW/h required to satisfy demand it is guaranteed that the price formation process is economically efficient for both parties.

For the market participants in the day-ahead trading platform Nord Pool offers different types of orders including single hourly orders and block orders. To better operate the system and handle congestions in the electricity grid more rapidly, there are several bidding areas.

The major role of a market is to lead supply and demand to converge, from which an equilibrium price arises. This equilibrium is especially important in power markets since electricity cannot be easily stored and failures in supply originate high costs. The trading of power is performed mainly in the day-ahead market. The exchange functions basically as an auction, where customers submit their orders and an equilibrium between the aggregated supply and demand curves is established for each of the bidding areas. Producers and consumers of electricity send their bids/offers to the day-ahead market which then calculates an hourly price that balances both sides. Nord Pool combines this set of orders and publishes a price for each hour of the following day, properly balanced and adjusted in real-time to face eventual problems. During this process, the single price for each hour (of the following day) in each bidding zone is set by the intersection of the respective supply and demand curves, taking into account eventual transmission constraints.

Hourly clearing prices are then announced to the market and each buyer and seller is notified with the respective individual result. At hourly intervals of the second day the delivery will then occur, following an auction model: bidders who have submitted buying orders equal to or higher than the system price will be able to buy electricity at the market price; sellers whose orders are equal or lower than the system price will also be able to sell at the respective market price.

Several studies have already been pursued to assess which are the main factors that impact the system price in Nord Pool. From a fundamental approach, Määttä and Johansson (2011) sought to assess if the traditional factors related to the demand and supply of electricity have statistical significance in explaining the historical prices of the market. The results suggest that in fact fundamental variables that form the supply and demand explain the observed prices with high statistical significance. This capacity to use statistical models to predict, with a certain degree of accuracy, future day-ahead hourly prices based in demand and supply factors is supported by other authors such as Kristiansen (2012) and Weron and Misiorek (2008).

Aiming to compare Nord Pool electricity market with other commodity markets, Botterud *et al*. (2010) studied the relation between spot and future prices. Their results indicate that futures prices tend to be constantly higher than the respective spot prices but the robustness of such conclusion depends on cyclical factors. These results were later challenged by Weron and Zator (2014).

Analysing the volatility of Nord Pool hourly system price in a 12-year sample, Simonsen (2005) found evidence that this market shares many similarities with others financial and commodity markets, presenting phenomena like volatility clustering, log-normal distribution, and long-range volatility-volatility correlations. More uncommon features are also highlighted, such as an overall high level of volatility and price level-dependent volatility. Predictability regarding the volatility of Nord Pool day-ahead market was also studied by Haugom *et al*. (2011). The authors conclude that there is stronger predictive capacity of models where total variation is segregated in a continuous and a jump component, due to the strong degree of persistence shown by the realized volatility.

2.3. Price clustering in utility markets and commodities

The price clustering phenomena can be simply defined as the tendency for prices to accumulate around certain sets of values. In a purely theoretical approach, the occurrence of price clustering and market efficiency are two mutually exclusive hypotheses. The efficient market hypothesis, introduced by Fama (1970) posits that prices should absorb all the available public information. And since the future is unpredictable one can conclude that prices should follow a "random walk. Thus, since prices reflect the intrinsic value of an asset, there is no plausible reason to explain why they may accumulate around certain specific numbers, and what we should observe is a uniform distribution where each price level has the same probability to occur.

For the specific case of our study, it is relevant to consider similar studies in other utility markets with structures similar to that of the Nord Pool market. The utilities sector includes companies that provide basic goods and services such as water, electricity and natural gas. In this regard, Brooks *et al*. (2013) analyse the occurrence of price clustering in the Australian water market. Similarly, to Nord Pool electricity market, the Australian water market also allows to build risk hedging strategies for those entities whose activity is dependent on this utility, namely farmers who are now able to manage their intra-seasonal risk. Studying the prices for three different trading zones, the authors found significant evidence of clustering at integers dollar amounts. An additional analysis revealed that the tendency of prices to cluster was negatively correlated with trading activity.

3. Data and Methodology

In our empirical study, we will consider the bidding area prices for hourly prices during the year of 2019. The hypothesis to be tested is whether Nord Pool price data shows evidence of price clustering. Following the literature on the topic (e.g., Brooks *et al*., 2013; Lobão *et al*., 2019), we will recur to a frequency table where prices from the sample are segregated by their ending number. Then we will compare the number of occurrences of whole digits versus decimal digits; within the prices that comprehend decimal values, a relative frequency for the figure in the hundredth place will be extracted. In the presence of price clustering, the threshold for the first test will be ten percent – i.e. prices ending in XX.X0 should have the same probability than those ending in XX.01; XX.02; …; XX.09.

We will also apply the Chi-squared goodness-of-fit statistics to the frequencies of the last hundredth digit of each price. This test aims to compare the observed level of price clustering with the expected level of price clustering under a uniform distribution, where the difference between the observed and expected number of occurrences are computed as follows:

$$W = \sum \frac{(O_i - A_i)^2}{A_i}$$

where O_i represents the observed absolute frequency and A_i represents the expected absolute frequency under a uniform distribution, for each ending digit. Note that for k possible digits there will be $(k-1)$ degrees of freedom under the null hypothesis of no price clustering. In our case, k will therefore assume the value of 10, as there are 10 possible ending digits for the hundredth decimal place. Under the null hypothesis H_0 each outcome should have the same probability to occur (one-tenth) while under the alternative hypothesis H_1 there is evidence that the sample is significantly concentrated around certain values. A higher divergence from the observed and expected frequencies will lead to a higher value of the W statistic, suggesting a higher divergence from the uniform distribution hypothesis.

Finally, we will compute the Herfindahl- Hirschman Index (HHI), a measure widely used to assess the concentration of a certain market by calculating the sum of the squared market shares of all market participants. When applied to assess the price clustering of the hundredth decimal number, the index is defined as follows:

$$HHI = \sum (f_i)^2$$

where f_i is equal to the frequency (in percentage) of prices that occur for each ending digit i. Thus, if there is not price clustering it is expected that HHI will take a value close to 1/k, in our case 1/10, meaning that prices ending in a certain digit should represent a portion close to 10% of the whole number of observations. If values obtained for the HHI are higher than 0.10, evidence of price clustering is found.

4. Empirical Results

Panel A of Table 1 presents the absolute and relative frequency for the number of occurrences of each figure in the hundredth decimal place, highlighting also the number of prices ending in XX.X0 and XX.05 due to its relevance within the existing literature. The Herfindahl-Hirschman Index (HHI) statistic and the Chi-squared goodness-of-fit statistic are displayed in Panel B. In this study, the bidding areas' prices were analysed, as well as the clustering in the whole sample.

Table 1 - Frequency distribution for the hundredth decimal number and whole digits of Nord Pool day-ahead market hourly prices

Panel A: Distribution of the last digit or last two digits of the price.														*Panel B: Clustering tests and HHI*	
Last Digit		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**	**0 & 5**	**X2**	**HHI (%)**
SE1	#	944	899	865	881	839	815	888	874	917	838	8,760	1,759	15.5959	10.02
	%	10.78	10.26	9.87	10.06	9.58	9.30	10.14	9.98	10.47	9.57		20.08	(0.0758**)	
SE2	#	943	900	864	881	840	815	888	874	917	838	8,760	1,758	15.4384	10.02
	%	10.76	10.27	9.86	10.06	9.59	9.30	10.14	9.98	10.47	9.57		20.07	(0.0796**)	
SE3	#	971	903	881	876	839	811	891	855	898	835	8,760	1,782	20.7808	10.02
	%	11.08	10.31	10.06	10.00	9.58	9.26	10.17	9.76	10.25	9.53		20.34	(0.0137**)	
SE4	#	960	915	895	883	833	832	870	861	863	848	8,760	1,792	15.9658	10.02
	%	10.96	10.45	10.22	10.08	9.51	9.50	9.93	9.83	9.85	9.68		20.46	(0.0676*)	

FI	**#**	952	874	855	890	847	832	877	894	880	859	8,760	1,784	11.2146	10.01
	%	10.87	9.98	9.76	10.16	9.67	9.50	10.01	10.21	10.05	9.81		20.37	(0.2613)	
DK1	**#**	1251	842	816	840	810	821	797	848	852	883	8,760	2,072	184.5982	10.21
	%	14.28	9.61	9.32	9.59	9.25	9.37	9.10	9.68	9.73	10.08		23.65	(0.0000***)	
DK2	**#**	1129	887	840	865	799	824	815	862	861	878	8,760	1,953	89.4132	10.10
	%	12.89	10.13	9.59	9.87	9.12	9.41	9.30	9.84	9.83	10.02		22.29	(0.0000***)	
Oslo	**#**	919	897	901	873	805	844	883	870	858	910	8,760	1,763	12.0479	10.01
	%	10.49	10.24	10.29	9.97	9.19	9.63	10.08	9.93	9.79	10.39		20.13	(0.2106)	

Panel A: Distribution of the last digit or last two digits of the price.														*Panel B: Clustering tests and HHI*	
Last Digit		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**	**0 & 5**	**X2**	**HHI (%)**
Kr.sand	#	916	909	894	869	816	838	882	867	859	910	8,760	1,754	11.0365	10.01
	%	10.46	10.38	10.21	9.92	9.32	9.57	10.07	9.90	9.81	10.39		20.02	(0.2732)	
Bergen	#	913	897	893	875	806	838	889	871	863	915	8,760	1,751	11.7900	10.01
	%	10.42	10.24	10.19	9.99	9.20	9.57	10.15	9.94	9.85	10.45		19.99	(0.2254)	
Molde	#	908	906	873	866	861	833	893	887	873	860	8,760	1,741	5.4589	10.01
	%	10.37	10.34	9.97	9.89	9.83	9.51	10.19	10.13	9.97	9.82		19.87	(0.7926)	
Tr.heim	#	908	906	873	866	861	833	893	887	873	860	8,760	1,741	5.4589	10.01
	%	10.37	10.34	9.97	9.89	9.83	9.51	10.19	10.13	9.97	9.82		19.87	(0.7926)	
Tromsø	#	893	895	863	858	870	859	902	880	874	866	8,760	1,752	2.5845	10.00
	%	10.19	10.22	9.85	9.79	9.93	9.81	10.30	10.05	9.98	9.89		20.00	(0.9785)	

EE	#	917	908	871	893	839	828	877	904	866	857	8,760	1,745	9.0616	10.01
	%	10.47	10.37	9.94	10.19	9.58	9.45	10.01	10.32	9.89	9.78		19.92	(0.4316)	
LV	#	932	898	874	907	850	823	867	900	857	852	8,760	1,755	11.0320	10.01
	%	10.64	10.25	9.98	10.35	9.70	9.39	9.90	10.27	9.78	9.73		20.03	(0.2735)	
LT	#	933	903	865	897	851	824	869	894	863	861	8,760	1,757	9.8584	10.01
	%	10.65	10.31	9.87	10.24	9.71	9.41	9.92	10.21	9.85	9.83		20.06	(0.3621)	
AT	#	674	417	409	404	377	378	385	439	406	456	4,345	1,052	159.9321	10.37
	%	15.51	9.60	9.41	9.30	8.68	8.70	8.86	10.10	9.34	10.49		24.21	(0.0000***)	

Panel A: Distribution of the last digit or last two digits of the price.														*Panel B: Clustering tests and HHI*	
Last Digit		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Total**	**0 & 5**	**X2**	**HHI (%)**
BE	#	806	408	389	384	394	401	353	401	366	443	4,345	1207	365.0783	10.84
	%	18.55	9.39	8.95	8.84	9.07	9.23	8.12	9.23	8.42	10.20		27.78	(0.0000***)	
DE-LU	#	697	433	400	391	384	419	354	431	393	443	4,345	1116	191.1818	10.44
	%	16.04	9.97	9.21	9.00	8.84	9.64	8.15	9.92	9.04	10.20		25.68	(0.0000***)	
FR	#	722	403	388	382	388	409	365	443	373	472	4,345	1131	233.5339	10.54
	%	16.62	9.28	8.93	8.79	8.93	9.41	8.40	10.20	8.58	10.86		26.03	(0.0000***)	
NL	#	1045	366	377	370	367	371	347	376	340	386	4,345	1416	957.0046	12.20
	%	24.05	8.42	8.68	8.52	8.45	8.54	7.99	8.65	7.83	8.88		32.59	(0.0000***)	
All	#	19,333	16,366	15,886	15,951	15,276	15,248	15,785	16,118	15,852	16,070	161,885	34,581	746.1811	10.05
	%	11.94	10.11	9.81	9.85	9.44	9.42	9.75	9.96	9.79	9.93		21.36	(0.0000***)	

Panel A presents the frequency table regarding Nord Pool hourly prices decimal values, for all the available bidding areas. The symbol # represents the absolute frequency, while % represents the relative frequency. The names of the bidding areas are represented by the following: *SE1*, *SE2*, *SE3* and *SE4* refer to Sweden; *FI* refers to Finland; *DK1* and *DK2* refer to Denmark; *Oslo*, *Kr.sand*, *Bergen*, *Molde*, *Tr.heim* and *Tromsø* refer to cities in Norway; EE stands for Estonia; LV refers to Latvia; *LT* refers to Lithuania; *AT* refers to Austria; *BE* refers to Belgium; *DE-LU* refers to Germany; *FR* refers to France; *NL* refers to Netherlands. Panel B shows the price clustering tests applied in each bidding area. HHI stands for Hirschman-Herfindahl Index, while X2 is the Chi-squared goodness-of-fit test, with the respective p-value displayed below in brackets. *** represents values statistically significant for a level of confidence of 99%; ** represents values statistically significant for a level of confidence of 95%; * represents values statistically significant for a level of confidence of 90%.

The occurrence of price clustering at the hundredth decimal place does not seem to be a generalized phenomenon in the bidding areas of the Nord Pool market. As predicted by Goodhart and Curcio (1991), the number zero shows a relatively higher frequency relatively to others, with such conclusion being more salient for the bidding areas of Denmark (DK1, DK2), Austria (AT), Belgium (BE), Germany (DE-LU), France (FR) and the Netherlands (NL). In fact, with the exception of two bidding areas, zero was the number most frequently observed. The bidding area of the Netherlands is noteworthy as it presented the highest level of clustering among all the areas under analysis: in this case, more than 24% of the prices observed were round numbers. On the other hand, the number 5, pointed as the second most frequent number by Goodhart and Curcio (1991), does not present an abnormal number of occurrences in any bidding area.

When analysing the whole sample, the conclusions remain the same. Out of the more than 160,000 prices, the final digit 0 appears 11.94% of the time, higher than the expected 10% if the prices were uniformly distributed.

Panel B of Table 1 shows the statistical tests for the detection of price clustering. The results reveal that the previous conclusions are statistically significant. In fact, in 11 of the 21 bidding areas under scrutiny, statistically significant levels of clustering were observed according to the Chi-squared goodness-of-fit test. For the bidding areas of DK1, DK2, AT, BE, DE-LU, FR and NL the results present a level of confidence of 99%, and the Swedish bidding areas (SE1, SE2, SE3, SE4) present a level of confidence of 90%. For the entire sample, results remain statistically significant for a 99% confidence of level.

5. Conclusion

Energy markets are essential for many stakeholders including the buyers and sellers of energy, the households and the companies that use energy as final consumers. Investors depend also on this utility market for several purposes, using for example derivative instruments to either diversify their portfolio, achieve exposure to this asset, or hedge their investment position against adverse outcomes. This raises the need for a deep understanding of how energy prices, such as those of the Nord Pool market, are formed.

In this chapter, we present evidence that Nord Pool hourly prices tend to cluster. Goodhart and Curcio (1991) suggest that each ending figure as a different "gravitational" strength within human minds – with numbers ending in 0 being the strongest - that makes them more compelling by facilitating the required mental calculations. The evidence presented in this chapter supports to a certain degree such expectation, as hourly prices show a relatively higher number of frequencies for both numbers ending in 0 at the hundredth decimal place. The presence of number 5, the second "strongest" number according to Curcio and Goodhart (1991), shows already no direct support from the results obtained. Overall, the evidence presented in this chapter is difficult to reconcile with the idea that prices follow a random walk, one of the basic tenets of the efficient market hypothesis.

There is much to be studied regarding the price patterns exhibited by energy prices. For example, it would be interesting to assess whether the price clustering observed in the final prices is also a feature of bidding and asking prices.

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CHAPTER 9

THE IMPACT OF PUBLIC FEAR OF COVID-19 ON STOCK MARKET RETURNS: EVIDENCE FROM THE SPANISH AND PORTUGUESE STOCK MARKETS

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Abstract

This chapter analyses the impact of public fear of COVID-19 on the returns of the two Iberian stock markets. The Spanish and Portuguese markets represent the two European economies that were most affected by the coronavirus in the short term. Search volumes of Google Trends with four search engines (Web, Images, News, and YouTube) during the period March 2, 2020 to August 21, 2020 were used as proxies to measure public fear. Applying Panel Data and Simple Linear Regression with Ordinary Least Squares (OLS) analysis, findings suggest that public fear of COVID-19 had a significant negative impact on the returns of the Iberian stock markets. In particular, the Portuguese market was found to be more sensitive to this sentiment than the Spanish market. The study contributes to the previous literature on the impact of the sentiment of fear on stock market returns.

Key-words: public fear, stock returns, COVID-19, google trends, Iberian stock markets

1. Introduction

The unexpected arrival of COVID-19 created significant uncertainty. Whilst the spread of the contagious virus affected people's health, resulting in higher medical costs and changed lifestyles, it also contributed to a decline in economic growth and financial market volatility (Baker et al. 2020). The rapid contagion that spread across borders led governments to adopt strong containment measures causing the "great lockdown" with more severe negative economic and financial consequences than seen in previous crises (Shehzad, Xiaoxing and Kazouz 2020).

The world was faced with the greatest challenge that it had seen since World War II with an unprecedented socio-economic crisis (United Nations 2020). Whilst the risk of a health crisis had been analysed before, studies had been focussed on pandemics principally that were locally contained. SARS, Ebola, Zika, or HIV affected certain countries and some economic sectors such as tourism (Haacker 2004, Hoffman and Silverberg 2018 or Bloom, Cadarette and Sevilla 2018, between others). Economic globalization plays an important role in spreading infectious diseases (Lee and Mckibbin 2004) and during that time, the spread of the disease was across the borders.

In a short period of time, multiple studies addressed the impact of COVID-19: on geopolitical risk (Sharif, Aloui and Yarovaya 2020), the economy (Jordà, Singh and Taylor 2020, Barro, Ursúa and Weng 2020, Conlon and McGee 2020), the labour market and employment (Coibion, Gorodnichenko and Weber 2020), large companies (Hassan et al. 2020) and small business (Fairlie 2020). Other studies provided evidence of the immediate impact of confirmed cases and deaths by COVID-19 on all the financial markets (Al-Awadhi 2020, Sansa 2020, Liu et al. 2020a). Short selling activity was banned for certain stocks in some European stock markets inducing higher information asymmetry, lower liquidity, and lower abnormal returns compared with non-banned stocks (Siciliano and Ventoruzzo 2020). The overreaction to the announcements of lockdowns was stronger for stocks with lower institutional ownership (Huo and Qiu 2020) or belonging to sectors perceived to be most affected by the disease (Haroon and Rizvi 2020). The pandemic benefited sectors such as pharmaceutical manufacturing, software and IT services, but it had a negative impact on stock returns of the transportation, lodging and catering sectors (Liu et al. 2020b). Stock volatility was also affected by the reports of new cases and significantly by the death ratio (Albulescu 2020), recording levels that were higher than those observed during October 1987, December 2008 and the

1929 crash, reaching the highest level registered in history in the United States (Baker et al. 2020).

Whilst most of the prior research had been focused on the equity markets, assessments of the impact on other markets had also been attempted. Fixed income initially experienced an abnormal disruption with significant losses incurred, but these disappeared with aggressive interventions by the US Federal Reserve (Haddad, Moreira and Muir 2020). In the case of the European debt markets, a mix of policies had the near-term effect of amplifying the negative effect of a rise in CDS spreads (Andries, Ongena and Sprincean 2020). Commodity prices rapidly declined along with the broader market and the uncertainty related to COVID-19 had a strong negative impact on volatility, especially in the oil market (Bakas and Triantafyllou 2020). In addition to experiencing severe downturns in their own markets, commodities and equities also experienced more cross shocks across markets than in prior periods (Salisu, Ebuh and Usman 2020), although gold and soybeans were observed to be strong safe-haven assets (Ji, Zhang and Zhao 2020). Related to currency markets, Gunay (2020) noted that the turmoil in the currency exchange markets was not as bad as during the Global Financial Crisis of 2008. Notably bitcoin failed as a safe-haven asset during the COVID-19 pandemic (Conlon and McGee 2020, Corbet, Larkin and Lucey 2020).

The effect of the COVID-19 pandemic on financial markets was also studied from a behavioural finance perspective. Here it was found that the negative sentiments driven by the uncertainty generated by COVID-19 played an important role in the performance of stock markets. Bansal (2020) discussed how cognitive errors and biases affected financial institutions and markets during and after the COVID-19 crisis. Salisu and Vo (2020) showed that health and financial news were good predictors of stock returns since the emergence of the pandemic. Based on a regression model, Smales (2020) found a negative influence in the global stock indexes with a heterogeneity of returns across stock market sectors and Liu (2020) showed the impact of the disease on the return and volatility of China's composite index and its sector indexes using the EGARCH model. Baig et al. (2020) also confirmed a strong and statistically significant negative relationship between coronavirus indicators (number of infected cases, deaths, social distancing and lockdowns) and stock market liquidity. Papadamou et al. (2020), using panel data analysis of thirteen major stock markets along with several model specifications, distinguished between a direct effect on implied volatility and an indirect effect via stock returns as a result of a risk-aversion sentiment over the pandemic.

Research that focused on retail investor attention used Google Trends as a proxy of the sentiment of fear (Da, Engelberg and Gao 2011) and followed past literature that evaluated the impact in terms of returns (Peng and Xiong 2006, Li and Yu 2012), volatility (Andrei and Hasler 2015, Aouadi, Arouri, and Teulon 2013) and liquidity (Ding and Hou 2015). The unanswered question that we attempted to address was directed at examining the relationship between public fear of the Coronavirus and stock market movements during the COVID-19 pandemic.

General population anxiety is reflected in a desire to be informed and measured through internet search behaviour. Google Trends has converted one of the academic sources to evaluate public attention on stock markets in times of financial turmoil (Heiberger 2015). Early evidence showed that the dynamic of public concern (measured by Google Trends COVID-19) in Italy was also a driver in other countries (Germany, France, Great Britain, Spain, and the United States) and that the Italian index was more relevant than others in explaining stock index returns (Costola, Iacopini and Santagiustina 2020). Given these results and based on Internet search data being a good proxy of populations' underlying beliefs in Portugal (Oliveira 2020), our study extended the previous analyses by focusing on the impact of the public's fear of COVID-19 on the Iberian stock markets. The results can shed more light on the performance of the Spanish and Portuguese stock market considering that they were the two European economies most impacted by COVID-19 during the second quarter of 2020 (Eurostat 2020). Our research used Panel Data and Simple Linear Regression with Ordinary Least Squares (OLS) with data from March 2, 2020 to August 21, 2020.

The results show how public fear of the coronavirus impacted the Spanish and Portuguese stock market returns. This study confirmed and contributed to the past literature related to the role of biases in the financial markets and the effect of the pandemic on the stock markets using Google Trends as a proxy of public fear of disease.

The rest of the chapter is organized as follows. The following sections describe the data and the methodology used in this study. The next section describes and analyses the empirical results. And the last section provides our conclusions.

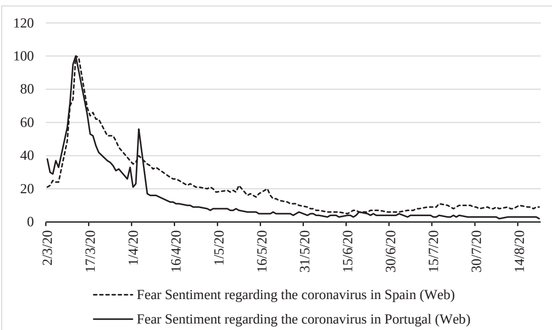
2. Data

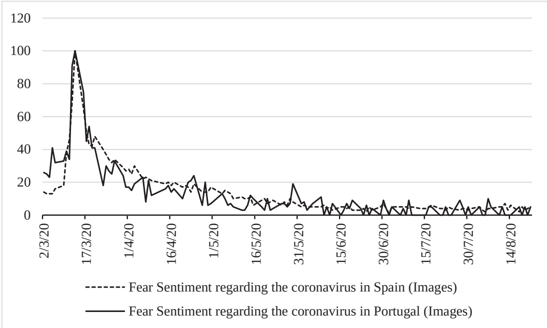
In order to analyse the influence of public fear generated by COVID-19 on the return of the Spanish and Portuguese stock markets, a sample of daily data was taken from March 2, 2020 to August 21, 2020.

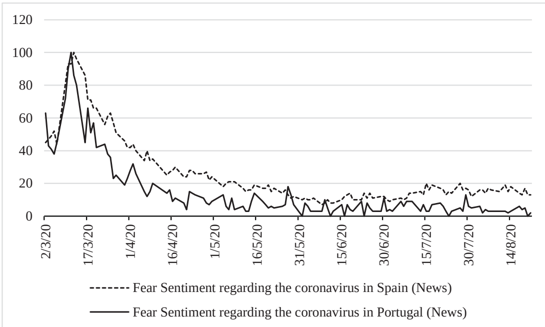
To measure public fear, internet search data from Google Trends was selected in line with methods used by Da, Engelberg and Gao (2011) and Chen, Liu and Zhao (2020). Since its inception in 2006, Google Trends has been used as source of primary data in multiple research studies. Google offers a free and publicly available query index that describes search volume as a number between zero and one hundred and allows for data to be sorted by categories such as geographic location, activity, etc. (see https://trends.google.com/trends/). In our study, the "search by topic" was chosen, and the topic "coronavirus" was selected. The coronavirus topic included the queries related to the virus instead of an exact term. This topic choice allowed for several synonyms, spelling errors and translations from different languages to be included in the analysis (Szmuda et al. 2020). The search data was extracted for both Spain and Portugal, and the queries of four specialized search engines was collected: Web, Images, News and YouTube.

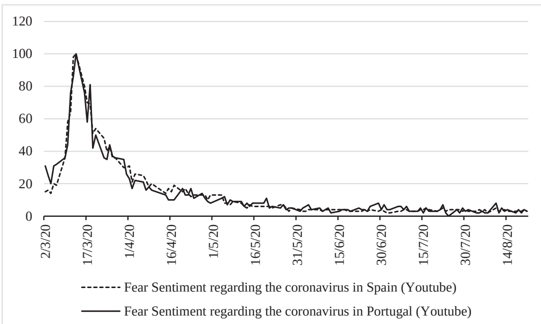
In Figure 1, the public fear generated by the coronavirus can be observed, extracted from each of the search engines selected for each country from March 2, 2020 to August 21, 2020. It is noteworthy that the period between March 10 and 13 generated the greatest interest in COVID-19 and when the fear index peaked as this is the period just before the declaration of the State of Alarm in Spain and the State of Alert and Emergency in Portugal.

Figure 1. Evolution of the public fear due to the coronavirus in Spain and Portugal between March 2 and August 21, 2020.









The IBEX-35 and PSI-20 indexes were selected as being representative of the Spanish and Portuguese stock markets. Both indexes are recognized as the most representative for the stock indexes for these markets. The change in closing price of these indexes on consecutive days was selected as a measure of return. Listing data was obtained from Investing (https://es.investing.com/).

Table 1 shows the descriptive statistics of the target variables studied. The data indicate that during the analysed period, the mean daily return of the IBEX-35 and the PSI-20 (R_{IBEX} and R_{PSI}) were at negative values (-0.2% and -0.1%, respectively). Both indexes registered their biggest single day drops with returns of -14.1% (IBEX-35) and -9.8% (PSI-20) on March 12, 2020. In addition, it can be observed that the return variables present a high dispersion measured by the Coefficient of Variation (CV) (18.299 and 37.574, respectively).

Regarding the variables of public fear of the coronavirus, it was found that the Web and News search engines for Spain ($Fear_{\text{Web,Spain}}$ and $Fear_{\text{News,Spain}}$) captured the highest levels of fear with means of 20.270 and 26.033, respectively (out of 100). The highest levels registered by all measures of fear was the fear captured by the News search engine for both stock markets. The lowest levels for fear were captured by the Images search engine ($Fear_{\text{Images,Spain}}$ and $Fear_{\text{Images,Portugal}}$) in both countries with values of 13.656 for Spain and 12.475 for Portugal. Thus, it was be observed that the population was more interested on searches for other media sources than on searches for Images when it came to be informed about the coronavirus.

Table 1. Descriptive statistics of the variables under study.

Variable	Mean	Median	Min.	Max.	S.D	C.V.
R_{IBEX}	-0.002	-0.001	-0.141	0.078	0.027	18.299
R_{PSI}	-0.001	0.000	-0.098	0.078	0.021	37.574
$Fear_{\text{Web,Spain}}$	20.270	11.000	5.000	100.000	19.399	0.957
$Fear_{\text{Images,Spain}}$	13.656	6.500	1.000	100.000	15.413	1.129
$Fear_{\text{News,Spain}}$	26.033	17.000	7.000	100.000	21.265	0.817
$Fear_{\text{Youtube,Spain}}$	14.082	5.000	2.000	100.000	19.427	1.380
$Fear_{\text{Web,Portugal}}$	13.861	5.000	2.000	100.000	19.715	1.422
$Fear_{\text{Images,Portugal}}$	12.475	6.500	0.000	100.000	16.778	1.345
$Fear_{\text{News,Portugal}}$	15.139	7.000	0.000	100.000	20.173	1.333
$Fear_{\text{Youtube,Portugal}}$	14.033	6.000	0.000	100.000	18.675	1.331

When the bivariate correlations of the target study variables by country (Table 2) were analysed, it was shown that the four measures of public fear due to the coronavirus were negatively correlated with the return of the IBEX-35 and the PSI-20, all being significant with more than 95% confidence except the correlation between $Fear_{\text{Images,Spain}}$ and R_{IBEX}. And, as expected, the different measures of coronavirus fear were highly positively correlated with each other with more than 99% confidence.

Table 2. Matrix of bivariate correlations of the variables under study.

SPAIN					
Variable	$R_{IBE.}$	$Fear_{\text{Web,Spa}}$	$Fear_{\text{Images,Spa}}$	$Fear_{\text{News,Spai}}$	$Fear_{\text{Youtube,Spa}}$
R_{IBEX}	1				
$Fear_{\text{Web,Spa}}$	-0.189** (0.038)	1			
$Fear_{\text{Images,S}}$	-0.142 (0.118)	0.965*** (0.000)	1		
$Fear_{\text{News,Spa}}$	-0.219** (0.015)	0.962*** (0.000)	0.900*** (0.000)	1	
$Fear_{\text{Youtube,}}$	-0.222** (0.014)	0.979*** (0.000)	0.970*** (0.000)	0.945*** (0.000)	1
PORTUGAL					
Variable	R_{PSI}	$Fear_{\text{Web,Por}}$	$Fear_{\text{Images,Por}}$	$Fear_{\text{News,Port}}$	$Fear_{\text{Youtube,Por}}$
R_{PSI}	1				
$Fear_{\text{Web,Por}}$	-0.277*** (0.002)	1			
$Fear_{\text{Images,P}}$	-0.286*** (0.001)	0.890*** (0.000)	1		
$Fear_{\text{News,Po}}$	-0.236*** (0.009)	0.948*** (0.000)	0.825*** (0.000)	1	
$Fear_{\text{Youtube,}}$	-0.236*** (0.009)	0.944** (0.000)	0.932*** (0.000)	0.944*** (0.000)	1

Note: ***, ** and * indicate the significance at 1%, 5% and 10% levels, respectively.

3. Methodology

The proposed methodology to evaluate the impact of the public fear of COVID-19 on the Spanish and Portugal market return has been: (1) panel data to analyse the general impact of this sentiment of fear on the stock markets of the Iberian Peninsula; (2) Simple Linear Regression with OLS to analyse the individual impact of the public fear of the coronavirus on the most representative stock index of each country.

Panel Data

The Panel Data analysis evaluated the explanatory capacity of some variables over others when available data combined a temporal dimension with another transversal one. This method considered independently the data set of each unit of analysis over time, which is known as individual effects.

There were two models that we considered: the fixed effects model and the random effects model. The fixed effects model assumes that the individual effect is correlated with the explanatory variables. However, the random effects model assumes the condition that the individual effects are not correlated with the explanatory variables of the model. Applying the Hausman test, the results reveal that the fixed effects model is more consistent.

Thus, the Panel Data models proposed to analyse the impact of the public fear of COVID-19 on the Spanish and Portuguese stock market return are:

$$\mathrm{R}_{\mathrm{it}} = \alpha + \beta Fear_{\mathrm{Web,kt}} + v_{\mathrm{i}} + u_{\mathrm{it}}, \quad \mathrm{t} = 1,2,\dots,\mathrm{T}. \tag{1}$$

$$\mathrm{R}_{\mathrm{it}} = \alpha + \beta Fear_{\mathrm{News,kt}} + v_{\mathrm{i}} + u_{\mathrm{it}}, \quad \mathrm{t} = 1,2,\dots,\mathrm{T}. \tag{2}$$

$$\mathrm{R}_{\mathrm{it}} = \alpha + \beta Fear_{\mathrm{Images,kt}} + v_{\mathrm{i}} + u_{\mathrm{it}}, \quad \mathrm{t} = 1,2,\dots,\mathrm{T}. \tag{3}$$

$$\mathrm{R}_{\mathrm{it}} = \alpha + \beta Fear_{\mathrm{Youtube,kt}} + v_{\mathrm{i}} + u_{\mathrm{it}}, \quad \mathrm{t} = 1,2,\dots,\mathrm{T}. \tag{4}$$

Where R_{it} represents the return of the stock index i in period t, α is the independent parameter of the model, β is the model's dependent parameter, $Fear_{\mathrm{Web,kt}}$, $Fear_{\mathrm{News,kt}}$, $Fear_{\mathrm{Images,kt}}$ and $Fear_{\mathrm{Youtube,kt}}$ represent the public fear of COVID-19 captured in country k through the level of searches for this virus on the Web, News, Images and YouTube in period t, v_{i} is the constant fixed part of the model error that represent the individual effects and u_{it} is the random part of the error term.

Simple Linear Regression with Ordinary Least Squares

The Simple Linear Regression method with OLS was used to analyse the influence of public fear of the coronavirus in Spain and Portugal on the return of the most representative stock indexes of these countries individually.

This method tries to explain the relationship between a dependent variable and an independent variable, and the application of OLS allows for the reduction of the distances between the real values and those estimated by the regression by minimizing the sum of the residuals or squared errors.

The Simple Linear Regression models proposed to study the influence of public fear of COVID-19 on the return of the stock markets of the Iberian Peninsula are:

$$\mathrm{R}_{\mathrm{IBEX,t}} = \alpha + \beta Fear_{\mathrm{Web,Spain,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{5}$$

$$\mathrm{R}_{\mathrm{IBEX,t}} = \alpha + \beta Fear_{\mathrm{News,Spain,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{6}$$

$$\mathrm{R}_{\mathrm{IBEX,t}} = \alpha + \beta Fear_{\mathrm{Images,Spain,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{7}$$

$$\mathrm{R}_{\mathrm{IBEX,t}} = \alpha + \beta Fear_{\mathrm{Youtube,Spain,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{8}$$

$$\mathrm{R}_{\mathrm{PSI,t}} = \alpha + \beta Fear_{\mathrm{Web,Portugal,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{9}$$

$$\mathrm{R}_{\mathrm{PSI,t}} = \alpha + \beta Fear_{\mathrm{News,Portugal,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{10}$$

$$\mathrm{R}_{\mathrm{PSI,t}} = \alpha + \beta Fear_{\mathrm{Images,Portugal,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{11}$$

$$\mathrm{R}_{\mathrm{PSI,t}} = \alpha + \beta Fear_{\mathrm{Youtube,Portugal,t}} + \varepsilon_{\mathrm{t}}, \quad \mathrm{t} = 1,2, \dots, \mathrm{T}. \tag{12}$$

Where $\mathrm{R}_{\mathrm{IBEX,t}}$ y $\mathrm{R}_{\mathrm{PSI,t}}$ represent the return of the IBEX-35 and the PSI-20, respectively, in period t, and ε_{t} the error term in period t.

4. Results

This section shows the results obtained with the application of the proposed methodologies.

Table 3 shows the results obtained by applying the Panel Data models to analyse the influence of public fear generated by the coronavirus on the return of the main stock indexes in Spain and Portugal. The existence of a negative and significant relationship, with more than 99% confidence, between the public fear of the coronavirus and stock market returns was observed. It showed that a one-point increase in fear generated by the coronavirus is associated with a 0.03% reduction in the stock market return in the same day, with the explanatory power of the proposed models oscillating between 4.37% and 5.27%. These results showed that changes in public fear of the coronavirus explained around 5% of the variations recorded in the return of the main stock indexes in the period analysed.

Table 3. Influence of public fear of the coronavirus on the return of the main stock indexes of Spain and Portugal with Panel Data.

Variable	(1) Coef. (p value)	(2) Coef. (p value)	(3) Coef. (p value)	(4) Coef. (p value)
Const	0.0030 (0.126)	0.0041** (0.049)	0.0036* (0.068)	0.0030 (0.110)
$Fear_{\text{Web,t}}$	-0.0003*** (0.001)			
$Fear_{\text{Images,t}}$		-0.0003*** (0.001)		
$Fear_{\text{News,t}}$			-0.0003*** (0.004)	
$Fear_{\text{Youtube,t}}$				-0.0003*** (0.000)
R^2	0.0437	0.0511	0.0520	0.0527

Note: ***, ** and * indicate the significance at 1%, 5% and 10% levels, respectively.

Table 4 shows the results of the influence of public fear of COVID-19 on the return of the IBEX-35 and the PSI-20 with the proposed Simple Linear Regression models. It can be seen how, in both markets, public fear of the coronavirus had a negative impact on the return of the IBEX-35 and the PSI-20, with all measures of public fear of the coronavirus being significant except for $Fear_{\text{Web,t}}$. Thus, it was found that variations in public fear of the coronavirus were associated with reductions of between 0.02% and 0.04% in the return of the IBEX-35 and the PSI-20, respectively. Regarding the explanatory power of public fear about the stock market return in two countries, it was shown how while in the Spanish case the R^2 of the different models was between 2.02% and 4.93%, in the Portuguese case, it was between 5.58% and 8.19%. We can therefore confirm that the PSI-20 is more sensitive to public fear generated by COVID-19.

Table 4. Influence of public fear of the coronavirus on the return of the main stock indexes of Spain and Portugal with Simple Linear Regression.

Variable	$R_{IBEX,t}$				$R_{PSI,t}$			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Coef. (p value)	Coef. (p value)	Coef. (p value)	Coef. (p value)	Coef. (p value)	Coef. (p value)	Coef. (p value)	Coef. (p value)
Const	0.0019 (0.555)	0.0057 (0.131)	0.0038 (0.274)	0.0028 (0.334)	0.0038* (0.090)	0.0031 (0.176)	0.0035 (0.119)	0.0031 (0.175)
$Fear_{\mathrm{Web,t}}$	−0.0003 (0.118)				−0.0004*** (0.001)			
$Fear_{\mathrm{Images}}$		−0.0003** (0.015)				−0.0002*** (0.009)		
$Fear_{\mathrm{News,t}}$			−0.0003** (0.038)				−0.0003*** (0.002)	
$Fear_{\mathrm{Youtub}}$				−0.0003** (0.014)				−0.0003*** (0.009)
R^2	0.0202	0.0480	0.0356	0.0493	0.0819	0.0558	0.0765	0.0559

Note: ***, ** and * indicate the significance at 1%, 5% and 10% levels, respectively.

Thus, the results obtained by the proposed methods demonstrate how public fear of the coronavirus harms the performance of the Spanish and Portuguese stock markets. This result is in line with the findings of Bansal (2020), who showed how biases play an important role in the performance of financial markets during the pandemic and also with the conclusions of Liu (2020) who showed the negative relationship between the uncertainty generated by COVID-19 and the Chinese stock market.

5. Conclusions

This chapter analysed the impact of public fear of COVID-19 on the Spanish and Portuguese stock markets, the two European economies most negatively impacted after the quick spreading of the disease. Using Google Trends for four search engines, fear reflected in the News is the highest in both countries in relation to the fear captured by Web, Images, and YouTube. The results obtained from the Panel Data show that public fear of COVID-19 has a significant negative impact on the Iberian market. Changes in public fear of COVID-19 explain around 5% of their variations in return. Although the Portuguese mean of public fear and its falling prices were lower, the results obtained by a Simple Linear Regression OLS showed that public fear of COVID-19 has a significant negative impact on both markets individually, with the Portuguese market being much more sensitive to public fear of COVID-19 than the Spanish market.

The majority of the literature focuses on the impact of retail investor attention on the stock markets, but these results show that public fear also plays a significant role in the performance of the stock markets, thus contributing with more evidence to the existing literature.

Finally, based on the obtained results, we suggest future investigation lines that provide much deeper evidence and understanding the impact of public fear of COVID-19 on other stock markets.

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CHAPTER 10

FINANCIAL TSUNAMIS FROM THE INVESTOR SENTIMENT PERSPECTIVE: EVIDENCE FROM INTERNATIONAL STOCK MARKETS

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Abstract

This chapter examines the investor sentiment effects generated by two terrorist attacks (the 9/11 attacks and London train bombing in 2005) and by two events of political nature (the Brexit referendum and the U.S. presidential election of 2016) on several international stock markets regarding these events. Trading volume data is selected as an investor sentiment proxy and regressed against multiple macroeconomic data. The residuals of these analyses are used as investor sentiment indices respectively. Then, an EGARCH model is developed to observe the sentiment effects. Through the analyses, it is concluded that stock markets of the developed countries are affected more than the developing countries. However, it is examined that the developing countries are influenced more than the developed countries by the September 11 Terrorist Attacks.

Key-words: investor sentiment, financial tsunamis, elections, terrorist attacks, EGARCH

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1. Introduction

A generation ago, the Efficient Market Hypothesis (Fama 1970) was acknowledged among all academic societies. Efficient Market Hypothesis asserts that if any mispricing occurs, the market will return instantaneously to its equilibrium price since it would be immediately arbitraged away. Hence, stock price over-reaction or under-reaction to extreme shocks cannot be expressed with finance-theoretic approaches. For instance, the stock market history consists of events such as the Great Crash Depression of 1929, the Black Monday Crash of October 1987, the Dot.com Bubble of the 1990s (Baker and Wurgler 2007) and the Subprime Mortgage Crisis that began in 2007. Consequently, the traditional financial models have faced difficulty in fitting these patterns. Through this attention, the field of behavioral finance has emerged.

Behavioral finance is considered as a sub-field of behavioral economics which expresses that psychological impacts and biases influence the financial behaviors and decisions of investors. The alternative model that researchers in behavioral finance have been studying, depends on two basic assumptions. The initial assumption laid out by De Long, Shleifer, Summers and Waldmann (1990) is that irrational noise traders with inaccurate stochastic beliefs both have an impact on prices and earn greater expected returns, which in short indicates that investors are subject to sentiment. The other assumption that is highlighted by Shleifer and Vishny (1997) states that arbitrage is costly, risky and limited. Consequently, rational investors, also known as arbitrageurs, are not completely effective in bringing prices to fundamental values as the standard model would assume. The phenomena of biased self-attribution, herding behavior, investor overconfidence and speculation (Barberis and Thaler 2003) are considered to be associated with the investment decisions of investors. Investor sentiment is also one of the many concepts which express investor irrationality and can be described as investor opinion that is generally affected by emotion.

The initial assumption regarding the motivation of this study is that several global incidents, mostly the ones which are sudden and unexpected, have been causing various impacts over society and economy. Such incidents, generally crises, are referred to as “financial tsunamis” in the literature (Cooper 2008; Fratianni 2008). They are basically defined as a number of economic and financial issues caused by a single significant incident. The influence of these events usually spread to several industry sectors, broad geographic areas, or both. Thus, regarding the assumption indicated hereinabove, these impacts may have led to substantial effects on the stock markets. Hence, this assumption seems to be consistent with the literature since previous studies imply that incidents such as wars, terrorism activities and elections have significant influences on the stock market behavior. The second assumption is that investors with stochastic beliefs may tend to overreact or underreact to such incidents. The literature on investor sentiment states that the investors are prone to over- or underreact to multiple events (Michayluk and Neuhauser 2006; Hoffmann, Post and Pennings 2013; Hood, Kamesaka, Nofsinger and Tamura 2013; Corbet, Gurdgiev and Meegan 2018) Hence, considering both assumptions and regarding the literature, this study examines the behavior of several developed and developing countries' stock markets, associated with various global incidents. The study benefits from investor sentiment methodology.

The literature consists of event studies that concentrate on the stock market behavior before, during or in the aftermath of an incident. The measurement of shocks generated and over- or under reaction to such incidents is another concern in the literature. Moreover, there exist various studies which determine the contagion effects, herding behavior or spillover effects through the stock markets. Many studies even examine the behavioral shifts between the stock markets and various incidents. Furthermore, investor sentiment phenomenon is studied broadly throughout the literature. Hence, Zouaoui, Nouyrigat and Beer (2011) determine the impact of investor sentiment on the Global Financial Crisis of 2008 by taking consumer sentiment index, various macroeconomic and stock market variables into account. However, of our knowledge, a study considering the influence of investor sentiment on several global incidents does not exist in the literature. Also, the studies that adopt an investor sentiment methodology generally appoint direct measures of sentiment in observing its influence. Thus, this study uses a market-based proxy, constructs indices for each incident respectively. Therefore, it fills the gap by providing evidence that investor sentiment generates substantial impact over the stock markets with regard to various global events.

The study mainly aims to find whether the developed or the developing countries are influenced more by the investor sentiment concept regarding the selected global incidents. The selected events which are September 11 Terrorist Attacks, London Train Bombings that took place in 2005, Brexit Referendum and the US Presidential Election of 2016 are discussed broadly in Section 2. There exist two political events and two terrorist activity incidents considered through this study, since the other goal of this study is to determine whether the political events or the terrorist activities lead to higher investor sentiment effects over the selected stock markets.

The outline of the chapter is as follows: Initially, the literature is examined thoroughly where investor sentiment is defined, studies that benefit from investor sentiment methodology are evaluated, various proxies of investor sentiment are introduced and the incidents that are considered through this study are discussed. Furthermore, the model which is used in this study is introduced, the equations considering the model are constructed and the data that is used through this study are represented. Then, the results of the analyses are presented respectively for each incident. Finally, a brief conclusion of this study is mentioned, the discussions on the results are expressed and the further implications that might be performed are determined.

2. Literature on Investor Sentiment and Global Incidents

2.1. Investor sentiment

The term "sentiment" is used in a variety of ways by the academic researchers, financial analysts and the media. Some researchers suggest that investor sentiment is a tendency to trade on noise instead of information, while the term is also noted as investor optimism or pessimism (Uygur and Tas 2014). Hence, Baker and Wurgler (2007, 129) point out that "investor sentiment, defined broadly, is a belief about future cash flows and investment risks that is not justified by the facts at hand". Regarding these definitions, investor sentiment may be defined as investor opinion that is generated by irrational and impulsive decisions.

The literature implies that investor sentiment is related to future stock returns. For instance, Schmeling (2009) finds that sentiment is a substantial indicator of expected returns across the countries. Furthermore, Aissia (2016) determines that both home and foreign investor sentiments affect stock returns. Moreover, Hirshleifer (2001) states that noise trading causes overreaction and the overreaction leads to excess volatility in returns. Verma and Verma (2007) observe significant and positive investor sentiment impacts on stock returns and remarkable negative effects of investor sentiment on volatilities, both for institutional and individual investors. Taking significant earthquake incidents into consideration, Tas and Sen (2019) determine that there exist substantial investor sentiment effects on a considerable number of stock markets' returns and conditional volatilities.

Through the history of financial markets, measuring investor sentiment and its impacts has been a great concern. Since there does not exist such an investor sentiment gauge which is accurate and efficient, plenty of investor sentiment measures are existent. For instance, Baker and Wurgler (2007) construct a compound investor sentiment index using proxies such as dividend premium, mutual fund flows and trading volume. They regress each proxy on macroeconomic data to eliminate the impacts of the fundamental macroeconomic news. While Lee, Shleifer and Thaler (1991) try to explain the closed-end fund discount (CEFD) puzzle in terms of investor sentiment; Qui and Welch (2004) suggest that considering only the CEFD as a proxy may not be a significant indicator. Frazzini and Lamont (2008) use mutual fund flows as an individual investor sentiment measure while Baker and Stein (2004) use trading volume as a sentiment proxy. Instead of using an indirect measure of investor sentiment, Brown (1999) uses the data collected for the American Association of Individual Investors (AAII). Lee, Jiang and Indro (2002) appoint Investors' Intelligence while Lemmon and Portniaguina (2006) employ Michigan Consumer Confidence Index (MCCI) as an investor sentiment proxy. They develop a time-series framework and conclude that consumer confidence is useful in revealing the time variation in equity portfolio returns.

Regarding the literature (Chordia, Subrahmanyam and Anshuman 2001; So and Lei 2011; Tas and Akdag 2012), through this study, trading volume is applied as an investor sentiment measure since it is considered to be practical and plausible to appoint this measure. It is also easier to find convenient trading volume data for the stock markets of many countries. Consequently, trading volume appears to be the only compatible approach to obtain an investor sentiment measure which can be compared across a wide range of countries.

2.2 Global events

Nowadays, the flow of information is substantially rapid and its getting faster each day with the help of globalization. It ensures an extreme connection between different regions of the world. It is one of the many causes that the shocks, brought by financial tsunamis, can be felt on the other side of the globe. Through this section, the global incidents, which are considered as financial tsunamis, are introduced.

2.2.1. 2001, September 11 Terrorist Attacks

On September 11, 2001 suicide terrorists crashed hijacked commercial airplanes into the World Trade Centre twin towers and the Pentagon, murdering more than 3,000 people. Besides the direct effects like loss of human life and property destructions, the terrorist attacks also left dramatic economic impacts. The shock in the US market generated by the terrorist attacks gave rise to a simultaneous downturn across nearly all major regions.

Arin, Ciferri and Spagnolo (2008) determine that terror has a substantial effect on the stock markets and also, the magnitude of the impacts is higher in emerging markets. In consistence, Brounrn and Derwall (2010) assert that financial markets respond intensely to terror incidents. However, they recover swiftly and soon return to its usual, while only the September 11th attacks caused long-term effects. Thus, Charles and Darné (2006) determine that the international stock markets exposed large shocks as a reaction to the terrorist attacks and its aftermath.

2.2.2. 2005, London Train Bombings

July 7, 2005, London bombings were a “coordinated terrorist bomb blast series” that hit the city's public transportation system during the morning rush hour. 52 people were killed and 700 people were injured in the terrorist attacks. The incident is noted to have seen the largest mass casualty count in the UK since World War II.

Kollias, Papadamau and Stagiannis (2011) evaluate how two major terrorist attacks in Madrid and London influenced stock exchanges in Spain and the UK. They conclude that the general effect on the stock markets for both was temporary. Furthermore, Graham and Ramiah (2012) express that the response of Japanese stock markets to the London attack is insignificant on both returns and systematic risks in Japan. Thus, Spiliers (2015) implies that London bombings have impacts on both European markets and UK national markets, as expected.

2.2.3. 2016, Brexit Referendum

With the UK referendum on European Union membership, shortly Brexit, most of the British citizens have decided that the UK should leave the European Union. This referendum event was indicated to be unique since it was unpredictable until the final day and the influence of the referendum result would undoubtedly be substantial in any case, since a vote for "leave" would also refer to an increase of uncertainty specifically in the UK financial markets.

Belke, Dubova and Osowski (2018) evaluate the interactions between UK policy uncertainty around Brexit and the UK financial market volatilities. They find that the uncertainty resulted in huge spillovers with unprecedented magnitudes to financial markets. However, Quaye, Mu, Abudu and Agyare (2016) mention that Brexit should not have led to any financial tsunami on the financial markets since it was announced earlier. Bashir, Zebende, Yu and Hussein et al. (2019) look for behavioral shifts in stock markets, before and after the UK's Brexit Referendum. They find instant impacts in the UK markets as compared to other European markets. Also, they indicate that the negative correlation between the UK, Germany, France and Netherlands stock market indices point that the international investors invest more prospectively in the stock markets.

2.2.4. 2016, US Presidential Election

On September 26, 2016, post-debate polls regarded Hillary Clinton to have defeated Donald Trump in the first Presidential debate. This led to a sudden shift in the dynamics of the race by rising the occasions of Clinton presidency while decreasing the chance of Trump presidency. Therefore, most observers were surprised by the election of Donald J. Trump as the 45th President of the United States of America on November 8, 2016. The election's unexpected outcome led to remarkable reactions in the financial markets.

The research of Shaikh (2017) expresses that global equity market has been into a turbulence phase during the election period and almost all markets have responded substantially on the election poll announcement day. Using poll data of post-election of Trump as a sentiment, Angelini, Foglia, Ortolano and Leone (2018) analyze the relationship among stock, currency, and commodities markets. They determine that the change of Trump's favorable opinions causes a positive change on the stock market and Treasury bond returns.

3. Materials and Methods

As mentioned before, the aim of this study is to model the investor sentiment effects through various major worldwide events. Therefore, the initial assumption of this study is that the volatility of the stock markets was influenced by major incidents. Regarding this assumption, the second assumption is that the mean - variance relations would explain the effects substantially with regards to these events. Therefore, in order to observe the impacts of investor sentiment on the markets' volatility diversions in addition to the changes in returns, it is decided that a volatility model should be applied.

There exist various studies on how investor sentiment contributes to the stock market volatilities. For instance, Verma and Verma (2007) investigate the relative impact of investor sentiment on conditional volatility for both the individual and institutional investors regarding the stock market indices of DJIA and S&P 500. They then examine whether "noise" or "rational risk factors" lead to sentiment effects over volatility. In order to determine the asymmetric impacts, they estimate a multivariate EGARCH model and adopt AAII as an investor sentiment proxy. Consequently, they express that stock market volatilities are substantially impacted by investor sentiment. Yu and Yuan (2011) present various volatility models which consist of GARCH (1,1) and asymmetric GARCH (1,1) in order to explain the impact of investor sentiment on the mean-variance trade-off of the stock market. They apply a composite sentiment index using the first principal component of six measures that are CEFD, NYSE share turnover, number of and the average first-day returns on IPOs, equity share in new issues and dividend premium. They then regress these sentiment gauges on the growth of industrial production, growth of durable consumption, growth of nondurable consumption, growth of service consumption, growth of employment and a dummy variable for National Bureau of Economic Research (NBER) recessions, to control the macroeconomic conditions. They determine that the mean-variance trade-off is highly impacted by investor sentiment.

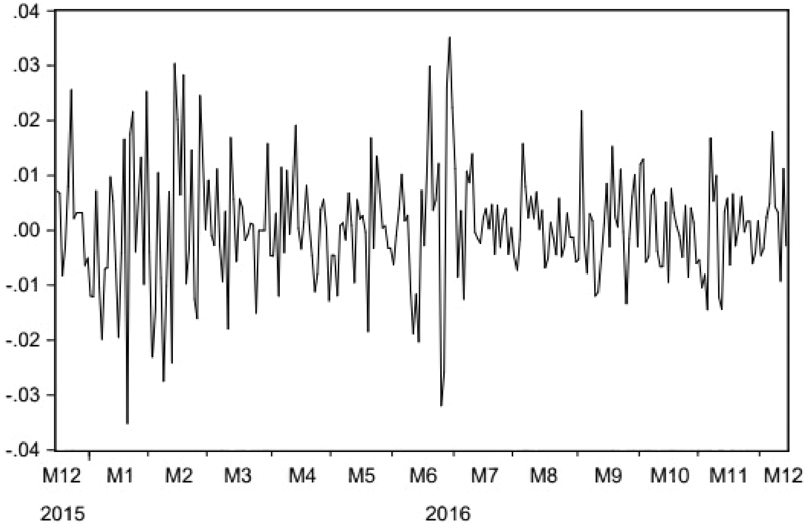

Figure 1. Daily logarithmic returns of FTSE 100 between December 2015 – December 2016

Throughout this study, the considered data on the stock market indices (the data is mentioned further in detail through this section) seems to show asymmetric behavior. In Figure 1, the asymmetry can be seen in the daily logarithmic returns of FTSE 100 index between the period of December 2015 and December 2016, referring to the time period before and after the Brexit Referendum. Since the asymmetry is a significant concern in the data of the study, it is decided that the model implied in this research should be able to explain these asymmetric shifts among the data. So, with regards to the studies mentioned above and after careful consideration, in this study, the EGARCH model is selected among the other GARCH models since the model helps to overcome the non-negativity constraints and to understand the asymmetric effects efficiently. Also, since the major incidents may lead to both negative and positive effects over the stock markets, EGARCH model is found suitable to address these impacts substantially. The conditional mean and conditional variance equations (1, 2) are expressed respectively.

$$\mu_t = \theta_0 + \theta_1 Sent_t + \varepsilon_t$$

$$log\ (h_t)\ = \gamma_0 + \gamma_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma_2 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3 log\ (h_{t-1}) + \gamma_4 Sent_{t-1} \quad (2)$$

$Sent_t$ in the mean equation represents the investor sentiment, which is used to control the macroeconomic shocks. The coefficient θ_0 is the constant term of the mean equation. Hence, the coefficient θ_1 indicates the influence of investor sentiment on the returns. h_t is the conditional volatility of the stock market index and is used to define the variance of the residuals and h_{t-1} is the first order autoregressive lag term of conditional volatility. ε_t represents the residuals of the mean equation while ε_{t-1} is the first order autoregressive lag term of the residuals. The coefficient γ_0 is the constant term of the variance equation. The coefficient γ_2 in the variance equation evaluates the influence of negative shocks on returns, which also determines the leverage effect. The coefficient γ_3 is the persistence parameter whereas the coefficient γ_4 represents the investor sentiment effect on the conditional variance of returns. The selected EGARCH model is applied to all analyses that are constructed through this study.

In the very first part of the analyses, daily trading volume data of stock market indices of the considered countries, where the events took place in, are applied as investor sentiment proxies. However, since the changes in trading volume data not only indicates the investor sentiment effects but also are the indicators of many macroeconomic events, the data are not directly appointed as investor sentiment proxies in this research. In order to generate new investor sentiment indices specific to the events and to capture the sentiment effects substantially, a regression analysis is carried out for each case, where daily trading volume data of the countries are the dependent variables and a group of macroeconomic data that are Gross Domestic Product (GDP), Consumer Price Index (CPI), Producer Price Index (PPI), Unemployment Rate, Money Supply, Industrial Production and Treasury Bill Yields are the independent variables. Also, for the events that took place in the US, Michigan Consumer Confidence Index (MCCI) data and for the events that happened somewhere besides the US, the consumer confidence indices of the countries are appointed as dummy variables in the analyses. The general formula of the model that is constructed to generate an investor sentiment index is as follows (Equation 3):

$$TRADE\_VOLUME_t = \theta_0 + \theta_1 GDP_t + \theta_2 CPI_t + \theta_3 PPI_t + \theta_4 UNEMP_t + \theta_5 M2_t + \theta_6 IND\_PROD_t + \theta_7 T\_BILL_t + \theta_8 DUMMY\_CCI_t + \varepsilon_t$$

However, in some cases GDP is not used as an independent variable and for the cases in which the MCCI data are used, the $DUMMY\_CCI_t$ variable is indicated as $DUMMY\_MCCI_t$, and ε_t stands for the error term. Since the GDP data is mostly released on a quarterly frequency and the macroeconomic data are generally released on a monthly basis, they need to be transformed into a daily frequency. Therefore, the cubic spline interpolation method is applied to change these control variables into a daily frequency. The trading volume and most of the macroeconomic data are retrieved from Thomson Reuters DataStream, whereas MCCI data and some of the macroeconomic variables are retrieved from Fred St. Louis.

For the second part of the analyses, daily stock market index returns of several developed countries such as Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are used as dependent variables in the EGARCH models to examine the effects of investor sentiment related to the incidents that are considered in the study. The daily closing prices of these indices are also retrieved from Thomson Reuters DataStream.

The time periods of the analyses differ from each other. To generalize, the political events are analyzed for 1 year-period and the terrorist activities are examined for 9 months-period, considering the time before the accidents occurred and their aftermaths respectively. Since each incident is evaluated exclusively, the associated time periods for each event are mentioned in detail through the Results section.

4. Results

4.1. Investor Sentiment Effect Related to 2001, September 11 Terrorist Attacks

Initially, a regression analysis is applied where daily trading volume data of DJIA, for the period between July 2001 and April 2002, is the dependent variable and various macroeconomic data are the independent variables. The residuals of this regression are appointed as the investor sentiment index in the following analyses. To examine the effects of investor sentiment related to 2001, September 11 Terrorist Attacks, daily stock market index returns of the developed and developing countries, for the period between July 2001 and April 2002, are used as dependent variables in the EGARCH models. The outcomes of the EGARCH models are shown in Table 1. Through the analyses of AEX and DAX, convergence cannot be achieved; therefore they are eliminated in the study associated with the September 11 terrorist attacks.

Coefficient θ_1 is monitored to see the effects of investor sentiment on returns. θ_1 seems to be significant for ATG, KOSPI and MXSE. However, the coefficients are positive for KOSPI and ATG. Therefore, it is concluded that the returns of these stock markets are positively influenced while the returns of MXSE IPC are negatively influenced by the investor sentiment related to 2001, September 11 Terrorist Attacks event. Coefficient γ_2 is controlled to determine the asymmetric volatility in the model. γ_2 is significant and negative for BEL 20, CAC 40, DJIA, FTSE 100, IBEX 35, IBOVESPA, FTSE MIB, MXSE IPC, SENSEX and SSEC, which remarks that the negative shocks exert a higher impact on each h_t than the positive shocks do. Coefficient γ_3 measures the persistence in conditional volatility. If γ_3 is large, volatility is going to take long time to fade away following 2001, September 11 Terrorist Attacks incident in the market. Since γ_3 is significant, positive and high for the stock market indices such as BEL 20, CAC 40, DJIA, FTSE 100, IBEX 35, FTSE MIB, IBOVESPA, MXSE, IPC, SENSEX and SSEC, they seem to show high persistence. Besides, coefficient γ_4 is evaluated to explore the investor sentiment effects on the conditional volatility. Though, γ_4 is statistically significant and positive only for ATG, BIST 100, JTOPI, KOSPI and KSE 100.

Table 1. EGARCH results related to the September 11 terrorist attacks.

		θ_0		θ_1		γ_0		γ_1		γ_2		γ_3		γ_4	
DEVELOPED COUNTRIES	**AEX**	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	BEL	-0.0004	(0.5011)	-0.0032	(0.4518)	-1.4399	(0.0002)	0.4918	(0.0000)	-0.1703	(0.0108)	0.8871	(0.0000)	0.5563	(0.4256)
	CAC	-0.0019	(0.0028)	0.0008	(0.8998)	-0.1144	(0.2198)	-0.0152	(0.7942)	-0.2105	(0.0000)	0.9836	(0.0000)	-0.0665	(0.8492)
	DAX	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	DJIA	-0.0011	(0.0817)	0.0004	(0.9337)	-0.2547	(0.0275)	-0.0708	(0.2547)	-0.1253	(0.0098)	0.9642	(0.0000)	-0.2095	(0.6079)
	FTSE	-0.0009	(0.2019)	0.0008	(0.8446)	-0.2957	(0.1273)	0.0860	(0.3467)	-0.2734	(0.0000)	0.9743	(0.0000)	-0.7325	(0.1426)
	IBEX	-0.0012	(0.2768)	-0.0043	(0.5713)	-0.0773	(0.6630)	0.0719	(0.2068)	-0.1508	(0.0016)	0.9975	(0.0000)	-0.0871	(0.8082)
	KOSPI	0.0042	(0.0010)	0.0144 **	(0.0320)	-7.6348	(0.0000)	0.7621	(0.0000)	-0.0066	(0.9573)	0.1053	(0.4575)	1.5359 **	(0.0245)
	MIB	-0.0008	(0.4337)	-0.0043	(0.5130)	-0.2359	(0.0441)	0.0457	(0.4389)	-0.2314	(0.0000)	0.9761	(0.0000)	-0.1121	(0.7966)
	NIK	0.0002	(0.8981)	0.0061	(0.3776)	-9.5052	(0.0001)	-0.0552	(0.7123)	0.1996	(0.0329)	-0.1803	(0.5435)	0.9790	(0.1934)

	ATG	*-0.0015*	*(0.1010)*	*0.0079**	*(0.0827)*	*-6.6231*	*(0.0000)*	*0.2785*	*(0.0848)*	*0.6334*	*(0.0000)*	*0.2475*	*(0.0047)*	*1.3937**	*(0.0637)*
DEVELOPING COUNTRIES	**BIST**	0.0019	(0.3439)	0.0028	(0.8048)	-6.7195	(0.0103)	0.2067	(0.3262)	-0.0900	(0.4986)	0.0974	(0.7860)	1.2893*	(0.0816)
	IBOV	-0.0002	(0.8819)	-0.0001	(0.9869)	-2.1707	(0.1876)	0.2444	(0.1651)	-0.2142	(0.0220)	0.7505	(0.0001)	-0.3581	(0.5952)
	JTOPI	0.0015	(0.1202)	-0.0016	(0.7871)	-10.6915	(0.0000)	0.5266	(0.0002)	0.1203	(0.2674)	-0.1947	(0.3082)	1.5369***	(0.0021)
	KSE	0.0022	(0.0641)	-0.0023	(0.7372)	-15.5216	(0.0000)	0.2742	(0.0000)	-0.0372	(0.3811)	-0.8458	(0.0000)	0.6793***	(0.0052)
	MERV	-0.0003	(0.8850)	0.0196	(0.2076)	-10.9779	(0.0000)	0.2477	(0.0093)	0.1929	(0.0083)	-0.5972	(0.0038)	0.1926	(0.7193)
	MOEX	0.0033	(0.0161)	0.0043	(0.5955)	-14.7638	(0.0000)	-0.1753	(0.1827)	-0.1922	(0.1058)	-0.8459	(0.0000)	0.4807	(0.2522)
	MXSE	0.0004	(0.1837)	-0.0065*	(0.0838)	-0.6516	(0.0000)	-0.2834	(0.0001)	-0.1643	(0.0000)	0.9010	(0.0000)	0.5105	(0.1448)
	SENSEX	0.0000	(0.9603)	0.0037	(0.5206)	-1.2287	(0.0144)	0.2801	(0.0051)	-0.1261	(0.0078)	0.8834	(0.0000)	0.1107	(0.7844)
	SSEC	-0.0010	(0.3749)	-0.0089	(0.1029)	-1.1912	(0.0001)	0.3470	(0.0006)	-0.2608	(0.0000)	0.8897	(0.0000)	0.4358	(0.3120)

Significance Levels 0.01 (*******) 0.05 (******) 0.10 (*****)

The coefficient θ_0 is the constant term of the mean equation while the coefficient θ_1 indicates the influence of investor sentiment on the returns. The coefficient γ_0 is the constant term of the variance equation and the coefficient γ_2 determines the influence of negative shocks on returns. The coefficient γ_3 is the persistence parameter whereas the coefficient γ_4 represents the investor sentiment effect on the conditional variance of returns. The p-values of the coefficients are also indicated in brackets.

Daily stock market index returns of several developed countries that are Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are the dependent variables.

4.2. Investor Sentiment Effect Related to 2005, London Train Bombings

Firstly, a regression analysis is applied where daily trading volume data of FTSE 100, for the period between May 2005 and February 2006, is the dependent variable and multiple macroeconomic data are the independent variables. The residuals of this regression are assigned as the investor sentiment index in the following analyses. To determine the effects of investor sentiment associated with 2005, London Train Bombings, daily stock market index returns of the developed and developing countries, for the period between May 2005 and February 2006, are appointed as dependent variables in the EGARCH models. The outcomes of the EGARCH models are presented in Table 2.

Table 2. EGARCH results associated with London train bombings.

		θ_0		θ_1		γ_0		γ_1		γ_2		γ_3		γ_4	
DEVELOPED COUNTRIES	**AEX**	0.0013	(0.0081)	0.0034*	(0.0751)	-8.7452	(0.0041)	0.0162	(0.9181)	-0.1834	(0.0675)	0.1353	(0.6529)	1.2419**	(0.0243)
	BEL	0.0010	(0.0100)	0.0019	(0.3114)	-2.2838	(0.1936)	-0.1268	(0.3205)	-0.1715	(0.0772)	0.7738	(0.0000)	0.0621	(0.8505)
	CAC	0.0006	(0.2199)	0.0042*	(0.0636)	-0.7996	(0.0462)	-0.0047	(0.9532)	-0.2110	(0.0013)	0.9182	(0.0000)	0.0924	(0.6797)
	DAX	0.0016	(0.0061)	0.0021	(0.4580)	-12.383	(0.0061)	0.1532	(0.3518)	0.0738	(0.4216)	-0.2710	(0.5639)	0.6476	(0.2404)
	DJIA	0.0002	(0.7180)	0.0016	(0.4405)	-6.2038	(0.0155)	0.0339	(0.7937)	-0.3217	(0.0075)	0.4031	(0.1077)	0.6780	(0.2255)
	FTSE	0.0006	(0.1071)	0.0006	(0.7305)	-7.2641	(0.0002)	0.2530	(0.2896)	-0.3156	(0.0053)	0.3215	(0.0756)	0.9789*	(0.0751)
	IBEX	0.0009	(0.0269)	0.0032*	(0.0578)	-2.1352	(0.0379)	0.0769	(0.5776)	-0.1994	(0.0103)	0.7978	(0.0000)	0.9876*	(0.0706)

	KOSPI	0.0017	(0.0272)	0.0001	(0.9870)	-2.0143	(0.0000)	0.0549	(0.6385)	-0.4573	(0.0000)	0.7864	(0.0000)	0.6542	(0.2104)
	MIB	0.0003	(0.3680)	0.0054**	(0.0186)	-0.9817	(0.0000)	-0.2839	(0.0001)	-0.2747	(0.0000)	0.8792	(0.0000)	0.5715**	(0.0168)
	NIK	0.0015	(0.0109)	0.0018	(0.5585)	-1.3373	(0.0017)	0.3684	(0.0014)	-0.2238	(0.0171)	0.8872	(0.0000)	-0.2151	(0.5835)
DEVELOPING COUNTRIES	**ATG**	0.0025	(0.0000)	0.0023	(0.3985)	-18.991	(0.0000)	0.2991	(0.0037)	-0.1213	(0.0649)	-0.9047	(0.0000)	0.1460	(0.3515)
	BIST	0.0027	(0.0056)	-0.0006	(0.9014)	-10.900	(0.0202)	0.3120	(0.0379)	-0.0845	(0.3454)	-0.2363	(0.6654)	0.1604	(0.7168)
	IBOV	0.0017	(0.0893)	0.0056	(0.3171)	-1.8241	(0.1501)	0.0915	(0.4358)	-0.1506	(0.1269)	0.7942	(0.0000)	-0.3887	(0.3469)
	JTOPI	0.0018	(0.0156)	-0.0005	(0.8960)	-12.742	(0.0001)	-0.0794	(0.5938)	-0.2487	(0.0314)	-0.3897	(0.2635)	-0.3622	(0.6125)
	KSE	0.0023	(0.0000)	-0.0006	(0.8302)	-2.2021	(0.0010)	0.7797	(0.0000)	-0.0919	(0.3708)	0.8243	(0.0000)	-0.4907	(0.1567)
	MERV	0.0006	(0.5564)	-0.0031	(0.5776)	-10.740	(0.0166)	-0.0387	(0.8349)	-0.1044	(0.3692)	-0.2423	(0.6356)	0.5040	(0.2982)

MOEX	0.0040	(0.0000)	0.0016	(0.6666)	-1.0360	(0.0060)	0.4099	(0.0002)	0.0841	(0.3149)	0.9155	(0.0000)	-0.2041	(0.5839)
MXSE	0.0012	(0.0560)	-0.0006	(0.8647)	-0.3129	(0.0008)	-0.0835	(0.3771)	-0.1169	(0.0714)	0.9577	(0.0000)	-0.4123	(0.1323)
SENSEX	0.0026	(0.0001)	0.0030	(0.2752)	-4.8305	(0.0000)	-0.1086	(0.6518)	-0.4980	(0.0000)	0.4758	(0.0000)	-0.1204	(0.8151)
SSEC	0.0003	(0.7221)	0.0004	(0.9289)	-13.142	(0.0000)	-0.1851	(0.1266)	-0.0712	(0.4790)	-0.5048	(0.0594)	1.1120***	(0.0045)

Significance Levels

0.01 (*******) 0.05 (******) 0.10 (*****)

The coefficient θ_0 is the constant term of the mean equation while the coefficient θ_1 indicates the influence of investor sentiment on the returns. The coefficient γ_0 is the constant term of the variance equation and the coefficient γ_2 determines the influence of negative shocks on returns. The coefficient γ_3 is the persistence parameter whereas the coefficient γ_4 represents the investor sentiment effect on the conditional variance of returns. The p-values of the coefficients are also indicated in brackets.

Daily stock market index returns of several developed countries that are Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are the dependent variables.

Coefficient θ_1 seems to be significant for AEX, CAC 40, IBEX 35, FTSE MIB. However, the coefficients are also positive for these stock market returns. Therefore, it is concluded that the returns of these stock markets are positively influenced by the investor sentiment related to 2005, London Train Bombings event. Coefficient γ_2, which is explored to ascertain the asymmetric volatility in the model, is significant and negative for AEX, ATG, BEL 20, CAC 40, DJIA, FTSE 100, IBEX 35, JTOPI, KOSPI, FTSE MIB, MXSE IPC, Nikkei 225 and SENSEX, which remarks that the negative shocks exert a higher impact on each h_t than the positive shocks do. Since coefficient γ_3 is significant, positive and high for the stock market indices such as BEL 20, CAC 40, IBEX 35, IBOVESPA, FTSE MIB, KOSPO, KSE 100, FTSE MIB, MOEX, MXSE IPC and Nikkei 225, they seem to show high persistence and the volatility is said to take a long time to fade away following 2005, London Train Bombings incident in the market. Besides, coefficient γ_4 is evaluated to explore the investor sentiment effects on the conditional volatility. Though, γ_4 is statistically significant and positive only for AEX, FTSE 100, IBEX 35, FTSE MIB and SSEC.

4.3. Investor Sentiment Effect Related to 2016, Brexit Referendum

Firstly, a regression analysis is applied where daily trading volume data of FTSE 100, for the period between December 2015 and December 2016, is the dependent variable and multiple macroeconomic data are the independent variables. The residuals of this regression are used as the investor sentiment index in the following analyses. To examine the impacts of investor sentiment related to Brexit Referendum, daily stock market index returns of the developed and developing countries, for the period between December 2015 and December 2016, are used as dependent variables in the EGARCH models. The outcomes of the EGARCH models are shown in Table 3.

Table 3. EGARCH results associated with Brexit referendum.

		θ_0		θ_1		γ_0		γ_1		γ_2		γ_3		γ_4	
DEVELOPED COUNTRIES	**AEX**	-0.0010	(0.0000)	-0.0057**	(0.0479)	-0.1357	(0.0000)	-0.0559	(0.0128)	-0.2274	(0.0000)	0.9785	(0.0000)	-0.2231*	(0.0842)
	BEL	-0.0004	(0.4874)	-0.0077***	(0.0033)	-0.7249	(0.0661)	0.1729	(0.0470)	-0.1418	(0.1690)	0.9351	(0.0000)	0.0640	(0.7926)
	CAC	-0.0003	(0.6782)	-0.0059*	(0.0911)	-0.4780	(0.1425)	0.1918	(0.0101)	-0.1015	(0.0654)	0.9623	(0.0000)	-0.0601	(0.8019)
	DAX	-0.0003	(0.5198)	-0.0060*	(0.0897)	-0.1227	(0.0260)	-0.0393	(0.1862)	-0.1586	(0.0002)	0.9825	(0.0000)	-0.2819*	(0.0888)
	DJIA	0.0003	(0.4102)	-0.0033**	(0.0284)	-0.1728	(0.0007)	-0.0531	(0.0013)	-0.1490	(0.0000)	0.9790	(0.0000)	-0.1835*	(0.0868)
	FTSE	-0.0006	(0.0000)	-0.0042**	(0.0246)	-0.1884	(0.0000)	-0.0648	(0.0379)	-0.2329	(0.0000)	0.9729	(0.0000)	0.3444***	(0.0018)
	IBEX	0.0000	(0.9986)	-0.0074**	(0.0309)	-5.5811	(0.0000)	0.8235	(0.0000)	0.3039	(0.0019)	0.4110	(0.0015)	0.4686	(0.1937)
	KOSPI	-0.0005	(0.1537)	-0.0055***	(0.0000)	-0.3715	(0.0209)	-0.0660	(0.0003)	-0.2140	(0.0000)	0.9564	(0.0000)	0.0149	(0.8859)

	MIB	-0.0002	(0.8309)	-0.0079*	(0.0711)	-0.8559	(0.0196)	0.3922	(0.0000)	-0.0512	(0.3453)	0.9315	(0.0000)	-0.3759	(0.2401)
	NIK	-0.0006	(0.5715)	-0.0129***	(0.0000)	-0.5171	(0.0000)	-0.0591	(0.0107)	-0.3152	(0.0000)	0.9341	(0.0000)	-0.0676	(0.5288)
DEVELOPING COUNTRIES	**ATG**	0.0003	(0.7275)	-0.0064***	(0.0083)	-0.4623	(0.0012)	0.2641	(0.0001)	-0.0909	(0.0373)	0.9663	(0.0000)	-0.2724	(0.1563)
	BIST	0.0012	(0.1302)	-0.0058**	(0.0175)	-13.843	(0.0000)	-0.3138	(0.0005)	-0.3316	(0.0000)	-0.5991	(0.0000)	0.3088	(0.4094)
	IBOV	0.0017	(0.0978)	-0.0048	(0.2528)	-14.678	(0.0000)	-0.1597	(0.0309)	0.0936	(0.1012)	-0.7871	(0.0000)	0.5705	(0.2384)
	JTOPI	-0.0007	(0.2920)	-0.0088***	(0.0000)	-0.7499	(0.1128)	0.1620	(0.1569)	-0.1464	(0.0150)	0.9318	(0.0000)	0.3162	(0.1871)
	KSE	0.0014	(0.0036)	-0.0042***	(0.0076)	-1.1124	(0.0285)	0.1545	(0.0063)	-0.1256	(0.0009)	0.9003	(0.0000)	0.1870	(0.4256)
	MERV	0.0013	(0.2268)	-0.0030	(0.5332)	-1.0819	(0.0160)	0.2651	(0.0023)	-0.1359	(0.0154)	0.8922	(0.0000)	0.1393	(0.5711)
	MOEX	0.0009	(0.1031)	-0.0058***	(0.0117)	-0.0945	(0.0029)	-0.0820	(0.0325)	-0.0061	(0.8606)	0.9840	(0.0000)	-0.0453	(0.7691)

MXSE	0.0002	(0.7264)	-0.0078***	(0.0000)	-2.8780	(0.1733)	0.2065	(0.0152)	-0.0285	(0.5922)	0.7181	(0.0010)	0.5782	(0.2077)
SENSEX	-0.0002	(0.7469)	-0.0078***	(0.0000)	-0.6453	(0.0064)	-0.0209	(0.6790)	-0.1978	(0.0002)	0.9301	(0.0000)	-0.0016	(0.9880)
SSEC	0.0004	(0.5590)	-0.0004	(0.8494)	-0.2221	(0.0000)	0.1139	(0.0001)	-0.0937	(0.0038)	0.9848	(0.0000)	-0.1932	(0.1130)

Significance Levels

0.01 (*******) 0.05 (******) 0.10 (*****)

The coefficient θ_0 is the constant term of the mean equation while the coefficient θ_1 indicates the influence of investor sentiment on the returns. The coefficient γ_0 is the constant term of the variance equation and the coefficient γ_2 determines the influence of negative shocks on returns. The coefficient γ_3 is the persistence parameter whereas the coefficient γ_4 represents the investor sentiment effect on the conditional variance of returns. The p-values of the coefficients are also indicated in brackets.

Daily stock market index returns of several developed countries that are Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are the dependent variables.

Coefficient θ_1 seems to be significant and negative for all the stock market returns, except for IBOVESPA, MERVAL and SSEC. Therefore, it is concluded that the returns of these stock markets are negatively influenced by the investor sentiment related to 2016, Brexit Referendum event. Coefficient γ_2, which is explored to ascertain the asymmetric volatility in the model, is significant and negative for all the stock markets, except for BEL 20, IBOVESPA, FTSE MIB, MOEX and MXSE IPC, which remarks that the negative shocks exert a higher impact on each h_t than the positive shocks do. Since coefficient γ_3 is significant, positive and high for all the stock market indices, except for BIST 100, IBEX 35, MXSE IPC and IBOVESPA, they seem to show high persistence and the volatility is said to take a long time to fade away following 2016, Brexit Referendum. Besides, coefficient γ_4 is evaluated to explore the investor sentiment effects on the conditional volatility. Though, γ_4 is statistically significant only for AEX, DAX, DJIA and FTSE 100. However, the conditional volatility of the stock returns for AEX, DAX and DJIA are negative. Thereby, it seems that the conditional volatilities of these stock returns are negatively influenced while the conditional volatility of FTSE 100 is positively influenced by investor sentiment related to 2016, Brexit Referendum event.

4.4. Investor Sentiment Effect Related to 2016, US Presidential Election

Initially, a regression analysis is applied where daily trading volume data of DJIA, for the period between June 2016 and June 2017, is the dependent variable and multiple macroeconomic data are the independent variables. The residuals of this regression are assigned as the investor sentiment index in the following analyses. To determine the effects of investor sentiment associated with 2016, US Presidential Election, daily stock market index returns of the developed and developing countries, for the period between June 2016 and June 2017, are appointed as dependent variables in the EGARCH models. The outcomes of the EGARCH models are shown in Table 4.

Table 4. EGARCH results related to US presidential election.

		θ_0		θ_1		γ_0		γ_1		γ_2		γ_3		γ_4	
DEVELOPED COUNTRIES	**AEX**	0.0002	(0.6526)	0.0007	(0.7443)	-0.4214	(0.0000)	-0.0492	(0.3102)	-0.1830	(0.0000)	0.9537	(0.0000)	0.0594	(0.7619)
	BEL	0.0008	(0.1042)	-0.0017	(0.4640)	-6.8004	(0.0000)	0.5645	(0.0000)	0.2316	(0.0154)	0.3399	(0.0067)	1.5020***	(0.0005)
	CAC	0.0010	(0.0490)	-0.0028	(0.2249)	-4.9211	(0.0000)	0.7015	(0.0000)	0.1813	(0.0647)	0.5401	(0.0000)	0.8184*	(0.0552)
	DAX	0.0005	(0.4125)	-0.0046*	(0.0800)	-4.9592	(0.0000)	0.5335	(0.0000)	0.1216	(0.2116)	0.5219	(0.0000)	0.9752***	(0.0045)
	DJIA	0.0009	(0.0151)	-0.0017	(0.3267)	-7.2367	(0.0000)	0.5642	(0.0000)	0.0734	(0.3267)	0.3507	(0.0111)	0.4779	(0.2012)
	FTSE	0.0003	(0.4866)	-0.0031	(0.1294)	-0.3398	(0.0420)	-0.0009	(0.9855)	-0.1344	(0.0000)	0.9671	(0.0000)	-0.1270	(0.5460)
	IBEX	0.0015	(0.0063)	-0.0028	(0.3562)	-6.1268	(0.0000)	0.6876	(0.0000)	0.4556	(0.0000)	0.3889	(0.0001)	1.8530***	(0.0000)
	KOSPI	0.0007	(0.0648)	-0.0051***	(0.0000)	-9.9416	(0.0001)	-0.0384	(0.7779)	-0.1914	(0.0356)	0.0268	(0.9147)	1.4352***	(0.0006)

	MIB	0.0016	(0.0296)	-0.0018	(0.6761)	-5.0980	(0.0021)	0.5942	(0.0000)	0.1464	(0.1103)	0.4630	(0.0138)	0.1811	(0.6273)
	NIK	0.0003	(0.6388)	-0.0105***	(0.0014)	-5.8956	(0.0000)	0.4772	(0.0002)	0.0344	(0.6842)	0.3938	(0.0008)	1.4096***	(0.0009)
DEVELOPING COUNTRIES	**ATG**	0.0016	(0.0436)	0.0037	(0.3456)	-0.5067	(0.0000)	0.0063	(0.8743)	0.0592	(0.1112)	0.9445	(0.0000)	0.3645***	(0.0033)
	BIST	0.0012	(0.0599)	-0.0016	(0.4803)	-10.2550	(0.0000)	-0.3272	(0.0110)	-0.2656	(0.0010)	-0.1574	(0.2440)	2.1424***	(0.0000)
	IBOV	0.0015	(0.0423)	-0.0146***	(0.0003)	-6.2931	(0.0000)	0.2034	(0.0248)	-0.3513	(0.0000)	0.3014	(0.0061)	1.8246***	(0.0000)
	JTOPI	-0.0003	(0.4851)	-0.0041	(0.1470)	-0.5058	(0.0039)	0.0564	(0.3249)	-0.1795	(0.0000)	0.9523	(0.0000)	0.1525	(0.4194)
	KSE	0.0009	(0.0385)	-0.0018	(0.3654)	-0.5222	(0.0189)	0.2433	(0.0000)	-0.1334	(0.0004)	0.9654	(0.0000)	-0.1608	(0.5130)
	MERV	0.0017	(0.0343)	-0.0073**	(0.0390)	-0.9480	(0.0234)	0.1943	(0.0421)	-0.0830	(0.1414)	0.9092	(0.0000)	0.6392***	(0.0046)
	MOEX	-0.0002	(0.6596)	-0.0016	(0.4758)	-5.2352	(0.0684)	0.2208	(0.1612)	0.0446	(0.6407)	0.4731	(0.1103)	0.7566*	(0.0930)

MXSE	0.0003	(0.5265)	-0.0090***	(0.0000)	-8.9452	(0.0000)	0.2387	(0.0735)	0.1304	(0.1766)	0.1088	(0.5492)	1.6772***	(0.0000)
SENSEX	0.0003	(0.4393)	-0.0028	(0.1212)	-0.7782	(0.0001)	-0.1198	(0.0421)	-0.1817	(0.0000)	0.9137	(0.0000)	0.1813	(0.2132)
SSEC	0.0002	(0.5449)	-0.0034**	(0.0399)	-15.4290	(0.0000)	0.1657	(0.0800)	0.1467	(0.0092)	-0.4993	(0.0300)	0.5405**	(0.0409)

Significance Levels

0.01 (*******) 0.05 (******) 0.10 (*****)

The coefficient θ_0 is the constant term of the mean equation while the coefficient θ_1 indicates the influence of investor sentiment on the returns. The coefficient γ_0 is the constant term of the variance equation and the coefficient γ_2 determines the influence of negative shocks on returns. The coefficient γ_3 is the persistence parameter whereas the coefficient γ_4 represents the investor sentiment effect on the conditional variance of returns. The p-values of the coefficients are also indicated in brackets.

Daily stock market index returns of several developed countries that are Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are the dependent variables.

Coefficient θ_1 is significant and negative for DAX, IBOVESPA, KOSPI, MERVAL, MXSE IPC, Nikkei 225 and SSEC, which represents that the returns of these stock market indices are negatively affected by the investor sentiment associated with 2016, US Presidential Election incident. Coefficient γ_2, which is explored to ascertain the asymmetric volatility in the model, is significant and negative for the stock market indices which are AEX, BIST 100, FTSE 100, IBOVESPA, JTOPI, KOSPI, KSE 100 and SENSEX. This demonstrates that the negative shocks generate a greater influence on each h_t than the positive shocks do. Since γ_3 is significant, positive and high for the stock market indices such as AEX, ATG, FTSE 100, JTOPI, KSE 100, MERVAL and SENSEX, they exert a high persistence and the volatility takes a long time to vanish following 2016, US Presidential Election incident in the market. Likewise, coefficient γ_4 is checked to examine the impacts of investor sentiment on conditional volatility. Herewith, γ_4 is statistically significant and positive for the stock market indices, except for AEX, DJIA, FTSE 100, JTOPI, KSE 100, FTSE MIB and SENSEX.

4.5. Brief Summary Regarding the Analyses

The returns and the conditional volatilities regarding the analyses relevant to each incident are listed and shown in Table 5. The outcomes indicate that the returns of nearly all stock market indices are impacted by the investor sentiment generated by the Brexit Referendum incident whereas the conditional volatilities of over than 50% of the selected stock markets are influenced by the investor sentiment associated with the US Presidential Election event.

However, regarding the September 11 Terrorist Attacks and London Train Bombings, the returns and conditional volatilities of in an average of only four stock markets seem to be influenced by the investor sentiment related to each incident. These results are discussed broadly in Section 5.

Table 5. Outcome summary of the EGARCH analyses relevant to global incidents.

		2001, SEPTEMBER 11 ATTACKS		*2005, LONDON BOMBINGS*		*2016, BREXIT REFERENDUM*		*2016, US ELECTION*	
		RET	**VOL**	**RET**	**VOL**	**RET**	**VOL**	**RET**	**VOL**
DEVELOPED COUNTRIES	**AEX**	-	-	0.0034 *	1.2419 **	-0.0057 **	-0.2231 *	0.0007	0.0594
	BEL	-0.0032	0.5563	0.0019	0.0621	-0.0077 ***	0.0640	-0.0017	1.5020 ***
	CAC	0.0008	-0.0665	0.0042 *	0.0924	-0.0059 *	-0.0601	-0.0028	0.8184 *
	DAX	-	-	0.0021	0.6476	-0.0060 *	-0.2819 *	-0.0046 *	0.9752 ***
	DJIA	0.0004	-0.2095	0.0016	0.6780	-0.0033 **	-0.1835 *	-0.0017	0.4779
	FTSE	0.0008	-0.7325	0.0006	0.9789 *	-0.0042 **	0.3444 ***	-0.0031	-0.1270
	IBEX	-0.0043	-0.0871	0.0032 *	0.9876 *	-0.0074 **	0.4686	-0.0028	1.8530 ***
	KOSPI	0.0144 **	1.5359 **	0.0001	0.6542	-0.0055 ***	0.0149	-0.0051 ***	1.4352 ***
	MIB	-0.0043	-0.1121	0.0054 **	0.5715 **	-0.0079 *	-0.3759	-0.0018	0.1811
	NIK	0.0061	0.9790	0.0018	-0.2151	-0.0129 ***	-0.0676	-0.0105 ***	1.4096 ***

	ATG	*0.0079* *	*1.3937* *	*0.0023*	*0.1460*	*-0.0064* ***	*-0.2724*	*0.0037*	*0.3645* ***
DEVELOPING COUNTRIES	**BIST**	0.0028	1.3937 *	-0.0006	0.1604	-0.0058 **	0.3088	-0.0016	2.1424 ***
	IBOV	-0.0001	-0.3581	0.0056	-0.3887	-0.0048	0.5705	-0.0146 ***	1.8246 ***
	JTOPI	-0.0016	1.5369 ***	-0.0005	-0.3622	-0.0088 ***	0.3162	-0.0041	0.1525
	KSE	-0.0023	0.6793 ***	-0.0006	-0.4907	-0.0042 ***	0.1870	-0.0018	-0.1608
	MERV	0.0196	0.1926	-0.0031	0.5040	-0.0030	0.1393	-0.0073 **	0.6392 ***
	MOEX	0.0043	0.4807	0.0016	-0.2041	-0.0058 ***	-0.0453	-0.0016	0.7566 *
	MXSE	-0.0065 *	0.5105	-0.0006	-0.4123	-0.0078 ***	0.5782	-0.0090 ***	1.6772 ***
	SENSEX	0.0037	0.1107	0.0030	-0.1204	-0.0078 ***	-0.0016	-0.0028	0.1813
	SSEC	-0.0089	0.4358	0.0004	1.1120 ***	-0.0004	-0.1932	-0.0034 **	0.5405 **

Significance Levels

0.01 (***) 0.05 (**) 0.10 (*)

Daily stock market index returns of several developed countries that are Belgium (BEL 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), Netherlands (AEX), South Korea (KOSPI), Spain (IBEX 35), the UK (FTSE 100) and the US (DJIA) and daily stock market index returns of multiple developing countries which are Argentina (MERVAL), Brazil (IBOVESPA), China (SSEC), Greece (ATG), India (SENSEX), Mexico (MXSE IPC), Pakistan (KSE 100), Russia (MOEX), South Africa (JTOPI), Turkey (BIST 100) are the dependent variables.

RET indicates the effect of investor sentiment on the stock returns whereas VOL represents the impact of investor sentiment on the volatility of stock returns for the September 11 Attacks, London Train Bombings, Brexit Referendum and US Election incidents. RET and VOL values are gathered from the analyses of each event. RET values are obtained from the coefficient θ_1 results of the analyses while VOL values are taken from the coefficient γ_4 results of the analyses.

5. Conclusions

The initial outcome of this study is that there exist substantial impacts of investor sentiment through the developed countries more than the developing countries regarding London Train Bombings and Brexit Referendum events. However, in consistence with Arin, Ciferri and Spagnolo (2008), the September 11 Terrorist Attacks and the US Presidential Election of 2016 exert considerable investor sentiment effects through the developing countries more than the developed countries.

The response of investors among the stock market indices of developed countries might be more efficient than the reaction of investors through the stock market indices of developing countries since the trading volume of developed countries are higher than for the developing countries. Higher trading volume leads to a more active market, whereas it tends to increase when investors hesitate about the direction of the stock market. The literature also suggests that major incidents like political events and terror activities have significant impacts over the stock market behavior. For instance, Brounrn and Derwall (2010) find out that financial markets react intensely to terrorist attacks while Bashir, Zebende, Yu and Hussein et al. (2019) state that the international investors invest more prospectively in the stock markets than the national investors do, during the Brexit referendum period. Al-Thaqeb (2018) also indicates that the international markets explicitly over- and underreact to local events experienced in the US. Moreover, during the period when such an event takes place, investors are prone to overreact or underreact. As the literature implies the overreaction or under reaction results in an investor sentiment effect. Therefore, the findings those present a greater influence of investor sentiment on the stock market indices of developed countries than for the developing countries are determined to be consistent and significant for London Train Bombings and Brexit Referendum incidents.

The second outcome of this study implies that political events exert higher investor sentiment effects on the stock markets rather than the terrorist activities do. It seems that Brexit Referendum and 2016 US Presidential Election both generate substantial and mostly long-term impacts (especially Brexit) over many developed and developing countries. Since incidents like these have direct impact over the economic and political relations of the countries, regarding the uncertainty that arises from the event, the results seem to be consistent. Specifically, the study exerts remarkable evidence that Brexit shook nearly all the stock markets over the globe. In contrast, the impact of the terrorist activities on the stock markets seems to be temporary, especially for the London Train Bombings incident.

For further study, herding behavior of investors might be examined regarding the global incidents. Thus, contagion effects of the events might be studied in order to examine their long-term impacts over the stock markets. Hence, in the measurement of investor sentiment, multiple proxies might be considered in particular rather than the trading volume. Consequently, an investor sentiment index using panel data might be constructed by taking several sentiment proxies into consideration in addition to trading volume. This index might consist of proxies which are both direct and indirect measures of sentiment.

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PART III:

FINANCIAL LITERACY

CHAPTER 11

THE RELATIONSHIP BETWEEN THE LEVELS OF FINANCIAL LITERACY AND DIGITAL FINANCIAL LITERACY: EVIDENCE FROM AN ONLINE SURVEY

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Abstract

This chapter explores the relationship between digital financial literacy (DFL) in its different dimensions and financial literacy (FL) levels using an online survey applied to 1136 Portuguese individuals. The data was collected in 2018 by the Portuguese Securities Market Commission. We found that the dimensions of DFL have low correlations with the levels of FL, which may be the source of inappropriate use of digital media. Therefore, our results highlight the danger of an unsuitable use of financial tools.

Key-words: Financial literacy, digital literacy, digital financial literacy, factor analysis

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1. Introduction

This chapter focuses on a complementary vision between levels of financial literacy (FL) and the use of information and communication technologies (ICT). In fact, with the development of ICT came the need to learn, relearn, and adapt existing knowledge to new digital tools. Several studies have tried to understand the levels of digital literacy (DL) (Ng, 2012a; Ng, 2012b), and how DL levels affect individuals (Meyers et al., 2013; Eshet-Alkalai and Chajut, 2009). DL has become increasingly relevant in modern society and its interdisciplinarity with the various areas has been intensifying. One of the areas that have benefited from digital knowledge is the financial area, and the use of financial tools is linked to the use of programs and several other digital tools (Li et al., 2020).

However, the use of digital tools linked to the financial area is not limited only to digital knowledge. It is necessary to have levels of FL that allow the proper use of these tools to improve financial well-being (Li et al., 2020). The financial area is complemented with the use of tools and technologies that have contributed to its development and reduction of its weaknesses, as well as has allowed the increase in the use and access to financial markets (Li et al., 2020). The combination of the two areas gave rise to new types of knowledge that interconnect the digital and financial areas.

In this work, the multiplicity of literacies associated with the use of digital technologies linked to financial areas will be called digital financial literacy (DFL). DFL comprises the knowledge necessary for the use of new tools, sources of information, etc. However, to analyze the levels of DFL it is necessary to evaluate and quantify their multidimensionality (Morgan et al., 2019). For example, DFL covers knowledge of online shopping, online payment in different ways, the online banking system (Prasad et al., 2018), and the use of the Internet for information collection (Manfield et al., 2018; Zheludev et al., 2015).

Through the use of a database of 1136 individuals collected in Portugal by CMVM, and using exploratory factor analysis, we generated 3 dimensions for DFL (the technique, information, and self-rated knowledge). Later, through the linear combination of the correct answers, similar to strategies previously used by other authors (Welsh and Wright, 2010; Bianchi, 2018) we have generated a measure of FL. Our results indicate that there is a weak and negative association between the levels of FL and the dimensions of DFL. In the future, the two measures that we used as a proxy for FL and DL can be used to understand how these two variants of literacy can be affected by behavioral deviations (risk aversion, overconfidence, among others).

This chapter is organized as follows. Section 2 reviews the literature on the topic. Section 3 describes the data and methodology used in the empirical study. Section 4 presents the empirical results. Section 5 concludes the chapter.

2. Financial literacy and digital literacy

Nowadays, acquiring knowledge about several areas has become a constant need, because understanding a specific area involves understanding the interdisciplinarity of that area with different ones. So, to understand DFL, it is necessary to understand DL and FL first.

2.1. Digital literacy

Digital and financial knowledge have to be mobilized when individuals make financial decisions (Baker et al., 2019). It is plausible to assume that DL refers to the multiplicity of literacies associated with the use of digital technologies[1] (Ng, 2012a) that can be captured by three dimensions (technical dimension, cognitive dimension, and socio-emotional dimension) that intersect (Ng 2012b).

Thus, digitally literate individuals should be able to adapt quickly to new and emerging technologies, and easily acquire a new semiotic language for communication as they emerge (Ng, 2012a). In this way, DL includes the

[1] Digital technologies are a subset of electronic technologies that include hardware and software commonly used for educational, social and / or entertainment purposes in schools and at home.

ability to find relevant information and assess its credibility, successfully communicate with other invisible people (mainly through written text) and create original content to express itself consistently with personal or professional goals (Iordache et al., 2017). The digital/technological area has extended to all areas providing tools, forms of learning, dissemination of information, and generating a set of new needs and knowledge in individuals.

2.2. Financial literacy

FL comprises the ability to read, analyze, manage, and communicate on individuals' financial conditions affecting material well-being. FL includes the ability to discriminate financial choices, discuss financial issues, plan the future, and respond competently to situations affecting everyday financial decisions, including general economic events (Welsh and Wright, 2010). In the literature, there is a discussion about what FL is and how it should be quantified. Kimiyaghalam and Safari (2015) report that the methods applied to test the level of FL in individuals are not consistent, but vary according to the definition of FL adopted.

Van Rooij et al. (2011) created two forms of measuring FL and study its relationship with stock market participation. They concluded that most respondents exhibit basic financial knowledge and have some basic notion of concepts such as interest composition, inflation, and the time value of money. Migliavacca (2020) studied the extent to which the presence of a financial advisor improves the FL of its clients. It was found that financial advisers are an effective way to raise investors' financial awareness. Moreover, financial advisors can be an appropriate link between financial information issuers and investors, enabling clients to acquire financial knowledge, thereby narrowing the gap in FL.

2.3. Digital financial literacy

Nowadays, there is a convergence between the technological areas and the financial area that gave rise to several developments (financial instruments, financial products, software, etc.) with repercussions on positive and negative externalities.

Financial products have become increasingly sophisticated, but are often considered to be too complex by the majority of people whose financial knowledge has not kept pace. Thus, financial illiteracy correlates with financial problems (Patwardhan, 2018). To Förster et al. (2019) obtaining financial knowledge does not derive solely from training programs, as it can be obtained from experience and the search for information on financial products. Lee (2019) points out that low levels of FL can be addressed by providing online financial education, including information publications on the site, online financial calculators, external links, social media communication, etc. However, the use of digital tools can play a significant role in reducing the impact of low levels of FL on financial decisions. We have seen the emergence of digital tools, digital information sources, among others, linked to financial areas, which creates the need for new knowledge. This points to the emergence of DFL, which comprises the multiplicity of literacies associated with the use of digital technologies linked to financial areas.

We can easily see how FL and DL jointly affect the choice of assets and instruments. For example, Panos and Karkkainen (2019) report that levels of digital (technological) literacy in recent years have increased the willingness to acquire assets such as cryptocurrencies, while higher levels of FL decrease the likelihood of acquiring cryptocurrencies. Recently, Tony and Desai (2020) measured the impact of DFL on digital financial inclusion. They concluded that DFL contributes to the increase in the digital inclusion rate, as individuals with greater knowledge have greater ease of use of digital media. They report that FL contributes to financial inclusion, development, and stability, and all this contributes to economic growth. Ozili (2020) points out that financial inclusion affects and derives from the level of financial innovation.

Li and Meyer-cirkel (2019) evaluated the impacts of using a DFL platform on the performance of student portfolios. They found that, in general, their portfolios converged on the portfolio of benchmarks, suggesting the clear influence of the use of the platform. The authors report that the composition of the portfolio varies according to the sharing of information in the classroom and through publications on Facebook, and also found strong influences of opinions of colleagues in the construction of the portfolio.

Also, financial and digital inclusion can play a key role in long-term financial stability (Panos and Wilson, 2020). The use of digital tools (robotic consultants) is especially motivated by investors who fear being victims of investment fraud. Thus, robotic consultants seem to offer a valid alternative for those seeking investment advice (Brenner and Meyll, 2020), which demonstrates a relationship between DFL and FL.

3. Methodology and data

In this section, we will explain the three dimensions of DFL and the FL measure. We will employ a database from the Portuguese Comissão do Mercado de Valores Mobiliários (CMMC) which conducted an Online Survey of the Portuguese investor profile in 2018, whose goal was to promote investor protection and the integrity of financial markets with a view to their development (Gabinete de Estudos da CMVM, 2019). A total of 2381 individuals answered the survey but all individuals who left at least one unanswered question were removed from the dataset leaving us with a final sample of 1136 individuals (Ribeiro et al., 2020).

3.1. Financial literacy index

In the literature, we found studies such as those of Migliavacca (2020) and Van Rooij et al. (2011) that used issues that cover knowledge ranging from the functioning of interest rates and interest composition to the effect of inflation, discount, and nominal values versus real values to infer a measure of basic FL. Thus, the measure of FL consists of the linear combination of the correct answers (Welsh and Wright, 2010; Bianchi, 2018).

Table 1 presents the variables that will be considered in the computation of the measures of literacy to be used in this chapter.

Table 1. Variables included in the financial literacy measure

Question	Cod/ Answers	Justification
Suppose you have €100 in a bank account whose interest rate is 1% per year. After 5 years, how much will the account balance be if no money is withdrawn, nor are there commissions or associated taxes (i.e. at the end of each year you let the interest amount stay in that same bank account)?	1. More than €105 0. Exactly €105 0. Less than €105	Evaluates interest knowledge, and 1 encoding was attributed for individuals who assumed compound interest and 0 for those who missed

Variable-Financial_literacy_rate		
Suppose you have €100 in a bank account whose interest rate is 1% per year and that inflation is 2% per year. A year from now, what do you think you could buy with the money in that account? Variable-Financial_literacy_inflation	0. I would buy more stuff than I do today. 0. I would buy the same things as today. 1. I would buy less stuff than I do today. 0. Depends on what you would buy.	Evaluates the knowledge about inflation, being assigned 1 for the individuals who got it right and 0 for those who got it wrong
You have invested in a bond that pays a fixed interest rate. Meanwhile, market interest rates have decreased. If you sell that bond after this decrease, the price of this bond shall be: Variable-Financial_literacy_bond	0. Lower than the price at which you bought it 0. Equal to the price at which you bought it 1. Higher than the price at which you bought it	Evaluates the knowledge about a bond, being coded with 1 for the individuals who got it right and 0 for those who selected the wrong answer
In your opinion, please indicate whether the following statement is true or false: "Investing in a company's share typically provides a safer return than investing in a stock fund." Variable-Financial_literacy_Investing	0. True 1. False	Evaluates the knowledge about investments, assigning 1 to the individuals who got it right and 0 to those who selected the wrong answer

What does it mean that security has guaranteed capital on the maturity date? Variable-Financial_literacy_capital	0. I am entitled to receive the money invested at any time 0. On the due date I always receive the money invested 1. The issuer of the securities reimburses the money invested on the maturity date, provided that it has financial conditions to do so	Evaluates knowledge about capital, having been assigned the value 1 for the individuals who got it right and 0 for those who missed

Source: own elaboration based on the questionnaire of the Gabinete de Estudos da CMVM (2019).

As in the work of Welsh and Wright (2010), the linear sum of the variables allows obtaining the overall classification of individuals concerning the 5 questions presented in Table 1. Given that our goal is to evaluate the result, we chose to present it on a scale of [0;1] where 0 corresponds to individuals who did not get it right in any issue revealing a poor level of FL and 1 corresponds to the individuals who got it right in all questions revealing a good level of FL. The scale results from the division of the individual's grade by the maximum price obtained. Table 2 shows that the individuals had an average rating of 0.723, a standard deviation of 0.210, a maximum value of 1, and a minimum value of 0.

Table 2. Descriptive statistics of the financial literacy variable

	Count	**Average**	**Standard deviation**	**min**	**max**
FL_index	1136	0.723	0.210	0.000	1.000

3.2. Dimensions of digital financial literacy

Modern markets are characterized by their complexity and sophisticated technology and individuals must make lifelong efforts to acquire technical expertise to adapt to markets (Lusardi and Mitchell, 2014). There is a need to redefine traditional FL to include DL, considering financial and DL as a dual approach to improving the long-term financial resilience of families (Lyons et al., 2020).

There is a need to understand how digital and financial knowledge affects everyday life and how individuals use new sources of information to minimize the uncertainty of decisions. DFL includes financial literacy and digital at the same time to meet daily challenges. Although there is still no concrete definition for DFL, we find studies that have examined its implication. Tony and Desai (2020) used 7 questions on a Likert scale and the method of structural equations to infer a latent measure of DFL and digital financial inclusion. Morgan et al. (2019) report that DFL is a multidimensional concept and should be analyzed based on its dimensions[2]. DFL is taking a greater emphasis on education, and the development of new tools (technological products and services) creates greater opportunities for financial inclusion, giving consumers greater knowledge. Thus, we point out that DFL consists of the combination of financial knowledge applied to the use of digital tools. However, the complexity of DFL is expressed in its multidimensionality being captured by its dimensions.

Thus, we propose in this study three dimensions of DFL, which result from the application, collection of information, and evaluation of digital knowledge in financial areas. First, the technical dimension comprises the ability to use digital tools to satisfy everyday problems. We found in the literature some studies that focus on the use of tools. Prasad et al. (2018) have found that more and more people are betting on digital payments, such as Internet banking, debit, and credit card. Shen et al. (2020) used a set of variables that express the use of financial tools (such as financial transactions) to generate, through a method of structural equations, a latent index of the "use of digital financial products". Thus, we propose a set of questions where individuals express the frequency of using certain digital tools as a proxy to capture the technical dimension that will be representative of aptitude, knowledge, and practical skills.

Secondly, we have the information dimension. Literacy and learning result from the information collection process. Friedman (2005) points out that the collection of information by individuals involves the use of the Internet to

[2] They pointed out as dimensions: dimension of knowledge of digital financial products and services; dimension of digital financial risk awareness, which is awareness of the risks of digital finance; digital financial risk control, corresponding to digital financial risk control, and the dimension of knowledge of consumer rights and repair procedures.

inform them about anything they are interested in. Anderson-Inman (2009) states that the "digital revolution" has had implications for our knowledge, creating markets, new sources of information, how and with whom we communicate, what we do for entertainment, how we elect a president, and how we read, write and learn. Thus, the collection of information will be a variable factor.

However, the impact of social networks on financial behavior is important for those interested in how technology can be leveraged to improve the outcomes of financial education and financial well-being because social networks are increasingly being mediated by Web 2.0 (they are web applications such as Facebook, Twitter and other Internet forums that facilitate access to interactive information sharing and collaboration) (Way and Wong, 2011). Souza and Aste (2019) found that the models that considered financial and social information (information taken from the social network Twitter) fit better to the data when compared to a restricted model that considers only financial information, and demonstrated that social information improves the prediction of the structure of the financial market. Manfield et al. (2018) found that social media (Twitter) signals may partially lead to changes in daily financial volatility in NASDAQ and NYSE-listed companies. Thus, to quantify this dimension we propose two questions that capture the importance given to information taken from the Internet (social networks and other channels), and through factor analysis, we will aggregate the information of the two questions in a single indicator.

The last dimension pointed out in this study relates to the self-assessment of individuals and the ability to invest through the Internet, and the knowledge of the Internet and new technologies, which we will designate by the dimension of self-evaluated knowledge. To this end, we used two questions that capture the self-assessment of individuals about their capacities and abilities. Gross and Latham (2012) report that skill issues and self-perceptions of skill can also be useful for work that focuses on human behavior derived from information, development of user interfaces, and evaluation of information systems and services. Porat et al. (2018) compared the skills perceived by participants in DL programs and their actual performance in relevant digital tasks. They pointed out that there is a difference between the perceived level and the real level of digital skills, which implies an effect of "digital overconfidence".

Understanding the dimension of self-rated knowledge can help to understand what the factors are that affect the levels of knowledge about a given area, however, it can also present overly favorable views of their abilities in many social and intellectual domains (Kruger and Dunning, 1999). Despite the limitations of self-assessment issues, they allow us to understand how individuals evaluate themselves and how they make certain decisions. We used two self-assessment questions to evaluate the dimension of self-assessed knowledge.

Thus, we propose the following questions: the first 4 questions in Table 3 capture the technical dimension of DFL; questions 5 and 6 capture the dimension of information and the last two questions capture the dimension of self-evaluated knowledge. We highlight that the methodology applied in this article aims to validate the proposed structure and generate three dimensions of DFL.

Table 3. Digital financial literacy

Dimensions	Question	Answers	Order	Justification
Technical_dimension	Indicate how often you use digital tools (Internet, mobile app) in the following financial decisions: Bank balances consult Variable- Use_bank	Never	1	Increased use expresses greater aptitude to use - 1 individual who does not use it and 5 individuals who use it daily
		Rarely	2	
		A few times (once a week)	3	
		Frequently (2 to 3 times a week)	4	
		Every day	5	
	Indicate how often you use digital tools (Internet, mobile app) in the following financial decisions: Trading (buying and selling) of stocks, company bonds, investment funds Variable- Use_Trading	Never	1	Increased use expresses greater aptitude to use - 1 individual who does not use it and 5 individuals who use it daily
		Rarely	2	
		A few times (once a week)	3	
		Frequently (2 to 3 times a week)	4	
		Every day	5	
	Indicate how often you use digital tools (Internet, mobile app) in the following financial decisions: Payment of purchases and services Variable- Use_payment	Never	1	Increased use expresses greater aptitude to use - 1 individual who does not use it and 5 individuals who use it daily
		Rarely	2	
		A few times (once a week)	3	
		Frequently (2 to 3 times a week)	4	
		Every day	5	

	Indicate how often you use digital tools (Internet, mobile app) in the following financial decisions: Bank transfers Variable- Use_transfers	Never Rarely A few times (once a week) Frequently (2 to 3 times a week) Every day	1 2 3 4 5	Increased use expresses greater aptitude to use - 1 individual who does not use it and 5 individuals who use it daily
Information_dimension	Information on the Internet, including YouTube and others, but not on social networks Variable- Information _Internet	Nothing important Rarely important Not too much or too little important Very important Extremely important	1 2 3 4 5	Expresses the importance given to sources of information in choosing your investment(s)
	Information obtained on social networks, e.g. Facebook, LinkedIn, and similars Variable- Information_networks	Nothing important Rarely important Not too much or too little important Very important Extremely important	1 2 3 4 5	Expresses the importance given to sources of information in choosing your investment(s)
Dimension_of_self-rated knowledge	When I need financial advice, just access the Internet without having to talk or meet a financial professional Variable- Advice_Internet	I totally disagree I disagree a little I neither agree nor disagree I agree a little bit I totally agree	1 2 3 4 5	Self-evaluated ability to fit in, learn from information technologies.

How do you evaluate your knowledge of the Internet and new technologies, given the average Portuguese population with characteristics similar to yours?	Much lower than average	1	Self-evaluated ability to fit in, learn from information technologies.
	Less than average	2	
	Equal to average	3	
	Higher than average	4	
Variable- knowledge_Internet	Much higher than average	5	

To analyze the three dimensions, we will apply an exploratory factor analysis, with the principal factor method with policychic correlations (Holgado-Tello et al., 2010; Baglin, 2014). Thus, the principal factor specification is the most appropriate because it does not require the assumption of multivariate normality (Laros, 2014), and simultaneously the principal factor technique is the most appropriate to obtain two or more latent variables that represent interpretable dimensions of some concept (Acock 2005). Finally, an Oblique Promax rotation will be applied, since the factors result from the multidimensionality of DFL and as such we admit that there is a correlation between them. Subsequently, the factors will be extracted, and three factors will be generated given the division proposed in Table 3 and factor analysis, representative of the three dimensions.

Table 4. Test to variables

Bartlett test of sphericity ($Chi^2(28)$)	1346.942***
Kaiser-Meyer-Olkin	0.663
The determinant of the correlation matrix	0.304

Note: *p < 0.10, ** p < 0.05, *** p < 0.01.

Table 4 presents the results of the two tests used to validate the use of exploratory factor analysis, the Kaiser-Meyer-Olkin test (KMO), and the Bartlett test of sphericity. The KMO test presented a value of 0.66 that is reasonable (Hair et al., 2009). In the Bartlett test of sphericity, we reject the null hypothesis in the model, which leads us to conclude that the variables are significantly correlated. Thus, based on the results of the two tests we can apply the factor analysis method.

Table 5 shows the results of the exploratory factor analysis. We expect each item (variable) to have a load close to 0.40 or higher in one factor and a lower load on the other factors (Acock, 2005). As we observed, three factors are attributed to the model, suggesting the three dimensions mentioned above. We will use items that have relatively large loads on each factor to decide how the factor should be designated. In Table 5 (panel B), the first factor represents the technical dimension with the lowest factor load of 0.25 and the highest of 0.82 (although the variable Use_Trading presents a low factorial load, the theoretical structure holds the variable and therefore was not removed). The second factor presents all factor loadings greater than 0.4, representing the dimension of self-evaluated knowledge, and the third factor presents all factor loadings close to 0.5, being representative of the information dimension. Finally, we found that the model presented rejects the null hypothesis and is completely saturated.

Table 5. Exploratory factor analysis

Method	Principal factor			
Rotation:	Oblique promax			
Panel A) Commonalities and initial factors				
Factor	Eigenvalue	Proportion	Rotated factors are correlated	
Factor1	1.79	0.80		
Factor2	0.97	0.44		
Factor3	0.79	0.36		
Panel B) Rotated factor loadings (pattern matrix) and unique variances				
Variable	Factor1	Factor2	Factor 3	Uniqueness
Use_bank	0.49	0.16	-0.03	0.65
Use_Trading	0.25	0.20	-0.00	0.84
Use_payment	0.82	-0.05	0.02	0.37
Use_transfers	0.82	-0.06	0.02	0.37
Information_Internet	-0.02	0.10	0.60	0.60
Information_networks	0.09	-0.06	0.59	0.66
Advice_Internet	-0.18	0.47	0.16	0.77
knowledge_Internet	-0.06	0.42	0.08	0.79
Panel C) Scoring coefficients (method = regression; based on factors rotated in promax (3))				
Variables	Factor1	Factor2	Factor 3	
Use_bank	0.17	0.18	-0.02	
Use_Trading	0.09	0.15	0.01	
Use_payment	0.40	0.11	-0.01	

Use_transfers	0.39	0.10	-0.02
Information _Internet	-0.01	0.13	0.41
Information_networks	0.00	0.01	0.37
Advice_Internet	0.01	0.28	0.12
knowledge_Internet	0.06	0.26	-0.01
LR test: independent vs. saturated Chi^2 (28)		1791.57 ***	

Notes: the table presents the results after a Promax rotation. The table is divided into three panels. Panel A includes the commonalities of the factors; panel B contains the factor loadings by the factor for each variable; panel C presents the coefficients of regressions used to calculate the latent variables. The underlined values represent the higher factor loadings that are used to identify the factor (the latent variable). The results of the model saturation test (LR test) are presented in the last line of the table. *p < 0.10, ** p < 0.05, *** p < 0.01.

Finally, we have estimated the three dimensions of DFL by the regression scoring method.

Table 6 shows descriptive statistics of the three dimensions pointed to DFL. As we have mentioned above, the concept of DFL is based on its multidimensionality, a fact that was demonstrated in the previous analysis, corroborating the results of Morgan et al. (2019). However, it could make sense to combine the three dimensions into a single factor, but when we analyze this possibility we found that the KMO test has a value of 0.384 that cannot be accepted at the conventional significance levels (Hair et al., 2009), refuting the possibility of creating a measure composed by the dimensions and revealing that subsequent analyses should focus on all three dimensions individually.

Table 6. Dimensions of digital financial literacy

Factor	Variable	Count	Average	Standard deviation	min	max
Factor 1	Technical_dimension	1136	3.704	0.752	1.079	5.564
Factor 2	Dimension_of_self-rated_knowledge	1136	3.874	0.655	1.481	5.824
Factor 3	Information_dimension	1136	2.000	0.732	0.607	4.205

Source: Own Elaboration.

4. Empirical results

In this section, we analyze the relationship between FL and the dimensions of DFL. As mentioned in the previous sections, financial development and information technologies are related. Thus, we try to understand the relationship between the two types of literacy and how a set of key variables enables the increase of literacy in the financial technical areas and the digital areas.

Table 7 presents the Pearson's correlation coefficients between the different dimensions of DFL and FL.

From the analysis of table 7, we conclude that the dimensions of DFL are weakly correlated with the levels of FL. The technical dimension and the dimension of self-evaluated knowledge are positively correlated and are significant (5% and 1%), while the information dimension is negatively correlated, not being significant. This result suggests that self-assessed skills, information, and knowledge do not relate to levels of FL, revealing that individuals can use digital resources with unsuitable financial training. Therefore, we may be faced with the inappropriate use of digital media by individuals. Given these results, we highlight that the use of digital media should be accompanied by adequate financial knowledge because if this does not happen individuals may be subject to fraud (Engels et al., 2020). When we analyze the relationship between the dimension of information and FL we find that it is negative and weak which reveals that the use of the Internet to collect information about investments does not seem to be associated with the levels of FL of individuals.

Table 7. Pearson correlation coefficients

	FL_ index	Technical_ dimension	Dimension_of_self-rated knowledge	Information_ dimension
FL_index	1.00			
Technical_dimension	0.07^{**}	1.00		
	(0.02)			
Dimension_of_self-rated knowledge	0.18^{***}	0.63^{***}	1.00	
	(0.00)	(0.00)		
Information_dimension	-0.03	0.00	0.43^{***}	1.00
	(0.33)	(0.99)	(0.00)	

Note: P-values in parentheses $^{*}p< 0.10$, ** $p< 0.05$, *** $p< 0.01$.

Our results can also be understood in the context of the issue of financial inclusion. Financial inclusion is defined as the availability and equal opportunities for access to financial services (Shen et al., 2020). The use of the Internet can only promote financial inclusion indirectly by presenting digital financial products to people. For FL and internet use to be effective in affecting financial inclusion, it is necessary to promote the use of digital financial products (Shen et al., 2020).

5. Conclusion

In this chapter, we establish a link between the dimensions of DFL and FL. We designate DFL as the multiplicity of literacies associated with the use of digital technologies related to financial areas, proposing a theoretical description, empirically validated, of its dimensions.

We suggest three dimensions associated with DFL, based on eight questions that allow observing the ability to use digital tools, the collection of information on the Internet, and the self-assessment of digital knowledge. We proposed to divide the eight questions as follows: four express the technical dimension, two the dimension of information, and two the dimension of self-evaluated knowledge. The variables were combined through the use of an exploratory factor analysis with the principal factor method and with Oblique Promax rotation where we validated the proposed structure. To obtain the FL measurement, we use the ratio of correct questions related to interest rates and interest composition, the effect of inflation, etc.

Our results show that the proposed division for the three dimensions is validated by factor analysis. Subsequently, we conclude that there is a weak relationship between the dimensions of DFL and FL, drawing attention to the dangers of the unsuitable use of financial tools. There was a demonstration of a gap between the levels of FL and DFL.

Our study suffers from some limitations. We emphasize the fact that we propose three dimensions of DFL based on the ability to use digital tools, information collected on the Internet, and self-assessment of digital knowledge. However, other dimensions can be pointed out to DFL that have not been studied in this work and a more thorough analysis of the determinants influencing the levels of DFL and FL would also be necessary.

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CHAPTER 12

DETERMINANTS OF DIGITAL FINANCIAL LITERACY AND FINANCIAL LITERACY: EVIDENCE FROM AN ONLINE SURVEY IN PORTUGAL

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Abstract

In this chapter, we used an online survey administered to 1136 individuals in Portugal to investigate the determinants of financial literacy and digital financial literacy. Our results show that male individuals, with lower levels of risk aversion, with higher levels of education and income tend to present higher levels of financial literacy and digital financial literacy (self-rated knowledge dimension). Additionally, older individuals tend to have a lower level of digital financial literacy. There seem to be no significant differences in literacy levels between investors and non-investors. Our results may be of interest to promoters of financial literacy and digital financial literacy programs.

Key-words: Financial literacy, digital literacy, digital financial literacy, survey, investors, Portugal

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1. Introduction

Economic and technological development has created paths that can help to eliminate problems related to low literacy levels. Daily, knowing just one area is not enough to face financial challenges. The financial and technological areas are an example of the complementarity of different areas since the financial area has been complementing itself with the use of tools and technologies that have contributed to its development and reduction of its weaknesses (Li et al., 2020).

Thus, the need to acquire financial and digital knowledge gave rise to digital financial literacy (DFL). Also, financial literacy (FL) includes the ability to read, analyze, manage, and communicate about financial conditions that affect individuals' material well-being. In the literature, few studies have been conducted to understand how individuals' characteristics, behavioral deviations, and knowledge affect DFL. Recurring to the results of an online survey of 1136 individuals collected in Portugal we examined the sociodemographic determinants of FL and DFL in their different dimensions. Thus, we contribute to the literature that aims to understand the factors capable of explaining the two types of literacy.

Our results show that there are variables that influence both levels of literacy (risk aversion, eduction, subjective knowledge, among others) and that the creation of measures that stimulate these variables can induce increased financial well-being. Therefore, we emphasize that one of the biggest challenges in finance is the reduction of the impact of cognitive deviations and low levels of FL on financial decisions and that the correct adequacy of the two areas can contribute to the minimization of these effects. The results of this study are important for both the individual investor and for organizations in their day-to-day investment decisions, as well as indicate important strategies to be followed for the correct development of the levels of FL and DFL to policymakers.

This chapter is organized as follows. Section 2 reviews the literature on the topic. Section 3 describes the data and methodology used in the empirical study. Section 4 presents the empirical results. Section 5 concludes the chapter.

2. Determinants of literacy

2.1. Digital literacy and financial literacy

In a constant development society, it is necessary to acquire new financial and digital knowledge. However, the ability to acquire this knowledge is related to the characteristics of individuals and the need to respond to day-to-day challenges. Graduate students with technological knowledge are generally better able to use unknown technologies in their learning processes to create useful tools (Ng, 2012). Quintanilha et al. (2018) found that the increases in digital literacy (DL) rates coincided with the awareness of individuals about concepts such as identity, privacy, and content relevance.

Digital knowledge interferes with all other areas and the lack of DL increasingly affects the potential to be a competent student or employee or an enlightened citizen (Meyers et al., 2013). Eshet-Alkalai and Chajut (2009) studied the changes over time in DL amongst a group of participants over 5 years and analyzed their performance by comparing it to the new corresponding control groups. They found an improvement over time among all age groups, especially for adults, in tasks that require proficiency and technical control, in the use of technologies. By comparing with the corresponding control groups, they suggest that experience with technology, not age, is responsible for lifelong changes in DL skills.

Currently, all major areas of study are linked to digital areas and this interconnection is growing stronger. A heavily affected area is the financial area. Accordingly, in the literature, we find studies that address FL and compare the determinants of FL and DL. Cavezzali et al. (2015) report that financial education significantly alters the investment process of investors. Lusardi and Mitchell (2007) found that many families are not familiar with the most basic economic concepts needed to make savings and investment decisions. This financial illiteracy is widespread among young and old people in the US and other countries and may carry serious implications for decisions regarding reform planning and income, and others.

Individuals with poor FL face a variety of problems when making financial decisions because they do not have the necessary technical knowledge to understand the variables that influence investment. Hastings and Mitchell (2018) found that the level of impatience is a strong predictor of wealth and investment in health. However, they also conclude that FL is correlated with wealth, although it seems to be a weaker predictor of sensitivity to the framework in investment decisions. Connor (2019) studied how the relationships between consumer cognitive style, subjective knowledge, and objective knowledge, and how these relationships vary according to demographics. The author found that investors' perception of their subjective financial knowledge varies according to cognitive style. For example, investors with an intuitive cognitive style tend to have a greater perception of their subjective financial knowledge than those who are more analytical in their reasoning.

Rothwell and Wu (2019) examined the impact of subjective and objective financial knowledge on the effectiveness of financial decisions. In the analysis of the PSM (Propensity Score Matching*)*, they found that the participants in financial education programs obtained higher scores in the three results compared to the non-participants. Muñoz-Murillo et al. (2020) pointed out that sociodemographic factors generally disguise the final determinants of the acquisition of financial knowledge, such as risk aversion, time preferences, cognitive and behavioral deviations, and personality traits, cognitive and non-cognitive abilities, among others. Having financial knowledge can contribute favorably to different dimensions of decision-making. Lusardi et al. (2017) found that financial knowledge is a key variable in the way individuals generate their wealth throughout life and Engels et al. (2020) reported that individuals with more financial knowledge are more likely to detect fraud.

The conventional view of FL, which is based only on the existence of financial knowledge, does not consider the diversity of knowledge that is necessary to make financial decisions today. Knowledge of several areas is required to analyze all the existing information.

2.2. Digital financial literacy

DFL arises from the need to acquire various types of knowledge (Ribeiro et al., 2020b). Thus, the multiplicity of knowledge can be the solution to minimize the low levels of FL. Low levels of FL need not imply poor decision-making. Consumers can make up for gaps in knowledge and analytical skills by consulting with financial professionals or employing appropriate tools such as planning software and financial calculators. However, in practice, relatively few consumers implement these features. Studies show that most baby boomers rely on relatives and friends, or simply on their judgment when making financial choices, while only 15% said their financial decisions were mainly based on financial professionals (Bernheim and Taubinsky, 2018; Bernheim, 1998).

The use of information technologies efficiently can contribute to mitigating errors that negatively affect financial decisions (Panos and Wilson, 2020). For example, using smartphone applications can improve financial behaviors (French et al., 2020). Chlouba et al. (2011) showed that through the combination of information and communication technologies (ICT) and the basic concepts of FL, the user could navigate different topics learning about financial concepts, and increasing their levels of FL. In a world of uncertainty and imperfect information, individuals with higher levels of financial knowledge are more prone to use new information technologies and can demonstrate better performance in financial markets.

2.3. Main determinants of financial literacy and digital financial literacy

In the literature, we find some results associated with DL and FL, as well as how these can affect DFL. It is expected that a set of psychological, sociodemographic, and financial knowledge-revealing variables will explain FL and DFL. One of these variables is risk aversion. Cavezzali et al. (2015) state that risk tolerance affects the level of FL. They found that the more tolerant the individual is to risk, the higher their levels of FL will be. Schleich et al. (2019) report that more averse individuals are less likely to acquire new technologies. Muñoz-Murillo et al. (2020) state that one of the key factors that explain people's acquisition of financial knowledge is risk aversion. Königsheim et al. (2017) found that financial knowledge and risk tolerance were positively associated with the use of digital financial services. Thus, the perceived risks in Internet banking are responsible for some of the hesitations in adopting this tool (Bauer and Hein, 2006).

Studying the determinants of FL is key. According to Garg and Singh (2018), the level of FL among young people is reduced in most of the world, making it a cause for growing concern. Moreover, they found that several socio-economic and demographic factors such as age, gender, income, marital status, and education influence the level of FL. Thus, understanding DFL and FL can help to understand how decisions are made and enable the creation of solutions to the problem of low literacy.

Several studies have been reporting significant cross-sectional differences in FL. For example, Cavezzali et al. (2015) found that men have higher levels of FL than women. Further, Fonseca et al. (2012) concluded that men have more FL than women, a consequence of everyday experience, as men manage family accounts more often than women. Regarding age, Cavezzali et al. (2015) documented a positive association between age and FL. Connor (2019) reports that older individuals tend to have more objective knowledge (accurate product-related information) and that the elderly (individuals 65 years and older) get the highest score on objective measures of financial knowledge. Other authors disagree. For example, Eshet-Alkalai and Chajut (2009) report that the use of technology is associated with increased experience and not with increasing age. The debate about the impact of age on financial decisions continues to be intense today. For example, Bouteska and Regaieg (2018) and Talpsepp (2010) found that with increasing age there is a decrease in behavioral biases. Elliott et al. (2008) and Veld-Merkoulova (2011) found evidence that the older the individual, the lower the preference for high returns and the lower the percentage of investment in risky assets. This is explained by an increase in the investors' conservatism (Persico et al., 2004), accompanied by a greater fragility concerning health (Edwards, 2008), which reveals a decrease in the cognitive capacity of individuals, and may increase the probability of having losses (Korniotis and Kumar, 2011).

Concerning education, Ng (2012) found that graduate students, who were raised with more awareness of digital capabilities, tend to reveal higher levels of digital skills and Cavezzali et al. (2015) found that higher education levels are reflected in higher levels of FL. Fonseca et al. (2012) and Scheresberg (2013) confirm that higher levels of education reflect better levels of FL. Finally, considering income, Lusardi and Mitchell (2011) found that the increase in income level significantly increases the level of FL, even when several control variables are introduced in the analysis.

3. Methodology

We use the results of the "Portuguese Online Survey of investor profile" conducted by the Portuguese Securities Market Commission in 2018 (CMVM Study Office, 2019) to examine the determinants of DFL and FL in their several dimensions. We follow the procedures explained in detail in Ribeiro et al. (2020b) to explore such determinants.

The model that we have been describing can be represented as follows.

$$Dep_t = \alpha + \beta_1 Risk\ aversion_t + \beta_2 Loss\ aversion_t + \beta_3 Gender_t + \beta_4 Age_t + \beta_5 Employment_t + \beta_6 Education_t + \beta_7 Income_t + \beta_8 Technical\ Analysis_t + \beta_9 Knowledge\ investing_t + \beta_{10} Financial\ knowledge_t + \beta_{11} Investor_t + e_t \qquad (1)$$

where:

$Dep =$ dependent variable that can be FL or any of the three dimensions of DFL (technical dimension, information dimension, and the dimension of self-rated knowledge;

$t = indicates\ the\ independent\ variable\ of\ the\ regression$),

$Risk\ aversion =$ measure of risk aversion (takes values between [1.018;4.95] in which the most averse individual takes the lowest value and the most likely individual takes the greatest value)[1].

$Loss\ aversion =$ measure of loss aversion (takes values between [1,056, 5.28] in which the most loss-prone individual has the lowest value and the most loss-averse has the highest value),

$Gender =$ dummy variable, with a value of 1 if the subject is male, and 0 otherwise,

$Age =$ age of the subject in the survey,

[1] The measure of risk and loss aversion was estimated based on the questions and procedure present in Annex B of the work of Ribeiro et al. (2020a). Thus, through the use of 6 questions in which three are related to the attitude towards risk and three with the attitude towards loss and using a factor analysis by maximum likelihood with correlations of policychic (for each measure) and the regression scoring method to estimate the two latent factors we capture the attitude of individuals in relation to the scenarios of loss and risk.

$Employment =$ dummy variable, with a value of 1 if the subject was employed at the time of the survey, and 0 otherwise,

$Education =$ maximum level of schooling (from 1 – no education at all to 6 – Master, MBA or Ph.D.) of the subject in the survey,

$Income =$ available monthly income of the subject in the survey,

$Technical\ Analysis =$ measure of importance attributed by the subject in the survey to concepts of technical analysis (from 1 – not important to 5 – extremely important),

$Knowledge\ investing =$ measure of the self-assessed knowledge about financial investments (from 1 – not knowledgeable at all to 5 – very knowledgeable),

$Financial\ knowledge =$ measure of the tendency to rely on one's knowledge to invest (from 1 – not likely to 5 – very likely),

$Investor =$ dummy variable, with a value of 1 if the subject has current investments in financial markets, and 0 otherwise.

We considered as dependent variables the three dimensions of DFL (technical dimension, information dimension, and the dimension of self-rated knowledge) and the measure of FL. We include as explanatory variables several individual characteristics also captured by the survey: the risk aversion profile, the loss aversion profile, and a set of sociodemographic characteristics (gender, age, employment situation, education, and income). Our model also includes variables related to the individual importance attributed to technical analysis, the self-assessed knowledge about financial investments, and the tendency to rely upon their knowledge to invest. Finally, the differences between investors and non-investors are captured by a dummy variable that takes the value 1 for investors and 0 for non-investors. The measure of financial literacy results from the percentage of correct answers to questions and statements i) Suppose you have €100 in a bank account whose interest rate is 1% per year. After 5 years, how much will the account balance be if no money is withdrawn, nor are there commissions or associated taxes (i.e. at the end of each year you let the interest amount stay in that same bank account)?, ii) Suppose you have €100 in a bank account whose interest rate is 1% per year and that inflation is 2% per year. A year from now, what do you think you could buy with the money in that account?, iii) You have invested in a bond that pays a fixed interest rate. Meanwhile, market interest rates have decreased. If you sell that bond after this decrease, the price of this bond shall be:, iv) In your opinion, please indicate whether the following statement is true or false: “Investing in a company's share typically provides a safer return than investing in a stock fund.” and v) What does it mean that security has guaranteed capital on the maturity date?.

The technical dimension of DFL considers the ability to use digital tools to solve everyday problems. The four survey questions that were considered to capture this dimension were as follows: Indicate how often you use digital tools (Internet, mobile app) to conduct the following tasks: i) consultation of bank balances; ii) trading (buying and selling) of financial securities, iii) payment for purchases and services and iv) bank transfers.

The information dimension intends to capture the ability to collect information from the internet and social networks. Thus, the two questions of the survey that were used to capture this dimension were as follows: i) how important is the information obtained from the Internet, including YouTube and others (but not from social networks) and ii) how important is the information obtained on social networks (e.g., Facebook, LinkedIn and similar).

Finally, the dimension of self-rated knowledge aims to capture the degree of autonomy perceived by the individuals in their use of digital tools. These capabilities will be reflected by agreeing to the first statement i) and the answer to question ii): i) when I need financial advice, I just access the Internet, without having to talk or meet with a financial professional, and ii) how do you assess your knowledge of the Internet and new technologies compared to the average Portuguese population with characteristics similar to yours?.

The model regarding the dimensions of DFL was estimated using the ordinary least squares (OLS) technique. For the dependent variable FL, we performed a different regression given the characteristics of the variable. The variable FL is measured on a scale of [0;1], and therefore, following Papke and Wooldridge (1996) and Botelho (2012), the conditional statistical analysis of FL rate data was performed by estimating a generalized linear model (GLM) with the binomial family and logit link and adjusting standard errors by a scale parameter equal to the Pearson's chi-square, divided by the residual degrees of freedom (Botelho, 2012). Since the coefficients are not linear in the model parameters, we used the average marginal effects to read the effects of the explanatory variables on the dependent variable FL.

4. Empirical results

Table 1 shows the estimates for each of the three dimensions of DFL and the average marginal effects on FL (to note that the Wald test result revealed that GLM regression has overall significance at 1% (Wald test $Chi^2(10)=275.47$)). The set of explanatory variables is the same for all dependent variables.

We found that all regressions related to the dimensions of DFL are overall significant at a 1% confidence level. It is noteworthy that no significant differences were found between investors and non-investors, both for the three dimensions of DFL, as well as for the FL index.

Table 1. Regressions of the dimensions of DFL and average marginal effects of FL

	Dimensions of Digital Financial Literacy			Average marginal effects-FL_index#
	Technical_dimension	Information_dimension	Dimension_of_self-rated knowledge	
Risk_aversion	0.0903***	0.0161	0.0696***	0.0179***
	(4.00)	(0.71)	(3.94)	(3.09)
Loss_aversion	0.0379	-0.0214	-0.00737	0.00231
	(0.91)	(-0.51)	(-0.23)	(0.22)
Gender_(male)	-0.00985	-0.0135	0.146***	0.0621***
	(-0.16)	(-0.21)	(3.13)	(3.70)
Age	0.000308	-0.00778***	-0.00911***	0.000301
	(0.15)	(-3.59)	(-5.62)	(0.57)
Employment	0.104	-0.151**	-0.0139	0.0165
	(1.45)	(-2.14)	(-0.26)	(0.97)
Education	0.0590*	0.0428	0.0658***	0.0413***
	(1.91)	(1.51)	(2.94)	(5.90)
Income	0.0749***	-0.0267	0.0477**	0.0148**
	(3.13)	(-1.14)	(2.53)	(2.53)
Technical_analysis	0.0688***	0.0402	0.0497**	-0.0263***
	(2.64)	(1.47)	(2.25)	(-3.80)
Knowledge_about_investing	0.0243	0.0254	0.131***	0.0168***
	(1.30)	(1.33)	(8.94)	(3.52)
Financial_knowledge	0.112***	-0.0392	0.0629***	0.0458***
	(3.91)	(-1.38)	(2.85)	(6.22)

Dummy_ investor	0.0266	-0.0427	0.0805	-0.000211
	(0.29)	(-0.43)	(1.20)	(-0.01)
_cons	1.922***	2.360***	2.680***	
	(6.22)	(7.34)	(10.67)	
N	1136	1136	1136	1136
R^2	0.0969	0.0311	0.277	
AIC	2482.7	2503.5	1918.6	
BIC	2543.1	2563.9	1979.0	
F	9.492	3.390	37.27	
P	0.000	0.000	0.000	

Notes: The models used present robust standard-errors for the variables, and the t-statistics based on robust standard errors are in parentheses. * p< 0.10, ** p< 0.05, *** p< 0.01. # The column FL_index presents the average marginal effects of the explanatory variables of the FL model. Values of the z statistic between parentheses. The number of observations (N), Akaike information criterion (AIC), Bayesian information criterion (BIC), R-squared (r2), F test to assess the overall significance of the model, and p-value of the test (p).

4.1. Results for the technical dimension

The first regression in Table 1 concerns the technical dimension and how we can see the variable degree of risk aversion is significant at 1% and has a positive effect. This result shows that individuals more likely to be at risk have greater skills to use information and communication technologies (ICT) in everyday life, while the more averse the individual is, the lowest is his ability to use ICT. This result may be linked to the dangers associated with digital tools, and more averse individuals are more afraid of the tools compared to those prone to risk and as such do not make use of it, so the perception of risk is not homogeneous and the risk is important in the decision to the adoption of digital tools (Bauer and Hein, 2006). Our results also corroborate the results found by Schleich et al. (2019) who found that the most averse individual is less likely to acquire new technologies. Additionally, Königsheim et al. (2017) verified that financial knowledge and risk tolerance are positively and significantly correlated with the likelihood of using digital financial services.

The variable education is statistically significant at a 10% significance level and has a positive impact, which suggests that the higher the education of the individual, the more frequent the use of ICT will be. More educated individuals tend to have higher digital capabilities which facilitate the use of new technologies (Duasa et al., 2019). Additionally, the use of technology by teachers can be a mediating variable, and thus, the adoption of technology can complement the teaching and learning process by increasing literacy and skill levels (Margaryan et al., 2011). Duasa et al. (2019) found that the higher the education, the greater the probability of the individual resorting to the services of the online bank.

The variable income is significant at 1% and has a positive impact, which indicates that the higher the income, the more often individuals will tend to recur to the use of ICT. For example, Individuals with higher incomes have a greater need to control their banking movements, which will have repercussions on the use of digital tools to facilitate control.

The results of the variable related to technical analysis reveal that the greater the importance is given to technical analysis, the greater the technical dimension (result significant at a 1% significance level). This result is probably linked to the fact that individuals who give great importance to technical analysis perform their analyses using a given software, thus revealing greater skills to use this type of tool. The variable, financial knowledge, is statistically significant at the conventional levels, revealing that individuals who consider themselves to be financially knowledgeable are more willing to use digital tools (Lusardi et al., 2017).

Finally, we emphasize that the variables aversion to loss, age, and knowledge about investing have no significant impact on the technical dimension. Regarding the age variable, our evidence corroborates the results of Eshet-Alkalai and Chajut (2009) because the authors suggest that the experience with technology is responsible for the changes observed throughout life in the skills of using digital technologies and not age. Over the years the technical differences in the use of digital tools tend to decrease, which corroborates our results (Eshet-Alkalai and Chajut, 2010). We did not find differences in gender or the employment situation in the technical dimension.

4.2. Results for the information dimension

The second regression in Table 1 relates to the dimension of information. Age has a negative and statistically significant impact on this dimension which suggesting that older individuals use less digital information (Ng, 2012), i.e., older individuals are not as sensitive to new sources of information as younger individuals. Younger generations grew up within the “digital revolution” which enabled them to interact more with new forms of research and information gathering. In particular, sources of information such as Facebook, Twitter, and other Internet forums that facilitate interactive information sharing and collaboration have been achieving increasing prominence in financial markets (Way and Wong, 2011).

The dummy variable employment captures the employment situation of the subject. The result suggests that there is a negative association between being employed and the information dimension. We conjecture that this may be because unemployed people may have more time available to recur to the internet. Finally, we found that the variables relating to risk aversion, loss aversion, gender, education, income, technical analysis, knowledge about investing, and financial knowledge do not have a significant impact on the information dimension.

4.3. Results for the dimension of self-rated knowledge

The third regression in Table 1 relates to the determinants of the dimension of self-rated knowledge. We found that only the variables degree of aversion to loss and employment have no statistically significant impact on this dimension of DFL. On the other hand, the variables, degree of risk aversion, gender, education, income, technical analysis, knowledge about investing, and financial knowledge are significant at least 5% and have a positive impact. The age variable is significant at 1%, with a negative impact. We highlight that individuals who are risk-prone, male, young, with high levels of education, with high income, who give importance to technical analysis, and who are self-rated with knowledge on how to invest are found to have better capacities to invest through the Internet and to have a deeper knowledge of the Internet and new technologies. The results indicate that several factors help to explain perceived knowledge.

Only age negatively leads to a decrease in self-rated knowledge, which can be explained by two factors. First, the older the individual, the lower his digital knowledge, aptitude, and self-assessment. Older individuals with lower education have lower demand for digital access to financial services (Conrad et al., 2019). However, older individuals are more experienced with adequate and sufficient training in digital environments, which can lead to better internalization of individual capabilities and greater self-awareness (Porat et al., 2018). Experience with task and in-depth processing can alleviate overconfidence, but the effectiveness of learning improvement methods depends on the context of the study and preferences (Lauterman and Ackerman, 2014).

4.4. Results for financial literacy

In the last column of Table 1, we present the marginal effects on financial literacy. We observed that the variable degree of risk aversion has a positive sign and is significant at a 1% significance level, suggesting that the more risk-prone the individual is, the higher his level of FL (Cavezzali et al., 2015). This result indicates that individuals who are more willing to risk tend to seek and have greater financial knowledge. On the other hand, the variable aversion to loss seems to have no statistically significant impact on FL.

We found that the male gender has higher levels of FL than the female gender and the variable is significant at a 1% significance level. According to Fonseca et al. (2012), this finding is because men are more involved in the management of financial investments than women thus acquiring more financial knowledge.

The variable age has no significant impact on FL. The variable education is significant at 1% revealing that individuals with more education have better levels of FL. This result corroborates other findings in the literature (Fonseca et al., 2012; Scheresberg, 2013; Cavezzali et al., 2015).

Income is found to positively impact FL at the 5% significance level, showing that individuals with higher incomes have higher levels of FL, which attests to the result of Lusardi and Mitchell (2011). Individuals with higher incomes are incentives to acquire better financial knowledge to manage their wealth in the best way.

The variables related to subjective knowledge, such as the importance given to technical analysis, knowledge about investing, and financial knowledge are all statistically significant at a 1% significance level. However, the coefficient regarding the technical analysis shows a negative sign suggesting that there is a negative association between the importance attributed to technical analysis and the level of FL. This may indicate that individuals who have higher financial knowledge do not value technical analysis, possibly because they prefer to recur to more sophisticated techniques such as fundamental analysis. We also found that the variable knowledge about investing, which expresses self-rated knowledge to invest, has a positive sign showing that individuals who agree with this statement tend to have higher levels of FL. The variable self-rated financial knowledge is positively associated with FL which is consistent with the view that individuals who think are more knowledgeable in the realm of finance have higher levels of FL.

5. Conclusion

In this chapter, we studied the determinants of DFL and FL through the use of a survey administered to 1136 individuals in Portugal. Our results reveal that male individual, with lower levels of risk aversion, with higher levels of education and income, tend to have a higher level of financial literacy and digital financial literacy in the dimension of self-rated knowledge. On the other hand, older individuals tend to present a lower level of digital literacy. There seems not to be significant differences in literacy levels between investors and non-investors.

The results of the present study can be useful for the promoters of financial literacy and digital financial literacy programs as they will allow defining with greater accuracy the segments of the population that have the greatest lack of knowledge in these areas.

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