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Price Clustering in Bank Stocks during the Global Financial Crisis

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Bibliographical Note

Luís Miguel Alves was born on September 9, 1993, in Porto, Portugal. In 2013, he began his degree in Economics at School of Economics and Management of the University of Porto, FEP, which he concluded in 2016. He has always been interested in the fields of Economics and Finance, particularly in financial markets and the behavior of its participants, hence, in the same year, he joined the Master in Finance course at the same university, having completed the curricular part in 2018.

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Abstract

Price Clustering has been one of the most studied phenomena within financial markets over the last few decades. This is one of the anomalies that contradicts the Efficient Market Hypothesis which states that prices should follow a random walk. There is, indeed, extensive evidence suggesting that certain prices are more frequently traded than others, however, no studies have ever analyzed this anomaly for the Banking Industry, nor for such a critical stage of its history.

The purpose of this study is to analyse the incidence of price clustering in this industry's stocks before and during the recent financial crisis, investigating whether the uncertainty around the financial system and the panic that plagued investors around the world during the international banking crisis had or not some kind of influence on the level of price clustering observed in the stocks of these particular companies. The aim of this study is to use two samples, one with US banks and the other with European banks, and investigate the impact of the financial crisis on the clustering observed in this industry's stock prices, as well as the determinants of this phenomenon.

For these purposes, we performed a univariate analysis and two multivariate analyses (cross-section and time-series). Besides, a study of the impact of the European sovereign debt crisis on price clustering was also performed.

The primary findings of the study show the existence of price clustering for the European and US banks' samples, providing evidence that contradicts the Efficient Market Hypothesis, with the Attraction and the Price Resolution/Negotiation Hypotheses being only partially confirmed. Moreover, the results reveal an insignificant impact of the financial crisis in the observed levels of clustering, but there is a tendency to less clustering in crises, as the results of the European sovereign debt crisis' analysis suggest.

Key-words: price clustering, financial crisis, behavioral finance, microstructure, banking industry

JEL-Codes: G12, G14, G01, G4

Sumário

O *clustering* de preços tem sido um dos fenómenos mais estudados nos mercados financeiros nas últimas décadas. Esta é uma das anomalias que contradiz a Hipótese da Eficiência do Mercado, que afirma que os preços devem seguir um "passeio aleatório". Há diversas evidências que sugerem que certos preços são mais frequentemente observados do que outros, no entanto, nenhum estudo analisou até agora esta anomalia para o sector bancário, nem para um período tão crítico da sua história.

O objetivo deste estudo é analisar a incidência da concentração de preços nas ações do sector bancário antes e durante a recente crise financeira, investigando se a incerteza em torno do sistema financeiro e o pânico que assolou investidores em todo o mundo teve algum tipo de influência no nível de *clustering* de preços das ações dessas empresas em particular. Serão usadas duas amostras, uma com bancos dos EUA e outra com bancos europeus, para investigar o impacto da crise financeira e de todas as suas consequências no nível de *clustering* dos preços, bem como os determinantes deste fenómeno.

Para esse efeito, realizamos uma análise univariada e duas análises multivariadas (*cross-section* e *time-series*). Além disso, também foi realizado um estudo do impacto da crise da dívida soberana europeia sobre o *clustering* de preços.

As principais conclusões do estudo mostram a existência de *clustering* de preços para as amostras de bancos europeus e dos EUA, evidências que contrariam a hipótese da Eficiência de Mercado, com as hipóteses da Atração e da Resolução de Preço/Negociação sendo apenas parcialmente confirmadas. Além disso, os resultados revelam um impacto insignificante da crise financeira nos níveis observados de *clustering*, mas existe uma tendência para menos *clustering* em períodos de crise, como sugerem os resultados da análise ao impacto da crise da dívida soberana na Europa.

Palavras-chave: clustering de preços, crise financeira, finanças comportamentais, microestrutura, indústria bancária

Códigos JEL: G12, G14, G01, G4

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Chapter 1

Introduction

Market anomalies are one of the most intriguing and fascinating phenomena possible to observe in financial markets. One of the most studied over the last decades has been price clustering, with the first evidence published in the 1960s (Osborne, 1962). The Efficient Market Hypothesis posits that prices should follow a random walk and fully reflect all available information. Being prices, theoretically, the reflection of the assets' fundamental value, there is no apparent reason to observe an accumulation of prices in certain levels or numbers. The suggestion that this theory makes is that, in the absence of market frictions, prices should be uniformly distributed, yet there is extensive evidence over the years showing that certain prices are traded more frequently than others (Niederhoffer, 1965; Harris, 1991; Ikenberry and Weston, 2008). This phenomenon can be defined as price clustering and it can affect the integers, the decimal part or both.

Price clustering is a phenomenon that extends to many types of assets and markets, with abundant evidence not only for stock markets but also for several others, such as the foreign exchange markets (Mitchell, 2001) or commodity markets (Ball et al., 1985). Furthermore, it is also an anomaly found in distinct regions of the world, from the US to Europe, and even in some emerging markets (Brown et al., 2002; Harris, 1991; Palao and Pardo, 2012).

Several explanations have been given in an attempt to justify the vast empirical evidence related to price clustering. Two of the main hypotheses, the price resolution (Ball et al., 1985) and the negotiation hypotheses (Harris, 1991), are based on the uncertainty about the fundamental value of the assets, arguing that this uncertainty results in a greater probability of clustering, each with slightly different mechanisms. Another theory suggests that clustering is simply a preference of individuals for certain numbers, the attraction hypothesis (Goodhart and Curcio, 1991), while another suggests that it is the collusion between market participants that underlies this phenomenon, the collusion hypothesis (Christie and Schultz, 1994). We will discuss later in more detail these and other explanations that have emerged, but only the fact that there is such a vast and diverse literature regarding not only the empirical evidence on price clustering but also literature with a more theoretical nature, with the objective of finding explanations for the phenomenon, makes this market anomaly one of the most fascinating.

The aim of this dissertation is to extend previous studies by seeking comprehensive evidence on price clustering in the banking sector equity market in a critical period of its recent history, that is, before and during the recent financial crisis. This period was characterized by enormous uncertainty and volatility in the markets, especially in the banking sector which was in the origin of the worst financial crisis since the Great Depression of the 1930s. The importance of the financial system in modern societies is tremendous, since there is a strong link between the financial side of the economy and the "real" economy. Indeed, the global financial crisis has revealed just that. The financial system was fraught with systemic risk, and the deterioration in the balance sheets of banks and other financial institutions led many companies and households to struggle to finance their operations and needs. As a consequence of this financial meltdown, the effects felt deeply in the “real” economy, with the unemployment rate increasing rapidly and the global economy going into a tremendous recession. A strong financial system is extremely important and beneficial to all specters of society, but when something goes wrong, the consequences can be disastrous and can lead to profound changes in the behavior of economic agents. Hence the importance of expanding the study of this phenomenon to this sector and to this particular period.

Hypothetically, one would expect greater clustering in times of crisis and uncertainty. It is this hypothesis that we intend to test, verifying if the panic that overwhelmed investors and the uncertainty that characterized this period, had or not some influence in the type and level of clustering observed in the stocks of the companies of this sector. Moreover, this study also aims to understand which factors explain the cross-section variation of price clustering.

For this purpose, two sub-samples will be used, one with US banks and another with European banks, and obviously the crisis period will have to be different for each of the samples.

We found evidence of price clustering for both samples, with an insignificant impact of the global financial crisis on the observed levels of clustering, but our results reveal a tendency to lower levels in crises, as suggested by our findings regarding the impact of the European sovereign debt crisis on clustering. Besides, this study also partially confirms the Attraction and the Price Resolution/Negotiation Hypotheses.

Besides this chapter, this report is structured as follows: in the second chapter, a literature review of the topic is made; in the third chapter the methodology used is described; in the fourth chapter we present and analyze our results and, finally, in the fifth chapter we expose our main conclusions.

Chapter 2

Literature Review

The theory of market efficiency has been challenged over the past decades. In fact, much evidence strongly suggests that economic agents are not entirely rational (Simon, 1955). The concepts of bounded rationality and limited cognition brought about by the behavioral finance field are nowadays practically accepted by the entire academic community and are certainly at the root of several market anomalies observed over time. Price clustering is one of those market inefficiencies that goes against the ideas of economic rationality and that prices should follow a random walk (Aitken et al., 1996). This trading behavior led to the justification of the analyses that have been made of this phenomenon for several markets and also to the numerous hypotheses that have been put forward in an attempt to explain it. Beyond its definition, it is this empirical evidence and these possible explanations that we intend to address throughout this chapter.

2.1. Definition of Price Clustering

The concept of price clustering originates from the studies of Osborne and Niederhoffer published in the 1960s. Osborne (1962) presented evidence of a phenomenon that at the time he termed "congestion" which is nothing more than the tendency for certain share prices to spend an inordinate amount of time at a certain price range.

Several definitions of this phenomenon have been suggested and few differences can be drawn between them. What seems to us to be the most adequate is the one presented by Brown and Mitchell (2008) that define the price clustering as the concentration of stock prices on some numbers rather than others as a result of human bias, imprecise beliefs or haziness about the underlying value of the security. Of course, this concept extends to all types of assets, as the extensive empirical evidence that we will present later will reveal, however, since our study will focus on the stock market, we think this definition is the one that best fits the objective of this dissertation.

In an efficient market, prices should be uniformly distributed and price clustering is a demonstration of a market inefficiency (Niederhoffer, 1965; De Grauwe and Decupere, 1992). Assuming that the price of an asset is nothing more than the reflection of its intrinsic value, in the absence of market frictions, there would be no reason for certain prices to be observed more frequently than others, but this numbers anomaly has been found in various types of assets and in many parts of the globe.

It would be expected that this irrational behavior of some economic agents could be reversed by other more informed investors who through their actions in the markets could eliminate or mitigate this anomaly. However, this is not the case, and Mitchell (2001) suggests four reasons why this phenomenon may emerge and be observed so often in various types of financial markets. One of these conditions is the dominance of a certain market by a small number of investors, which makes it difficult for a certain biased behavior to be traded out of that market. Other reasons pointed out by the author include the existence of trading impediments that prevent the observance of some values, the generalized preference of the market participants for certain numbers and the existence of biases in the decision-making environment. One or more of these conditions will be sufficient for this trading behavior to be reflected in an empirically observable phenomenon.

2.2. Price Clustering Hypotheses

There are several theoretical reasons that can explain price clustering, ranging from behavioral reasons to rational economic incentives.

Regarding behavioral reasons, several studies over the last decades, especially in the areas of psychology, economics and behavioral finance, have pointed to certain deviations from the concept of the perfectly rational agent.

Individuals use simple heuristics to facilitate their decisions, making use of rough approximations rather than precise estimators (Yule, 1927). This behavior simplifies the decision process which is involved in an environment full of complex information and uncertainty. Yule (1927), as Kendal and Smith (1938) found evidence of human bias in the selection of numbers, revealing a preference for some numbers rather than others. Moreover, the greater the uncertainty in the decision environment, the more individuals tend to use these mechanisms and make biased choices. In periods of crisis, uncertainty increases and market participants more abruptly face uncertain outcomes due to the volatility adjacent to the stock prices, which makes investors more vulnerable to a "sphere of haziness" as shown by Loomes (1988), which leads them to use these heuristics, rounding up their evaluations. These simplifying rules of the decision process lead to a higher frequency of prices ending in 0, 5 or even numbers, an evidence of price clustering (Brown et al., 2002).

Economic reasons may be the source of price clustering and may be somewhat related to the human bias and the haziness to which we referred before in the behavioral reasons. Preece (1981) found that individuals, to reduce the costs and time required to make a decision, tend to simplify information when mentally dealing with number processing. The greater the uncertainty, the greater the tendency to observe this trading behavior and the consequent clustering in prices.

Other theoretical reasons that might explain this phenomenon are the existence of a decimal place-value system which encourages individuals to think in groups of ten or multiples thereof, leading to the existence of number preferences and a natural tendency to round (Mitchell, 2001) and finally the natural order of the data series, that is, the idea that price clustering is a product of the number progression or the numbers themselves, also analysed by Mitchell (2001).

These theoretical reasons that may help to clarify the origin of this anomaly in the market's microstructure have been used in recent years to formulate more concrete hypotheses.

Several hypotheses that aim to explain the price clustering phenomenon in financial markets have been suggested in the literature, among which the following four stand out: 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).

2.2.1. The Price Resolution Hypothesis

The Price Resolution Hypothesis proposed by Ball et al. (1995) states that the uncertainty about the intrinsic value of a given security causes market participants to use coarser price grids, which in turn causes clustering to be detected in the prices of several markets. This hypothesis suggests that the degree of price resolution is particularly related to the amount of information in the market. It is expected, for example, that larger companies, because they are more closely followed by market analysts, to have a higher level of information about them compared to smaller ones, which in turn will allow for a larger price set and lower levels of clustering. On the other hand, the level of price resolution is negatively related to the price level (the higher the value of an asset, the greater the tendency for market participants to use a coarser price grid) and to the stock price volatility, which is nothing more than a reflection of the uncertainty regarding the intrinsic value of a given asset. Besides, the level of liquidity can lead to a higher level of information and thus less uncertainty. This happens for several reasons, which include the reduction of information asymmetry and the consequence of having more traders in the market, i.e. higher trading frequency, which ends up having a positive impact in the assimilation of information in prices in terms of both time and quality.

Several authors found evidence supporting this hypothesis, such as Harris (1991), Goodhart and Curcio (1991), Aitken et al. (1996), Gwilym et al. (1998), Brown et al. (2002), Ohta (2006) or Ikenberry and Weston (2008). However, Aşçıoğlu et al. (2007) found only limited support for the price resolution hypothesis.

In short, the lower the quantity and quality of information in the market, the greater the uncertainty, the lower the level of price resolution (to reduce the search and cognitive costs) and the more likely price clustering will be observed.

2.2.2. The Negotiation Hypothesis

This hypothesis turns out to be an extension of the Price Resolution Hypothesis. According to this explanation, it would be expected to observe greater clustering when the negotiation costs are larger, such as for high volume transactions, when the market, industry or firm are characterized with greater volatility and, on the other hand, also when negotiation benefits are not significant, as is the case when the price level is high or when the trade size is insufficient to justify significant negotiation benefits.

Harris (1991) based on the conclusions of Ball et al. (1985) asserts that price clustering occurs because investors use discrete price sets as a mechanism to reduce the cost of negotiating transactions. In periods of abnormally heavy trading, as is the case of periods of crisis, where uncertainty levels soar to very high levels, the need to execute trades quickly and with the least possible cost means that market participants tend to reduce their terms of trading. By using a coarser price grid, individuals are reducing the amount of information that has to be processed, making transactions occur more swiftly, as bid and offer prices converge more rapidly. Many empirical studies have tested the Negotiation Hypothesis. Aitken et al. (1996) found some support for this theory, but unlike Harris (1991), their results show greater clustering for larger firms, while Hammed and Terry (1998) also reported evidence in support of this hypothesis despite their findings showing no consistent relationship between clustering and stock price volatility. Palao and Pardo (2012), in a study of price clustering in European Carbon Markets, confirmed the Negotiation Hypothesis.

2.2.3. The Attraction Hypothesis

The Attraction Theory, also referred to as natural clustering hypothesis, proposed by Goodhart and Curcio (1991), suggests that there is a natural tendency for individuals to feel more attracted to certain numbers rather than others without any apparent rational motivation, which has the consequence of creating clustering in certain price points. Several studies that have been conducted to test the attraction hypothesis have concluded that in a decimal system, transaction prices ending in zero are more often observed because this number is more salient. After 0, the 5 is the stronger attracter, followed by the even numbers 2 and 8. The 1 and 9 are the least observed digits, because there will be, according to this hypothesis, a natural attraction for 0 (the most observed digit). The relative frequency of 3 will be the same as 7. The same can be said for 4 and 6. However, there is no clear evidence as to which of these groups, {3 = 7} and {4 = 6} is more common, depending on the "gravitational pull" of the 5 in relation to the adjacent even numbers, that is, the tendency of individuals to round to 5, and the preference of the individuals for even rather than odd numbers. Thus, it is possible, according to the attraction hypothesis, to predict that transaction prices tend to concentrate on some numbers following a pecking order of preferences:

$$\mathbf{0 > 5 > \{2=8\} > \{3=7, 4=6\} > \{1=9\}}$$

There is some evidence that goes against this formalization, namely the favorite numbers in lotteries (Mitchell, 2001), but these figures do not represent quantities and therefore we do not make calculations with them. Aitken et al. (1996), Kandel et al. (2001), Brown et al. (2002) or Narayan et al. (2011), to cite a few, presented evidence supporting the Attraction Hypothesis. However, Gwilym et al. (1998) found only limited evidence for this explanation. Psychological factors may lead to the level of clustering being even higher than would be expected considering only the level of price resolution desired by market participants or trading costs. As we have mentioned before, there are in fact particularities in human behavior that cause phenomena such as price clustering to arise only because certain numbers are easier to recall and process than others, leading us to be naturally attracted for them.

2.2.4. The Collusion Hypothesis

The Collusion Hypothesis was proposed in an empirical microstructure study by Christie and Schultz (1994) that presents evidence that the structure of multiple dealers in the NASDAQ market leads to an incentive to maintain non-competitive bid-ask spreads through an agreement to avoid odd eight quotes. The result is an increase in their profit margins per transaction and price clustering. Booth et al. (2000) conclude that an internal market is more prone to price manipulation or collusion. It should be noted that several studies point to the superior importance of other explanations. For example, Aşçıoğlu et al. (2007), analyze this phenomenon on the Tokyo Stock Exchange, where trading takes place electronically without market markers, so that there can be no explicit collusive behavior and still find evidence of price clustering. Grossman et al. (1997) believe that price clustering may be a natural result of competitive markets and Huang and Stoll (1996) claim that collusion in a multiple dealer market with easy entry is extremely unlikely to occur. Nevertheless, Barclay (1997) and Bessembinder (1997) find evidence consistent with the collusion argument.

2.3. Empirical Evidence

In this section, we will present the main empirical studies on price clustering. As we have already mentioned, this phenomenon is well documented in several studies that have focused not only on numerous equity markets but also on other markets, from derivatives to the in-vogue Bitcoin.

2.3.1. Evidence on Price Clustering – Equity Markets

Osborne (1962), Harris (1991) and Christie and Schultz (1994) were among the first to study the microeconomics of price formation and to document that prices (both stock quotes and transaction prices) cluster around whole numbers and common fractions.

Osborne (1962) was the first author to present evidence of price clustering in the stock market, at the time designating this phenomenon as "congestion". Osborne found in US shares, particularly in a sample of closing stock prices traded on the New York Stock Exchange (NYSE), a "pronounced tendency for (closing) prices to cluster on whole numbers, halves, quarters and odd one-eights in descending preference" (p. 370) when it would be expected that, in an efficient market, prices would be uniformly distributed.

Niederhoffer (1965) was another pioneer in the study of price clustering and his article documents this phenomenon in the limit orders taken from the order book of a specialist on the NYSE. As Osborne (1962), Niederhoffer found that the limit order closing prices at the even eights, which can be compared to the even numbers in the current decimal system, were incomparably superior in frequency to those at the odd eights (odd numbers in the decimal system). The NYSE had an auction market mechanism at the time, which, in the author's opinion, allowed regularity in price changes due to behavioral preferences and trading strategies of the specialists. The author believed that clustering was due to the tendency for agents to place their requests at "numbers to which they are accustomed to deal" and that it could stem from deviations from human behavior, but also partially from a profit-seeking strategy, despite the small scale of this effect.

After about 25 years, Harris (1991) confirmed that price clustering was an anomaly that had prevailed since the early studies of Osborne and Niederhoffer, documenting the same pattern of clustering in the daily closing stock prices at the NYSE that those same authors had observed a quarter of a century ago, that is, a greater frequency of integers, followed by halves, odd quarters, and lastly odd-eights, which in turn are more often observed than any other fractions.

As discussed earlier, one of the most tested hypotheses explaining price clustering has been precisely the one proposed by Harris (1991), the Negotiation Hypothesis, which suggests that this phenomenon results from the agents' behaviour motivated by a desire to reduce trading costs. To complement his study, the author made a multivariate analysis in which, as dependent variable, he used the price clustering and as independent variables he had a series of specific attributes of the share price, namely volatility, firm size, transaction frequency, price level and a dummy variable to test the impact of the market structure on the level of price clustering. Harris, in contrast to Niederhoffer's argument that clustering arises due to the existence of limit orders, argued that in a dealer market, where these limit orders do not exist, we are more likely to find price clustering. Harris claims that the incentive to reduce negotiation costs is the main cause of clustering and in a market structure in which the dealers build their reputation through their performance in the negotiations, this turns out to be quite relevant. The results of his study reflect this, with price clustering being more prevalent in dealer markets than in public auction markets, demonstrating that the market structure has an impact on the observed level of clustering, but also being more prevalent for higher volatility and price levels, nonetheless decreasing with the transaction frequency and the size of the company. In his study, the author found no support for the Attraction Hypothesis.

One of the first studies on this market anomaly outside the US was conducted by Aitken et al. (1996) and it was also one of the first to demonstrate the existence of price clustering in equity markets that use decimal trading rather than fractions. The authors analyzed the last digit of individual trade prices on the Australian Stock Exchange (ASE) using intraday transaction data. Like Harris (1991), the results confirmed the Price Resolution Hypothesis, but also showed evidence in favor of the Attraction Hypothesis, unlike Harris' study, with prices ending in 0 being the most preferred, followed by prices ending in 5 and prices whose last digit was an even number (2,4,6,8). As expected by the author, clustering increased with the market-wide volatility, own stock volatility, price level, trade size and the size of the bid-ask spread. In addition, they were able to observe in their sample a lower level of clustering for shares with options traded on them, for stocks which short selling was allowed and in more liquid stocks. Other results of this analysis were the finding of more clustering in buyer-initiated trades than in seller-initiated trades and two unexpected results: greater clustering for larger firms (contrary to what Harris had found in his study and to what would be predicted by the Price Resolution Hypothesis) and less clustering for resource stocks relative to the others.

Hameed and Terry (1998) studied price clustering in limit orders in the Stock Exchange of Singapore (a fully electronic order-driven market). The authors found clustering at all price ranges, with whole dollars being more frequent than half dollars, which in turn were more often observed than prices ending in multiples of 10 cents. After this, in descending order of frequency, prices ending in odd-multiples of 5 cents were the most observed. They were more likely to end at even cents than odd cents. The authors found support for the Negotiation Hypothesis of Harris (1991), with clustering increasing with price level and decreasing with trading volume, but unlike Harris, no significant relationship between clustering and price volatility was detected.

Brown et al. (2002) were the first authors to analyze the impact of cultural factors on the level and type of price clustering. To do so, they investigated six Asia-Pacific stock markets, trying to find evidence of clustering in the last or penultimate price digits. The results clearly showed the pervasiveness of stock price clustering in all markets and supported the price Resolution/Negotiation Hypothesis, but also the Attraction Hypothesis, with cultural factors showing an insignificant influence on clustering, especially when compared to the effects that the other hypotheses suggest to exist and which explain the appearance of this phenomenon.

Ohta (2006) investigated price clustering on the Tokyo Stock Exchange with intraday data and his results were consistent with the Price Resolution Hypothesis, finding evidence of a greater deal of clustering just after the market opening when the level of uncertainty is higher.

However, Aşçıoğlu et al. (2007), using quotes from the same exchange, found only limited support for the Price Resolution Hypothesis and conclude that this anomaly is explained by the Attraction Theory.

Ikenberry and Weston (2008) in their study on the impact of decimalization on price clustering found evidence in support of the Negotiation and Price Resolution hypotheses, though the results point to other psychological factors that can cause the phenomenon, suggesting the existence of "a more fundamental human bias for prominent numbers".

Than (2017) examines the determinants of price clustering on the Euronext Stock Market using the tick-by-tick transaction price data and the results partially confirm the Price Resolution/Negotiation Hypothesis.

2.3.2. Evidence on Price Clustering – Other Markets

Price clustering has been found in many other markets beyond the equity markets, such as the derivatives market, exchange rates markets and even in betting markets. In this subsection, we will present some of the most relevant evidence of this phenomenon for other markets.

Ball et al. (1985), in an article that became notorious by having suggested the Price Resolution Hypothesis, found evidence of clustering in the London gold market (a market with near ideal conditions, according to the authors) and that this derives from the level of information underlying the decision process, which in turn implies a desired level of price resolution. The results suggest that the lower the level of information, the lower the price resolution and the higher the level of clustering. The evidence also pointed to a positive relationship between clustering with price level and volatility.

Goodhart and Curcio (1991), in a study that focused on the spot foreign exchange market, particularly in the bid-ask prices and spreads of the Deutsche Mark/US dollars spot rate, found evidence of clustering in the last digit of the quotes supporting the conclusions of Ball et al. (1985) and its Price Resolution Hypothesis. Besides, clustering was also found in bid-ask spreads, but here the results pointed out that the anomaly stems from the attractiveness of investors to certain numbers, consistent with the Attraction Hypothesis.

Gwilym et al. (1998) were the first to find clustering in a financial derivatives market, namely in the quoted and traded prices of equity futures and options contracts traded on the London International Financial Futures and Options Exchange. The results support the Price Resolution Hypothesis and on a smaller scale the Negotiation Hypothesis and also point to an increase in the level of clustering with the trade frequency, contrary to what was found by Harris (1991).

Kahn (1999) find that clustering is also present in bank interest rates, with a concentration of interest rates on integers and "even" fractions.

Kandel et al. (2001) analyzed this phenomenon in initial public offer auctions, reporting round number clustering, suggesting that due to the characteristics of this market this anomaly cannot arise by incentives to reduce the negotiations costs, neither by a strategic behavior of the market makers, but by a preference of individuals for certain numbers, findings consistent with the Attraction Hypothesis.

Narayan et al. (2011) and Palao and Pardo (2012) found evidence of clustering in commodity markets. Narayan et al. (2011) obtained results that clearly indicate the existence of clustering in oil futures market prices, with findings consistent with the Price Attraction Hypothesis, while Palao and Pardo (2012) also found support for this theory, with prices in European Carbon Markets ending in the digits 0 and 5 being relatively more observed, but also for the Negotiation Hypothesis.

Brown and Yang (2016) extend this analysis to the betting market and suggest that clustering is related to the limited cognition of agents. They find that limited cognition does indeed lead to asset price clustering. Relating their conclusions to our study, it will be expected that the higher the cognitive load, the higher the level of clustering. One would also expect, at another level, a greater and more intense cognitive load in periods of crisis and therefore greater clustering.

In Table 1 we can find a summary of the primary findings of the main empirical studies we mentioned above.

Table 1 - Summarizing the main empirical studies

Author/'s (Year)	**Market**	**Remarks**
	Equity Market	
Osborne (1962)	NYSE	It was the first study to present evidence of price clustering in the stock market.
Niederhoffer (1965)	NYSE	The author argued that clustering stems from behavioural biases, but also partially from a profit-seeking strategy.
Harris (1991)	NYSE	The results support the Price Resolution/Negotiation Hypothesis.
Aitken et al. (1996)	NYSE	The results support both the Price Resolution and the Attraction Hypotheses.
Hameed and Terry (1998)	Stock Exchange of Singapore	The results support the Price Resolution/Negotiation Hypothesis.
Brown et al. (2002)	Six Asia-Pacific stock markets	The results support both the Price Resolution/Negotiation and the Attraction Hypotheses.
Ohta (2006)	Tokyo Stock Exchange	The results support the Price Resolution Hypothesis.
Aşçıoğlu et al. (2007)	Tokyo Stock Exchange	The results support the Attraction Hypothesis and partially the Price Resolution Hypothesis.
Ikenberry and Weston (2008)	NASDAQ and NYSE	The results support the Price Resolution/Negotiation Hypothesis.
Than (2017)	Euronext Stock Market	The results partially confirm the Price Resolution/Negotiation Hypothesis.
	Other Markets	
Ball et al. (1985)	London gold market	The results support the Price Resolution Hypothesis.
Goodhart and Curcio (1991)	Spot foreign exchange market	The results support both the Price Resolution and the Attraction Hypotheses.

Gwilym et al. (1998)	London International Financial Futures and Options Exchange	The results support the Price Resolution Hypothesis.
Kahn (1999)	Bank interest rates	The authors argue that deposit rate clustering is based on the limited recall of retail depositors.
Kandel et al. (2001)	IPO auctions	The results support the Attraction Hypothesis.
Narayan et al. (2011)	Oil futures market	The results support the Attraction Hypothesis.
Palao and Pardo (2012)	European Carbon Markets	The results support the Negotiation and the Attraction Hypotheses.
Brown and Yang (2016)	Betting market	The authors argue that clustering is related to the limited cognition of agents.

Chapter 3

Methodology

3.1. Data

We will use closing prices from two subsamples, one with US banks and the other with European banks, with a different crisis period for each one, based on previous literature.

Following Davis et al. (2009), we define the crisis period for the US banks' subsample as the period starting on October 9, 2007 to March 9, 2009. Regarding the subsample of European banks, based on the study by Attinasi et al. (2009), we define the European crisis period as the period between 31 July, 2007 and 25 March, 2009. To set the periods before the crisis, we will use a range of 24 months before each of the above defined periods, i.e. 9 October, 2005 to 8 October, 2007 for the sub-sample of US banks and July 31, 2005 to 30 July, 2007 for the European banks' subsample. All data for the univariate and multivariate analyses was obtained from Thompson Reuters DataStream.

3.2. Univariate analysis

In order to study the type and level of price clustering for the two subsamples, in the periods before and during the crisis, and also to make comparisons between periods and subsamples, several methods will be used. Initially, we will carry out a univariate analysis in which basic statistics will be used, namely the frequency with which the last digit of the stock prices was observed, being expected, according to the null hypothesis of non-existence of price clustering, a frequency of 0.10 for each digit. This basic statistical analysis will give us a clear idea of the type of price clustering and in part of its level. However, to better measure the level of price clustering, following Ikenberry and Weston (2008), we will apply an adaptation of the Herfindahl-Hirschman-Index (HHI). This index is usually used to measure market concentration and how far it distances itself from a perfect competition market, but in this case, it will be used to measure the concentration of prices and how different it is from a uniform distribution. In the original version, the HHI is calculated by adding the squared values of the market shares of all market participants, but in this case, we will replace the market shares by the percentage of prices ending in certain digits. Specifically, we construct:

$$H = \sum_{i=1}^{B} (f_i)^2 \tag{3.1}$$

where f_i is the frequency (in percent) of closing stock prices that occur at fractions i=1,2,…B possible bins. We estimate H based on the last digit of the closing price (Ikenberry and Weston, 2008; Palao and Pardo, 2012). If there was no price clustering, it would be expected, under the null hypothesis, this measure to be the sum of the squares of the various frequencies, all equal to 1/B. That is, under the null hypothesis of price clustering, H should be equal to 1/10 = 0.1, since each digit would have a frequency of 10%. In the case of perfect price clustering, where prices are concentrated entirely on a single digit, H would equal unity. In order to compare the price clustering between the two periods under analysis, before and during the crisis, and to determine whether the level of price clustering actually changed in the financial crisis period, we will use two statistics that are frequently used in this kind of analysis (Ikenberry and Weston, 2008; Palao and Pardo, 2012). First, to test the significance of price clustering in a given sample over a given period, we use the standard Chi-square goodness-of-fit statistic that, according to the null hypothesis (H1 hypothesis, from now on) of absence of difference between the observed distribution and the expected uniform distribution should be below some critical value. We define this statistic, D, as follows:

$$D = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i} \tag{3.2}$$

where O_i is the observed frequency of observations in bin i=1,…,N and E_i is the expected frequency of observations under the null uniform distribution. D is the distributed Chi-square with N-1 degrees of freedom under standard regularity conditions. A larger value of D would signify a significant deviation from the expected distribution, which in our case is uniform, thus implying a significant level of price clustering.

After this first step, to compare the level of price clustering between the two periods under analysis and between subsamples, we use the following statistic:

$$\widetilde{D} = \left(\frac{D_2}{D_1}\right) \sim F_{N_2-1, N_1-1} \tag{3.3}$$

where $D_i \sim \chi^2_{N-1}$

Under the null hypothesis (H2 hypothesis, from now on), the two samples considered are equally clustered. We intend to use this statistic to test the hypothesis that the level of price clustering has changed between the periods before and during the financial crisis for each subsample (US and European Banks). Higher values of $\widetilde{\mathrm{D}}$ would mean a higher level of clustering during the crisis period, with D_2 representing the sample of this exact period.

3.3. Multivariate analysis

After the univariate analysis, we will carry out a multivariate analysis, following previous literature and empirical studies. The aim is mainly to try to understand what variables can explain this phenomenon at the firm level. As we have already explained, the motivation of this study was trying to understand whether or not there was a change in the level of price clustering in the period of the financial crisis, a period inevitably characterized by higher uncertainty in the markets. Therefore, the main objective of this analysis is to investigate the relationship between variables that serve as proxies for uncertainty regarding the fundamental value of the stocks of these companies and the level of price clustering. As a dependent variable, to estimate the level of price clustering at the firm level using all closing prices over the sample period, we will use the HHI (measuring clustering at the last digit), as a measure of the firm's stock price concentration over that period, less the level of clustering that would be expected under the null hypothesis, that is, a HHI value of 0.1. This construction of the dependent variable is based on Ikenberry and Weston (2008), although these authors use a different measure of clustering, and implies that, under the null hypothesis, the constant term (α) in the regression should equal zero. Each independent variable is log-transformed and standardized to have a zero mean and unit variance. This facilitates the interpretation of the coefficients, reduces skewness and ensures that our constant term captures the expected mean level of clustering for the average firm in our sample (Feng et al., 2014; Ikenberry and Weston, 2008).

As independent or explanatory variables, we will rely on previous empirical works, in particular, the work of Ikenberry and Weston (2008), which aim to test the Price Resolution/Negotiation hypothesis. Besides these variables that normally are included in this kind of studies, some other firm-specific characteristics that might have an impact on price clustering will also be included in the model.

The description of the variables is given in the following table:

Table 2 – Description of the variables

Dependent variable		
Variable		**Description**
Dependent variable	*Clustering – E(Clustering)*	HHI (measuring clustering at the last digit) will be used as a measure of the firm's stock price concentration, less the level of clustering that would be expected under the null hypothesis, that is, a HHI value of 0.1.
Independent variables		
Variable		**Description**
Traditional variables	*Size*	Daily average of the equity market value of the firm.
	Price	Daily average of the stock price of the firm over the sample period.
	RetVol	Return Volatility. Calculated as the squared time-series standard deviation of daily returns over the sample period.
	Turnover	Average turnover (by volume) of the firm over the sample period.
	Illiquidity	Arithmetic mean of the of the ratio of the bid-ask spread to its midpoint over the sample period.
Added variables	*PastReturns*	Cumulative return of the company over the 6 months before the sample period.
	BTM	Average Book Value of Equity over the sample period/Average market capitalization over the sample period.
	AnalystCoverage	Average of the number of analysts following the company over the sample period.

Bank Opacity Proxies	*Loans*	Share of Loans in Total Assets. Opacity measure calculated as the daily average of this ratio over the sample period.
	Investments	Share of Investment (trading) Assets in Total Assets. Opacity measure computed as the daily average of this ratio over the sample period.
	Deposits	Share of Deposits in Total Assets. Opacity measure calculated as the daily average of this ratio over the sample period.
Risk Indicators	*SizeAssetsBV*	Log of the book value of total assets. Risk measure calculated as daily the average over the sample period.
	TobinQ	Adaptation of Tobin Q. Risk measure – measured at the beginning of the period. Sum of the market value of common equity (price per share times number of shares) plus the book value of liabilities divided by the book value of assets.
	CreditRisk	Risk measure calculated as the daily average of the loan-loss provisions to loans ratio (PL) over the sample period.
	ROAVOL	The volatility of return on assets (ROA). Risk measure computed as the standard deviation of ROA over the sample period.
	NIMVOL	The volatility of return on net interest margin (NIM). Risk measure computed as the standard deviation of NIM over the sample period.

Risk Indicators	*ZCORE*	z = (ROA+CAR)/σ(ROA), where ROA is earnings before taxes and loan loss provisions divided by assets, CAR is the capital-asset ratio, and σ(ROA) is the standard deviation of ROA. ROA and CAR are mean values estimated over the sample period, and σ(ROA) is the standard deviation of ROA estimated over the same period.

Specifically, the following model is estimated using OLS:

$$\begin{aligned} Clustering - E(Clustering) \\ &= \alpha + \beta_1 Size + \beta_2 Price + \beta_3 Retvol + \beta_4 Turnover \\ &+ \beta_5 Illiquidity + \beta_6 PastReturns + \beta_7 BTM \\ &+ \beta_8 AnalystCoverage + \beta_9 Loans + \beta_{10} Investments \\ &+ \beta_{11} Deposits + \beta_{12} SizeAssetsBV + \beta_{13} TobinQ \\ &+ \beta_{14} CreditRisk + \beta_{15} ROAVOL + \beta_{16} NIMVOL + \beta_{17} ZSCORE \end{aligned} \tag{3.4}$$

The variables “Size”, “Price”, “RetVol”, “Turnover” and “Illiquidity” can be considered “traditional” variables which are usually included in models that aim to study the variation of price clustering at the firm level. According to the Price Negotiation/Resolution Hypothesis, larger companies, as they are supposedly more scrutinized by analysts, have, consequently, a higher level of information than smaller companies, so a negative relation between the size factor and the level of clustering should be expected. Moreover, this hypothesis also suggests that the stock price has a highly significant explanatory power in the variation of the level of price clustering, and it is expected that as the price level increases, the "minimum tick size" will gradually become a smaller percentage of the share’s value, which leads investors to use a coarser price grid. Theoretically, it should also be expected that greater volatility of returns generates greater uncertainty about the value of stocks and that this uncertainty will lead investors to round prices, making certain digits more observed than others. As for the variable “Turnover”, the Price Resolution Hypothesis suggests that banks for which there is higher turnover, that is, whose shares are more transacted, should present a lower level of clustering. Besides, the greater is the liquidity of a stock, the lower should be the level of clustering, since prices are known more precisely.

The variable "PastReturns" is also included to test if it has a negative relation with price clustering, since higher returns in the past should lead to an increased attention and coverage by both investors and analysts (Lee and Swaminathan, 2000), which in turn should decrease the level of uncertainty about the stock price, at least theoretically. In theory, growth stocks should be more affected by clustering, that is, the lower the book-to-market ratio that characterizes this same type of stocks, the higher the level of clustering should be. As Lakonishok et al. (1994) say in their article, this type of stocks can attract more naïve investors whose biases might lead to more clustering in prices. The variable "AnalystCoverage" can also have some explanatory power of this phenomenon with, in theory, a higher number of analysts covering a stock leading to less uncertainty and, consequently, less price clustering. We also included in the model three variables that serve as measures of bank's opacity. We should expect banks that are opaquer to have a higher degree of price clustering in their shares. Following Wen (2016), we included in the model the variables "Loans" and "Investments". As the author mentions "Loans are customized, privately negotiated and illiquid" which makes them "major contributors to bank opacity." (p. 140). Besides, the author also considers trading assets as a major contributor to bank opacity, since some of them are difficult to value for outside investors, they are very liquid, traded frequently and prone to management manipulations. The variable "Deposits" is a measure of banks' opacity as well and its inclusion in the model is supported by the work of Berger et al. (2000) who use this variable as a source of informational opacity.

Some risk measures were also included in the model. Following Anderson and Fraser (2000), the variables "SizeAssetsBV" and "TobinQ" are two of those included in the model, the variable "CreditRisk" is included based on the article by Athanasoglou et al. (2008) and the explanatory variables "ROAVOL", "NIMVOL" and "ZSCORE" are risk measures used by Kanagaretnam et al. (2013). Anderson and Fraser (2000) based on Demsetz and Strahan (1997) argue that the size of a bank (measured by the book value of total assets) is positively related with risk since the potential benefits of diversification of larger banks are more than offset by their adoption of more risky loan portfolios and more leverage. These authors also claim that the variable "TobinQ" is inversely related with risk, i.e., the lower its value the higher the risk of the banks, which, in theory, should imply more price clustering. Athanasoglou et al. (2008) argue that credit risk is "normally associated with decreased firm profitability" (p.14), hence it is a variable that is closely linked to the present and future levels of risk. Kanagaretnam et al. (2013) use two traditional accounting-based measures of bank's risk, the volatility of return on assets and the volatility of net interest margin, as well as z-score. The first two reflect the degree of risk-taking in a bank's operations and the variable "ZSCORE" is a measure of the stability of a bank. As the authors remark, "Z-score indicates the number of standard deviations a bank's return on assets has to drop below its expected value before equity is depleted and the bank is insolvent" (p.14), thus the higher the value of the z-score, the more stable and the less risky is the bank.

The expect relationship of the independent variables with price clustering is presented in Table 3.

Table 3 – Expected signs for the explanatory variables coefficients

Variables	Expected sign	References
Size	-	Harris (1991)
Price	+	Harris (1991)
RetVol	+	Harris (1991)
Turnover	-	Ikenberry and Weston (2008)
Illiquidity	+	Palao and Pardo (2012)
PastReturns	-	Lee and Swaminathan (2000)
BTM	-	Lakonishok et al. (1994)
AnalystCoverage	-	Blau and Griffith (2016)
Loans	+	Wen (2016)
Investments	+	Wen (2016)
Deposits	+	Berger et al. (2000)
SizeAssetsBV	+	Anderson and Fraser (2000)
TobinQ	-	Anderson and Fraser (2000)
CreditRisk	+	Athanasoglou et al. (2008)
ROAVOL	+	Kanagaretnam et al. (2013)
NIMVOL	+	Kanagaretnam et al. (2013)
ZCORE	-	Kanagaretnam et al. (2013)

Chapter 4

Price Clustering Results

4.1. Univariate analysis

4.1.1. US Sample

Table 4 shows the frequency with which the last digits of closing prices are observed in the US Sample, the results of the clustering tests and also the values of the HHI.

Table 4 – Price clustering in the US banks' subsample

Last Digit	Before the crisis		Crisis		Whole Period	
	Frequency	%	Frequency	%	Frequency	%
Panel A: Distribution of last digit of the price						
0	17216	15.43	12123	15.30	29339	15.38
1	10338	9.27	7313	9.23	17651	9.25
2	9894	8.87	7102	8.96	16996	8.91
3	9837	8.82	6935	8.75	16772	8.79
4	9865	8.84	7189	9.07	17054	8.94
5	14104	12.64	9726	12.28	23830	12.49
6	10104	9.06	7119	8.99	17223	9.03
7	9779	8.76	6981	8.81	16760	8.78
8	9892	8.87	7195	9.08	17087	8.96
9	10540	9.45	7541	9.52	18081	9.48
Total	111569		79224		190793	
% at 0 & 5		28.07		27.58		27.87

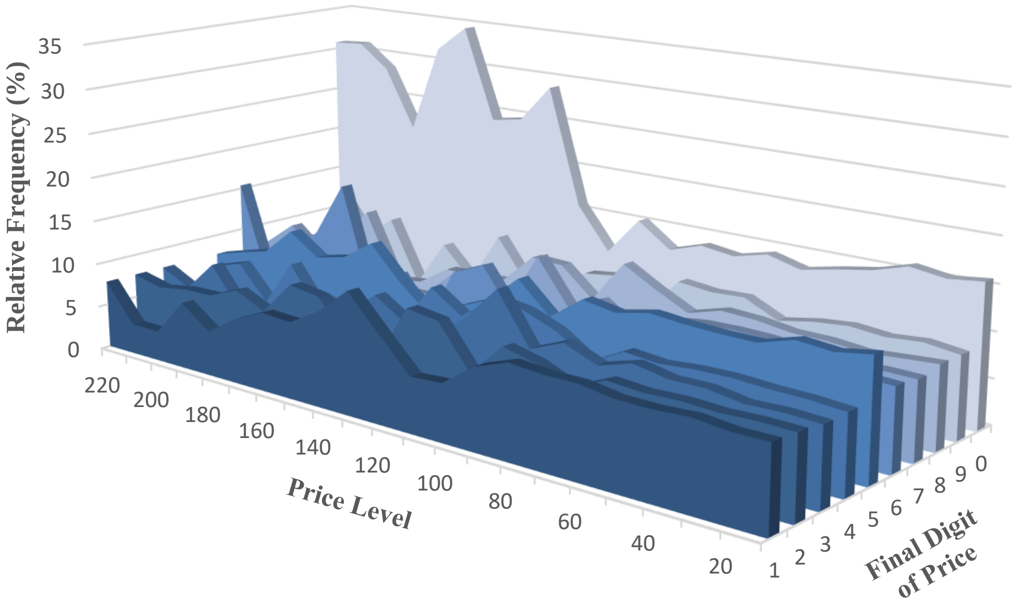
	Before the crisis	Crisis	Whole Period
Panel B: Clustering tests and indices			
χ^2_9	5024.92	3239.11	8251.20
H1 (p-value)	0.0000	0.0000	0.0000
HHI (%)	10.45	10.41	10.43
$F_{9,9}$	0.64		
H2 (p-value)	0.7383		

Note: Panel A shows the absolute and the relative frequencies of prices. Panel B presents the p-value of the H1 and H2 hypotheses, as well as the HHI, which stands for the Hirshmann-Herfindahl index.

As we can see, we found clear evidence of price clustering for both periods of the sample of US banks, with digits 0 and 5 being the most frequent, as suggested by the literature. About 30% of prices have the last digit as 0 or 5, which is clearly an evidence of clustering, since if the price distribution was uniform, a 20% weight would be expected for these observations. Panel B, which presents the results of the performed statistical tests, confirms the existence of clustering for the periods before the crisis and for the crisis period. The H1 null hypothesis of absence of difference between the observed distribution and the expected uniform distribution is clearly rejected for both periods for a significance level of 1%. HHI values decrease slightly from the pre-crisis period to the crisis period, but this difference is not statistically significant, as shown by H2, which leads us to conclude that the level of clustering did not change between the two periods.

To complement this analysis and with the intention of clarifying the relationship between the stock price level and clustering, we constructed the graph presented in Figure 1, based on the work of Aitken et al. (1996).

Figure 1 - Relative frequency of final digit of price (US Sample)



For this construction, we first divided the prices according to their level (for example, the value 20 on the *Price Level* axis symbolizes the class that includes prices from 10 to 20 dollars). Next, we calculated the relative frequency of all final digits for each price class. As we can see, the level of clustering seems to increase with the price level, which is mainly visible by the higher concentration in the last digit 0 relative to the others as stocks become more expensive.

Table 5 shows a more detailed analysis of price clustering as a function of some traditional variables representative of company-specific attributes.

Table 5 - Clustering of the final digit of price for various partitions of the US sample

	Percentage of cases clustered at a final digit of										
Quintiles	0	1	2	3	4	5	6	7	8	9	HHI (%)
All prices	14.52	9.40	9.06	8.99	9.07	11.99	9.16	9.01	9.10	9.69	10.30
Size											
1	18.49	8.91	8.14	8.10	8.32	13.94	8.61	8.05	8.29	9.16	11.08
2	15.04	9.16	8.92	8.66	9.04	12.16	9.22	8.91	8.89	10.00	10.38
3	13.62	9.62	9.34	9.27	9.50	11.36	9.29	9.26	9.21	9.53	10.18
4	12.79	9.64	9.58	9.35	9.33	11.17	9.39	9.45	9.51	9.78	10.11
5	12.70	9.69	9.33	9.57	9.14	11.30	9.31	9.39	9.62	9.95	10.11
Price											
1	15.46	9.22	9.21	8.59	8.94	12.65	8.97	8.55	9.01	9.40	10.46
2	14.95	9.18	8.78	8.93	9.03	12.23	9.21	8.85	8.95	9.91	10.37
3	14.62	9.42	9.19	8.63	9.14	11.82	9.23	9.06	8.98	9.91	10.31
4	14.05	9.54	9.02	9.35	9.07	11.61	9.41	9.13	9.14	9.67	10.23
5	13.54	9.64	9.13	9.44	9.16	11.63	9.00	9.47	9.43	9.54	10.19
Volatility											
1	14.47	9.28	9.41	9.10	9.13	12.10	8.84	8.86	9.12	9.67	10.30
2	14.40	9.48	9.05	8.95	9.12	11.92	9.07	8.82	9.19	10.00	10.29
3	14.03	9.43	9.26	9.12	9.24	11.76	9.26	9.22	9.21	9.46	10.24
4	15.15	9.23	8.69	8.95	8.74	12.36	9.33	9.01	8.94	9.60	10.40
5	14.58	9.59	8.90	8.82	9.11	11.79	9.32	9.14	9.06	9.70	10.30
Turnover											
1	17.93	9.06	8.30	8.19	8.37	13.68	8.69	8.18	8.29	9.30	10.95
2	15.45	9.10	8.97	8.63	9.01	12.17	9.24	8.86	8.90	9.65	10.42
3	13.89	9.55	9.19	9.13	9.33	11.80	9.13	9.12	9.14	9.72	10.23
4	12.96	9.53	9.40	9.34	9.34	11.25	9.33	9.56	9.45	9.84	10.13
5	12.40	9.77	9.46	9.65	9.28	11.04	9.43	9.33	9.72	9.91	10.09
Illiquidity											
1	12.40	9.81	9.42	9.41	9.50	10.85	9.45	9.62	9.56	9.98	10.08
2	12.91	9.70	9.57	9.47	9.12	11.40	9.01	9.29	9.62	9.91	10.13
3	14.15	9.34	9.15	9.23	9.30	11.45	9.41	9.11	9.04	9.81	10.24
4	14.33	9.20	9.10	8.97	9.12	12.18	9.37	9.12	9.09	9.52	10.29
5	18.85	8.96	8.07	7.86	8.29	14.07	8.57	7.92	8.21	9.20	11.17

Note: This table shows the clustering of the final digit of price for various partitions of the US Sample during the whole period, englobing the pre-crisis and the crisis period. Only the stocks with data available for all variables were included. *Size* is measured by market capitalization, *Volatility* as the standard deviation of daily returns, *Turnover* is the number of shares traded per day and *Illiquidity* is measured as the ratio of the bid-ask spread to its midpoint. HHI, our measure of clustering, stands for the Herfindahl-Hirschman Index.

The firm attributes used are size (measured by market capitalization), price level, volatility (measured by the standard deviation of daily returns), turnover (by volume) and illiquidity (measured by the bid-ask spread in relation to its midpoint). For each of the variables, we sort the stocks into quintiles from low to high (Ikenberry and Weston, 2008). According to the Price Resolution/Negotiation Hypothesis, one would expect a higher level of clustering for smaller and more volatile banks, for higher price levels, for less traded shares and for higher levels of illiquidity.

The results of this analysis for the sample of US banks partially confirm the assumptions of the Price Resolution/Negotiation Hypothesis. In fact, it is noticeable that the factors size and turnover are negatively related to clustering and that there is a higher price concentration for higher levels of illiquidity. From the results for the Price and Volatility variables we cannot reach clear conclusions about the relationship between these attributes and the level of clustering, although Figure 1 revealed that clustering increases with price.

4.1.2. European Sample

In this section we will present and discuss the univariate results for the sample of European Banks. In Table 6, we show the measures of price concentration and the results of the clustering tests. These point in the same direction as the ones we obtained for the US Sample.

Table 6 - Price clustering in the European banks' subsample

Last Digit	Before the crisis		Crisis		Whole Period	
	Frequency	%	Frequency	%	Frequency	%
Panel A: Distribution of last digit of the price						
0	5489	27.79	4143	25.62	9632	26.81
1	1017	5.15	988	6.11	2005	5.58
2	1878	9.51	1479	9.15	3357	9.34
3	1043	5.28	936	5.79	1979	5.51
4	1883	9.53	1623	10.04	3506	9.76
5	2313	11.71	1818	11.24	4131	11.50
6	1880	9.52	1490	9.21	3370	9.38
7	1036	5.24	993	6.14	2029	5.65
8	2016	10.21	1563	9.66	3579	9.96
9	1198	6.06	1139	7.04	2337	6.51
Total	19753		16172		35925	
% at 0 & 5		39.50		36.86		38.31

	Before the crisis	Crisis	Whole Period
Panel B: Clustering tests and indices			
χ^2_9	7979.98	4907.53	12810.72
H1 (p-value)	0.0000	0.0000	0.0000
HHI (%)	14.04	13.03	13.57
$F_{9.9}$	0.61		
H2 (p-value)	0.7599		

Note: Panel A shows the absolute and the relative frequencies of prices. Panel B presents the p-value of the H1 and H2 hypotheses, as well as the HHI, which stands for the Hirshmann-Herfindahl index.

It is clear that there is an abnormal concentration in prices, even more pronounced than in the sample of US banks, as can be seen from the percentage of prices whose last digit is 0 or 5, which in this case is around 40% and 37% for the period before the crisis and for the crisis period, respectively, values significantly higher than those of the sample of US banks. Again, the results indicate a clear rejection of the null hypothesis H1 and, consequently, the presence of price clustering in both periods. HHI is slightly higher in the period before the crisis, but the results of the H2 hypothesis test, as in the US sample, do not allow the rejection of the null hypothesis of similar clustering levels in the two periods.

Additionally, we constructed a graph shown in Figure 2 which demonstrates the relationship between price level and clustering. Furthermore, an analysis of clustering of the final digit of price for various partitions of the European sample is shown in Table 7.

Figure 2 - Relative frequency of final digit of price (European Sample)

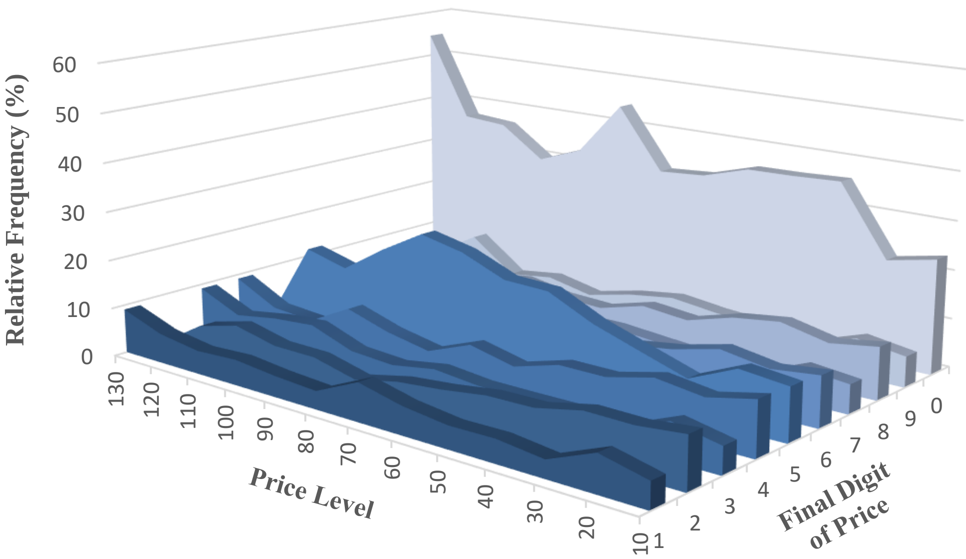


Table 7 - Clustering of the final digit of price for various partitions of the European sample

Quintiles	Percentage of cases clustered at a final digit of 0	1	2	3	4	5	6	7	8	9	HHI (%)
All prices	24.97	5.68	9.82	5.67	10.39	10.56	9.88	5.86	10.58	6.60	12.91
Size											
1	19.04	4.72	11.97	5.41	12.77	7.97	12.19	6.33	12.58	7.02	11.80
2	23.91	6.45	8.65	6.73	10.13	12.87	8.71	5.86	9.31	7.37	12.53
3	24.61	5.96	9.75	5.57	10.12	11.66	9.59	5.93	10.37	6.45	12.82
4	28.71	4.75	10.41	4.33	10.83	7.38	11.31	5.13	11.91	5.26	14.69
5	28.53	6.53	8.34	6.29	8.10	12.88	7.60	6.08	8.75	6.91	14.16
Price											
1	21.55	4.39	11.86	4.44	14.55	8.04	12.59	4.49	12.81	5.30	12.91
2	15.25	7.24	10.88	8.18	10.10	10.33	10.47	8.34	10.72	8.49	10.45
3	31.10	4.40	9.86	4.28	10.08	8.26	10.56	4.57	11.87	4.99	15.71
4	22.67	7.03	9.43	6.53	9.76	11.95	9.31	6.98	9.00	7.33	12.03
5	34.31	5.33	7.07	4.88	7.45	14.19	6.45	4.93	8.52	6.87	17.22
Volatility											
1	20.98	6.45	9.40	7.10	9.80	10.44	9.46	7.80	10.14	8.44	11.50
2	18.90	7.52	9.47	7.83	10.29	11.39	9.57	7.35	9.97	7.71	11.05
3	29.71	2.21	14.03	1.83	15.28	3.15	14.59	2.13	14.81	2.27	17.73
4	26.30	4.94	9.94	5.47	10.04	10.93	9.20	5.67	11.15	6.37	13.47
5	28.99	7.25	6.31	6.06	6.57	16.81	6.62	6.34	6.88	8.18	14.93
Turnover											
1	30.81	3.34	11.80	3.06	11.85	6.73	12.11	3.12	13.25	3.92	16.42
2	26.66	5.33	9.49	5.61	9.82	9.96	9.60	5.92	11.03	6.60	13.49
3	23.20	4.74	10.78	5.28	12.65	9.66	11.06	5.00	11.50	6.11	12.76
4	26.38	6.61	8.34	5.55	9.12	12.73	8.23	6.58	8.40	8.06	13.32
5	17.85	8.35	8.71	8.78	8.52	13.68	8.40	8.66	8.75	8.29	10.92
Illiquidity											
1	17.82	8.23	8.97	8.50	8.83	13.29	8.18	8.66	8.72	8.81	10.88
2	21.61	7.22	7.98	7.64	8.15	14.54	7.88	8.07	8.19	8.73	11.89
3	28.76	6.37	8.12	6.03	8.10	12.58	7.63	5.83	9.30	7.28	14.26
4	25.74	5.52	8.91	5.33	9.94	10.91	10.19	5.86	10.32	7.28	13.16
5	31.03	0.99	15.22	0.66	17.06	1.26	15.63	0.82	16.49	0.82	20.06

Note: This table shows the clustering of the final digit of price for various partitions of the European Sample during the whole period, englobing the pre-crisis and the crisis period. Only the stocks with data available for all variables were included. *Size* is measured by market capitalization, *Volatility* as the standard deviation of daily returns, *Turnover* is the number of shares traded per day and *Illiquidity* is measured as the ratio of the bid-ask spread to its midpoint. HHI, our measure of clustering, stands for the Herfindahl-Hirschman Index.

In Figure 2, the concentration of prices at the final digits 0 and 5 is evident in all ranges but mainly for the highest price levels, which seems to confirm what is claimed by the Price

Resolution/Negotiation Hypothesis.

In Table 7, we can see that in this sample, at least according to this univariate analysis, there is not a negative relationship between the size of the banks and the level of clustering. In fact, the results seem to point to a positive relationship between the variables, with more clustering for partitions with larger banks. As for the other specific attributes, the results confirm the Price Resolution/Negotiation Hypothesis with respect to Turnover, i.e., less clustering for the banks with the highest turnover, and illiquidity, i.e., a higher degree of clustering for the more illiquid stocks. This analysis also seems to indicate to more clustering for higher price levels. Regarding volatility, the results are inconclusive. It should be noted that the smaller size of the sample of European banks may introduce some biases in the results and thus not reveal such a consistent trend between these attributes and the clustering measures as seen in the US sample, which is of a larger size. In short, we can conclude that these European sample results partially confirm the Price/Resolution Hypothesis.

In sum, the results point to the clear presence of clustering in all periods of both samples, and, as expected, the digits 0 and 5 are invariably the most frequently observed. It should be noted that the level of clustering is higher in the sample of European banks, as shown by the values of the HHI. Surprisingly, we did not find statistically significant differences between the pre-crisis and the crisis clustering levels, either for the sample of European banks or for the sample of US banks, which leads us to conclude that investors are not significantly affected by behavioral factors in periods of greater pessimism and uncertainty, such as periods of crisis. The univariate analysis also confirmed, in part, the assumptions of the Price Resolution/Negotiation Hypothesis, as well as the Attraction Hypothesis, with the final digits 0 and 5 being the most frequently observed for both samples.

4.2. Multivariate analysis

4.2.1. US Sample

Firstly, it should be noted that for each sample and for each period two models were estimated, one with all the explanatory variables and other where some variables whose correlation coefficient with other factors is high (greater than 0.6) were excluded from it to avoid problems of multicollinearity. The results of the multivariate analysis for the US Sample are presented in Tables 8 and 9 (see “Annexes” for the results of this reduced model).

Table 8 – Determinants of price clustering (US sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0066	0.0005	14.7318	0.0000	
Size	0.0128	0.0050	2.5523	0.0116	-
Price	-0.0004	0.0006	-0.6756	0.5002	+
RetVol	-0.0012	0.0006	-2.0928	0.0378	+
Turnover	-0.0027	0.0010	-2.6573	0.0086	-
Illiquidity	0.0041	0.0007	5.6832	0.0000	+
PastReturns	-0.0005	0.0006	-0.8204	0.4131	-
BTM	-0.0027	0.0013	-2.1224	0.0352	-
AnalystCoverage	0.0010	0.0008	1.1644	0.2459	-
Loans	-0.0005	0.0010	-0.4977	0.6193	+
Investments	-0.0010	0.0008	-1.2456	0.2146	+
Deposits	0.0000	0.0009	-0.0244	0.9806	+
SizeAssetsBV	-0.0123	0.0050	-2.4759	0.0143	+
TobinQ	-0.0044	0.0018	-2.4423	0.0156	-
CreditRisk	-0.0011	0.0005	-1.9931	0.0478	+
ROAVOL	0.0019	0.0101	0.1906	0.8491	+
NIMVOL	-0.0003	0.0005	-0.6153	0.5391	+
ZSCORE	0.0018	0.0102	0.1783	0.8587	-
R-squared	0.4334	F-statistic		7.7385	
Adjusted R-squared	0.3774	Prob(F-statistic)		0.0000	

Table 9 – Determinants of price clustering (US sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0061	0.0003	19.8174	0.0000	
Size	0.0035	0.0019	1.8222	0.0702	-
Price	-0.0006	0.0005	-1.2082	0.2286	+
RetVol	-0.0019	0.0005	-3.8353	0.0002	+
Turnover	-0.0012	0.0008	-1.5194	0.1305	-
Illiquidity	0.0044	0.0005	8.6309	0.0000	+
PastReturns	-0.0005	0.0004	-1.2492	0.2133	-
BTM	0.0000	0.0007	0.0378	0.9699	-
AnalystCoverage	-0.0005	0.0004	-1.1986	0.2323	-
Loans	-0.0011	0.0007	-1.6817	0.0944	+
Investments	-0.0013	0.0006	-2.1281	0.0348	+
Deposits	0.0002	0.0006	0.3308	0.7412	+
SizeAssetsBV	-0.0015	0.0018	-0.8194	0.4137	+
TobinQ	-0.0009	0.0007	-1.2977	0.1961	-
CreditRisk	-0.0002	0.0005	-0.3314	0.7408	+
ROAVOL	-0.0024	0.0089	-0.2645	0.7917	+
NIMVOL	0.0000	0.0003	0.1246	0.9010	+
ZSCORE	-0.0024	0.0089	-0.2644	0.7918	-
R-squared	0.5625	F-statistic		13.0066	
Adjusted R-squared	0.5192	Prob(F-statistic)		0.0000	

As a preliminary note, the adjusted coefficients of determination are satisfactory for all regressions, but especially for the crisis period, where the independent variables explain more than 50% of the variation in the level of clustering.

According to the Price Negotiation/Resolution Hypothesis, the variables "Price", "RetVol" and "Illiquidity" should have a positive relationship with clustering, while the variables "Size" and "Turnover" should be negatively associated with this phenomenon. Our results show that the relation predicted by the theory for the variables "Turnover" and "Illiquidity" is confirmed at a statistically significant level of 1% for the "Illiquidity" variable in both periods, with the "Turnover" variable being also statistically significant at a level of 1% in the period before the crisis, despite having a p-value higher but close to 10% in the crisis period. Nevertheless, the expected results for the variables "Size" and "RetVol" according to the Price Negotiation/Resolution Hypothesis are not confirmed. Moreover, the variable "Price" is not statistically significant. Therefore, on an overall assessment, we can conclude that the Price Negotiation/Resolution Hypothesis is only partially confirmed in our sample of US banks.

At a significance level of 10%, the variable “Size” is statistically significant for both periods under analysis in the model with all the explanatory variables, however, in the reduced model this variable only has explanatory power for the crisis period. As we have mentioned above the results show a relationship between this variable and the dependent variable that is surprising according to the Price Resolution Hypothesis since the regression coefficients have a positive sign for both periods. However, the variable "SizeAssetsBV", which is included in the model as a measure of the banks' risk, but which obviously also serves as a measure of their size, using accounting values instead of market values, has coefficients with a negative sign for both periods, precisely what would be expected according to the Price Resolution/Negotiation Hypothesis.

It turns out that these two variables that can serve as a measure of the size of the banks have a very high positive correlation coefficient, as expected, and hence the variable "SizeAssetsBV" has been eliminated from the least complete model. In this second model, the “Size” variable continues to show a coefficient with a positive sign in the crisis period (the only one in which it is statistically significant), which leads us to conclude that the relationship between the size factor and the level of clustering can diverge from what is theoretically predicted by this hypothesis.

The "PastReturns" variable is not statistically significant for any of the periods under analysis. Theoretically, higher returns in the past would lead to a lower level of price clustering, since shares with higher returns lead to greater coverage by investors and analysts which results in a higher level of information, which should imply a lower level of clustering. On the other hand, this type of stocks also attracts more biased investors, which can be a factor that leads to more clustering. Given the statistical insignificance of the variable, we can only conclude that this factor does not contribute to explain the clustering of prices.

With respect to the "BTM" variable, the results are curious, since this variable is statistically significant only for the period before the crisis, having negative regression coefficients. In theory, growth stocks should be more affected by clustering, that is, the lower the book-to-market ratio that characterizes this same type of stocks, the higher the level of clustering should be. In fact, it is this relationship that occurs for the period before the crisis in the sample of US banks. As mentioned above, this variable does not seem to explain the variation of the dependent variable in the crisis period.

The "AnalystCoverage" variable is not statistically significant in all estimated models (for significance levels of 5% and 10%).

Regarding the variables that measure the banks' opacity, we should expect a positive relationship between them and price clustering, since more opacity means a higher level of uncertainty from banks' consumers and investors, which should lead to a greater clustering of prices. However, the variables "Loans" and "Investments" only seem to be statistically significant in the crisis period, while the variable "Deposits" has no statistical significance in any of the periods. The opacity of the banks is an explanatory factor of clustering in the crisis period, but the relationship with the level of clustering does not conform to what was expected.

As for the variables that are included in the model to measure some forms of the banks' risks, the variables "SizeAssetsBV", "TobinQ" and "CreditRisk, such as the "BTM" variable, are only statistically significant for the periods before the crisis. One can expect, in theory, that the lower the value of the variable "TobinQ", the higher is the risk of the bank and the higher the level of uncertainty should be, which should, therefore, imply a higher level of price clustering. The signal of the coefficient of this variable in this period is negative, a result that is in agreement with the theory. As for the variables "SizeAssetsBV" and "CreditRisk", they have a negative coefficient, contrary to what was expected. The remaining variables, "ROAVOL", "NIMVOL" and "ZSCORE" are not statistically relevant and do not contribute to explain the variation of the clustering level in this sample. Thus, we can conclude that risk only seems to be a factor in explaining clustering in this sample in the period before the crisis, with the results partially confirming the theory that more risk leads to more clustering since only "TobinQ" supports this relation between the variables.

The variables that best appear to explain clustering are "Size", "RetVol", and "Illiquidity". "Size" and "Illiquidity" positively affect the level of clustering. On the other hand, the volatility of returns has a negative impact on it. Only the relationship between "Illiquidity" and the dependent variable is consistent with what the Price Negotiation/Resolution Hypothesis holds. The "Turnover", "BTM" and three of the risk variables ("SizeAssetsBV", "TobinQ" and "CreditRisk") only seem to have explanatory power in the period before the crisis, while the inverse happens for two of the variables that measure opacity of banks, "Loans" and "Investments", that is, variables that have statistical significance only for the period of crisis.

Although our regression is successful in explaining much of the cross-sectional variation in price clustering, the huge relative size and significance of the constant term in all specifications shows that although much of the cross-sectional variation in the clustering can be explained by bank-specific characteristics, these characteristics seem to explain only a modest amount of the total level of price clustering in the data.

4.2.2. European Sample

In this section, we will analyze the regressions' results for the sample of European banks, which are illustrated in Tables 10 and 11.

Table 10 – Determinants of price clustering (European sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0671	0.0068	9.9015	0.0000	
Size	0.2124	0.0764	2.7819	0.0128	-
Price	0.0364	0.0117	3.1072	0.0064	+
RetVol	0.0198	0.0112	1.7761	0.0936	+
Turnover	0.0040	0.0131	0.3055	0.7637	-
Illiquidity	0.0347	0.0139	2.4949	0.0232	+
PastReturns	-0.0077	0.0094	-0.8130	0.4275	-
BTM	-0.0847	0.0253	-3.3528	0.0038	-
AnalystCoverage	-0.0173	0.0138	-1.2553	0.2263	-

Loans	-0.0065	0.0159	-0.4091	0.6876	+
Investments	0.0088	0.0159	0.5523	0.5879	+
Deposits	-0.0152	0.0207	-0.7311	0.4747	+
SizeAssetsBV	-0.2388	0.0789	-3.0284	0.0076	+
TobinQ	-0.1095	0.0339	-3.2340	0.0049	-
CreditRisk	-0.0141	0.0086	-1.6367	0.1201	+
ROAVOL	-0.0381	0.0393	-0.9689	0.3462	+
NIMVOL	-0.0174	0.0085	-2.0632	0.0547	+
ZSCORE	-0.0496	0.0405	-1.2254	0.2371	-
R-squared	0.8204	F-statistic		4.5665	
Adjusted R-squared	0.6407	Prob(F-statistic)		0.0016	

Table 11 – Determinants of price clustering (European sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0507	0.0063	8.0417	0.0000	
Size	0.0807	0.0508	1.5892	0.1304	-
Price	0.0275	0.0117	2.3531	0.0309	+
RetVol	-0.0012	0.0126	-0.0968	0.9240	+
Turnover	-0.0265	0.0130	-2.0414	0.0570	-
Illiquidity	0.0240	0.0123	1.9496	0.0679	+
PastReturns	-0.0052	0.0083	-0.6269	0.5390	-
BTM	0.0136	0.0215	0.6348	0.5340	-
AnalystCoverage	0.0031	0.0106	0.2958	0.7710	-
Loans	-0.0060	0.0180	-0.3347	0.7419	+
Investments	-0.0105	0.0147	-0.7151	0.4843	+
Deposits	-0.0034	0.0188	-0.1827	0.8572	+
SizeAssetsBV	-0.0581	0.0571	-1.0169	0.3234	+
TobinQ	0.0026	0.0221	0.1166	0.9085	-
CreditRisk	0.0001	0.0129	0.0101	0.9921	+
ROAVOL	0.0036	0.0320	0.1127	0.9116	+
NIMVOL	-0.0050	0.0112	-0.4485	0.6595	+
ZSCORE	-0.0100	0.0316	-0.3161	0.7557	-
R-squared	0.8133	F-statistic		4.3550	
Adjusted R-squared	0.6265	Prob(F-statistic)		0.0021	

The adjusted coefficients of determination that we obtained are quite satisfactory, above 60% for both periods.

As already mentioned, according to the Price Negotiation/Resolution Hypothesis, the variables "Price", "RetVol" and "Illiquidity" should have a positive relationship with clustering, while the variables "Size" and "Turnover" should be negatively related with price clustering. Our results show that the relation predicted by the theory for the variables “Price”, “RetVol”, "Turnover" and "Illiquidity" are confirmed at a statistically significant level of 10%, although some of these variables are only significant for one of the periods. The variable "RetVol" seems to have some explanatory power in the period before the crisis, but it does not explain price clustering in the crisis period. The variable "Turnover", in turn, only has some explanatory power in this geographical area in the crisis period. However, the expected results according to the Price Negotiation/Resolution Hypothesis for the variable "Size" are not confirmed. This variable seems to explain the price clustering phenomenon better in the period before the crisis than in the period of crisis. Statistically, the difference between the coefficients from one period to the other is not significant, and it can be concluded that the effect of this factor in the level of clustering is not affected by the economic and financial environment and the consequent emotional instability that this provokes in market participants. It should also be noted that, because they showed high correlation coefficients with other variables, the "Size" and "SizeAssetsBV" variables were eliminated from the most complete model and a new regression without these variables was estimated for each of the periods. Therefore, we can conclude that the Price Negotiation/Resolution Hypothesis is only partially confirmed in our sample of European banks.

The results also show that the variables "PastReturns" and "AnalystCoverage" do not contribute to explain the price clustering in this geographical area. The "BTM" variable is statistically significant for the period before the crisis and it has a negative coefficient, which supports what would theoretically be predicted, as already explained in the comments we made about the results for the US banks sample.

The variables we include in the model as measures of bank opacity, "Loans", "Investments" and "Deposits", do not contribute to explain the variation in the level of clustering in the sample of European banks in any of the periods, which leads us to conclude that the opacity factor is not relevant in the sense of impacting the market participants to trigger this phenomenon in financial markets.

Regarding the risk measures, the variable "SizeAssetsBV" is statistically significant for the period before the crisis, in which it has a negative regression coefficient. As a measure of the size of the banks, this relationship with the dependent variable is in accordance with the Price Resolution theory, that is, the larger the bank size, the higher the level of information, the lower the uncertainty and, consequently, the lower the level of clustering. As a measure of risk, and in line with what is argued by Demsetz and Strahan (1997), i.e. larger banks, although having better capacity to diversify risk, adopt loan portfolios with higher risk and use more leverage, and therefore, present a greater degree of risk, hence we can conclude that the relationship that we find in the results between this explanatory variable and clustering is not in agreement with what is claimed by these authors, since one would expect that greater risk would lead to greater clustering. This factor can thus have contradictory impacts since larger banks are more scrutinized and analyzed, thus having superior levels of information than smaller ones, which can reduce uncertainty and clustering. However, there are authors such as those mentioned above who say that a larger size may be associated with higher risk. In the case of the European sample, the reduction of uncertainty through the size of the bank seems to overlap with the possible increase in uncertainty through the risk-taking of larger banks. Another measure of risk is represented by the variable "TobinQ". This variable only explains the clustering in the period before the crisis, showing a negative regression coefficient, which confirms the theory that more risk leads to a higher degree of clustering. As for the other risk measures included in the model, we can say that the variables "CreditRisk", "ROAVOL" and "ZSCORE" are not statistically significant for any of the periods, hence they do not contribute to explain price clustering. The variable "NIMVOL" is statistically significant, with a level of significance of 10%, for the period before the crisis of the sample of European banks, with a negative coefficient, contrary to what the theory suggests. These results lead to the conclusion that in this sample of European banks risk only seems to be a factor in explaining clustering in the period before the crisis, with the results partially confirming the theory.

In sum, the independent variables that best seem to explain the variation of the level of clustering in the sample of European banks are "Price" and "Illiquidity", and there are factors that contribute to explain this variation in only one of the periods, namely "Size", "RetVol", "BTM", and some risk factors such as "SizeAssetsBV", "TobinQ" and "NIMVOL" for the pre-crisis period; in the period of crisis a factor that seems to contribute to explain this phenomenon is "Turnover". Again, it is important to note the statistical significance and the size of the constant term, which leads us to conclude that in addition to these bank-specific characteristics, other factors also seem to contribute to explain the level of clustering observable in the stocks of the banks that are included in our data.

4.2.3. Comparison between the two samples

Comparing the results obtained for the two geographical areas, we can start by noting that these characteristic factors of the banks that were included in the models as possible explanatory variables of price clustering contribute to a greater degree for this explanation in the sample with European banks than in the sample of US banks, as evidenced by the higher adjusted coefficients of determination that were obtained in the results of the European sample. This leads us to intuit that in the United States the impact of other factors, such as more acute behavioral biases, in the level of clustering may be higher than in Europe. Hofstede (2003) and the Hofstede's Index of Individualism show that the US culture is more individualistic than most of the European cultures and Chen (2014) finds results that support that individualism is positively associated with price clustering and price barriers. Berk et al. (2017) also found that psychological barriers, a phenomenon closely related to price clustering, are most present for equities in countries that have high cultural measures of individualism. This is a psychological bias that has a strong impact on risk perception, risk aversion and uncertainty avoidance. Koellinger et al. (2007) also found that North Americans have more overconfidence than individuals in mainland Europe. Kitayama et al. (2009) predicted and found that North Americans are more likely than Western Europeans (British and Germans) to exhibit focused (vs. holistic) attention, to experience emotions associated with independence (vs. interdependence), to associate happiness with personal achievement (vs. communal harmony), and to show an inflated symbolic self.

For both samples the relative size and significance of the constant term also shows that in the absence of any variation of the explanatory variables of the model, there is a higher level of clustering than what would be expected under the null hypothesis that is not explained by these specific characteristics of the banks and which may originate in a natural attraction that individuals feel for certain numbers, that is, a behavioral or psychological bias that seems to affect the distribution of prices, as Ikenberry and Weston (2008) refer in their article.

Our results partially confirm the Price Negotiation/Resolution Hypothesis. In both samples, the variables "Turnover" and "Illiquidity" (the only explanatory variable that helps to explain the price clustering for both geographical areas and for both periods), have a relation with price clustering as predicted by the theory, although "Turnover", in the European sample, is only statistically significant in the crisis period. The results for the variables "Price" and "RetVol" in the European banks' sample also support the Price Negotiation/Resolution Hypothesis, while "Size" has a relation with clustering contrary to what was expected in both samples.

Regarding the "BTM" variable, the results are interesting, since this variable is statistically significant only for the periods before the crisis, in both samples, having negative coefficients which constitutes evidence that supports the theory.

There are two variables that measure the opacity of the banks that contribute to explain this phenomenon during the crisis period in the US, namely "Loans" and "Investments", but the relationship with clustering does not conform to what was expected. In the European sample, all opacity variables are not statistically significant. Regarding the risk measures, "SizeAssetsBV" and "TobinQ" have some explanatory power but only in the periods before the crisis. The variable "Credit Risk" is also relevant to explain clustering in this period but only in the US. The results for the variable "TobinQ" support the theory, however, the other variables have coefficients that contradict it. We can conclude from these results that opacity and risk do not contribute significantly to the degree of clustering at the company level, however, future studies may include other variables that measure these factors and reach other conclusions.

There are variables that do not contribute to this explanation in any of the periods and geographic areas under analysis, namely "PastReturns", "AnalystCoverage", "Deposits", "ROAVOL" and "ZSCORE".

Another interesting fact of these results is that the difference between the coefficients of a large part of the variables between the periods before the crisis and the periods of crisis is not statistically significant. In the sample of US banks, for example, we see only a decrease in the positive impact that the "Size" variable has on the level of clustering from the pre-crisis period to the crisis period. This might mean that the crisis and its effects do not have the theoretically expected impact on investors since certain factors maintain the same influence on the level of observed price clustering. The constant term is also not significantly different from one period to the other, but there is a slight decrease in the crisis period, as our univariate analysis has shown.

We also estimated the model for the whole period, during and before the crisis, for each sample. These results are shown in the Annexes and generally confirm the conclusions discussed above. "Illiquidity" is a relevant variable in explaining price clustering in the stocks of US and European banks, while "Price" and "RetVol" are only significant in the European Sample. All these variables have coefficients with signs as expected by the Price Resolution/Negotiation Hypothesis. "Size" only appears to explain this phenomenon in the US Sample, though the results do not support this hypothesis.

4.3. Time-series analysis

In addition to the cross-section multivariate analysis presented above, we also consider it appropriate to perform a time-series analysis of price clustering.

For this purpose, a model will be estimated for each of the samples, where as dependent variable we have the level of price clustering of the sample on a given day *t* (measured by the HHI) and as explanatory variables we have measures of stock market volatility and uncertainty, the VIX and the VSTOXX, for the sample of the US and European banks, respectively. These implied volatility of stock option indices are often used as measures of market uncertainty and volatility (see, for example, Rose and Spiegel, 2012).

Daily historical data for the independent variables were collected from the CBOE[1] and STOXX[2] websites, respectively.

The estimated models using OLS are as follows:

$$Clustering(HHI)_t = VIX_t + e_t \tag{4.1}$$

$$Clustering(HHI)_t = VSTOXX_t + e_t \tag{4.2}$$

As can be seen from the results, the adjustment of the models is not good, as the values of the coefficients of determination show. We also estimated the models with the independent variable lagged in one day and the quality of the model, according to this parameter, also does not improve. The models were also estimated for the full sample period, including both the period before the crisis and the crisis period. These results can be seen in the Annexes and confirm what was obtained for all the sub-samples. Thus, we can conclude that volatility and uncertainty do not contribute to explain the variation in the level of clustering over time.

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[1] http://www.cboe.com/publish/scheduledtask/mktdata/datahouse/vixcurrent.csv

[2] https://www.stoxx.com/documents/stoxxnet/Documents/Indices/Current/HistoricalData/h_v2tx.txt

Table 12 – Time-series analysis (US sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value
VIX	0.0072	0.0001	77.9651	0.0000
R-squared	-29.8833			

Table 13 – Time-series analysis (US sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value
VIX	0.0028	0.0001	41.6755	0.0000
R-squared	-24.0375			

Table 14 – Time-series analysis (European sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value
VSTOXX	0.0096	0.0001	97.0931	0.0000
R-squared	-0.7939			

Table 15 – Time-series analysis (European sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value
VSTOXX	0.0039	0.0001	42.9848	0.0000
R-squared	-6.5326			

4.4. Impact of the European sovereign debt crisis on Price Clustering

In addition to the analyzes that we have already presented, it seemed appropriate to extend this study to the sovereign debt crisis that occurred in Europe and which still has effects at the time we are writing this text.

There were many reasons that have led some countries in this geographical area to enormous difficulties in complying with and repaying their public debt, including the bursting of the speculative bubble in the real estate sector, unsustainable fiscal policies that produced significant deficits, and of course, the global financial crisis, which has had wide repercussions in an increasingly global financial market, especially in those countries with chronic problems with their public debt.

The sovereign debt crisis had a tremendous economic and political impact on the affected countries, including Greece, Italy, Portugal and Spain. The purpose of this analysis is to separate the sample of European banks into two subsamples: one with the banks of countries affected by this crisis and another with the other banks of European countries in which this crisis did not have a significant impact; the purpose of this division is to analyze the impact of a crisis which has caused drastic consequences in the affected countries, at all levels, on the behavior of economic agents in the financial markets and the consequent distribution of prices.

For this, we will develop a method that is similar to that implemented in the univariate analysis, that is, based on the comparison between the price clustering levels between the two subsamples of European banks. The period of analysis will be the period between 1 September 2008 and 4 August 2011, based on Beirne and Fratzscher (2013).

Table 16 - Impact of the European sovereign debt crisis on Price Clustering

Last Digit	Affected countries		Non-affected countries	
	Frequency	%	Frequency	%
Panel A: Distribution of last digit of the price				
0	2727	16.39	2333	26.80
1	1401	8.42	671	7.71
2	1585	9.53	599	6.88
3	1346	8.09	588	6.75
4	1529	9.19	537	6.17
5	2099	12.62	1463	16.80
6	1496	8.99	587	6.74
7	1339	8.05	497	5.71
8	1640	9.86	682	7.83
9	1476	8.87	749	8.60
Total	16638		8706	
% at 0 & 5		29.01		43.60

	Affected countries	Non-affected countries
Panel B: Clustering tests and indices		
χ^2_9	1011.97	3520.18
H1 (p-value)	0.0000	0.0000
HHI (%)	10.61	14.04
$F_{9.9}$	3.48	
H2 (p-value)	0.0387	

Note: Panel A shows the absolute and the relative frequencies of prices. Panel B presents the p-value of the H1 and H2 hypotheses, as well as the HHI, which stands for the Hirshmann-Herfindahl index. The sample of

European banks was divided into two subsamples: a sample with the banks of countries affected by the European sovereign debt crisis (Greece, Italy, Portugal and Spain) and other with the other banks of European countries in which this crisis did not have a significant impact (Austria, Denmark, Finland, Germany, Romania).

Given these results, we can conclude that there is evidence of an abnormal concentration of prices for both samples, as demonstrated by the p-values of the H1 hypothesis. Once again, digits 0 and 5 are the most frequently observed, reaching a percentage of more than 40% in the sample of non-affected countries, more than twice what would be expected if the price distribution was uniform. Analyzing the results of Panel B, we can also see that the HHI for the sample of countries where the sovereign debt crisis has not been felt is significantly higher than for the sample of countries affected by this crisis. The p-value for the H2 hypothesis reveals this, i.e. the clustering observed in the stock prices of the banks of unaffected countries is, at a level of statistical significance of 5%, higher than that observed in the sample of the countries that had issues with their public debt.

These results are theoretically surprising, however they are in line with those that were obtained in the other analyzes we performed in this study, i.e., evidence of a lower level of clustering at times of crisis (although the univariate analysis did not show statistically significant differences between the levels of clustering for both periods, the HHI was lower during the crisis).

This relationship between the level of clustering and periods of crisis suggests that investors are less affected by behavioral factors in periods of greater pessimism, since this is a phenomenon that stems from the irrational behavior of market participants. Lucey and Dowling (2005) suggest that investors' emotions and feelings influence their stock price decisions. The mood-as-information hypothesis argues that our moods inform our decisions and that, as argued by Schwarz (1990, p. 527), "negative affective states, which inform the organism that its current situation is problematic, foster the use of effortful, detail-oriented, analytical processing, whereas positive affective states foster the use of less effortful heuristic strategies. " Moreover, Alloy and Abramson (1979) conclude that individuals, at depressive times, tend to be more realistic and more analytical in their appraisals, that is, "sadder but wiser," as these authors suggest. In addition to these studies, some articles in the area of Finance suggest that investors are better at processing information at times when the market sentiment is negative. For example, Cooper et al. (2004) find that the profits to momentum strategies depend critically on the state of the market, in particular, at times when the market registers upward trends, results that reveal that the information is more quickly incorporated in the prices in periods of negative feelings, hence the difficulty in profiting from this type of investment strategy. In turn, Garcia (2013) shows that prices reflect much more quickly the news published in the financial section of *The New York Times* during periods of recession. Sinclair and Mark (1995) find that negative affective states lead to systematic and more detailed information processing. Moreover, Isen (1987) and Durant et al. (2009) suggest that individuals make logical, consistent and unbiased decisions when they find themselves in a negative affective state, a consequence of an instinct to turn a bad situation into a good one. Peng et al. (2011) show that investors are smarter in pessimistic market phases, that is, they become less confident and do not overreact to their private opinions, which causes them to make decisions in a more logical and rational way, which translates into better choices at the time of liquidation of the funds.

In short, there is enough theoretical basis to sustain the results we obtained, since in times of crisis investors become more rational and therefore are less affected by emotional and cognitive biases, which, in turn, is reflected in a lower level of price clustering.

Chapter 5

Conclusion

Price clustering is one of the market anomalies that puts into question the arguments of the Efficient Market Hypothesis and the perfect rationality of economic agents. According to this hypothesis, stock prices would be expected to follow a uniform distribution, but as we have already mentioned, there are several empirical studies that reveal an abnormal concentration of prices, with certain digits being more frequently observed than others. The objective of our study was to extend the analysis of this phenomenon to the banking sector and to investigate the effects of the global financial crisis on the level of price clustering. For this purpose, two samples were used, one with US banks and another with European banks, in order to compare the levels, the type, the impact of the crisis and the causes of price clustering between the two geographic areas.

The univariate analysis confirmed the existence of price clustering in both samples, with the last digits 0 and 5 being invariably more observed than the others, but the results did not reveal a significant difference between the levels observed between the analyzed periods, which leads us to conclude that the financial crisis and the uncertainty and volatility associated with it do not have a significant impact on the behavior of investors regarding price formation. The time-series analysis that we have performed, which aimed to evaluate the relationship between the level of clustering and market volatility and uncertainty, points precisely in this direction, since these factors do not seem to contribute to explain the variation of the level of clustering over time. It should also be noted that the level of clustering is higher in the sample of European banks.

Europe, in addition to being affected by the global financial crisis, also had problems regarding the public debt of some of its countries, giving rise to the so-called European sovereign debt crisis. In this sense, we think it was relevant to analyze the impact of this crisis on price clustering, adopting to that effect a methodology identical to that of the univariate analysis of the European and US banks samples, except in this case the samples were those of non-affected European countries and that of countries affected by this crisis. The results of this analysis were theoretically surprising, since they point to a lower clustering in the sample of affected countries. At the origin of this relationship between the periods of crisis and the level of price clustering might be a greater rationality and analytical capacity of investors in periods of negative sentiment, which implies that this market anomaly is not so observable in the distribution of prices.

We also performed a multivariate analysis of price clustering in order to understand the specific characteristics of the banks that best explain this phenomenon. One of the conclusions of this analysis is that these specific characteristics have a greater weight in explaining the clustering variation in the sample of European banks, which leads us to intuit that US investors are more affected by behavioral factors, as a result of a more individualistic culture that gives rise to more behavioral deviations and the consequent occurrence of phenomena such as this that oppose the ideal of a perfectly efficient market. The level of significance and the relative size of the constant term of the model in both samples also suggests that psychological biases and a natural attraction for certain numbers may partly explain price clustering. In fact, the results of the univariate analysis partially support the Attraction Hypothesis, with the digits 0 and 5 being the most observed in both samples and periods. The Price Resolution / Negotiation Hypothesis is also partially supported by our results. Some of the variables have a relation with clustering according to what the hypothesis suggests, however, others are contrary to the theory or are not even significant. Hence, we can conclude that the uncertainty about the shares' intrinsic value does not have the expected impact on the behavior of investors, which can be sustained by the greater rationality of the market participants in periods of greater volatility and uncertainty, as we have already mentioned.

In short, the primary findings of our study show evidence of price clustering for the European and US banks' samples, with the Attraction and the Price Resolution/Negotiation Hypotheses being only partially confirmed by these results. Furthermore, the results revealed a minor impact of the financial crisis in the observed levels of clustering, however the study on the effects of the European sovereign debt crisis on price clustering showed lower levels of clustering for the banks of affected countries.

Finally, as suggestions for further research, it would be interesting to ascertain the impact of other crises on clustering in the banking sector or others, or even to use a definition of the crisis period distinct from the one that was implemented in this study. Other variables that serve as a measure of company-specific characteristics should also be included in models that aim to perceive the determinants of this phenomenon, both at the company level and regarding its variation over time. In addition, it would also be of interest to divide these samples between bull market and bear market periods performing a similar analysis such as with the division between crisis periods and to extend this study to the phenomenon of psychological barriers.

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Annexes

Table 17 – Determinants of price clustering – Reduced model (US sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0066	0.0005	14.5181	0.0000	
Size	0.0007	0.0012	0.6123	0.5411	-
Price	-0.0004	0.0006	-0.7004	0.4846	+
RetVol	-0.0013	0.0006	-2.2235	0.0275	+
Turnover	-0.0018	0.0010	-1.9101	0.0578	-
Illiquidity	0.0046	0.0007	6.5291	0.0000	+
PastReturns	-0.0001	0.0006	-0.2266	0.8210	-
BTM	-0.0012	0.0011	-1.0807	0.2814	-
AnalystCoverage	0.0004	0.0008	0.4730	0.6368	-
Loans	-0.0012	0.0009	-1.2506	0.2128	+
Investments	-0.0016	0.0008	-1.9553	0.0522	+
Deposits	0.0006	0.0008	0.7127	0.4770	+
TobinQ	-0.0009	0.0011	-0.7991	0.4253	-
CreditRisk	-0.0010	0.0005	-1.8447	0.0668	+
ROAVOL	0.0104	0.0097	1.0757	0.2835	+
NIMVOL	-0.0002	0.0005	-0.4526	0.6514	+
ZSCORE	0.0100	0.0098	1.0286	0.3051	-
R-squared	0.4132	F-statistic		7.6133	
Adjusted R-squared	0.3589	Prob(F-statistic)		0.0000	

Table 18 – Determinants of price clustering – Reduced model (US sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0061	0.0003	19.8363	0.0000	
Size	0.0021	0.0008	2.6229	0.0095	-
Price	-0.0006	0.0005	-1.3020	0.1947	+
RetVol	-0.0021	0.0005	-4.3267	0.0000	+
Turnover	-0.0011	0.0008	-1.4407	0.1515	-
Illiquidity	0.0044	0.0005	8.6010	0.0000	+
PastReturns	-0.0005	0.0004	-1.3712	0.1721	-
BTM	-0.0001	0.0007	-0.1446	0.8852	-
AnalystCoverage	-0.0005	0.0004	-1.3400	0.1820	-
Loans	-0.0012	0.0007	-1.8935	0.0600	+
Investments	-0.0015	0.0006	-2.4154	0.0168	+
Deposits	0.0003	0.0006	0.5369	0.5920	+
TobinQ	-0.0007	0.0006	-1.0786	0.2823	-
CreditRisk	-0.0002	0.0005	-0.3965	0.6922	+
ROAVOL	-0.0017	0.0089	-0.1940	0.8464	+
NIMVOL	0.0000	0.0003	0.1460	0.8841	+
ZSCORE	-0.0017	0.0089	-0.1954	0.8453	-
R-squared	0.5608	F-statistic		13.8037	
Adjusted R-squared	0.5201	Prob(F-statistic)		0.0000	

Table 19 – Determinants of price clustering – Reduced model (European sample – before the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0671	0.0080	8.3810	0.0000	
Price	0.0280	0.0129	2.1721	0.0427	+
RetVol	0.0110	0.0110	0.9991	0.3303	+
Turnover	0.0017	0.0127	0.1377	0.8919	-
Illiquidity	0.0391	0.0163	2.3978	0.0269	+
PastReturns	-0.0045	0.0109	-0.4145	0.6832	-
BTM	-0.0436	0.0245	-1.7780	0.0914	-
AnalystCoverage	-0.0124	0.0154	-0.8052	0.4307	-
Loans	-0.0065	0.0174	-0.3769	0.7104	+
Investments	-0.0015	0.0183	-0.0832	0.9346	+
Deposits	0.0147	0.0210	0.6976	0.4939	+
TobinQ	-0.0310	0.0256	-1.2108	0.2408	-
CreditRisk	-0.0088	0.0098	-0.9017	0.3785	+
ROAVOL	0.0183	0.0404	0.4528	0.6558	+
NIMVOL	-0.0091	0.0093	-0.9857	0.3366	+
ZSCORE	0.0070	0.0421	0.1667	0.8694	-
R-squared	0.7198	F-statistic		3.2533	
Adjusted R-squared	0.4985	Prob(F-statistic)		0.0085	

Table 20 – Determinants of price clustering – Reduced model (European sample – during the crisis)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0507	0.0067	7.5403	0.0000	
Price	0.0323	0.0122	2.6543	0.0157	+
RetVol	-0.0046	0.0114	-0.3990	0.6944	+
Turnover	-0.0183	0.0128	-1.4275	0.1697	-
Illiquidity	0.0236	0.0131	1.8070	0.0866	+
PastReturns	-0.0030	0.0086	-0.3472	0.7322	-
BTM	0.0212	0.0218	0.9723	0.3431	-
AnalystCoverage	0.0097	0.0097	0.9963	0.3316	-
Loans	-0.0055	0.0179	-0.3061	0.7629	+
Investments	-0.0037	0.0131	-0.2821	0.7809	+
Deposits	0.0094	0.0190	0.4946	0.6265	+
TobinQ	0.0230	0.0188	1.2223	0.2365	-
CreditRisk	-0.0046	0.0135	-0.3424	0.7358	+
ROAVOL	0.0032	0.0340	0.0937	0.9263	+
NIMVOL	-0.0175	0.0099	-1.7626	0.0941	+
ZSCORE	-0.0101	0.0337	-0.3001	0.7674	-
R-squared	0.7626	F-statistic		4.0692	
Adjusted R-squared	0.5752	Prob(F-statistic)		0.0024	

Table 21 – Determinants of price clustering (US sample – whole period)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0053	0.0003	16.2670	0.0000	
Size	0.0058	0.0034	1.7144	0.0883	-
Price	-0.0002	0.0004	-0.4427	0.6585	+
RetVol	-0.0016	0.0005	-3.3399	0.0010	+
Turnover	-0.0012	0.0008	-1.4672	0.1441	-
Illiquidity	0.0048	0.0005	8.9988	0.0000	+
PastReturns	-0.0005	0.0004	-1.2166	0.2254	-
BTM	0.0004	0.0008	0.5482	0.5842	-
AnalystCoverage	0.0007	0.0006	1.2451	0.2148	-
Loans	-0.0011	0.0007	-1.5997	0.1115	+
Investments	-0.0013	0.0007	-1.9928	0.0479	+
Deposits	0.0000	0.0007	-0.0602	0.9521	+
SizeAssetsBV	-0.0051	0.0032	-1.5615	0.1203	+
TobinQ	-0.0006	0.0010	-0.5647	0.5730	-
CreditRisk	-0.0005	0.0005	-1.0991	0.2733	+
ROAVOL	-0.0003	0.0019	-0.1383	0.8901	+
NIMVOL	-0.0009	0.0004	-2.6357	0.0092	+
ZSCORE	-0.0012	0.0020	-0.5888	0.5568	-
R-squared	0.5586	F-statistic		12.8043	
Adjusted R-squared	0.5150	Prob(F-statistic)		0.0000	

Table 22 – Determinants of price clustering (European sample – whole period)

Variable	Coefficient	Std. Error	t-statistic	p-value	Expected sign
α	0.0558	0.0056	10.0155	0.0000	
Size	0.0888	0.0882	1.0071	0.3280	-
Price	0.0225	0.0109	2.0675	0.0543	+
RetVol	0.0182	0.0102	1.7809	0.0928	+
Turnover	-0.0147	0.0110	-1.3374	0.1987	-
Illiquidity	0.0398	0.0114	3.4868	0.0028	+
PastReturns	-0.0024	0.0078	-0.3052	0.7639	-
BTM	-0.0193	0.0231	-0.8341	0.4158	-
AnalystCoverage	0.0031	0.0102	0.3073	0.7624	-
Loans	-0.0130	0.0186	-0.6986	0.4942	+
Investments	-0.0030	0.0145	-0.2033	0.8413	+
Deposits	0.0082	0.0181	0.4561	0.6541	+
SizeAssetsBV	-0.0803	0.0907	-0.8848	0.3886	+
TobinQ	-0.0277	0.0325	-0.8509	0.4066	-
CreditRisk	0.0034	0.0096	0.3530	0.7285	+
ROAVOL	0.0199	0.0264	0.7526	0.4620	+
NIMVOL	-0.0036	0.0124	-0.2903	0.7751	+
ZSCORE	0.0109	0.0294	0.3719	0.7145	-
R-squared	0.8391	F-statistic		5.2131	
Adjusted R-squared	0.6781	Prob(F-statistic)		0.0007	

Table 23 – Time-series analysis (US sample – whole period)

Variable	Coefficient	Std. Error	t-statistic	p-value
VIX	0.0036	0.0001	46.7753	0.0000
R-squared	-65.0632			

Table 24 – Time-series analysis (European sample –whole period)

Variable	Coefficient	Std. Error	t-statistic	p-value
VSTOXX	0.0051	0.0001	51.3091	0.0000
R-squared	-8.3813			