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The cost of equity of European banks before and after the crisis of 2008: CAPM and Panel Data approach

Sara Raquel Borges Guerreiro

Master in Finance

Supervisor:
Professor Doutor José Dias Curto, Prof. Associado com Agregação, ISCTE Business School, Departamento de Métodos Quantitativos para Gestão e Economia

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Department of Finance

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Resumo

O estudo realizado visa analisar o comportamento do custo de capital próprio do setor bancário europeu antes e depois da crise financeira de 2008, de forma a concluir se houve um aumento ou diminuição deste indicador financeiro. Com base em dados de onze países europeus, os nossos resultados são obtidos recorrendo ao modelo CAPM e estimando-o com base em dados em painel. A nossa metodologia difere de estudos anteriores, sendo que utilizamos um modelo de efeitos aleatórios para obter as estimativas necessárias, permitindo-nos assim criar duas janelas temporais, a primeira de 2004 a 2008 e a segunda para o período de 2010-2019.

O estudo começa por dar a conhecer o setor bancário europeu, fazendo uma contextualização do mesmo. Posteriormente, explora informações relevantes sobre a importância do custo de capital próprio, o modelo CAPM e os modelos de dados em painel usados para obter as estimativas dos coeficientes que posteriormente são utilizados para calcular o custo de capital próprio. Por fim, todos os modelos, resultados e outras conclusões deste estudo são apresentados.

Os nossos resultados mostram que o modelo CAPM fornece estimativas robustas do custo de capital próprio para o setor bancário europeu e que esta métrica sofreu um aumento do período pré para o pós-crise. Os resultados são consistentes com os do IIF (2011), concluindo que um aumento dos requisitos de capital e da regulamentação imposta pelo Acordo de Basileia III, e um maior índice de alavancagem aumentaram o custo de capital próprio no setor bancário europeu.

Palavras-chave: Custo de capital próprio; Modelos de dados em painel; Setor bancário Europeu

Classificação JEL: C33 – Panel Data Models

G21 – Banks

Abstract

This thesis goal is to analyze the behavior of the cost of equity of the European banking sector before and after the crisis of 2008, in order to conclude if there was an increase or a decrease of this metric and what is beyond its behavior. We use data from eleven European countries, and our results are obtained by using the CAPM model and estimating it based on Panel Data. Our inference differs from previous studies because we employ a random-effects model to obtain our estimates, which allow us to create two temporal windows, the first from 2004 to 2008 and the second one for the 2010-2019 period.

The project first acquaints the reader about the European banking sector, where a contextualization of it is displayed. Secondly, it explores and outlines important information regarding the importance of the cost of equity, the CAPM model, and Panel Data models used in order to obtain the best and reliable estimates used to compute the cost of equity. Finally, all models, results, and further conclusions are presented.

Our findings show that the CAPM model does provide the best estimates of the cost of equity for the European banking sector and that this metric suffered an increase from the pre- to the post-crisis period. Our results are consistent with those of IIF (2011), concluding that an increase of capital requirements and regulation imposed by the Basel III Accord, and a higher leverage ratio, increased the cost of equity in the European banking sector.

Keywords: Cost of Equity; Panel data Models; European Banking sector

JEL Classification: C33 – Panel Data Models

G21 – Banks

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List of Abbreviations

AFP: Association for Financial Professionals

AR: AutoRegressive

BHPS: British Household Panel Survey

CAPM: Capital Asset Pricing Model

DDM: Dividend Discount Model

EGLS: Feasible Generalized Least Squares

EU: European Union

G-10: Group of Ten

GDP: Gross Domestic Product

GLS: Generalized Least Squares

GMM: Generalized method of moments

GSOEP: German Social Economics Panel

IIF: Institute of International Finance

LSDV: Least Squares Dummy Variable

MM: Modigliani-Miller

NLS: National longitudinal Survey of Labor Market Experience

OLS: Ordinary Least Squares

PSID: Michigan Panel Study of Income Dynamics

SEP: Netherlands Socio-Economic Panel

US: United States

1. Introduction

The banking sector represents one of the most vital sectors for the economy, being the "lifeblood" of the economic activity. The 2008 financial crisis came to haunt the confidence placed in this "lifeblood" of the economic activity, generating notable anxieties and disparities in financial markets. As a resolution for this financial crisis, the Basel Committee on Banking Supervision decided to develop a set of proposals to complement and strengthen the global capital and liquidity resolution, to create a more stable banking system. As a result of these new norms created by the Basel Committee on Banking Supervision, the capital structure of a bank changed over the years. Therefore, one of the most important lessons drawn from this ongoing economic crisis is that banks should hold more common equity in their capital structure. Considering the importance of the banking sector for the health of the economy and being one of the most subjects of the moment, this thesis aims to analyze the behavior of the cost of equity of European banks before and after the crisis of 2008 in order to conclude if there was an increase or a decrease of this metric and what is beyond its behavior.

The cost of equity is one of the most important metrics investors need to consider when investing in a company. This metric can measure how much return a company needs to generate to keep its shareholders invested in the business and raise extra capital when required to keep operations ongoing. It is considered one of the most critical numbers for both investors and regulators, and bank managers. It provides a performance measure, and it is used as a hurdle rate for capital budget decisions. Having this said, the cost of equity plays an essential role in Finance, and in this case, in the banking sector, since it empowers investors, regulators, and bank managers to make important decisions. Thus, this study's motivation was to carry out a rigorous analysis using the best possible methodology to achieve reliable results.

Considering that the aim of this project, as the title suggests, is to compute the cost of equity, these estimates will be generated by the Capital Asset Pricing Model (CAPM), which the Federal Reserve System has used as its sole methodology since October 2005 (Barnes & Lopez, 2006). The CAPM implies that investors require a firm-specific premium for holding a company's stock, so this model assumes that all the investors compose their portfolio based on a trade-off between the expected return and the return variance of their portfolio (which give us the level of risk). Our focus on the CAPM is motivated by its widespread use in practice.

To achieve this project's final goal, and besides using the CAPM model, we use panel data to estimate the model and get the results. The development of econometric modeling techniques, advanced statistical methods and computer applications of data processing contributed to the appearance of panel data analysis. Panel data regression was firstly presented by F. Lazarsfeld, in the 1940s, in longitudinal studies of sociological problems.

Panel data econometrics are usually applied to microeconomic studies, like the one spoke before. However, it has become progressively common to use it in the macroeconomic field, as it is used to pool individual time series (companies, countries, industries) and analyze them simultaneously. This methodology, aside from being used to model or explain why individual units behave differently, is also used to model why a particular unit behaves differently at different periods.

The fundamental question we try to answer with this work is: If banks are expected to hold more common equity in their capital structure, how much will this extra equity cost?

Despite the importance of the cost of equity, most empirical corporate finance literature excludes banks and states that the role of leverage, regulation, large off-balance-sheet activities, and other factors are different in this sector. Consequently, only a handful of studies estimate the cost of equity for the banking sector outside the United States. Maher Asal, Professor at University West, conducted a study in 2015 about the cost of equity for the banking sector and used data from the Eurozone, United States of America, United Kingdom, Sweden, and Switzerland for the period 1999-2014. Asal applied a dynamic panel GMM model, containing fixed effect and a multi-factor asset pricing framework to explain the variation of the cost of equity across banks in terms of risk factors including bank size, leverage, business cycle, and regulations. He found out that a higher leverage ratio, an increase in the capital requirement, and regulation results in a rise in the cost of equity in the banking sector.

The present study is subdivided into chapters so that there is a logical sequence of all the theoretical and empirical analysis carried out. This study is primarily composed of a set of information regarding the post-crisis period and the financial regulation implemented during this period. Secondly, we present an overview of the bank's operating environment, and then we do an overview of several studies that have the same goal as ours but use different methods to accomplish it. Chapter 3 is composed of a set of information regarding the cost of equity, the panel data models, and an empirical explication of the CAPM model is presented. The empirical study is then presented to conclude if the cost of equity increased or decreased in the post-crisis period. By the end of this work and based on studies that consider the increase of the capital requirements, leverage ratio, and regulation, we hope to conclude that the estimate of the cost of equity for European banks has increased from the value observed before the crisis.

The adaptation of the banking sector to the post-crisis operating scenario deserves constant attention. So, we hope that this work provides a useful resource by documenting the state of the cost of equity before and after the 2008 financial crisis and the adaptation of banks to an ongoing structural change, providing, therefore, a starting point for further in-depth analysis.

2. Literature Review

The present chapter offers some insight and further knowledge of the topics addressed in this project. After going through several articles, publications, and books, it was selected and summarized the most appropriate information that enables the reader to understand better the post-crisis period and financial regulation implemented after it, the banks' operating environment, and the three main possible approaches used to compute the cost of equity.

2.1. Post Crisis Period and Financial Regulation

The global financial crisis of 2007-09, the ongoing Euro area growth, and debt crisis, led to great anxieties in financial markets. Despite the massive support programs of central banks in developed economies, banks, especially in the Eurozone, still face deleveraging, bailout, and capital flight problems (Noeth & Sengupta, 2012; Shambaugh, 2012). This ongoing global financial crisis chaos that has spread over the past half-decade (2007-12) has resulted in a significant economic slowdown, which currently plagues the world economy, especially Europe's countries.

Since 2007 banks have been suffering from pressure on both sides of banks' balance sheets. As stated in the study of Buch & Dages (2018), the development and improvement of economic data in the United States and in the main emerging countries were not sufficient to compensate for the euro area's economic weakness, which could have led to a sustained recovery-the past decade was a challenge for the banking sector, bringing about significant structural changes in the sector. Technological changes have increased non-bank competition, and globalization results are still difficult to capture by the banking system, while fintech innovations can be a competitive threat to some banks or banking business lines.

Regulators have responded to the crisis by creating more reforms, such as the Basel III, and enhancing supervision. These reforms aimed to increase banks' resilience through more reliable capital and liquidity buffers, strengthen, therefore, bank flexibility to adverse shocks. These measures aimed to reduce the probability of default of large internationally active banks to a lower level, thus reducing the impact of bank failures on the economy and taxpayers through better recovery and resolution regimes. These reforms were accompanied by more intense banking supervision, mainly for banks of systematic importance. One such adjustment is the extensive and stricter use of the supervisory stress tests used to supervise banks and other large financial institutions. In recent years, these efforts to strengthen the eurozone's financial system have made some progress. Although European Union banks remain more leveraged than their American counterparts, they have lowered their leverage. They are much better capitalized now than before the crisis (according to the European Central Bank statistics, the aggregate Tier 1 ratio for the eurozone, in the second quarter of 2019, stands at 15,55%).

As already mentioned before, one of the main problems at the heart of the financial crisis, which still haunts Europe, was a growing fear of the quality of bank balance sheets, with several banks having assets exceeding their country's GDP. By adapting to this new operating scenario, banks have been reevaluating and adjusting their business strategies and models, including their balance sheet structure, cost base, financial activities, and geographic presence. In the study by Buch & Dages (2018), they conclude that banks have reduced risk by switching to more stable and less complicated finance sources, which bring less risk to banks.

According to Simon Lewis (2018:1), chief executive of the Association for Financial Markets in Europe, "*banks are now better capitalized, better managed, with more pre- and post-trade transparency. (...). There is also much more global regulatory information sharing and coordination. As we look back over the last ten years, it is important to recognize that much progress has been made on the 'too big to fail' problem*." There is now an effective bank resolution regime in place, which makes banks less likely to fail, and when they do so, any losses are expected to be carried by bank investors rather than taxpayers. Nowadays, authorities have more power to deal with a failing bank than ten years ago, and they continue to build buffers to deal, eventually, with liquidity and solvency problems. An example was the breakdown of Spain's fifth-largest bank, Banco Popular, in 2017. Financial markets and regulators answered calmly to the bank's failure, showing that the mechanisms created to solve this kind of problem at the beginning of the financial crisis crash are working well (Lewis, 2018).

The crisis exposed the banking system's significant weakness and the prudential framework made until then, which eventually led to excessive lending and risk-taking unsupported by adequate capital and liquidity buffers (Buch & Dages, 2018). In result, the new regulatory framework of Basel III, settled by the Basel Committee on Banking Supervision in response to the financial crisis of 2007-09, requires banks to hold a higher proportion of equity capital requirements which is pointed out as an essential determinant of the cost of equity in the banking sector. "*The key goals of these reforms have been to increase banks' resilience through stronger capital and liquidity buffers, and reduce public subsidies and eventually lessen the impact of bank failures on the economy and taxpayers through enhanced recovery and resolution regimes*" (Buch & Dages, 2018:1).

The era since the beginning of the global financial crisis has brought uncertainty and structural changes in the banking sector, as already mentioned. These changes were especially felt by the countries directly impacted by the crisis, where there is a decrease in banking sectors relative to economic activity. Given this new reality, banks had to adjust, and they have taken actions in response to the experience of the crisis and the post-crisis operating environment. Worldwide, banks have reevaluated and changed their business strategy as they reoriented their businesses, moving away from their typical trade activity and more complex activities towards less capital-intensive activities.

2.2. The Basel Guidelines

As a resolution for the financial crisis, the Basel Committee on Banking Supervision published in December 2009 a set of proposals to complement and strengthen the global capital and liquidity resolution proposed in Basel II, to create a more stable banking system.

Basel III extends what has been done by Basel II, raising the quality and quantity of the regulatory capital base and enhancing the risk coverage of the capital framework.

The leverage ratio plays a vital role by serving as a backstop to the risk-based capital measures, providing extra protection against banks' risk exposure.

The regulatory capital imposed by this new set of proposals aims to absorb losses that a financial institution does not expect to make. The capital can be divided into two main types: the one that guarantees that the institution keeps its activities and prevents insolvency, and the other that makes sure that the depositors and senior creditors get repaid in case of bankruptcy.

What concerns banks about this new Basel Accord is the level of the new requirements and the changes in the definition of capital. So, the critical question is: What is the main difference between Basel III and Basel II? The difference between these two accords is in terms of what is countable as eligible capital under the different Tiers. The Tier 3 capital instruments of Basel II, which were used to cover market risks, are abolished. The Tier 2 capital instruments are composed mainly of undisclosed reserves and subordinated debt, which are not substantially changed, suffering only a decrease in their percentage. Tier 2 instruments must captivate losses before depositors, and general creditors do. The Tier 1 capital instruments are divided into Common Equity Tier 1 (CET1) and Additional Tier 1 (AT1). Common Equity Tier 1 capital (CET1) is considered to be the highest quality of regulatory capital since it absorbs losses as soon as they occur. The additional Tier 1 capital also absorbs losses on a going-concern basis, even though some AT1 instruments do not meet all the criteria for CET1 (Bank for International Settlement, 2010). AT1 involves continuous capital instruments, so there is no fixed maturity, such as preferred shares and high contingent convertible securities.

The total available regulatory capital is the sum of these two elements - Tier 1 capital, containing CET1 and AT1, and Tier 2 capital. Each group has a specific set of norms that capital instruments are mandatory to meet before their enclosure in the respective category. It is required that banks uphold a minimum level of CET1, Tier 1, and total capital, with each level set as a fraction of risk-weighted assets.

2.3. Impact of Regulation

To obey the new regulatory framework of a higher capital ratio, banks needed to increase their capital. As a result, banks can take on larger risks and may suffer large losses before the supervisor can detect them. As demonstrated by Berger, Herring, & Szeg (1995), the capital ratio can also be an incentive for banks to hold less equity than it would absent regulation, because they can take advantage of the so-called safety net, where there is a system of protection for bank customers provided through federal legislation.

In 2010, the committee on banking supervision conducted a quantitative impact study of the new Basel III framework. This study provides bank data collected by national supervisors during the period 2004-2009. A total of 263 banks from 23 Committee member jurisdictions were analyzed to compute the exercise. The study was separated into two groups: Group 1 banks are banks well-diversified and internationally active with Tier 1 Capital over €3 billion EUR. All other banks are Group 2 banks (BCBS, 2010a). The study was conducted based on comparing the banks' capital positions with the current regulatory framework (at the time Basel II) to the positions that would have been if the new rules were in place (Basel III rules). Considering all changes proposed by Basel III, the common equity Tier 1 for Group 1 banks would be, on average, 4,9%, and for Group 2 7,1%. The study predicted that the overall Tier 1 capital ratio would decrease from 10.3% to 7.6%, and the total capital ratio would decline from 13.1% to 10.3%.

Benjamin Cohen (2013) concluded that banks in advanced economies, to accomplish what has been proposed by the Basel Accord, have reduced dividend payouts while emerging economies have enjoyed high earnings and asset growth, increasing their capital ratios. Besides that, as a result of the higher proposed requirements, banks do not seem to have cut back suddenly on asset or lending growth. Nevertheless, one fact that points out for the importance of solid bank balance sheets is that the ones with higher capital ratios at the beginning of the process or strong profitability afterward tend to grow more than other banks.

Mr. Nout Wellink, a Dutch economist and former central banker, said that "*the Basel III capital and liquidity standards will gradually raise the level of high-quality capital in the banking system, increase liquidity buffers and reduce unstable funding structures. The transition period provides banks with ample time to move to the new standards in a manner consistent with a sound economic recovery while raising the safeguards in the system against economic or financial shocks*"(BCBS, 2010b:1). The evidence of the literature suggests that most banks worldwide have achieved most of the adjustment to date, and we have been experiencing more financial stability and more sustained economic growth. However, the process of adjustment to Basel III is not yet complete.

2.4. An overview of banks' operating environment during the crisis

It all started in 2001, when the United States economy experienced a short-term and smooth recession. Although the economy survived terrorist attacks (such as 9/11), the exploding of the dot-com bubble and the accounting scandals made the appearance of the recession inevitable. The Federal Reserve, to keep recession away, decided to lower the Federal funds rate from 6.5% in May 2000 to 1.75% in December 2001. This dramatic fall in the fund's rate created a flood of liquidity in the economy. As a result, people who had no income, no job, and no assets came to pursue loans and buying houses, which eventually lead to an appreciation in home prices. This easy credit environment and the upward spiral of home prices made investments in higher-yielding subprime mortgages look like suitable investments. Since this was not enough, in June 2003, the Fed lowered interest rates to 1%, the lowest rate in 45 years, making people get even more loans. By 2004, the interest rates started the decline, and United States homeownership peaked at 70%, indicating the beginning of the "Great Recession" (Singh, 2020).

The Great Recession of 2007-08 and the ongoing Euro area sovereign debt crisis, which started in early 2010, have led to a significant economic slowdown that plagues the world economy, especially in European countries (Noeth and Sengupta, 2012). Although central banks, in advanced economies, have conducted massive support programs, "*banks still face a challenging operating environment, which has been reflected in repeated rating downgrades, widening funding spreads, and declining equity prices*" (Chan-Lau, Liu, & Schmittmann, 2013:1). In Europe, the crisis started to reveal itself on August 9 of 2007, when the European Central Bank (ECB) injected €95 billion into the banking system because there was a complete evaporation of liquidity of some market segments following BNP Paribas' suspension of three of its investment funds. Their investors could not take money out of their funds since the company could not value the assets in them, i.e., it was no longer possible to value the underlying assets of each fund fairly, which generated complete evaporation of liquidity of the market. One year later, Lehman Brothers fell, revealing the great recession (Tannenbaum et al., 2018).

These events made European banks suffered tremendously. European banks were more undercapitalized than their American counterparts and faced liquidity problems. Unlike the U.S., the European Union's (EU) answer to the crisis was inefficiently caused by a complex economic governance structure. "*On the fiscal side, the eurozone was unable to use counter-cyclical* *spending to buffer the economic aftershocks of the crisis. In many countries, years of unsustainable government policies created huge deficits and high debt levels*" (Tannenbaum et al., 2018). According to Tannenbaum et al. (2018), countries like Portugal, Greece, and Ireland were at the edge of bankruptcy and needed immediate help. On the other hand, countries like German, which always had a strong fiscal position, have been hesitant to extend themselves for the common good.

As stated by Shambaugh (2012), banks typically have short-term liabilities, known as deposits, and at the same time, long-term, illiquid assets (loans), which leave them exposed to a bank run. As we know, the market is not perfect, which means that the information is imperfectly shared with depositors and other creditors, and eventually, this can result in a feeling of distrust, by these individuals, for not knowing if a bank is solvent or not. This feeling can lead them to withdraw their funds if they fear a problem, leaving banks without any liquidity. So, banks can face two problems: the first one is of liquidity, where banks are solvent but cannot get or retain funds because of uncertainty regarding their balance sheets, and the second one of solvency, where banks do not have assets, liquid or illiquid, of enough value to pay their creditors in full.

Buch & Dages (2018) reported that the period before the financial crisis was one where the economy was mostly grown, where the banking system assets, credit, and profits grew faster than economic activity. In 2007, liquidity problems started to emerge in both the United States and Europe, preceding the decline of the United States' home prices and uncertainty about the quality of assets tied to the United States mortgages. As a result, banks in both countries faced significant losses, and borrowing has become more difficult since people began to increase uncertainty about their assets' quality. The crisis revealed significant weaknesses in the banking system because of a lack of supervision by central banks and relaxing lending conditions, leading to excessive lending and risk-taking that were unsupported by adequate capital and liquidity buffers.

Although pre-crisis developments in the banking sector were at the heart of the crisis, other factors contributed. The inadequate bank regulation and supervision in many countries, the misaligned in the implicit government support of banks and the increasing leverage in the non-financial sector contributed to the appearance of the so-called Financial Crisis (Buch & Dages, 2018). Importantly, the banking sector's deleveraging in the real economy was more strongly felt in Europe than in the United States. United States companies usually have direct access to the capital market, while European companies rely more on intermediated finance, like banks (Financial, 2018). Moreover, the fact that European companies are more likely to have long-term relationships with their banks may intensify deleveraging's real costs, as companies involved in these credit relationships have difficulty switching banks (Shambaugh, 2012). Additionally, European banks not only have higher leverage and higher loan-to-deposit ratios but failed to reduce these variables as U.S. banks have done.

2.5. Past research on the cost of equity

Although the cost of equity is important, this metric's measurement is, in general, one of the most challenging and controversial matters. The cost of equity is an expected return rate that cannot be directly observed and extracted from the market; thus, three main approaches have been used to measure it. The first one uses the realized return, measured as the return on equity (ROE) or Price/Earnings ratios, as a proxy of the cost of equity or expected return (Maccario et al., 2002; Zimmer & McCauley, 1991). The second approach is the CAPM (Barnes & Lopez, 2006; Buch & Dages, 2018; Green, Lopez, & Wang, 2003; King, 2009; among others). The third and the most commonly used method, in recent literature, is the multi-factor model (Asal, 2015; Stiroh & Schuermann, 2006).

Regarding the first approach, Zimmer & McCauley (1991) estimated the real cost of equity (measured as real after-tax adjusted profit on the market price of equity) for 34 international banks from six countries over the period 1984–90. They used the cost of equity as a proxy by using the return on equity (ROE). To make reported earnings of banks from different countries comparable, they made four adjustments to stated profits: an adjustment for the differential treatment of developing country debt, an adjustment to impose equity accounting on shares held by Japanese and German banks, an adjustment for the interaction of growth and inflation with banks' net nominal asset position, and an adjustment for discrepancies between stated depreciation charges and economic depreciation. Their final results in terms of country averages of banks' cost of equity, summarized in Table I, show that between 1984 and 1990, German and Japanese banks enjoyed a low cost of equity, and the United States, United Kingdom, and Canadian banks confronted a high cost of equity.

Table 2.1. Bank real cost of equity estimates

Countries	***1984-90***
Canada	10.3%
France	10.3%
Germany	6.9%
Japan	3.1%
United Kingdom	9.8%
United States	11.9%

Source: Adapted from Zimmer & McCauley (1991)

Zimmer and McCauley's empirical analysis raises three methodological problems. The first two problems are a consequence of using actual reported earnings as a proxy for expected sustainable earnings. So, if investors expect an increase in the bank's profitability, using the current profit rate, we underestimate its real cost of equity since investors are paying up for earnings not yet in evidence. Zimmer and McCauley (1991:37) argue that growth in profits is different from growth in profitability because while a "*bank's profits may grow simply because a bank reinvests a high proportion of its earnings, growth in profitability requires more earnings from a given amount of capital*." This difference should be the result of a change in market structure, a change in the cost of the structure, or other fundamental changes that are difficult to capture. Growth in profits is indeed different from growth in profitability, but it is not certainly true that equity investors rarely expect changes in profitability. An example of expected growth in profitability is that a bank with one or more consecutive years of negative reported profits has a favorable market capitalization.

Moreover, the use of actual reported earnings gives rise to the problem of profits cyclicality. Thus, both these problems can be solved using earnings forecasts produced by banks' equity analysts instead of actual reported ones as proxies for market expectations. The third identified problem of this empirical analysis conducted by Zimmer and McCauley (1991) is the use of an identical tier 1 ratio for all banks from different countries considered in the sample. Since the costs of debt and equity for a company depend on its capital structure, estimating the cost of equity separately and its capital ratio represents a violation of Modigliani and Miller's proposition I, which states that the value of the firm is independent of the percentage of debt or equity in its capital structure, so that the choice of capital structure is irrelevant for maximizing the value of the firm. I.e., a higher cost of tier 1 (equity) could be the result of a lower-tier one ratio, as a higher cost of debt for non-financial companies could be the result of higher leverage. The solution to this problem is using the actual tier 1 ratio to estimate a bank's cost of capital (Maccario et al., 2002).

One of the primary objectives behind the Basel I Accord, created in 1988, was to level the international playing field, enhancing, therefore, financial stability across countries by improving supervisory knowhow and the quality of banking supervision worldwide. Although evaluating the contribution of the Accord remains a challenging task since there many factors involved, which is clear is that there are some relevant cross-country differences in the cost of equity capital between internationally active banks capable of undermining the effectiveness of the current and future evolvement of the Accord in pursuing this goal. Considering this issue, Maccario et al. (2002) decided to investigate the cost of equity for the non-US significant banks, from twelve countries for the 1993-2001 period, using a dividend discount model (DDM) approach. They estimated the cost of equity for the banking sector, defined as the inverse of price earning (the earnings yield) using earning' forecasts rather than historical earnings. They took three main conclusions out of this study. The first one is that the estimated G-10 countries' significant banks' average cost of equity has been decreasing from 1993 through 2001. Second, the differences between the cost of equity of the considered countries have been steadily decreasing between 1996 and 2002. Lastly, they also found out that the estimated costs of equity of individual banks are strongly related to both microeconomic and macroeconomic variables. The main conclusion of this study is that the banks located in Sweden, Netherlands, and Canada face the highest cost of equity, and Japanese and German banks the lowest. One of the implications that this approach brings is the fact that more profitable banks face a higher cost of equity because the authors consider analyst forecasts as the best estimate for the next year's earnings, which makes earnings to grow at the same rate as the economy, and a fixed proportion of earnings is rewarded as dividends. A direct consequence of this approach is that it is too sensitive to the inputs since the cost of equity for each country is strongly related to microeconomic and macroeconomic variables. Consequently, its adaption as a performance measure may result in a distortion of shareholder value.

To incorporate risk into the cost of equity, the model commonly used to estimate it is the Capital Asset Pricing Model (CAPM). A report released in 2013 by the Association for Financial Professionals (AFP), which allows companies to compare techniques against those of other organizations, discloses that the CAPM remains the most commonly used by practitioners and financial advisers to estimate a firm's cost of equity. Additionally, a study conducted by Stiroh and Schuermann (2006) examined the common factors that drive the returns of U.S bank holding companies from 1997 to 2005 by comparing a range of market models from a basic one-factor model (CAPM) to a nine-factor model that includes the standard Fama-French factors and additional factors, such as interest and credit variables. They conclude that the market factor (used in the CAPM approach) is the only risk factor that is significant in all considered years. In other words, market returns are the most critical factor for bank returns, so the CAPM is enough to estimate a firm's cost of equity since many interest rate-related factors, thought to be relevant for understanding banks returns, are merely informative and do not have statistical significance, and this is why we will apply the CAPM model.

Following the CAPM approach, King (2009) estimated the real cost of equity for banks in six countries (France, Canada, Germany, Japan, the United Kingdom, and the United States) from 1990 until 2009. The CAPM estimates were based on a constant equity market risk premium for each country based on its long-term average, where the expected returns are a function of risk-free rates and a bank-specific risk premium. King started by calculating monthly returns on the equity index and individual stock using month-end values and then subtracting the monthly yield on a risk-free instrument to obtain ex-post excess returns. The study adopts the approach of running rolling regressions using the past 60 months of observations to obtain time-varying CAPM betas estimates from 1990 to 2009. The primary assumption here is that history is the best, even though undoubtedly imperfect, guide to forecast. In this study, the bank-specific equity premium is equal to the product of the CAPM beta and a country's historical equity market risk premium. After this computation, the cost of equity is simply the sum of the risk-free rate and the bank-specific equity premium. The annual yield on a 10-year government bond is the risk-free rate since this longer maturity approximates a shareholder's investment horizon. Lastly, to obtain a monthly estimate of the cost of equity for each country's banking sector, the banks' monthly estimates in the considered countries are averaged on an equally weighted basis. King found out that the real cost of equity decreased steadily across all countries except in Japan between 1990 and 2005, but then it rose from 2006 onwards. He affirms that the main contributor to this phenomenon is the fall in the banking sector risk premium, which is the product of the CAPM beta and the historical equity market risk premium. The author believes that the fall in the risk premium is due to the decline in the beta of bank stocks, revealing the lower covariance of bank stock returns and market returns, showing that the sensitivity of banks returns to market movements (positive or negative) has diminished. This study supports the famous theorem of Modigliani-Miller (MM) (1958) "*maintained that an increase in the cost of capital caused by a higher proportion of equity would, under some assumptions, be offset by a decrease in the expected rate of return by investors*" (Asal, 2015:70). Consequently, this effect counterbalances the additional cost of a higher amount of expensive equity capital, in which the overall cost of capital remains unchanged.

Recently, Committee on the Global Financial System released a report by a Working Group led by B Gerard Dages (from the Federal Reserve Bank of New York) and Claudia Buch (from Deutsche Bundesbank) (2018) examining tendencies in bank business models, market structure and performance over the past decade, and evaluated their implications for the stability and efficiency of banking markets. Their study estimated the cost of equity for 75 globally active banks using the CAPM for the 2001–early-2017 period. They found out that the cost of equity for banks has declined from the high values observed at the peak of the crisis, and are at broadly similar levels than in the pre-crisis period, as much higher bank equity betas offset a substantial fall in risk-free rates. Buch & Dages (2018:37) state that "*this could also be due to uncertainty about capital actions for some banks, as any new equity issuance would dilute existing investors' claim* *on future earnings*.". Another possible explanation is the significant decrease in subsidies from the government due to the increase in bank resolution regimes, which could eventually result in the fall of the cost of equity after the crisis. Besides this conclusion about the cost of equity, there are other general conclusions taken by the researchers such as the fact that several indicators and stress test results, computed by them, suggest that banks have improved their resilience to adverse shocks by significantly building up capital and liquidity buffers, as a result of the impositions made by the supervisors. Moreover, advanced economy banks seem to have reduced their exposure to risk by shifting to more stable funding sources and assets that are less complex or have a lower risk.

Maher Asal, Professor at University West, conducted a study in 2015 about the cost of equity in the banking area using data from the Eurozone, United States, United Kingdom, Sweden, and Switzerland for the period 1999-2014. Asal applied a multi-factor framework to estimate the long-run cost of equity, employing a dynamic panel GMM model with a multi-factor asset pricing framework and a fixed effect to explain the variation of the cost of equity across banks in terms of risk factors including bank size, leverage, business cycle, and regulations. Policy variables are considered potential shift variables in the multi-factor model as the weights of the risk factors for a bank can change based on regulation and supervision changes, so the role of regulation on the cost of equity is allowed to vary across time and countries. sal started by measuring banks' performance against the broad markets index for the countries included in his sample. He found out that bank stocks, across all countries, performed strongly between 1999 and 2008, but then they underperformed from 2009-2015, due to the global financial crisis and the ongoing Euro area growth and debt crisis. The equity declines have been more strongly felt in European Banks, which are more exposed to European government securities and could be eventually affected by growth crunches in the Euro area. Asal used a Bank-Factor Model, which is the sum of the Fama-French model with the other nine factors considered relevant by the author to compute the cost of equity. In sum, the study results show that there are five risk factors most important when determining the cost of equity for the banking sector, such as the loading factor, regulations, leverage, tier 1 capital, and the loan-to-deposit ratio. He found out that a higher leverage ratio, an increase in the capital requirement, and regulation results in a rise in the cost of equity in the banking sector, while an increase in loan-to-deposit decreases it.

Given the context, the presented disadvantages of the other approaches in computing the cost of equity, and according to the empirical study conducted by Stiroh and Schuermann (2006), it was considered that the CAPM model is the best approach to reach our goal. Nevertheless, to complete the investigation performed with CAPM, a theoretical explanation of the model and its assumptions are presented.

3. Methodology

In this chapter, we do a theoretical explanation of the models we will apply to obtain the estimates for the cost of equity. We start by explaining how we can obtain the cost of equity and the importance of this metric in the financial field. Secondly, an explanation of the panel data models, and its advantages are presented. Finally, we present the CAPM model and its assumptions.

3.1. Cost of Equity

"*There is no number in finance that is used in more places or in more contexts than the cost of equity capital.*"(Damodaran, 2016:1). The cost of equity is the expected return of investing equity into a business, which can be written as (Damodaran, 2001)

$$\text{Expected Return} = \text{Riskless Rate} + \text{Beta} \times \text{Expected Risk Premium}$$

where the riskless rate should be, for example, the treasury bill rate of a country, the beta should be the historical and the risk premium the difference between the return on the market and the riskless rate. The cost of equity has a strong influence on decisions made by equity investors and the firm's managers. For equity holders, it is the rate of return they expect to earn as a compensation for the risk they took by investing in the firm. For managers, the cost of equity is considered as the rate "*they have to beat in terms of returns on their equity investments in projects*" (Damodaran, 2001:211). Thus, it is the return a company requires to decide if an investment meets capital return requirements.

The cost of equity is considered one of the most critical numbers for bank managers, regulators, and investors alike. According to Asal (2015), this metric provides a performance measure, and it is used as a hurdle rate for capital budget decisions by bank managers. Investors use it as the required rate of return to discount future cash flows, which are crucial to value equity securities when creating their portfolio. Lastly, for regulators, it helps them to provide a benchmark for policies aimed to enhance further risk management and financial stability.

The new regulatory framework, introduced by Basel III of higher capital requirements, was pointed out as an essential determinant of the cost of equity capital in the banking sector and gave rise to several studies to quantify the impacting consequences. However, the empirical evidence for the impact of regulation on a bank's cost of equity is still uncertain. There are two opposite views merged. Asal (2015:70) considers that the first one is built on the theorem of Modigliani-Miller (MM), 1958, which states that "*an increase in the cost of capital, caused by a higher proportion of equity will, under some assumptions, be offset by a reduction in the cost of equity*."

Consequently, the decrease of the cost of equity offsets the increase of the proportion of equity capital in the balance sheet, and the overall cost of capital (the sum of the cost of equity and capital) remains the same. The second approach is the view of the banking and financial industry, which defends that an increase in the proportion of equity, which is the most expensive form of capital, will negatively impact bank's profitability, increasing funding costs which, in turn, leads to a credit crisis and a decrease in economic growth. The researches that support this approach affirm that the initial hypothesis made by MM, which are no taxes, no frictions, and no information asymmetries, does not entirely fit reality because of the nature of banking activity and the size of the off-balance sheet activities in this sector (Asal, 2015).

Banks need to have a reliable and truthful benchmark for performance measures to establish new investments and the optimum capital structure.

3.2. Panel Data

The development of econometric modeling techniques, advanced statistical methods, and computer applications of data processing contributed to the appearance of panel data analysis. Panel data was first introduced by Paul F. Lazarsfeld, in the 1940s, in longitudinal studies of sociological problems.

Panel data - also called longitudinal data - are models that combine cross-section and time-series data, and attempt to follow the same individuals, firms, countries, or whatever, across time (Wooldridge, 2017). The cross-sectional units could be, as referred before, countries, states, commodities, groups of people, or individuals. The spatial dimension pertains to periodic observations of a set of variables that characterize those cross-sectional units over a particular period. The advantage of having repeated observations over the same units allows researchers to specify and estimate more complicated and more accurate models than a single cross-section or time series would do (Verbeek, 2012).

Panel data have been extensively used by both the developed and developing countries. In the United States, two very famous panel sets are the National Longitudinal Survey of Labor Market Experience (NLS) and the Michigan Panel Study of Income Dynamics (PSID). Both these panels were created during the 1960s and have since become the innovative and archetype examples for household panel data collection (Andreß, 2017). Also, in Europe, many countries have their annual reports, like the Netherlands Socio-Economic Panel (SEP), the German Social Economics Panel (GSOEP), the British Household Panel Survey (BHPS), and many others (Hsiao, 2003).

Panel data are usually applied to microeconomic studies. However, it has become progressively common to use it in the macroeconomic field, as it is used to pool individual time series (companies, countries, industries, etc.) and analyze them simultaneously. One of the most compelling advantages of using panel data instead of cross-sectional or time-series data sets is that it allows us to analyze changes in a discrete level (Verbeek, 2012), i.e., I can understand what is beyond a change (rise/fall) of a dependent variable. This methodology, aside from being used to model or explain why individual units behave differently, is also used to model why a particular unit behaves differently at different periods (Verbeek, 2012).

The appropriate use of panel data presents considerable advantages from a research view. For example, in a study about the responsible factors of corporate failure is crucial to use appropriate panel data modeling and estimation. This estimation methodology permits the researcher to control for unobservable firm-specific variables, which can impact an individual firm's probability of failing or even be correlated with the explanatory variables of interest, which can lead to model misspecification. Without any doubt, the proper use of panel techniques can (when compared with equivalent tests based on pooled estimation) significantly reduce the impact of correlated omitted variables on the statistical inference.

The static linear regression model in a panel data setting can be written as

$$y_{it} = \alpha_i + \lambda_t + x'_{it}\beta' + \varepsilon_{it}, \qquad (1)$$

where α_i is the individual-specific effects, λ_t the time-specific effects, β is a $K \times 1$ vector of parameters, and x_{it} represents the *it*th observation on K explanatory variables. All the variables are indexed with an *i* for the individual (*i* = 1, …, *N*) and a *t* for the time period (*t* = 1, …, *T*), since panel data regression models can have cross-section effects, time effects or both effects. The α_i and λ_t can be treated as fixed constants or random. When these two variables are considered as fixed constants, as coefficients of dummy explanatory variables, $d_{it} = 1$, if the observation matches to the ith individual at time t, and 0 if not; whether they are or are not correlated with X'_{it} is not a problem. When α_i and λ_t are treated as random, they become part of the error term and are, commonly, assumed to be uncorrelated with X'_{it}.

3.2.1. Advantages of Panel Data

Panel Data sets possess several advantages over cross-sectional or time-series models since they give the researcher a large number of data points by comprising time-series observations of several individuals. As a result, panel data contain more degrees of freedom compared to other methodologies, which reduces the collinearity among explanatory variables and increases the sample variability compared with cross-sectional data, hence improving the efficiency of econometric estimates (Hsiao, 2003). By including individual and time dimensions into the model, panel data can improve accuracy in estimating regression models and analyze the process of change over time, particularly at the level of the individual. Panel data also allow us to understand and study more complex economic issues that cannot be answered when using cross-sectional or time-series data sets; therefore, we can construct and test more complicated behavioral hypotheses. More importantly, longitudinal data can control the effect of omitted variables by including individual and time dimensions into the model. Additionally, panel data generate more accurate and trustful predictions for individuals' outcomes than other series models because panel data give the possibility of studying and learning about an individual behavior by observing others' behavior and the information on that individual's behavior. So, by pooling the data, we can obtain a more accurate description of an individual's behavior (Hsiao, 2003).

Another advantage of using panel data instead of other sources is that it will provide us more efficient estimators, not only if one is interested in changes from one period to another but also if one is interested in changes on the individual level since the same individuals are repeatedly observed (Verbeek, 2012). Nijman & Verbeek (1992) made a study where they analyze a pure random walk, a pure cross-section, and a combination of both sources. They concluded that when "*exogenous are included in the model, and one is interested in the parameters which measure the effects of these variables, a panel data set will typically yield more efficient estimators than a series of cross-sections with the same number of observations*" (Verbeek, 2012:375).

Moreover, the availability of panel data brings another advantage of reducing the identification problems such as the identification in the presence of endogenous regressors or measurement error, robustness to omitted variables, and the identification of individual dynamics. The last one refers to the often-observed phenomenon that individuals who already experienced some events in the past are more likely to experience it in the future, which may have two explanations: the first one is that the event may change his preferences and constraints, in such a way that in the future is more likely to occur. The second one is that individuals can differ in some characteristics, that cannot be observed, which may influence the probability of experiencing the event (Verbeek, 2012). One problem that complex models arise is that sometimes it is challenging to know all the determinants of the variables used in the analysis, and even when they are known, it can be difficult to measure them. The problem with these omitted variables is that they can be correlated with the included variables in the model. Verbeek (2012) uses the production function, to illustrate this problem, where the management quality cannot be included in the model since it is unobservable. To solve this problem, he decided to introduce a firm-specific effect to the model or, as an alternative, a fixed time effect to capture the effect of all observed and unobserved variables that do not vary over the individual units. Lastly, measurement error is a common problem of social science data, which can result in less reliable statistical inference, and, therefore, all the estimates become inconsistent- systematically different from what they meant to be. Panel data can, sometimes, provide "internal instruments" for regressors that are endogenous or subject to measurement error. These internal instruments are transformations of the original variables that are uncorrelated with the model's error term and correlated with the explanatory variables themselves, and, therefore there is no need for external instruments (Verbeek, 2012).

The combination of cross-section data with time-series data allows us to improve the quality and the quantity of data in specific ways that would be impossible when using only one of these two dimensions (Gujarati, 2003).

3.3. The Static Linear Model

In this section, we discuss the static linear model in a panel data set. We start by present the fixed effects model focusing our attention on the fixed effects estimator (also known as within estimator) and the first-difference estimator. Secondly, we study the random-effects model, and afterward, we discuss the choice between fixed effects and random effects to be applied to our model.

The most significant difference between the fixed effects model and the random-effects model is that the omitted variables may be correlated with the regressors in the model. These omitted variables are often called individual effects or unit effects, and they represent the ignorance about all the other systematic factors that predict y, other than x.

It is important to note that we will use a balanced panel, i.e., it is a panel where the individual i is observed in all periods t, so there are non-observed values.

3.4. The Fixed Effects Model

The fixed-effects model allows the unobserved individual effects to be correlated with the included variables. There are no significant temporal effects in this type of model, but there are significant differences in the cross-sectional level. So, this linear regression model that only focus on individual-specific effects (Verbeek, 2012), in which the intercept terms vary over the individual units i, can be specified as follows:

$$y_{it} = \alpha_i + x_{it}'\beta + \varepsilon_{it}, \qquad \varepsilon \sim IID(0, \sigma_\varepsilon^2), \tag{2}$$

where it is assumed that all x_{it} are independent of all ε_{it}, β is a $1 \times K$ vector of constants and α_i is a $N \times 1$ vector, ε_{it} is the error term which represents the effects of the omitted variables. The value of the dependent variable depends upon K exogenous variables, x_{it}' that differ among individuals in a cross-section at a given point in time and exhibit variation through time. The model can also be written, including dummy variables to allow for the individual effects (Hsiao, 2003), and it is usually referred to as the least squares dummy variable (LSDV) model. That is,

$$y_{it} = \sum_{j=1}^{N} \alpha_j \, d_{ij} + x'_{it}\beta + \varepsilon_{it}, \tag{3}$$

where $d_{ij} = 1$ if $i = j$ and 0 otherwise. N represents the set of dummy variables included in the model. The parameters $\alpha_1, \dots, \alpha_N$ and β (also known as least squares dummy variable (LSDV) estimator) can be estimated using ordinary least squares (OLS) in the equation presented above (Verbeek, 2012). Including dummy variables in the model is just one way of solving the unit effects problem, and as we have so many regressors in the regression model, it is computationally hard to estimate β through OLS. Fortunately, there is a more straightforward way to do it (Verbeek, 2012), i.e., the regression can be written as deviations from individual means to compute the estimator for β. By transforming the data, we can eliminate the individual effects α_i. By writing the regression as deviation from individual means we have

$$\bar{y}_i = \bar{x}'_i\beta + \bar{\varepsilon}_i, \tag{4}$$

where $\bar{y}_i = T^{-1} \sum_t y_{it}$ and so on. The regression can also be written as

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)'\beta + (\varepsilon_{it} - \bar{\varepsilon}_i). \tag{5}$$

This regression model in deviations from individual means does not contain the individual effects α_i. The transformation of the model above is often called the within transformation or the fixed effects transformation, which produces observations in deviation from individual mean. The OLS estimator for β obtained by the within transformation is called the within estimator or fixed effects estimator, and it is similar to the LSDV estimator described before. The estimator has the following formula

$$\hat{\beta}_{FE} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i). \tag{6}$$

If we assume that all x_{it} are independent of all ε_{it}, the fixed effects estimator is unbiased for β.Assuming the normality of ε_{it}, $\hat{\beta}_{FE}$ has a normal distribution. To be consistent, it is required that (Verbeek, 2012)

$$E\{(x_{it} - \bar{x}_i)\varepsilon_{it}\} = 0. \tag{7}$$

If we consider that x_{it} is uncorrelated with the μ_{it}, and eventually that $\bar{x}_{it}$ has no correlation with the error term then

$$E\{x_{it}\varepsilon_{is}\} = 0 \quad \text{for all s, t.} \tag{8}$$

This condition implied to x_{it} is often called strict exogeneity, i.e., a strictly exogenous variable means that the error term is unrelated to any instance of the variable: past, present or future. Since the explanatory variables are independent of all errors, the N intercepts are estimated unbiasedly as

$$\hat{\alpha}_i = \bar{y}_i - \bar{x}_i'\hat{\beta}_{FE}, \qquad i = 1, \dots, N\ . \tag{9}$$

Additionally, considering that ε_{it} is independent and identical distributed (i.i.d) across individuals and time with variance σ_ε^2, the covariance matrix for $\hat{\beta}_{FE}$ is

$$V\{\hat{\beta}_{FE}\} = \sigma_\varepsilon^2 \left(\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right)^{-1}. \tag{10}$$

The sum of the squares residuals of the within estimator divided by $N(T-1)$ will give the consistent estimator for σ_ε^2

$$\hat{\sigma}_\varepsilon^2 = \frac{1}{N(T-1)} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\varepsilon}_{it}^2,$$

with,

$$\hat{\varepsilon}_{it} = y_{it} - \bar{y}_i - (x_{it} - \bar{x}_i)'\hat{\beta}_{it}\ . \tag{11}$$

Under weak regulatory conditions, the fixed effects estimator is asymptotically normal, hence the usual inference procedures like t and Wald test can be performed (Verbeek, 2012).

As referred before, the fixed effects model focuses on differences ‘within’ individuals, modeling why y_{it} differs from $\bar{y}_i$ and not why the last one is different from $\bar{y}_j$. It is important to keep in mind that the parametric assumptions made about β appoint that a change in x (ceteris paribus) can be from a change of one period to the other or a change from one individual to another, having both the same effect. Lastly, when interpreting the results from a fixed-effects regression, it is crucial to be aware *“that the parameters are identified only through the within dimension of the data”* (Verbeek, 2012:379), since the fixed effects estimators depend only on deviations from their group means.

3.5. The first difference estimator

Instead of using dummy variables to eliminate the individual effects of α_i, we can eliminate it by applying the first differences to the equation (2). The results are

$$y_{it} - y_{i,t-1} = \left(x_{it} - x_{i,t-1}\right)'\beta + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)$$

or

$$\Delta y_{it} = \Delta x_{it}' + \Delta\varepsilon_{it}, \tag{12}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$. If we apply OLS to the equation above, we will obtain the following first-difference estimator

$$\hat{\beta}_{FD} = \left(\sum_{i=1}^{N} \Delta x_{it} \Delta x_{it}{}'\right)^{-1} \sum_{i=1}^{N} \sum_{t=2}^{T} \Delta x_{it}\, \Delta y_{it}. \tag{13}$$

To be consistent it is required that

$$E\left\{\left(x_{it} - x_{i,t-1}\right)\left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)\right\} = 0. \tag{14}$$

This condition is weaker than the strict exogeneity condition in (8), since it allows, for example correlation between x_{it} and $\varepsilon_{i,t-2}$ (Verbeek, 2012). It is important to consider that $\Delta\varepsilon_{it}$ exhibits serial correlation when computing the standard errors for $\hat{\beta}_{FD}$. The first-difference estimator is considered less efficient than the within estimator, but for $T = 2$ both estimators are identical. For instance, if both estimators give very different results, it means that there is a misspecification with the model, causing a violation of the assumption considered in (8) (Verbeek, 2012).

If we are focused on estimating the impact of a given treatment upon a particular outcome variable, we should instead choose to use the differences-in-differences estimator. This kind of estimator can be used to determine the impact of any social or economic intervention (for example a change in government policy) (Verbeek, 2012). Consider a fixed effects model

$$y_{it} = \delta r_{it} + \mu_t + \alpha_i + \varepsilon_{it}, \tag{15}$$

where $r_{it} = 1$ if individual *i* receives a treatment in period *t*; or 0 otherwise. μ_t is a time-specific fixed effects. The impact of a treatment can be measured by comparing people who receive the treatment with those who do not, and by comparing people before and after the treatment. Panel data is able to do both. To eliminate the individual effects, we must apply the first differences:

$$\Delta y_{it} = \delta \Delta r_{it} + \Delta\mu_t + \Delta\varepsilon_{it}. \tag{16}$$

Considering that $E\{\Delta r_{it}\Delta\varepsilon_{it}\} = 0$, "*the treatment effect δ can be estimated consistently by OLS of Δy_{it} upon Δr_{it} and a set of time dummies. Because the individual effects α_i are eliminated, this procedure allows correlation between α_i and the treatment indicator*" (Verbeek, 2012:380). This methodology is similar to the one of the fixed effects estimator with the difference that here it is applied the first-difference transformation instead of the within transformation (Verbeek, 2012).

To compute the differences-in-differences estimator let's consider two periods, where individuals may or not receive a treatment in period 2. So $r_{i1} = 0$ for all *i*, while $r_{i2} = 1$ for a subgroup of the individuals. "*OLS in* (16) *corresponds to a regression of $y_{i2} - y_{i1}$ upon the treatment dummy and a constant (corresponding to the time effect). The resulting estimate for δ corresponds to the sample average of $y_{i2} - y_{i1}$ for the treated minus the average for the nontreated*" (Verbeek, 2012:380). For the average of the treated ($r_{i2} = 1$) we have $\Delta\bar{y}_{i2}^{treated}$, and the average of the nontreated ($r_{i2} = 0$) is $\Delta\bar{y}_{i2}^{nontreated}$. So, the OLS estimator, called differences-in-differences estimator, is

$$\hat{\delta} = \Delta\bar{y}_{i2}^{treated} - \Delta\bar{y}_{i2}^{nontreated}. \tag{17}$$

This estimator besides estimating the time difference for the treated and untreated groups also takes into account the difference between the two. Thus, the sample involves four subgroups: the control group before and after the treatment and the treatment group before and after the treatment.

3.6. The Random Effects Model

If the individual effects are strictly uncorrelated with the regressors, then the most appropriate model to be applied would be the random effects model. This model assumes that the α_i are random factors, independently and identically distributed (i.i.d) over individuals, i.e., all factors that affect the dependent variable, but are not included in the regression, are considered in the so-called random error term. (Verbeek, 2012; Wooldridge, 2017). So, we write the model as

$$y_{it} = \beta_0 + x_{it}'\beta + \alpha_i + \varepsilon_{it},\ \ \varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2);\ \alpha_i \sim IID(0, \sigma_\alpha^2), \tag{18}$$

where $\alpha_i + \varepsilon_{it}$ has two components: an individual specific component, which is constant over time, and a second one, which is assumed to be uncorrelated over time. The assumption made is that α_i and ε_{it} are mutually independent and independent of all x_{js} (Verbeek, 2012). So, it is expected that the OLS estimator for β_0 and β from (18) to be unbiased and consistent. The problem is that the composite error term $\alpha_i + \varepsilon_{it}$ exhibits a specific form of autocorrelation, and consequently, the computed standard errors for the OLS estimator are incorrect. Considering that $v_{it} = \alpha_i + \varepsilon_{it}$, the variance matrix of the error term is

$$\Omega_{vi} = V(\alpha_i|X_i) = \begin{bmatrix} \sigma_v^2 & \cdots & \sigma_\alpha^2 \\ \vdots & \ddots & \vdots \\ \sigma_\alpha^2 & \cdots & \sigma_v^2 \end{bmatrix} \qquad (19)$$

where $\sigma_v^2 = \sigma_\alpha^2 + \sigma_\varepsilon^2$. This special case is called the equi-correlated random effects model (Schmidheiny, 2012), because the variance-covariance matrix of the error term is not diagonal, and the diagonal elements of the variance covariance matrix of the error term are:

$$E(v_{it}^2) = E(\alpha_i + \varepsilon_{it}) = E\left(\alpha_i^2\right) + E\left(\varepsilon_{it}^2\right) + 2cov(\alpha_i, \varepsilon_{it}) = \sigma_\alpha^2 + \sigma_\varepsilon^2. \qquad (20)$$

The least squares estimator is still consistent, but it is no longer BLUE. To overcome the problem of non-spherical variance-covariance matrix of the error term, and since generalized least squares is an estimator that takes into account non-spherical disturbances, we can use the generalized least squares (GLS) estimator, instead of using the OLS estimator. The GLS estimator can be written as

$$\hat{\beta}_{GLS} = W\hat{\beta}_B + (I_K - W)\hat{\beta}_{FE} \qquad (21)$$

where

$$\hat{\beta}_B = \left(\textstyle\sum_{i=1}^N (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})'\right)^{-1}\left(\textstyle\sum_{i=1}^N (\bar{x}_i - \bar{x})(\bar{y}_i - \bar{y})\right),$$

is the so-called between estimator for β, I_K is the K-dimensional identity matrix, W is a weighting matrix, which is proportional to the inverse of the matrix of $\hat{\beta}_B$ and $\hat{\beta}_{FE}$ is the fixed effects estimator. The GLS estimator is the combination of the fixed effects estimator and the between estimator and is, consequently, more efficient than either of these two estimators. Besides that, this estimator is more efficient and suitable for the model than the OLS.

If the variance components are known we can apply the GLS, but as this is unlikely to happen which means that the variance components σ_α^2 and σ_ε^2 are unknown, we must apply the feasible GLS estimator (EGLS), "*where the unknown variances are consistently estimated in a first step*" (Verbeek, 2012:383). The EGLS estimator is called random effects estimator, also known as the Balestra-Nerlove estimator, for β.

3.7. Testing for autocorrelation and heteroskedasticity

Several problems can affect panel data models. The two most significant problems that can arise are heteroskedasticity and serial correlation. The existence of heteroskedasticity and serial correlation (autocorrelation) in the error term can be a problem when we apply panel-data models since two problems arise. First, the usual computer output will be numerically misleading, as it will be based on the wrong formula, and finally, standard errors and t-statistics will be incorrect. Thus, it is essential to take this into account and compute the necessary tests to detect these non-spherical disturbances.

The autocorrelation and heteroscedasticity tests in the fixed effects model are relatively simple to do since the model is mainly estimated by OLS, but for the random-effects model is computationally exhaustive and complex (Verbeek, 2012). Fortunately, even if we make the random effects assumption that α_i is i.i.d and independent of the other explanatory variables, we can use the fixed effects model, and the tests that we usually apply to this model can also be used in the random effects situation.

3.7.1. Autocorrelation

Autocorrelation or Serial correlation corresponds to the correlation of the error term with its past values. An example could be

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + \eta_{it}, \tag{22}$$

where $\rho \in (0,1)$ and $\eta_{it} \sim N(0, \sigma_\eta^2)$. This is a case of an AR (1) process, which means that the current value is based on the immediately preceding value. We will only test for the first-order autocorrelation since we are analyzing data from low frequency (annual).

What are the main sources of autocorrelation?

- Omitted variables from the model can cause autocorrelation. The problem with omitted variables is due to misspecification of the model, which may be because either the data is not available or because the effect of the omitted variable on the dependent variable is unknown;
- The incorrect functional and incorrect data transformation of the model can lead to the autocorrelation problem;
- The misspecification of the error term can also be the cause of autocorrelation, since the disturbance term (error) may be autocorrelated because it can contain errors of measurement.

If there is autocorrelation the general consequences are:

- The estimators and forecasting from the OLS method are still unbiased and consistent. But if we have lagged dependent variables as explanatory variables the consistency does not hold anymore;

- The OLS estimators are not the most efficient ones, and therefore they are no longer BLUE;
- The estimated variances for the regression coefficients are biased, and the hypotheses testing are no longer valid, since the value of the standard errors for the coefficients are underestimated compared to its true value, and as a consequence, the value of t and F statistics are no longer valid;
- The value of R^2 is also overestimated, indicating a better fit than it should be.

There are two ways of detecting autocorrelation: the graphical representation and the statistical tests. The graphical representation of residuals and hypotheses testing are the most common ways to detect the presence of autocorrelation. In the statistical tests, the null hypothesis is common to most of them, where it is assumed the absence of autocorrelation.

To detect and test for autocorrelation in panel data models we can apply a modified Durbin-Watson test, in which the null hypothesis under the test is the following

$$H_0: \rho = 0, \tag{23}$$

and considering that $\hat{\varepsilon}_{it}$ represent the residuals from the within regressor (5). The generalization of the Durbin-Watson statistic created by Bhargava, Franzini and Narendranathan in 1983 (Verbeek, 2012) is the following

$$dw_p = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\left(\hat{\varepsilon}_{it} - \hat{\varepsilon}_{i,t-1}\right)^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2}. \tag{24}$$

An alternative test was created by Wooldridge and uses the residuals from a regression in first differences, which removes the unit effects from the model.

3.7.2. Heteroskedasticity

One of the conditions of the Gauss-Markov theorem is the error's homoskedasticity, where the conditional variance of each ε_i is constant and equal to σ^2:

$$var(\varepsilon_i|X) = E(\varepsilon_i^2|X) = \sigma^2, \qquad i = 1,2,3 \dots, n \tag{25}$$

or if we consider the vector of the errors ε,

$$var(\varepsilon|X) = \sigma^2\boldsymbol{I}, \tag{26}$$

where $\sigma^2\boldsymbol{I}$ is the errors' variance-covariance matrix and $\boldsymbol{I}$ represent the n identity matrix.

If this condition is true it means that the diagonal elements of the covariance matrix of ε are the same, which indicates that the variance of all ε_i is the same and the off-diagonal elements of the covariance matrix of ε are zero. Sometimes this condition is not conceivable, the variances do not remain the same and we say that the errors are heteroskedastic.

Possible reasons for heteroskedasticity:

- When an increase of independent variable results in an increase in the variance of the errors. For example, if we consider a model in which the dependent variable is the annual family expenditures on vacations and the annual family income is the independent variable. It is expected that the families with lower income will spend less than the families with higher income on vacations and that the variations in expenditures across these families are small. On the other hand, families with higher incomes will spend more. This difference between families makes the variance of the error term to be higher for families with a higher income than the ones associated with families with lower income.
- If the values of an independent variable range from extremely positive to extremely negative, it can increase the variance of the errors.
- Measurement error can also cause heteroskedasticity. This problem arises from the violation of other condition, which states that the variables are measured without error, i.e., the true value equals the measured value.
- The skewness in the distribution of one or more explanatory variables in the model can also give rise to the heteroskedasticity problem.
- The incorrect functional and incorrect data transformation of the model also causes heteroskedasticity in the model.

Consequences of heteroskedasticity:

- The OLS estimators are still unbiased and consistent since these properties depend upon some other two properties that are not violated in the presence of heteroskedasticity.
- The OLS estimator is no longer BLUE, so the estimators are no longer the most efficient ones because OLS does not provide the estimates with the smaller variance.
- If the errors are heteroskedastic, the estimators for the standard errors are biased and inconsistent. Consequently, the t and F tests can no longer be used because this leads to bias in test statistics (t and F tests) and confidence intervals.

In the case of panel data, we need to test for heteroskedasticity in ε_{it}, and as we did before to test for autocorrelation, we will use again the fixed effects residuals $\hat{\varepsilon}_{it}$. We will apply a variant of the so-known Breusch Pagan test for heteroskedasticity, which when talking about panel data

is usually associated with a Lagrange multiplier test in the random effects model. The auxiliary regression of the test regresses $\hat{\varepsilon}_{it}^2$ upon a constant and the K variables z_{it}, that we think may affect heteroskedasticity. The alternative hypothesis is given by

$$\sigma_i^2 = \sigma^2 h(z_{it}'\alpha), \tag{27}$$

where h is an unknown continuously differentiable function (Verbeek, 2012) with $h(0) = 1$. The null hypothesis is $H_0: \alpha = 0$ against $H_1: \alpha \neq 0$. Under the null hypothesis, the test statistic is $N(T-1)$ multiplied by R^2 of the auxiliary regression. This test will have an asymptotic Chi-squared distribution with J degrees of freedom. If we reject the null hypothesis it means that we have heteroscedasticity and we must look for an alternative estimator or to revise the specification of our model to solve the problem.

3.7.3. Unit Root

The econometric theory for dealing with panel data was first developed for data sets with a small number of time series observations (i) and a large number of groups or individuals (t). However, during the past two decades and with the development of panel data studies, new data sets have appeared where t and i are large, and one of the main features of these recent data sets is that they could have similar orders of magnitude. This new feature can have different implications for theoretical and empirical analysis, and understanding them is very important for economists planning to work on this kind of data. When t is large, there is an obvious need to consider serial correlation patterns in the panel more generally, including short memory and persistent components.

One of the problems that these panel data models can arise is whether the data generating process is stationary, which implies that the distribution of the variable of interest does not depend upon time. When this distribution depends upon time we are in the presence of non-stationarity, which can arise from different sources, but the most important one is the presence of unit roots. One of the main consequences of non-stationarity is that we can have a spurious regression, which can cause a misinterpretation of the estimated results.

In order to properly analyze large i and large t panel data with such characteristics, it will generally be inadequate to appeal to conventional methods of analysis, which are based on large i, small t data configurations.

The tests for unit roots in panels are quite recent, having the major developments in nonstationary panel models occurred since the middle of the 1990s.

The Levin and Lin test, also referred to as the LL test, treats panel data as composed of homogeneous cross-sections, thus performing a pooled data series test. The test procedure is designed to evaluate the null hypothesis that each individual in the panel has unit root properties versus the alternative hypothesis that all cross-section series in the panel are stationary. The null hypothesis is defined as $H_0{:}\rho_i = 0$ for all i, whereas the alternative hypothesis is given as $H_1{:}\ \rho_i$<0.

The Maddala and Wu panel unit root test, referred to as the MW test, is inspired in a Fisher type test that combines P-values from unit root tests for each cross-section i. The procedure recommended by MW does not require a balanced panel and is nonparametric. They suggest using nonparametric Fisher-type tests that approach the unit root test of panel data from a meta-analysis perspective. These tests conduct unit root tests for each time series individually and then combine the p-values of those tests to produce an overall test. This test is similar to the Levin and Lin test, but with the difference that it allows for different first-order autoregressive coefficients and has the same null and alternative hypothesis in the estimation procedure.

3.7.4. Fixed effects or random effects?

The choice between using fixed or random effects is not an easy one. It is important to note that when T is large, the LSDV estimator and the GLS estimator become the same estimator, so the choice between using fixed or random effects is indifferent (Hsiao, 2003). However, when T is small, and N is large, the choice between fixed or random effects becomes more difficult since the estimates of the parameters can be completely different from each other (Verbeek, 2012). Usually, the fixed effects model is applied when we are interested in predictions for a particular country, company, or industry (Verbeek, 2012). According to Hsiao (2003:43), "*the fixed effect model is viewed as one in which investigators make inferences conditional on the effects that are in the sample,"* so we cannot make inferences concerning the population characteristics. On the other side, the random-effects model's goal is not to estimate one true effect, but to estimate the mean of a distribution of effects, and by using the sample, we can take conclusions of the population. As Hsiao (2003:43) refers "*the random-effects model is viewed as one in which investigators make unconditional or marginal inferences with respect to the population of all effects."*

The random effects model states that

$$E\{y_{it}|x_{it}\} = \beta_0 + x'_{it}\beta, \tag{23}$$

while the fixed effects model estimates

$$E\{y_{it}|x_{it}, \alpha_i\} = x'_{it}\beta + \alpha_i. \tag{24}$$

In general, the choice between these two models depends upon the study the investigator is taking, "*the context of the data, the manner in which they were gathered, and the environment from which they came*" (Hsiao, 2003:34).

Hausman (1978) suggested a test that detects endogenous regressors in a regression model (in this case it tests if x_{it} and α_i are uncorrelated). The Hausman test is sometimes described as a test for model misspecification, and it can help the investigator to choose between fixed-effects model or a random-effects model. Assuming that $E\{\mu_{it}x_{is}\} = 0$ for all $s, t,$ so that the fixed effects estimator $\hat{\beta}_{FE}$ is consistent for β regardless of the question of whether x_{it} and α_i are uncorrelated. On the other hand, the random estimator, $\hat{\beta}_{RE}$, is consistent and efficient only if x_{it} and α_i are uncorrelated. The null hypothesis of the Hausman test is that the preferred model is random effects, so if we reject this hypothesis, the fixed-effect model should be the one to use. Although this seems intuitive, we need to have caution with this conclusion since one problem regarding this test is that it can have lower power, which eventually leads to severe pre-test biases (Verbeek, 2012). Power in statistic terms means the probability of rejecting the null hypothesis when the alternative one is true, so the low power of this test means that there is a lower odds of rejecting the null hypothesis when the alternative one is true, so we need to be careful when deciding on rejecting or not the random-effects model.

In this study, we will apply the Hausman test to decide which model is more suitable in our case. Since the European largest banks compose our sample and we would like, by the end of this work, to conclude about the cost of equity of all the European banks, we expect not to reject the null hypothesis and therefore apply the random-effects model, considering we want to make conclusions about the population, and we are not interested in the identification of individual units.

3.8. CAPM

"*The risk and return model that has been in use the longest and is still the standard in most real-world analyses is the capital asset pricing model*" (Damodaran, 2001, p. 163). Capital Asset Pricing Model (CAPM) is an equilibrium theory of risk and return. This theory states that there is a linear relationship between an asset's risk (Beta) and its required rate of return. The firm's cost of equity is the sum of a firm-specific premium plus the return on a risk-free asset, as the risk-free rate captures the time value of money. Based on this concept, the expected return of any stock is

$$E(R_j) = R_f + \beta_{jm} * (R_M - R_f), \qquad (25)$$

where $E(R_j)$ is the expected return on stock j, well-known as cost of equity, R_f denotes the riskless return, R_M is the expected return on the capital market and β_{jm} is known as the CAPM beta and measures the volatility of an individual stock.

This formula expresses the required return of a stock as the sum of the risk-free rate of return and the firm-specific risk premium- $\beta_{jm} * (R_M - R_f)$- which compensates the investor for the systematic risk, also known as market risk, of the financial asset. This firm-specific risk premium is time-varying, since, an individual company's beta can change based on firm-specific factors. The CAPM relationship is most commonly estimated using ex-post excess returns, measured as actual returns less the return on a risk-free asset,

$$E(R_j) - R_f = \beta_{jm}(R_M - R_f) \qquad (26)$$

3.8.1. Assumptions Underlying the CAPM

According to Emery & Finnerty (1991), there are two distinct groups of assumptions regarding CAPM. The first group comprises those assumptions that, if they do not hold, the application of the model could be at risk. The second one contains assumptions that seem to hold in the real world, but if they are violated, it does not affect the model's conclusions. These last ones are usually related to the assumption that CAPM is derived in a perfect market environment, making people skeptical about using it as a model. As stated by Emery & Finnerty (1991: 175) "*(...) scholars have extensively investigated the impact of relaxing each of these assumptions on the conclusions of the model. They have found that very similar conclusions are reached with considerably more complex models*". In other words, the advantage of using more sophisticated models to calculate the cost of equity is almost nil, and it seems that the effort and time required to study each model is not worth it. For this reason, we decided to apply CAPM to our study.

The three critical assumptions of CAPM are the following:

1. The mean and the standard deviation are sufficient statistics: This means that the mean and standard deviation of observed outcomes contain all the relevant information about the security;
2. The market is in equilibrium: it means that the capital market is efficient, that is, the Capital Market Efficiency Principle is applied. If this assumption is violated, the CAPM is no longer supported, but, although it is considered that the model cannot be a perfect

representation of reality, the model is adequate in practice, as it approximates reality and identifies an important determinant of an asset's return (Emery & Finnerty, 1991);

3. CAPM is a 1-period model: All investors plan for the same, single-holding period.

3.9. Empirical Model

A bank cost of equity is derived from the CAPM theory described and picked from the empirical study conducted by King (2009). Panel-data regression is run with the variables as defined in the equation (27) below. To control fixed and random effects, a Hausman test, as presented and explained before, is performed, which shows which model is appropriate.

The empirical models estimated in this paper are as follows:

$$excessstock_{it} = \beta_i + \beta_{jm} excessmarket + \mu_{it} \quad (27)$$

$$E(R_j) = R_f + \beta_{jm} * (R_M - R_f) \quad (28)$$

The variables used in the first equation are monthly excess stock returns and monthly excess market returns. The second equation variables are the cost of equity (as dependent variable), the return on a risk-free asset, the beta computed by the equation (27), and the excess market returns. The variables are defined in Table 2. below:

Table 3.1. Variables

Variable	*Definition*
excessstock	Return of banks' stocks-Yield of the risk-free asset
excessmarket	Return on the market capital-Yield of the risk-free asset

Source: Own production

Since we want to compare the cost of equity before and after the financial crisis, we decided to create two-time windows, the first from 2004-2008 and the second from 2010-2019. To compute the cost of equity using the CAPM, we first estimate the beta for both periods using the equation (27), and then replace it on the second one.

4. Data and Empirical study

In this chapter, we present the data that we used in our study and estimate the model to obtain the estimates of the cost of equity for the European banks before and after the crisis. Besides these analyses, we will also estimate the cost of equity per country and bank betas' evolution per year and analyze them. To finish, we discuss possible explanations for the changes in the cost of equity estimates through the years.

4.1. Data

The data consists of a cross-section of 21 different European banks in 11 countries, and time-series data are stretching from 2004-2008 and 2010-2019 (the 21 banks in the sample are listed in Appendix A., together with the country of origin). The different banks chosen for the sample are retrieved from Standard & Poor, "the largest 100 European banks" (2019). The banks included in the sample were those with sufficient available data for the considered period, which concluded to 21 European banks. The monthly data on banks' stocks and the monthly yield on the risk-free asset and the capital market were obtained from the Bloomberg platform. The monthly yield on the Germany 30-year government bond is used as the risk-free rate, as this longer maturity approximates a shareholder's investment horizon, and it is the only maturity that does not present negative values. To compute the monthly return of the capital market, we used the Euronext 100 index price. The study employed a panel-data approach, combining time-series and cross-section observations. Although not part of the European Union, three countries are included in the sample: the United Kingdom, Switzerland, and Russia. Since still situated in Europe, these observations are assumed not to bias the results significantly.

Table 4.1. Sample banks

Country	*Number of banks in sample*
Belgium	1
Denmark	1
Finland	1
France	3
Germany	2
Italy	2
Nederland	1
Russia	1
Spain	3
Switzerland	2
United Kingdom	4

Source: Own production

4.2. Empirical study

Estimates of the cost of equity for each period are calculated, as already mentioned, by estimating first the betas using the panel-data regression (27), since the CAPM relationship is most commonly estimated using realized excess returns. The panel-data regression (27) is computed using actual returns less the return (yield) on a risk-free asset. The assumption is that the historical returns are a good proxy for expected returns, and monthly excess returns are approximately independently and identically distributed (IID) through time and jointly multivariate normal. The market risk factor (or CAPM beta) is the slope coefficient in the regression (27), and by using this equation, we will obtain time varying CAPM betas.

CAPM estimates are generated as follows. First, we computed monthly returns on the equity index (the Euronext 100 index), and individual stock (for each bank) using month-end values. After this procedure, the monthly yield of Germany's government bond is subtracted from the monthly returns on the equity index and individual stock to generate ex-post excess returns. Next, the monthly excess stock returns for each bank are regressed on the excess market returns for the European stock market index. This data is introduced in R, and we define it as panel data. The next step is to estimate a fixed and a random model for each time window and apply the Hausman test to conclude which model is the most appropriate. Next, a battery of tests is run to test for the existence of a unit root, to see if the data are stationary or not, and to see if there is autocorrelation in the error term and if the errors are homoscedastic or not. This battery of tests is essential to have the most efficient estimators and the more accurate estimates for the CAPM betas.

The European bank-specific equity premium is equal to the product of the CAPM beta and a European historical equity market risk premium. After running the model in R, and deciding the best model for each period, we obtain the CAPM betas for both periods. To compute the cost of equity, we then sum up the risk-free rate to the European bank-specific equity premium. To compute the cost of equity, we considered that the value of the risk-free rate used for both time windows is the annual average yield. The same happens for the expected return on the capital market, which is simply the annualized average of the Euronext 100 index.

4.2.1. Results

As mentioned above, the first step is to generate ex-post excess returns by subtracting the risk-free rate to the banks' stock returns and the market index returns. From these computations, for the excess stock of the first period (2004-2008), we obtain an average of -0.046 and a median of -0.038. Regarding the excess market variable, we obtain an average of -0.044 and a median of -0.033. These results show that, on average, the risk-free rate is higher than the stock returns, which turns the results into negative ones. Concerning the second time window (2010-2019) for the excess stock variable, we obtain an average of -0.015 and a median of -0.013, and for the excess market variable an average of -0.013 and a median of -0.009. The second-period results are less negative than the first one mainly because there was a decrease in the risk-free rate from the first period to the second one, although this decrease was not, on average, enough to bring the values to positive ones.

After building the model to obtain the CAPM beta, a set of statistical tests are performed in R, in order to conclude if we should use a random or fixed model, to detect if the residuals are independent, to detect the presence of a unit root and to see if the statistical inference is valid or not.

The first test we compute is a panel unit root test to see if there is a unit root on our panel data. The panel unit root test we compute is the Levin-Lin-Chu test, which has the null hypothesis of all the panels containing a unit root. So, if we do not reject the null hypothesis, there is a unit root, which leads to the conclusion that the variable is non-stationary. We apply this test on both periods, and our results are:

Table 4.2. Levin-Lin-Chu test results

Period	*Statistic*	*P-value*
2004-2008	-22.714	(<2.2e-16)
2010-2019	-51.526	(<2.2e-16)

Source: Own production

Since we reject the null hypothesis in both periods, the results point for stationarity and there is no unit root. To confirm this result, we decided to apply a second test, the Maddala-Wu unit-root test, which has the same null hypothesis and the alternative one of stationarity. After running the test and obtaining the same results as in the Levin-Lin-Chu test, we conclude that both data do not have a unit root and therefore are stationary. This means we can proceed we our analyses.

Next, we perform the Hausman test, in both periods, to see which model is adequate. After running the test in R, we obtained the following results:

Table 4.3. Hausman test results

Period	*Statistic*	*P-value*
2004-2008	3.9675	(0.1376)
2010-2019	0.49157	(0.9743)

Source: Own production

By analyzing the Hausman test results, and since we do not reject the null hypothesis in both periods (p-value>0.05), we conclude that the preferred model is the one with random effects.

Succeeding the indicated tests above, we did an autocorrelation test to the error term. The autocorrelation test used is the modified Durbin-Watson test, which can detect autocorrelation in the residuals, and its null hypothesis is no autocorrelation in the error term. The results are:

Table 4.4. Modified Durbin-Watson test results

Period	*Statistic*	*P-value*
2004-2010	1.9884	(0.4147)
2010-2019	1.9896	(0.3967)

Source: Own production

Since both p-values are higher than 0.05, we do not reject the null hypothesis, and we can conclude that there is no autocorrelation in the error term in both periods.

Finally, to finalize the set of statistical tests, a homoscedasticity test is applied to our models. The test we used is the Breusch-Pagan test, which has a null hypothesis of the homoscedasticity of the model. The results we obtained are the following:

Table 4.5. Breusch-Pagan test results

Period	*Statistic*	*P-value*
2004-2008	302.41	(<2.2e-16)
2010-2019	3.3162	(0.0686)

Source: Own production

We reject the null hypothesis for the first period, which means that there is heteroscedasticity in this data set. For the second period, we do not reject the null hypothesis, so there is homoscedasticity. Considering that we have heteroscedasticity in the residuals of panel data from the first period, we need to compute the robust standard errors for the considered random model to obtain reliable estimates for this period's CAPM beta.

After computing all the necessary tests to our models and computing the robust standard errors for the first period to deal with heteroscedasticity problems, the CAPM beta estimates are the following:

Table 4.6. CAPM beta estimates

Period	*CAPM beta estimates*
2004-2008	1.2268595
2010-2019	1.3373173

Source: Own production

As said before, the beta is a statistical measure that compares a stock's volatility against the volatility of a large market, which is typically measured by a reference market index. In this case, the European bank's beta is greater than 1 in both periods, which means that the European bank's stocks returns are expected to increase more than the market when the market goes up and to decrease more than the market when it goes down. The volatility of European banks, according to this measure, is higher than the market volatility. The CAPM beta from the pre-crisis to the post-crisis period increased by 9%. According to the CAPM theory, the betas that we estimated should measure the systematic risk of the industry, and both country-specific and global events can explain this rise of the betas from the pre-crisis to the post-crisis period. While the dot-com bubble in 2000 increased the riskiness of the American banking sector and lowered it for other countries (Adam et al., 2012), the global financial crisis, started by the excessive risk-taking by the US banks before the market meltdown in 2007, increased the betas of most banking sectors all around the world at the same time, as we can see here with the European banking sector. One potential explanation of this phenomenon of the increase of betas in the post-crisis periods in most banking sectors can be explained by the degree of co-movement between the European countries in their banking sector betas. Nowadays, there is an international banking linkage that can contribute to the transmission of financial shocks and stress and contribute to similar patterns in the evolution of their systematic risk.

The next step on our computations is to estimate the risk-free rate and capital market return to apply the CAPM formula and reach the value of the cost of equity. We start by computing the annual average of the risk-free rate, and as already mentioned before, we use the monthly yield on the Germany 30-year government bond. To compute the capital market return, we calculate the average returns on the Euronext market, and afterward, to obtain the annual average, we need to annualize the values. From these computations, we obtain the following values:

Table 4.7. Risk-free rate and Capital market return estimates

Period	*Risk-free rate*	*Capital market return*
2004-2008	0.0428	-0.0098
2010-2019	0.0179	0.0884

Source: Own production

From these results, we can see a decrease in the risk-free rate from the first period to the second one, and on the opposite side, an increase in the capital market return. The risk-free rate fell after the financial crisis and stayed low. The capital market return suffered an increase from the pre-crisis period to the post-crisis period, taking into account that the value obtained for the pre-crisis period is negative, resulting from the extremely negative values of 2008, indicating the beginning of the financial crisis.

To compute the cost of equity, we apply the CAPM formula using the values computed above, and we obtain the following results for the two periods:

$$cost\ of\ equity_{2004-2008} = 0.0428 + 1.2268595(-0.0098 - 0.0428) = -0.0217 \tag{29}$$

$$\text{cost of equity}_{2010-2019} = 0.0179 + 1.3373173 * (0.0884 - 0.0179) = 0.1122 \tag{30}$$

We obtained a negative cost of equity for the first period, -2.17%, and a positive number for the second one of 11.22%. Regarding the value of the first period, in the theoretical model, it would be impossible to have a negative value, since in theory the CAPM is used to compute the cost of equity in an anticipation environment, so the prime of the market risk $(R_M - R_f)$ cannot be negative, but since we are not in an anticipation world but instead using historical data this is possible. Then, the negative result of the first period can be explained by the negative value of the capital market return.

The cost of equity suffered an increase from the pre-crisis to the post-crisis period, which is consistent with the findings of the Institute of International Finance (2010) in that a higher leverage ratio, an increase in capital requirement and regulation increases the cost of equity in the banking sector.

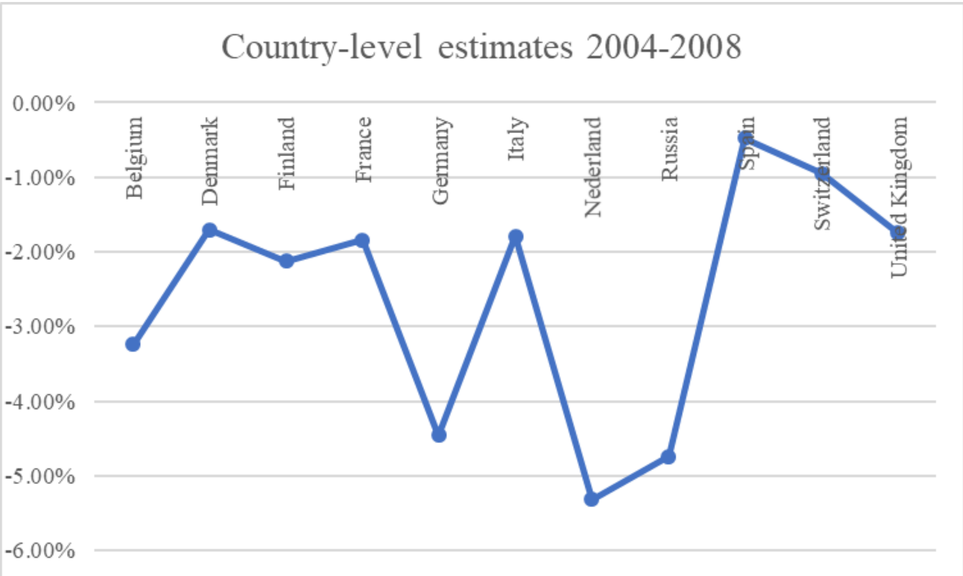
4.2.2. Country-level estimates

The following countries' estimates are estimated based on a panel data approach since there is more than one bank representing each of them: France, Germany, Italy, Spain, Switzerland, and the United Kingdom. Regarding the estimates of Belgium, Denmark, Finland, Nederland, and Russia, they are estimated using a time series approach because there is only one bank representing each country, so it does not make sense to compute them using the panel data methodology.

Graph 6.1 and 6.2 show the yearly estimates of the cost of equity for banking sectors in the eleven countries from 2004 to 2019. From 2004 to 2008, Dutch, Russian, and German banks enjoyed the highest negative values of the cost of equity, followed by Belgium banks. Denmark, Spanish, and Switzerland banks faced the lowest cost of equity due to their countries' lower betas. From 2010 to 2019, Italian, French, and Dutch banks are the ones that present the highest values of the cost of equity, and Denmark and UK banks faced the lowest cost. We have these results because Italian, French, and Dutch banks faced the highest betas compared to the other countries considered in the sample since they were among the economies most affected by the financial crisis.

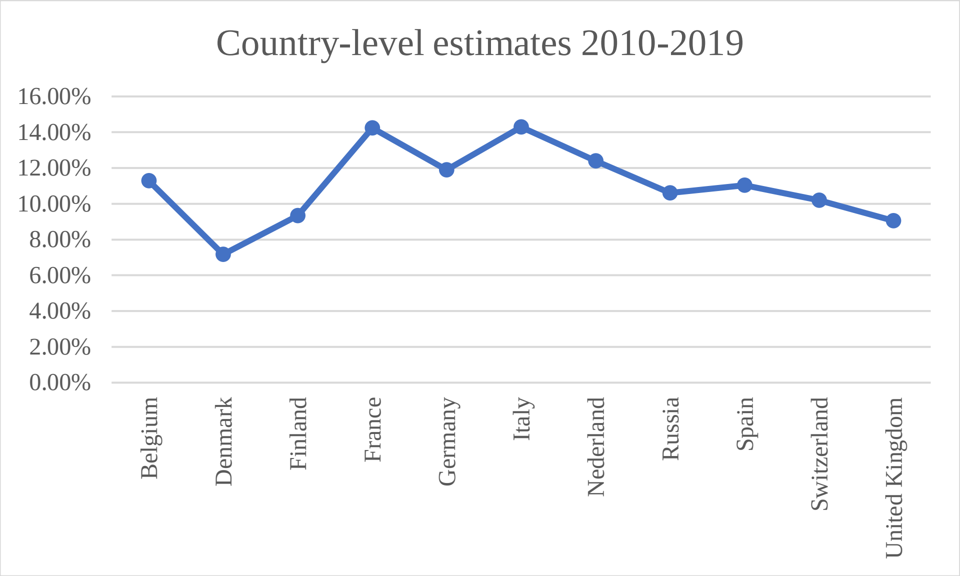
The history showed everyone that the global economic crisis, which started with the Lehman Brothers bankruptcy in September 2008, has, without a doubt, been the most important international event. It profoundly shaped the future of the EU's member states. The Lehman Brothers collapse exposed the gravity of the financial crisis, and it represents the starting point of the economic crisis in Italy. Until then, the American housing market's problems had not affected Italy, and Italian banks and investors had suffered little since Italian financial institutions did not own a large quantity of sub-prime bonds. The problem in Italy started when banks refused to lend money to each other because of a lack of liquidity and uncertainty about borrowers' financial soundness. The liquidity crisis-induced governments to support national banks with loans, and the European Central Bank cut the discount rate, which was the point in which the Italian economy joined the international crisis. A few large banks in Italy and many small and medium-sized banks operate on a regional scale. The crisis touched the larger banks, which lost funds due to the Lehman Brothers crash or found their assets devalued by the stock-market collapse. Apart from the reduction in liquidity, the main problem for Italian banks came from links with Central and Eastern European countries (Di Quirico, 2010).

Moreover, the economies of Italy and France are strongly linked, with annual trade flows of around €50 billion. Importantly, French banks are, by far, the biggest owners of Italian public and private debt, with total holdings of €311 billion as of the 3rd quarter of 2018, according to the Bank for International Settlements, up €34 billion from the 1st quarter of 2018. The relationship between these two countries makes France vulnerable and exposed to an Italian economic and financial slowdown. The Netherlands is the third country that presents the highest value of the cost of equity for the period of 2010-2019, since the Dutch economy and its banking sector are characterized by their connectedness to the international economy, which makes them, also, too vulnerable to any fluctuations on the international markets. For these reasons, Italy, France, and the Netherlands are the countries that present the highest values for the cost of equity.



Graph 4.1. Country-level estimates 2004-2008

Source: Own production



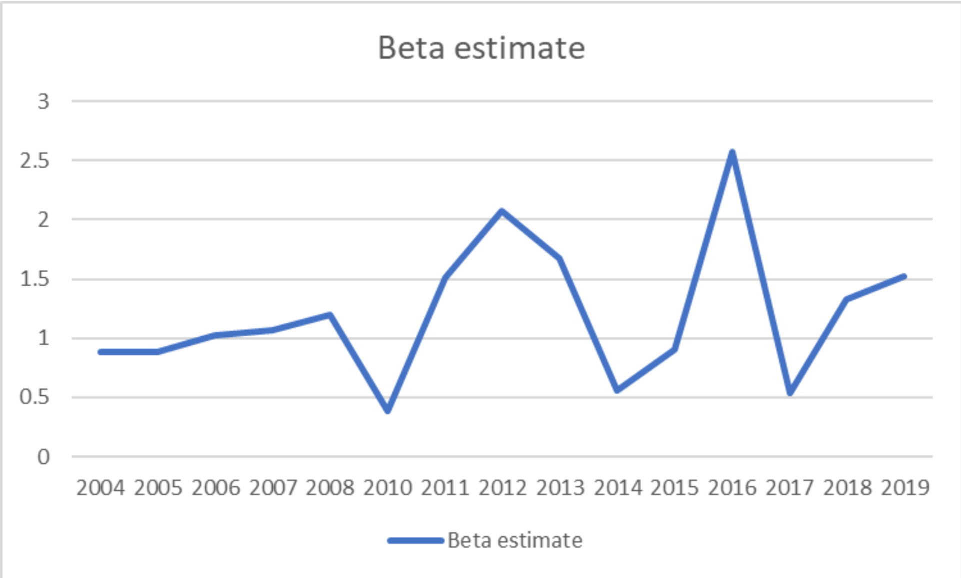
Graph 4.2. Country-level estimates 2010-2019

Source: Own production

4.2.3. Evolution of the estimates of beta per year

The beta estimates for each year are estimated based on a panel data approach, and the necessary statistical tests, indicated before, are performed to obtain the best and reliable estimates.

Graph 3 shows the evolution of the estimates for beta from 2004 to 2019. From 2004 to 2008, the beta of European banks increased from about 0.88 to 1.20, resulting from the long-term dynamics observed in European banking systems since the late 1980s and from the introduction of the common currency (Jens Hagandorff, Kevin Keasey, 2013). From 2006 to 2008, European banks' beta was above the market-neutral level of 1, suffering a significant drop in 2010, reaching the lowest historical beta for the considered period. From 2010 to 2012, it is possible to observe a drastic increase from 0.39 to 2.08, an increase of almost six times more resulting from a perceived risk in the banks' balance sheet emerging from the European crisis of 2011/2012. In 2016 the European banks' beta reached its highest value of 2.58 because of the negative stock price performance of almost every bank in the sample during this year, then it fell drastically in 2017. From 2017 onwards, we see an increase in banks' beta due to the UK referendum held in June 2016, when 17.4 million people voted for Brexit. This announcement was not well received by the market, as the banks' shares were crushed following this news, causing the betas to increase.



Graph 4.3. Beta estimates per year

Source: Own production

4.2.4. What explains changes in the cost of equity estimates?

In this section, we decompose the cost of equity estimates into two parts to explain what can be beyond the changes in the estimates. The CAPM cost of equity can be decomposed into two parts: is the sum of the current risk-free rate and the European bank-specific risk premium.

Under the CAPM, risk-free government bonds, in our case, the Germany treasury bond, provide the benchmark return when investors and managers evaluate an investment in equities. If the risk associated with equities is higher, the investor expects to be compensated and earn a premium over the risk-free rate. The Germany 30-year bond yield has declined from 2004 to 2019, which would, in theory, contribute to a decline in the cost of equity from the first period to the second one. However, from our analyses, we do not see this behavior of the cost of equity mainly because of the Euronext market index's performance. Its low performance during 2008 resulted in negative stock returns, which eventually contributed negatively to the cost of equity estimates of the period 2004-2008.

In the CAPM, the banking sector risk premium is firm-specific, and it rises for stocks with greater sensitivity to market risk. This phenom was what happened to our European bank-specific premium, which was negative for the first period because of the negative stock returns of the market index, and positive for the second one has a result of higher stock performance of the Euronext index. The level of our premium had increased from the pre- to the post-crisis period, making the cost of equity increase from one period to the second one.

The increase in the risk premium is also associated with an increase in the beta estimate of bank stocks. A higher beta shows that the sensitivity of bank returns to market movements (both positive and negative) has increased on average. The European bank beta trend upwards for over the 16 years (Graph 4.3 and Tabel 4.9), which has both a statistical explanation and an economic one. Statistically, betas increase because of either the covariance of bank returns with market returns increases (the numerator) or the variability of the market decreases (the denominator). According to our data, the covariances increase on average over the 16-year period, which leads to an increase in betas. Over the period 2006–08, covariance and variance are sharply lower, with similar variations for both variables, leaving betas relatively unchanged. Economically, the increased covariance of European bank stock returns with market returns reflects the changes in investors' perception regarding bank profitability and riskiness, especially after the beginning of the financial crisis in 2008. Over the recent period, and after the adjustments made in the Basel III Accord bank earnings have been stable, reflecting the growth in new sources of income. The onset of the financial crisis coincided with a rise in European bank beta (Graph 4.3).

European bank beta increased from 2006 to 2008, went up from 0.8836 in 2005 to 1.0219 in 2006, an increase of 15%. European bank beta rose again over 2007 through 2008 when Lehman Brothers went bankrupt. This beta movement is consistent with investors viewing bank stocks as riskier as the crisis progressed, with the risk declining following government and international interventions to support systemically important banks and economies at the end of 2008.

In summary, changes in the cost of equity estimates over time can be explained by variations in two factors: the lower performance of the market index over 2008, making the cost of equity negative, and the increasing sensitivity of bank stocks to market risk as measured by the CAPM beta. Higher betas are explained by a higher covariance of bank stock returns with market returns.

5. Conclusion

The global financial crisis experienced worldwide has had serious consequences for banking activities across the globe, and Europe was no exception. Without any doubt, the Lehman Brothers bankruptcy was the start of something bigger, which forever changed the international economic and financial landscape. This thesis provides an analysis of the cost of equity in the pre- and post-crisis periods for European banks, using CAPM and estimating it based on a panel data approach. The panel data approach allows us to analyze changes in a discrete level, being able to pool individual time series, in this case, banks, and analyze them simultaneously, over two periods of time, and obtain one output for each of them. There are banks from eleven European countries in the data sample, being considered the largest banks in terms of assets, making them a reliable sample of the overall European banks. The analyses of this work focused, as mentioned, in the cost of equity in the pre- and post-crisis periods of the European banks, and after the European analyses, it focused on two others: country-level analyses and beta analyses for each period. The estimates of betas, which are then used to compute the cost of equity for each period and country, are obtained by RStudio.

From our results, we conclude that the cost of equity suffered an increase from the pre- to the post-crisis period, from a negative value of -2.17% to 11.22%. The negative result of the first period comes from the low performance of the capital market index in 2008, which summed up with the risk-free rate of the period contributes negatively to the result. These findings are consistent with the Institute of International Finance (2010), in that a higher leverage ratio, an increase in capital requirement and regulation as a result of the creation of Basel III Accord after the financial crises of 2008, increases the cost of equity in the banking sector, in this case in the European banking sector.

Regarding the results per country, it is possible to conclude that Italian, French, and Dutch banks are the ones that face the highest cost of equity in the post-crisis period. These results are in line with what history has shown us that the global financial crisis shaped the financial future of public and private institutions, especially in Europe, and it was the starting point of the economic and financial collapse of strong economies such as Italy, France, and the Netherlands. The 2008 financial crisis was a turnover for European banks' health, with the cut of the discount rate by the European Central Bank, the lack of liquidity, and the strong link between Central and Eastern European Countries reflected in the years after 2008.

The European bank's beta estimates also suffered an increase from the pre- to the post-crisis period as a result of the perceived risk in the bank's balance sheet emerging from the European crisis of 2011/2012, and the UK referendum held in June 2016, which resulted in the crush of bank’s shares, causing the increase in beta.

We found out that the evolution of the estimated cost of equity has two possible reasons: the Euronext Index's performance in both considered periods and the increase of bank's stock sensitivity to market risk, measured by the CAPM beta. The Euronext Index had a lowered performance during 2004-2008, especially in 2008, which resulted in negative stock returns, which eventually contributed negatively to the cost of equity estimates of the period. The European bank beta trend upwards for over the 16 years has both a statistical explanation and an economic one. Statistically, the covariance between bank returns and market returns suffered an increase over the 16 years, leading to an increase in betas. Economically, the covariance increase reflects the changes in investors' perception regarding bank profitability and riskiness, especially after the beginning of the financial crisis in 2008.

Nowadays, we live again in a time of uncertainty, not only because of the withdrawal of the United Kingdom from the European Union but also from the epic misfortune playing out called Coronavirus. It all started on the other side of the world, just like the financial crisis of 2008, but it has shown us that globalization is not only capable of transport a financial crisis, as we have seen before, but also a disease in this case. In Europe, we saw Italy confronting the first ravages of this virus, which has already affected all countries worldwide, and fears intensify that the economic damage could trigger a far more familiar danger — a banking crisis. This could again be the beginning of a global financial crisis, as Italian banks and their history of accumulated bad loans have always been a central concern, especially in an economy that has not grown in over a decade. Besides, Italian creditors are large enough, sufficiently integrated into the world, and unstable enough to pose a constant threat to the global financial system. Asides that, measures aimed to stop this pandemic can further depress economic activity and contribute to a global recession. This pandemic arrived when private banks were already feeling the pressure to rejuvenate, but Covid-19 has accelerated changes in the expectations of clients, employees, and investors.

Although this research achieved its objectives, there were some unavoidable limitations. First, we thought about doing research-based only on banks from the Eurozone, but we ended up calculating the cost of equity for European banks due to the lack of financial information about the former. Second, due to the Covid-19 pandemic, we had to suspend the project for almost two months, as we needed some data that we were only able to obtain on the university premises, which were closed during that period. Lastly, although the CAPM can explain what can be beyond the changes in the estimates of the cost of equity, we consider that the application of a dynamic panel GMM model with a multi-factor asset pricing framework would suit better to explain the variation of the cost of equity across banks in terms of risk factors, including bank size, leverage, business cycle, and regulations.

Future research on the cost of equity of banks should bear in mind this pandemic of Covid-19, which will eventually have a financial impact worldwide, and the Brexit event. We live in a time when economies are collapsing, and sooner or later, government debt will go up, and international help will be needed to prevent another financial crisis. The future is uncertain, and banks need to stay flexible, given the uncertainty around the current crisis's development. European banks can come out stronger from this period in which we live, leveraging the trust they have built over the years by successfully safeguarding generations' wealth through other crises. However, this is only possible if they act quickly, and as Harry Truman, the 33rd President of the United States, said, "Imperfect action is better than perfect inaction."

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7. Appendixes

Appendix A. Banks on sample

Bank	*Country*
BNP Paribas	France
Crédit Agricole	France
Société Générale	France
Deutsche Bank	Germany
Commerzbank	Germany
UniCredit	Italy
Intesa Sanpaolo	Italy
BBVA	Spain
Banco Sabadell	Spain
Santander	Spain
UBS	Switzerland
Credit Suisse	Switzerland
HSBC	United Kingdom
Barclays	United Kingdom
Royal Bank of Scotland	United Kingdom
Standard Chartered PLC	United Kindom
KBC Bank	Belgium
Danske Bank	Denmark
Nordea	Finland
ING Group	Nederland
Sberbank	Russia

Appendix B. Statistical analyses of the variables

1) For the 2004-2008 period:

```
 excessstock          excessmarket
 Min.   :-0.6662160   Min.   :-0.19172
 1st Qu.:-0.0741590   1st Qu.:-0.05854
 Median :-0.0376238   Median :-0.03345
 Mean   :-0.0459443   Mean   :-0.04364
 3rd Qu.: 0.0001315   3rd Qu.:-0.01430
 Max.   : 0.3715305   Max.   : 0.02044
```

2) For the 2010-2019 period:

```
 excessstock        excessmarket
 Min.   :-0.51769   Min.   :-0.132476
 1st Qu.:-0.06991   1st Qu.:-0.045543
 Median :-0.01332   Median :-0.008681
 Mean   :-0.01489   Mean   :-0.012862
 3rd Qu.: 0.04048   3rd Qu.: 0.015793
 Max.   : 0.46512   Max.   : 0.084331
```

Appendix C. Results for the fixed effects model for the 2004-2008 period

```
Oneway (individual) effect Within Model

Call: plm(formula = excessstock ~ excessmarket, data = pdata, model = "within
")

Balanced Panel: n = 21, T = 60, N = 1260
```

	Estimate	Std. Error	t-statistic	Pr(>|t|)
excessmarket	1.226859	0.038343	31.997	< 2.2e-16 ***

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares:    8.6819
Residual Sum of Squares: 4.7521
R-Squared:      0.45264
Adj. R-Squared: 0.44336
F-statistic: 1023.78 on 1 and 1238 DF, p-value: < 2.22e-16
```

Appendix D. Results for the fixed effects model for the 2010-2019 period

```
Oneway (individual) effect Within Model

Call: plm(formula = excessstock ~ excessmarket, data = pddata, model = "withi
n")

Balanced Panel: n = 21, T = 120, N = 2520
```

	Estimate	Std. Error	t-statistic	Pr(>|t|)
excessmarket	1.33732	0.03717	35.979	< 2.2e-16 ***

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares:    21.477
Residual Sum of Squares: 14.146
R-Squared:      0.34133
Adj. R-Squared: 0.33579
F-statistic: 1294.47 on 1 and 2498 DF, p-value: < 2.22e-16
```

Appendix E. Results for the random effects model for the 2004-2008 period

```
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)

Call: plm(formula = excessstock ~ excessmarket, data = pdata, model = "random
")

Balanced Panel: n = 21, T = 60, N = 1260
```

	Estimate	Std. Error	z-statistic	Pr(>|z|)
(Intercept)	0.0075975	0.0027825	2.7305	0.006324 **
excessmarket	1.2268595	0.0383434	31.9966	< 2.2e-16 ***

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares:    8.7587
Residual Sum of Squares: 4.8289
R-Squared:      0.44868
Adj. R-Squared: 0.44824
Chisq: 1023.78 on 1 DF, p-value: < 2.22e-16
```

Appendix F. Results for the random effects model for the 2010-2019 period

```
Oneway (individual) effect Random Effect Model (Swamy-Arora's transformation)

Call: plm(formula = excessstock ~ excessmarket, data = ppdata, model = "rando
m")

Balanced Panel: n = 21, T = 60, N = 1260
```

	Estimate	Std. Error	z-statistic	Pr(>|z|)
(Intercept)	0.0023117	0.0015725	1.4701	0.1415
excessmarket	1.3373173	0.0371473	36.0003	< 2.2e-16 ***

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Total Sum of Squares:    21.573
Residual Sum of Squares: 14.243
R-Squared:      0.33981
Adj. R-Squared: 0.33954
Chisq: 1296.03 on 1 DF, p-value: < 2.22e-16
```

Appendix G. Results of the Unit Root test for the 2004-2008 period

```
   1) Levin-Lin-Chu Unit-Root Test (ex. var.: Individual Intercepts)

data:  unitroot
z = -22.714, p-value < 2.2e-16
alternative hypothesis: stationarity

   2) Maddala-Wu Unit-Root Test (ex. var.: Individual Intercepts)

data:  unitroot
chisq = 622.69, df = 42, p-value < 2.2e-16
alternative hypothesis: stationarity
```

Appendix H. Results of the Unit Root test for the 2010-2019 period

```
   1) Levin-Lin-Chu Unit-Root Test (ex. var.: Individual Intercepts)

data:  unitroot1
z = -51.526, p-value < 2.2e-16
alternative hypothesis: stationarity

   2) Maddala-Wu Unit-Root Test (ex. var.: Individual
        Intercepts)

data:  unitroot1
chisq = 1800.8, df = 42, p-value < 2.2e-16
alternative hypothesis: stationarity
```

Appendix I. Results of the Hausman test for the 2004-2008 period

```
Hausman Test

data:  excessstock ~ excessmarket
chisq = 3.9675, df = 2, p-value = 0.1376
alternative hypothesis: one model is inconsistent
```

Appendix J. Results of the Hausman test for the 2010-2019 period

```
Hausman Test

data:  excessstock ~ excessmarket
chisq = 0.49157, df = 4, p-value = 0.9743
alternative hypothesis: one model is inconsistent
```

Appendix K. Results of the Autocorrelation test for the 2004-2008 period

```
Durbin-Watson test for serial correlation in panel models

data:  excessstock ~ excessmarket
DW = 1.9884, p-value = 0.4147
alternative hypothesis: serial correlation in idiosyncratic errors
```

Appendix L. Results of the Autocorrelation test for the 2010-2019 period

```
Durbin-Watson test for serial correlation in
       panel models

data:  excessstock ~ excessmarket
DW = 1.9896, p-value = 0.3967
alternative hypothesis: serial correlation in idiosyncratic errors
```

Appendix M. Results of the homoscedasticity test for 2004-2008 period

```
Breusch-Pagan test

data:  excessstock ~ excessmarket
BP = 302.41, df = 1, p-value < 2.2e-16
```

Appendix N. Results of the homoscedasticity test for 2010-2019 period

```
Breusch-Pagan test

data:  excessstock ~ excessmarket
BP = 3.3162, df = 1, p-value = 0.0686
```

Appendix O. Results for the random effects model for the 2004-2008 period after controlling for the heteroscedasticity in the model

t test of coefficients:

	Estimate	*Std. Error*	*t-statistic*	*Pr(>|t|)*
(Intercept)	0.0075975	0.0036612	2.0751	0.03818 *
excessmarket	1.2268595	0.0743542	16.5002	< 2.2e-16 ***

Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1