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Essays on Financial Cycles and Banks' Risk

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PhD in Finance

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Resumo

Esta tese consiste na compilação de três artigos distintos:

A. Medir ciclos financeiros: evidência empírica para a Alemanha, Reino Unido e Estados Unidos da América

Este estudo contribui para a literatura ao identificar a medida mais apropriada para detetar e medir Ciclos Financeiros, à semelhança do Produto Interno Bruto (PIB) para os Ciclos Económicos. Quatro variáveis financeiras são incluídas no estudo: Crédito, Preço das Casas, Preço das Ações e Taxas de Juro. O filtro usado para estimar e extrair os ciclos das suas séries temporais originais foi o do Christiano e Fitzgerald (2003). De seguida, três métodos, nomeadamente o Concordance Index, o Granger Causality Test e o AUROC Test, foram usados para identificar qual das quatro variáveis é a proxy mais precisa e adequada para medir e estimar ciclos financeiros. Em todos os métodos, os resultados apontam para a mesma variável: Preço das Ações. Uma análise comparativa entre o Preço das Ações e o PIB mostra uma capacidade superior da variável financeira para prever crises financeiras e económicas, o que justifica o crescente interesse nos ciclos financeiros por parte dos supervisores e decisores macro-prudenciais. Estas conclusões são robustas para diferentes períodos temporais e processos de filtragem alternativos.

B. Regulação bancária e o comportamento de tomada de risco dos bancos: o papel das instituições políticas

Este artigo investiga se a influência da regulação bancária no risco dos bancos é canalizada através da qualidade das instituições políticas num determinado país, usando dados de painel de 535 bancos de países da OCDE, para o período 2004-2016. Como fatores de regulação bancária consideramos as restrições à atividade, as exigências de capital e o poder de supervisão. Concluímos que o efeito global da regulação bancária no risco dos bancos é condicionado pela qualidade das instituições políticas. Por um lado, restrições à atividade e exigências de capital têm um efeito positivo e estatisticamente significativo no risco dos bancos, sendo este efeito mitigado por melhores instituições políticas. Por outro lado, um maior nível de poder de supervisão tende a reduzir o risco dos bancos, sendo este efeito intensificado na presença de melhores instituições políticas. Os resultados são robustos a diferentes métodos de estimação e diferentes *proxies* para o risco dos bancos e para a qualidade das instituições políticas.

C. **Regulação bancária e o comportamento de tomada de risco dos bancos: o papel da proteção dos investidores**

Este artigo investiga se a influência da regulação bancária no risco dos bancos é canalizada através do nível de proteção dos investidores num determinado país, usando dados de painel de 535 bancos de países da OCDE, para o período 2004-2016. Como fatores de regulação bancária consideramos as restrições à atividade, as exigências de capital e o poder de supervisão. Concluímos que o efeito global da regulação bancária no risco dos bancos é condicionado pelo nível de proteção dos investidores, designadamente verificamos que um maior nível de proteção dos investidores intensifica o efeito individual de cada fator de regulação bancária no risco dos bancos. O nível de proteção dos investidores intensifica o efeito positivo das restrições à atividade e das exigências de capital e o efeito negativo do poder de supervisão no risco dos bancos. Estes resultados são robustos a um método alternativo de estimação e para uma *proxy* alternativa do risco dos bancos. Outros testes de robustez revelam que alguns efeitos da regulação bancária variam conforme a dimensão dos bancos e a existência ou inexistência de um período de crise sistémica bancária.

Keywords: Ciclos Financeiros, Risco dos Bancos, Regulação Bancária, Instituições Políticas, Proteção dos Investidores

JEL Classification: E32, G28

Resume

This thesis consists of a compilation of three separate and self-contained articles:

A. Measuring Financial Cycles: Empirical Evidence for Germany, United Kingdom and United States of America

This study contributes to the literature by identifying the most appropriate factor to detect and measure Financial Cycles, similar to Gross Domestic Product (GDP) for Business Cycles. Four financial variables were included in the study: Credit, House Prices, Share Prices and Interest Rates. The filter used to estimate and extract the cycles from the original time series was the Christiano and Fitzgerald (2003)'s one. Then, three methods, namely the Concordance Index, the Granger Causality Test and the AUROC Test, were used to identify which of the four variables is the most accurate proxy to measure and estimate financial cycles. In all of them, the results pointed to the same variable: Share Prices. A comparison between Share Prices and GDP shows a higher capacity of the financial variable to predict financial and economic crises, which justifies the recent increasing interest of macroprudential policymakers on Financial Cycles. Our conclusions are robust to different time periods and alternative filtering procedures.

B. Banking regulation and banks' risk-taking behavior: The role of political institutions

This paper examines whether the influence of banking regulation on banks' risk is channeled through the quality of political institutions, using panel data from a sample of 535 banks from OECD countries, for the 2004–2016 period. As banking regulatory factors, we consider activity restrictions, capital stringency and supervisory power. We find that the overall effect of banking regulation on banks' risk is conditional on the quality of political institutions. Activity restrictions and capital stringency have a statistically significant positive effect on banks' risk and this effect is mitigated by better political institutions. On the contrary, stringent supervisory power tends to reduce banks' risk and better political institutions reinforce this effect. The results are robust across different measures of political institutions, banks' risk and estimation methods.

C. Banking regulation and banks' risk-taking behavior: The role of investors' protection

This paper examines whether the influence of banking regulation on banks' risk is channeled through the level of investors' protection, using panel data from a sample of 535

banks from OECD countries, for the 2004–2016 period. As banking regulatory factors, we consider activity restrictions, capital stringency and supervisory power. We find that the overall effect of banking regulation on banks' risk is conditional on the level of investors' protection, with investor protection playing the role of reinforcing each of these individual effects. Investor protection reinforces the positive effect of activity restrictions and capital stringency on banks' risk and reinforces the negative effect of supervisory power on this risk. These results are robust to a different estimation method and a different proxy for banks' risk. Additional robustness tests reveal that some of the banking regulation effects are contingent on banks' size and the systemic banking crisis period.

Keywords: Financial Cycles, Banks' Risk, Banking Regulation, Political Institutions, Investors' Protection

JEL Classification: E32, G28

Table of Contents

1. Introduction

This thesis consists of a compilation of three separate and self-contained articles. The first article focus on which measure is the most accurate to define financial cycles. The second and third articles focus on the effect of banking regulation on banks' risk, channeled through political institutions and investors' protection, respectively.

The first article is motivated by the increasing interest of policymakers on financial cycles (FC) after the global financial crisis of 2007-08. This crisis led to a rethinking and re-evaluation of macroprudential policies, with focus on the procyclicality risks of the financial system. Now, the effectiveness of macroprudential policies depends on understanding financial cycles. This re-orientation of policymakers' attention to financial cycles and their features led to an ongoing debate on which measure is the most accurate to define them (Hansen, 2012). Contrarily to business cycles, which have Gross Domestic Product (GDP) as a common measure, financial cycles still do not have a worldwide accepted measure. The goal of the first article is to fill this gap in the literature. Based on the times series from 1960 to 2018 of four different variables recognized by the literature as potential proxies of financial cycles, for three different countries, we apply the frequency-based filter from Christiano and Fitzgerald (2003) in order to isolate and capture the corresponding medium-term cycles. The variables are Credit, House Prices, Share Prices and Interest Rates, and the countries under study are Germany, United Kingdom and the United States of America. Then, three techniques or tests are performed to identify the best proxy of financial cycles: The Concordance Index, the Granger Causality Test and the AUROC Test. The results suggest that Share Prices (Stock Price Index) is the most accurate variable to measure Financial Cycles. Following this conclusion, we perform a comparison analysis between the Financial cycle (Share Prices) and the Business cycle (GDP) and conclude that: 1) There is a higher synchronization among Financial Cycles of different countries than Business Cycles; 2) The financial variable shows a higher capacity to predict financial and economic crises than GDP.

The second article is motivated by the profound and structural reforms of the financial system after the 2008-09 global financial crisis, which led to a new regulatory environment with a direct impact on banks' risk. The goal of this article is to extend the literature, by studying the effects of different types of banking regulation on banks' risk, and how these effects change according to the quality of political institutions. The existing empirical literature shows that both banking regulation and the quality of political institutions have a direct effect on banks' risk, but, to the best of our knowledge, it is still to be investigated how the overall effect of banking regulation on banks' risk depends on the quality of political institutions. Therefore, in this article, we answer to the following important questions: is the effect of banking regulation on banks' risk contingent on the quality of political institutions? If so, can the quality of political institutions mitigate or reinforce the overall effect of banking regulation on banks' risk? The banking regulation factors considered in the analysis are activity restriction, capital stringency and supervisory power, while the quality of political institutions is proxied by the democratic accountability. Our analysis is based on a sample of 535 banks from the Organisation for Economic Co-operation and Development (OECD) countries, for the period of 2004-2016. We conclude that while stricter activity restrictions and capital stringency tend to increase banks' risk, higher levels of supervisory power tend to reduce this risk. Moreover, banks' risk tends to be lower in countries with better political institutions. Regarding the interplay between banking regulation, political institutions and banks' risk, we find that the quality of political institutions mitigates the positive effect of activity restriction and capital stringency on banks' risk and reinforces the negative effect of supervisory power on it. These results are robust to a different estimation method and distinct measures of banks' risk and political institutions.

The third article is related to the second one as it focuses on how the interplay between banking regulation and investors' protection affects banks' risk. We complement the existing literature on the direct effect of banking regulation and investors' protection on banks' risk-taking behavior by investigating how the protection of investors' rights (shareholders' and creditors' protection) shape the effect of banking regulation on banks' risk. Based on a sample of 535 banks from OECD countries for the period of 2004-2016, we find that activity restrictions and stricter capital stringency tend to increase banks' risk, whereas more supervisory power tends to reduce this risk. Furthermore, the results suggest that banks' risk increases in countries with high levels of shareholders' protection and decreases in countries with high levels of creditors' protection. Regarding the interplay between banking regulation, investors' protection and banks' risk, we find that investors' protection reinforces both the positive effect of activity restrictions and capital stringency on banks' risk and the negative effect of supervisory power on banks' risk. These results are robust to a different estimation method and a different proxy for banks' risk. Additional tests reveal that the effect of banking regulation on banks' risk is contingent on banks' size and that the systemic banking crisis reinforces (mitigates) the positive (negative) effect of regulation on banks' risk.

This thesis contributes to the literature in the following ways. From the first article, we add the finding that Share Price is the most accurate variable (among the variables mentioned in the literature) to measure Financial Cycles. Additionally, we find that Financial Cycles show a higher synchronization among them and a better predictive power of financial and economic crises than Business Cycles. These conclusions are useful not only for academic purposes, but for government policies too, namely in what concerns macroprudential decisions. Regarding the second and third articles, we start by providing further evidence of the direct effect of banking regulation (activity restrictions, capital stringency and supervisory power), political institutions and investors' protection on banks' risk. Additionally, we contribute to the literature by investigating how the overall effect of banking regulation on banks' risk is conditional on both the quality of political institutions and the level of investors' protection where banks have their headquarters. In the last article, we perform additional tests to understand how the effect of banking regulation on banks' risk, channeled through investors' protection, changes during the systemic banking crisis period and whether this effect is different for larger banks compared to smaller ones. Finally, these two articles contribute to the literature stream that investigates the determinants of banks' risk, extending studies such as Laeven and Levine (2009), Houston et al. (2010), Anginer et al. (2014), Haq et al. (2014), Fang et al. (2014), Luo et al. (2016), Ashraf (2017), Wang and Sui (2019) and Teixeira et al. (2020a), among others.

The remainder of the thesis is organized as follows. Chapters 2, 3 and 4 present the first, second and third articles, respectively, while Chapter 5 concludes.

2. Measuring Financial Cycles: Empirical evidence for Germany, United Kingdom and United States of America

Abstract

This contributes to the literature by identifying the most appropriate factor to detect and measure Financial Cycles, similar to Gross Domestic Product (GDP) for Business Cycles. Four financial variables were included in the study: Credit, House Prices, Share Prices and Interest Rates. The filter used to estimate and extract the cycles from the original time series was the Christiano and Fitzgerald (2003)'s one. Then, three methods, namely the Concordance Index, the Granger Causality Test and the AUROC Test, were used to identify which of the four variables is the most accurate proxy to measure and estimate financial cycles. In all of them, the results pointed to the same variable: Share Prices. A comparison between Share Prices and GDP shows a higher capacity of the financial variable to predict financial and economic crises, which justifies the recent increasing interest of macroprudential policymakers on Financial Cycles. Our conclusions are robust to different time periods and alternative filtering procedures.

Keywords: Financial Cycles, Business Cycles, Concordance Index, Granger Causality test, AUROC test

JEL Classification: E32, E44, E52, E61

2.1. Introduction

The global financial crisis of 2007-08, which had both financial and economic worldwide catastrophic effects, led policymakers (governments and central banks) to rethink and re-evaluate their macroprudential policies. Since then, a significant attention is paid to the analysis of financial stability and the causes of financial crises, with focus on the procyclicality risks of the financial system. Cyclical financial movements such as expansions (booms) and contractions (busts) are now associated with risks and potential serious financial and macroeconomic tensions. Having this reality into consideration and in order to obtain a useful monitoring tool for policymakers, questions such as whether and how macroprudential policies should be used to control financial cycles (FC) are being discussed.[1] This re-orientation of policymakers' attention led to an increasingly interest on studying financial cycles and their features (see BIS, 2014[2]). In fact, there is an ongoing debate in the literature on how to measure financial cycles and define macroprudential objectives (Hansen, 2012). According to Borio (2013), the effectiveness of macroprudential policies depends on understanding financial cycles, their actual phases and their drivers. Since the real economy is affected by imbalances captured by the financial cycles, being able to model them will help to improve real growth forecasts.

Although understanding financial cycles is now seen as critical to define macroprudential policies, there is still no consensus on which variable or set of variables should be used to measure and capture such cycles. Contrarily to business cycles, which have Gross Domestic Product (GDP) as a worldwide accepted measure, financial cycles still do not have an obvious "natural" indicator. According to the literature, while business cycle theory evolves over the short term (see for instance Baxter and King, 1999), financial cycles are thought to evolve over the medium term (see for instance Drehmann et al., 2012 and Aikman et al., 2015), higher amplitude and frequency, contributing to economic fluctuations, triggering imbalances or threatening macroeconomic stability. Given this difference between what is known about financial cycles and what is known about business cycles, this paper aims to reduce this gap by identifying the most suitable factor or indicator to measure financial cycles. In order to accomplish this purpose, time series of four different variables identified in the literature as potential proxies of financial cycles were gathered for Germany, United Kingdom (UK) and the United States of America (USA). These variables are Credit, House Prices, Share Prices

[1] See Borio (2014b) and Constâncio (2014).
[2] Bank for International Settlements.

and Interest Rates. For comparison purposes, GDP data, which is the indicator used for business cycles, is also analyzed.

Even though the study of financial cycles is not as much explored as the study of business cycles, existing literature has already come up with some definitions for FC. For instance, Borio et al. (2001), Brunnermeier et al. (2009), and Adrian and Shin (2010) define financial cycles as what captures systematic patterns in the financial system that may lead to macroeconomic consequences (concept of procyclicality of systemic risk) which are, consequently, useful for guiding macroprudential policies (see Schuler et al., 2015). The most common and generally accepted definition is the one from Borio (2014a) who sees financial cycles as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts". To simplify the understanding of FC, let us think about them as common fluctuations, i.e., imbalances followed by corrections, around a long-run equilibrium trend, in a variable or set of variables important for financial stability. In other words, financial cycles are a repeated process of common deviations from trend of a variable or a set of variables relevant for financial stability.

According to the literature, there are three different approaches, adapted from business cycles, that can be used to measure and capture financial cycles: the classic turning point analysis from Burns and Mitchell (1946), and some posterior variations; frequency-based filters; and unobserved component time series models. The final goal of all these approaches is the same: isolate the cycles that correspond to medium-term frequency intervals: the so-called financial cycles. Although each of these three approaches will be explained further, the one used in this paper is the frequency-based filter from Christiano and Fitzgerald (2003).

In this paper, the frequency-based filter from Christiano and Fitzgerald (2003) is applied to the different time series under study in order to isolate and capture the corresponding medium-term cycles. Then, some techniques and tests are used to identify the most appropriate variable to measure these cycles (Financial Cycles). The techniques and tests used are the Concordance Index, the Granger Causality Test and the AUROC Test. The results obtained show that, among the four variables mentioned above (Credit, House Prices, Share Prices and Interest Rates) the most accurate variable to measure Financial Cycles is the Share Prices (Stock Price Index). Our conclusions are robust to different time periods of the original sample, when using an alternative version of the band pass filter implementation of Christiano and Fitzgerald (2003), namely the Baxter and King (1999)'s filter, and when using a different filtering procedure based on a quadratic polynomial regression.

Following the conclusion above, a comparison between the Financial cycle/variable (Share

Prices) and the Business cycle/variable (GDP) is performed using the same tests and techniques: the Concordance Index, the Granger Causality Test and the AUROC Test. The results show that: 1) There is a higher synchronization among Financial Cycles of different countries than Business Cycles; 2) The financial variable shows a higher capacity to predict financial and economic crises than GDP.

This paper contributes to the literature in at least four important ways. The first and most significant one is the finding that Share Prices is the most accurate variable (among the variables mentioned in the literature) to measure Financial Cycles. Second, we found that Financial Cycles from different countries show a higher synchronization among them than Business Cycles. Third, Financial Cycles have a better predictive power of financial and economic crises than Business Cycles. Fourth, this research contributes to the under explored literature on Financial Cycles and its relationship with Business Cycles. Given the recent increasing interest on Financial Cycles, due to the need of better defining macroprudential policies, these contributions are useful not only for academic purposes but for government policies and business decisions too.

Unlike other researchers such as Jorda et al. (2015), Schularick and Taylor (2012) and Jorda et al. (2011), who analyze leverage and credit cycles (simply assuming them as proxies for financial cycles), their impacts on the economy and how monetary and macroprudential policymakers should respond to it, our study focus on identifying the most accurate variable to be considered as proxy for financial cycles. The study of financial cycles and how policymakers should act to prevent financial crises will be much more effective when a consensus among researchers is achieved on the best variable to measure it, similarly to what happens with GDP and Business Cycles.

The rest of the paper is organized as follows. Section 2.2. reviews the existing literature on this subject. Section 2.3. describes the data. Section 2.4. gives an overview on the approach used to measure Financial Cycles. The methodology applied and its results are presented in Section 2.5.. In Section 2.6. a comparison between Financial Cycles and Business Cycles is performed. Robustness checks are reported in Section 2.7.. In Section 2.8. final conclusions and some recommendations for future studies are presented.

2.2. Literature review

The literature on financial cycles is relatively new and less researched than business cycle theory. The existing research on what financial cycles are, which variables should be chosen and how to measure them is still in its infancy.

The research on cycles and seasonality of some variables such as Housing Prices, Credit, Stock Market, Bond Market, etc., started a long time ago, and still are subject of study nowadays.[3] These studies have been shown to be important mainly in two specific areas: investment and corporate governance decisions (Liang and Yen, 2014, Jeon and Nishihara, 2015, Laborda and Munoz, 2016 and Racicot and Theoret, 2018); and macroeconomic implications and monetary/macroprudential policies (Ghossoub, 2009, Cavallo and Ribba, 2015 and Duncan, 2016).

The first studies on financial cycles are from Fisher (1933), Kindleberger et al. (1978) and Minsky (1986, 1992). Fisher (1933) was the first to mention the importance of financial cycles for the real economy, i.e., that financial variables have an impact in the economy. Since that time, several definitions in the literature for Financial Cycles came up, for instance Borio et al. (2001), Brunnermeier et al. (2009), and Adrian and Shin (2010). However, the one more generally accepted is from Borio (2014a), who defines financial cycles as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts".

Since the 2008 financial crisis, there has been a re-orientation of policymakers' attention, with the focus on studying financial cycles and their features, rather than business cycles. Borio (2014b) and Constancio (2014) analyze the importance of policymakers on trying to 'control' these financial cycles and to define their macroprudential policies based on them. Schuler et al. (2015) also state that Financial Cycles can be interpreted as indicators of financial imbalances important for guiding macroprudential policies. Although the obvious focus of macroprudential policy on Financial Cycles, it is still not clear which financial indicator is the most appropriate one to measure them.

Also, the decomposition of time series into cycles (long and short term) gained relevance recently. For instance, Yi et al. (2019) show that predictors can consistently provide more predictive information after each of them is decomposed into a long-cycle mean component and a short-term deviation component. Chortareas et al. (2020) analyze the systematic patterns (cycles) between credit risk, measured through non-performing loans, and Business Cycles, measured through real GDP growth. Caporale and Gil-Alana (2017) analyze the cyclical behavior of the US Federal Funds effective rate, reinforcing the importance of this feature.

In the existing literature, different researchers consider and find the importance of different

[3] See for example Chan and Wu (1993), Gonzalez et al. (2005), Kizys and Pierdzioch (2010) and He et al. (2017).

variables to measure financial cycles. However, none of them studied which variable is the most significant one. Bernanke, et al. (1996), Gilchrist and Zakrajsek (2008) and Aikman et al. (2015) analyzed and confirmed the importance of credit variables. More specifically, Bush et al. (2014), Detken et al. (2014), Giese et al. (2014), Hiebert et al. (2014), and Borio (2014a) found significance in the credit-to-GDP ratio. Other researchers such as Ivashina and Scharfstein (2010), Mian and Sufi (2010), Drehmann et al. (2012), Borio (2014a), Runstler and Vlekke (2018) and Yan and Huang (2020) performed similar studies but including housing (property/real estate prices) cycles, in addition to credit. The interaction between these two variables (credit and house prices) are associated with the most thoughtful bouts of financial instability (see BIS, 2014; Jorda et al., 2016). Claessens et al. (2010) and Granville and Hussain (2017) proposed equity prices as a potential variable to measure financial cycles. In fact, Claessens et al. (2010) found high synchronization between credit and equity cycles across countries. Pagan and Sossounov (2003), Hall et al. (2006), and Sangvinatsos (2017) were the authors that included equity prices in the study of financial cycles. There are also other studies that consider a number of other variables as proxies for financial cycles, but less significant (see Schuler et al., 2015, and Borio, 2014a: bond prices, interest rates, volatilities, nonperforming loans, risk premia, among others). More recent studies from Claessens and Kose (2017) and Hiebert et al. (2018) provide a review of literature that compares business cycles with financial cycles, using variables such as credit, equity and housing markets to measure FC. Even more recent, there is the study from Schuler et al. (2020) who use credit and asset prices to estimate financial cycles, concluding that these variables outperform Basel II credit-to-GDP gap in predicting financial crises.

Apart from the choice of variables to be included in the study of financial cycles, the method to measure them, i.e., how to separate trend and cycles in the financial variables' time series, is also important. Given that existing literature has already concluded that financial cycles are much longer than the traditional business cycles, the de-trending method used has to be capable of modeling and capturing this specific feature. According to the recent literature, there are three main approaches that can be used: the turning point analysis of Burns and Mitchell (1946) and some posterior variations (see Claessens et al., 2011, 2012); non-parametric bandpass filters (see Schuler et al., 2015, and Aikman et al., 2015); and the unobserved component time series models (see Harvey et al., 1997, Koopman and Lucas, 2005, Chen et al., 2012, and Runstler and Vlekke, 2018).

The turning point method, started by Burns and Mitchell (1946), was first proposed to capture business cycles by identifying their troughs and peaks. Some other researchers, such as Bry and Boschan (1971) and Harding and Pagan (2002, 2006, 2016), adapted this algorithm in order to better capture the features of their data (such as consider quarterly data instead of monthly data). This method, applied by Watson (1994), King and Plosser (1994), and Artis et al. (1997) to study business cycles, is still used by the Euro Area Business Cycle Dating Committees and by the National Bureau of Economic Research (NBER). The first researchers to apply this method to financial cycles were Pagan and Sossounov (2003), Hall et al. (2006), and Claessens et al. (2011, 2012), who used data from a large number of countries, namely credit, equity prices and property prices. They found that financial cycles, compared to business cycles, tend to have a higher duration and a higher amplitude. Additionally, they found evidence that business cycles and financial cycles are highly synchronized as well as house price and credit cycles. Other researchers such as Drehmann et al. (2012) and Granville and Hussain (2017) also provided studies in financial cycles based on turning point analysis.

The second method relies on frequency-based filters (non-parametric bandpass filters) to identify FC. The most well-known filters are the ones from Hodrick and Prescott (1997) and Christiano and Fitzgerald (2003). These filters are also known as non-parametric filters because they require the researcher to pre-specify the duration of the cycles. Aikman et al. (2015), for instance, used the Christiano and Fitzgerald's filter to compare the features of the business cycle and the credit cycle. They estimated spectral densities of several financial variables and GDP for a large group of countries and from 1880 to 2008, and concluded that these estimations justify the lower frequency of financial cycles (medium-term frequency range) compared to business cycles (short-term frequency range). They also showed evidence of similarities between the credit cycle estimated by Christiano and Fitzgerald's filter and the one estimated by Turning Point analysis. Some papers apply both, Turning Point analysis and Bandpass filter, to achieve more robust conclusions. For example, Igan et al. (2009) used a frequency-based filter to estimate the cycles of house prices and credit. They also used the turning point analysis to calculate the amplitude and duration of these cycles, concluding that, over time, the characteristics of financial cycles became more similar due to financial integration. Other influential paper is the one from Drehmann et al. (2012) who uses both turning point analysis and the Christiano and Fitzgerald (2003)'s bandpass filter to estimate the cycles of credit, credit-to-GDP ratio, equity prices, property prices and an index of aggregate asset price (which combines equity prices and property) to a list of industrial countries from 1960 to 2011. They distinguish medium-term cycles (from 8 to 30 years) and short-term cycles (from 1 to 8 years – like business cycles), and concluded that a financial cycle is a medium-term phenomenon where the cycle's peaks tend to coincide with the onset of financial crises.

The third method applies the Kalman filter to unobserved components time series models (UCTSM) to estimate the cycles.[4] This approach is already seen in studies of business cycles (see Valle e Azevedo et al., 2006, Koopman and Azevedo, 2008, and Creal et al., 2010). There are few researchers who applied this method to financial variables, being Koopman and Lucas (2005), Galati et al. (2016), Grinderslev et al. (2017), and Runstler and Vlekke (2018) some of them. They used this method to estimate cycles in USA for variables such as business failure rates, credit spreads and real GDP. Their results show evidence of comparable medium-term cycles among different variables.

Although previous authors employ different metrics, they provide some important similar conclusions: FC tend to have a lower frequency and a higher amplitude in comparison to business cycles. Also, peaks in the financial cycles tend to coincide with the beginning of financial crises (see Drehmann et al., 2012).

Besides all these studies on Financial Cycles using different methodologies, none of them achieves any conclusion regarding which financial indicator is the best one to measure FC. Each study uses its own measure to represent and be a proxy of Financial Cycles. There is a lack of studies in the literature which focus on understanding which measure is effectively the best proxy for such cycles. Filling this gap is the main objective of our work.

2.3. Data

In this paper, four different variables, all of them identified by mostly of the existing literature (see the Literature Review section) as potential indicators[5] for Financial Cycles, are studied. These variables are Credit, House Prices, Share Prices and Interest Rates. All of them are seen as potential conditioners of financial stability.

Credit is considered by several authors as a potential variable to measure FC because it creates a linkage between different economic agents. Since it can be used as a proxy for leverage, i.e., as a link between savings and investment, a shock to borrowers can propagate directly to lenders. Additionally, the most recent worldwide financial crisis is closely related to credit and house prices (BIS, 2014 and Jorda et al., 2016), which is another variable included in this study. Strong growth in credit extension, mainly mortgage credit, often leads to higher house prices. In turn, higher property prices mean that the collateral to obtain more credit is now more valuable (and it keeps going). Regarding Equity Prices, it is the best variable to

[4] See Harvey (1991), Harvey and Jaeger (1993) and Durbin and Koopman (2012).
[5] Variables that can potentially capture the main characteristics of the FC.

reflect the performance of private companies in a country and economy, which is a pillar to financial stability. If most of the companies in an economy are not performing well, their stock prices will decrease and may create a crisis in that country and, in some cases, spread worldwide. Finally, Interest Rates are also a potential variable to measure FC since it is seen as a reference in many ways: it can reflect how healthy is a countries' economy; how expensive the money is; it is a tool for policymaking institutions to control an economy by restraining periods of expansion and high inflation and avoiding crises.

The sources of the time series are the same ones used by other authors. For Credit, two time series are initially considered, all obtained from BIS Statistics: Credit to Private non-financial sector from Banks (as % of GDP) and Credit to Private non-financial sector from all sectors (as % of GDP). For both House Prices and Share Prices, the respective time series are indexes with base year 2015, obtained from the Organization for Economic Co-operation and Development (OECD) Database. Regarding the House Prices, the index is already in real values. Finally, for the Interest Rates variable, two different time series were initially considered: long-term interest rates from OECD Database and long-term government bond yields from Federal Reserve Economic Data (FRED). For comparison purposes (with business cycles), data from GDP was also used. The time series obtained for this variable was the real GDP index from International Monetary Fund (IMF). Table 2.1. depicts a resume of the variables and time series under study is presented.

Table 2.1.
Variables' identification

Reference	Variables	Time Series	Source
#CreditBanks	Credit	Credit to Private non-financial sector from Banks (as % of GDP)	BIS Statistics
#CreditAllSectors	Credit	Credit to Private non-financial sector from all sectors (as % of GDP)	BIS Statistics
#HousePrices	House Prices	Real House Prices Index from OECD Database	OECD Database
#SharePrices	Share Prices	Share Prices Index from OECD Database	OECD Database
#InterestRateOECD	Interest Rates	Long term Interest Rates from OECD Database	OECD Database
#InterestRateFRED	Interest Rates	Long term Government Bond Yields from FRED	FRED
#GDP	GDP	Real GDP Index from IMF	IMF Database
#Crises	Financial Crises	Data collected by Carmen Reinhart	BFFS Project

In order to capture the medium-term patterns, known as cycles, the first step is to separate the long-term trend from the cycle. In other words, the time series is assumed to be formed by two distinct components: trend and cycle. Since the bandpass filter separates the time series into these two components, the ‘classical’ cycle is assumed.[6]

Considering that bandpass filters require as many observations as possible in order to capture and extract medium-term cycles, the time span considered is the longest one commonly available for all the four variables: from 1960 to 2018. The frequency of the data is quarterly, in line with the literature in Financial Cycles.

All the data mentioned before were gathered for three different countries: Germany, United Kingdom (UK) and United States of America (USA). These countries were chosen due to their systemically importance, i.e., they have a high capacity to influence and impact the behavior of the world economy and finance. Note that these countries top the list, for the purposes of mandatory monitoring, of the ones with systemically important financial sectors, identified by the IMF (2010) under its Financial Sector Assessment Program.

In line with Drehmann et al. (2012), all variables are deflated except for Real House Prices and Real GDP time series (which are already in real values) and Credit-to-GDP time series (which is a ratio and, therefore, deflating both Credit and GDP would cancel one another out).

To deflate the Share Price time series, the Consumer Price Index (CPI) of the respective country is used. To deflate the two time series representing the Interest Rate variable, Inflation Rate is used.

Then, natural logarithms are taken to the time series except for Credit-to-GDP variables (ratios) and the Interest Rate variables. Note that log series tends to have a more normal distribution, makes the trend linear and stabilizes the variance across time (constant variance). The logarithmic transformation is often useful for series greater than zero and that grow exponentially. Since Credit-to-GDP and Interest Rates do not grow exponentially neither have too high scales, log transformation was not applied to these variables.

At this point, there are two time series for the Credit variable and two for the Interest Rates variable. Before studying and analyzing which of the four variables is the best proxy of Financial Cycles, it is important to decide which of the two time series “Credit to Private non-financial sector from Banks, as % of GDP” and “Credit to Private non-financial sector from all sectors, as % of GDP” should represent the Credit variable and which of the two time series

[6] Remember that ‘growth’ or ‘deviation’ cycles focus on fluctuations around a trend and ‘growth rate’ cycles refer to fluctuations in the growth rate of the variable.

"long-term interest rates from OECD Database" and "long-term government bond yields from FRED" should represent the Interest Rate variable. The methods used to select the best time series for the same variable is explained next in the Methodology Section.

Finally, for one of the methods used in the current study (the AUROC test in section 2.5.5.) a time series for worldwide financial crises, represented as a dummy variable, is needed. This data was collected over many years by Carmen Reinhart (with her co-authors Ken Rogoff, Christoph Trebesch, and Vincent Reinhart) and includes banking crisis, exchange rate crises, stock market crises, sovereign debt growth and default, and many other data series for more than 70 countries from 1800-present. The BFFS Project keeps this data updated and available for download.

2.4. An overview on the approach used to measure Financial Cycles

There are three main approaches that can be used to extract and estimate (financial) cycles: turning point analysis; non-parametric bandpass filters; and the unobserved component time series models.

2.4.1. Frequency-based filters

The frequency-based filter (non-parametric bandpass filter) is one of the techniques that can be used to study financial cycles by isolating the cyclical patterns of a certain time series. It is known as a non-parametric filter because this kind of filters require the user to pre-specify the duration of the cycles (between 32 and 120 quarters for financial cycles and between 6 and 32 quarters for business cycles). The most well-known filters are the ones proposed by Hodrick and Prescott (1997) and Christiano and Fitzgerald (2003).

2.4.1.1. Christiano and Fitzgerald (CF) filter

According to Hamilton (1994) and the spectral representation theorem, a time-series can be represented in the frequency-domain. Therefore, the use of a bandpass filter will allow the user to separate different frequencies of a certain time-series by decomposing the following process:

$$y_t = \tilde{y}_t + residual_t. \quad (2.1.)$$

The intention is to eliminate all the unwanted time-frequency ($residual_t$) while keeping the complement unchanged ($\tilde{y}_t$). The final goal is to isolate the cycles of $\tilde{y}_t$ with period between $[p_l, p_u]$. Since the hypothetical ideal filter would require an infinite length of time series, it is not feasible. Consequently, an approximation for $\tilde{y}_t$ is needed. For this purpose, the frequency-based filter developed by Christiano and Fitzgerald (2003) —hereafter, CF filter— is commonly used. This bandpass filter is a linear approximation that attenuates both short-term noise in the high frequencies (cycles) and long-term variations in the low frequencies (trend). The CF filter estimates the cycles by minimizing the mean squared error between $\tilde{y}_t$ and y_t:

$$\tilde{y}_t = B_0 y_t + \sum_{j=1}^{T-t-1} B_j x_{t+j} + \tilde{B}_{T-t} x_T + \sum_{j=1}^{t-2} B_j x_{t-j} + \tilde{B}_{t-1} x_1, \tag{2.2.}$$

where

$$B_j = \frac{\sin(jb) - \sin(ja)}{\pi j},$$

$$B_0 = \frac{\mathrm{b} - \mathrm{a}}{\pi},$$

$$a = \frac{2\pi}{p_u},$$

$$b = \frac{2\pi}{p_l},$$

and under the assumption that y_t follows a random walk, and where $\tilde{B}_{T-t}$ and $\tilde{B}_{t-1}$ are functions of B_0 and B_j, and p_l and p_u are the frequency domain. As mentioned before, the lower and upper bounds are 32 and 120 quarters, respectively, for financial cycles, and 6 and 32 quarters, respectively, for business cycles. Setting $p_l = 32$ and $p_u = 120$ means that all frequencies outside this range are eliminated. For example, if a series has a cycle of 50 quarters (between 32 and 120), this cycle is captured. Increasing the p_u would make no difference to the filtered series (the time domain is still 50 quarters). However, if the series also has a cycle of 150 quarters, increasing p_u from 120 to 160 would make a difference in the filtered series: it would now capture the new cycle of 150 quarters too.

In sum, the frequency-based filter developed by Christiano and Fitzgerald (2003) is commonly used to isolate the cyclical component of a time series by pre-specifying a certain range of its duration (frequency range between 32 and 120 quarters for financial cycles). This bandpass filter takes a two-sided weighted moving average of the time series data, where the cycles in a "band" (given by a pre-specified duration range: lower and upper bound) are "passed" through, i.e., extracted.

In addition to the choice of a value for the upper bound and for the lower bound, the user also has to decide the way the bandpass filter will compute the moving average: choose between the fixed length symmetric filter or the full sample asymmetric filter. While the first one is time-invariant, i.e., the moving average weights on the leads and lags are not allowed to differ, the second one is time-varying, i.e., it allows the weights on the leads and lags to differ.

Given that the first method (the fixed length symmetric filter) always uses the same number (q) of lead and lag terms for every weighted moving average, the filtered series will lose q observations from the beginning and from the end of the original sample. Since the second method (the full sample asymmetric filter) does not have this requirement, i.e., a different number of lead and lag terms can be used for each weighted moving average, the filter can be computed using the full original sample, without losing any observation.

The output, i.e., the filtered series c, after running the CF filter is the cyclical component. To compute the non-cyclical component t, the difference between the actual (y) and the filtered series (c) must be taken:

$$\begin{gathered} y = t + c, \\ t = y - c, \end{gathered} \tag{2.3.}$$

where, comparing to formula 1, t stands for the residual and c for $\tilde{y}$.

According to the existing literature, bandpass filters (e.g. Christiano and Fitzgerald filter) are better than the Hodrick-Prescott (HP) filter due to their favorable characteristics from an analytical perspective, such as the easier comparison between time series and the smoother cycles obtained. Considering the preference of most researchers on bandpass filters, the CF filter is used in this study to estimate and extract financial cycles. Nevertheless, we apply different filtering procedures in the robustness checks section in order to verify if the results depend or not on the choice of the filter used. Regarding the method of the CF filter used in this research, the full sample asymmetric filter is chosen due to the advantage (compared to the fixed length symmetric filter) mentioned above.[7]

2.5. Methodology and empirical results

2.5.1. Christiano and Fitzgerald (CF) filter

In this research, the EViews software is used to run the CF filter over the transformed time series (as explained in the Data section) in order to estimate and extract the respective cycles. According to the methodology of this filter (highlighted in the previous section), the "Full Sample Asymmetric (C-F)" method is chosen, the lower bound is set to be 32 quarters and the upper bound to be 120 quarters. Since all the time series have a linear trend (due to the transformations performed and explained in the Data section), the "Remove Linear Trend"

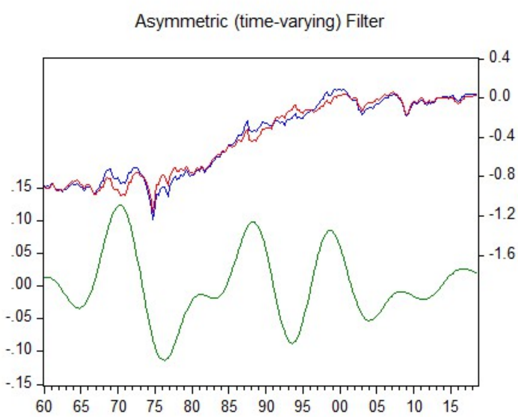
[7] For a better understanding of the CF band-pass filter, please see Christiano and Fitzgerald (2003).

option is selected. Regarding the stationary assumption, two options are given: the "I(1) – random walk" and the "I(0) – stationary assumption". Note that the CF filter assumes each time series is composed by two components: cycle and long-term trend. However, there are some time series that do not have a notorious long-term trend (the "I(0) – stationary assumption" option must be chosen), while there are other variables that do have a strong long-term trend (the "I(1) – random walk" option must be chosen). In order to test which time series has a Unit Root (non-stationary time series), the Augmented Dickey Fuller test for the original time series is performed. For completeness, all the results are available in Appendix A.

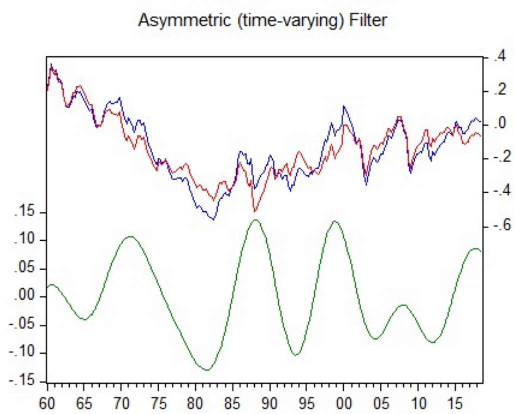
After running the CF filter using EViews, cycles of Credit, House Prices, Share Prices and Interest Rates are obtained for United States, United Kingdom and Germany. We recall that for the variables Credit and Interest Rate two time series were considered each. The same procedure was performed for the GDP variable in order to obtain the cycle but setting the lower bound equal to 6 quarters and the upper bound equal to 32 quarters.

Figure 2.1. highlights some examples of the graphical output obtained after running the CF filter.

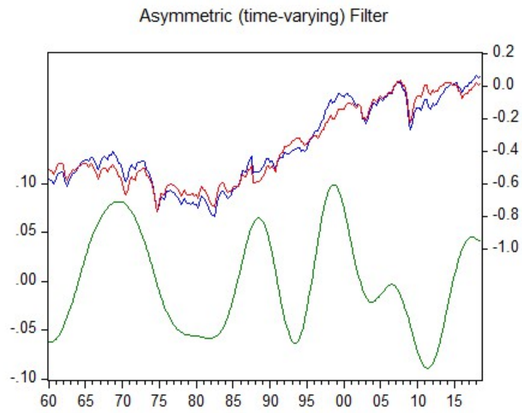
Since the goal of this investigation is to study the (financial) cycles, from now on only the green line time series (see Fig. 2.1.) is considered. As mentioned in the Introduction, in order to identify the most suitable variable (among Credit, House Prices, Shares Prices and Interest Rates) to be the measure of Financial Cycles, several techniques and tests such as the Concordance Index, the Granger Causality Test and the AUROC Test are performed. A brief explanation of each one is presented in the following subsections.



(a) Germany



(b) UK



(c) USA

Figure 2.1.
Graphical output after running the CF filter to the Share Prices' (transformed) time series.
The blue line represents the (transformed) time series under study, the red line is the non-cyclical component, i.e., the long-term trend, and the green line is the estimated cycle. The time-span under analysis (from 1960 to 2018) is represented in the x-axis, the cycles in the left-hand side y-axis and the original time series and long-term trend in the right-hand side y-axis. The rest of the graphs are shown in Appendix B.

2.5.2. Concordance Index

The Concordance Index was proposed by Harding and Pagan (2002) and give us the degree of synchronization between two different time series by considering the fraction of time the two series (cycles) are in the same phase:

$$CI_{x,y} = \frac{1}{T}\sum_{t=1}^{T}\left[p_t^x . p_t^y + (1 - p_t^x)(1 - p_t^y)\right], \qquad (2.4.)$$

where

$$p_t^x = \{0, if\ x\ is\ in\ downturn\ phase\ at\ time\ t; 1, if\ x\ is\ in\ expansion\ phase\ at\ time\ t\}$$

and

$$p_t^y = \{0, if\ y\ is\ in\ downturn\ phase\ at\ time\ t; 1, if\ y\ is\ in\ expansion\ phase\ at\ time\ t\}$$

where p_t stands for the phase of the cycle, i.e., if the cycle is in a downturn or in expansion. To determine the phase, the following rule is applied:

$$p_t = \begin{cases} 1\ (expansion)\ if\ c_t > c_{t-1} \\ 0\ (downturn)\ if\ c_t < c_{t-1} \end{cases}.$$

For a better understanding, consider the extreme case where the two series x and y are perfectly procyclical (resp., countercyclical). In this case, the Concordance Index is equal to unity (resp., zero).

The results of the Concordance Index calculated by comparing the time series of the same variable, but between different countries are presented in Table 2.2..

Table 2.2.
Concordance Index results
The Concordance Index is calculated for each combination of countries and for each variable's time series. Then, an average of the three CI values for each variable is computed. This average is used for comparison purposes between the different variables.

Variable	CreditBanks	CreditAllSectors	HousePrices	SharePrices
CI Germany-UK	48.18%	56.56%	43.23%	82.48%
CI Germany-USA	44.98%	61.30%	46.35%	74.79%
CI UK-USA	70.00%	81.45%	79.17%	82.05%
Average	**54.39%**	**66.44%**	**56.25%**	**79.77%**

Variable	InterestRateOECD	InterestRateFRED	GDP
CI Germany-UK	59.83%	61.54%	61.64%
CI Germany-USA	60.26%	58.55%	62.50%
CI UK-USA	55.13%	61.11%	64.66%
Average	**58.40%**	**60.40%**	**62.93%**

Table 2.2. allows us to conclude which variable has the greatest Concordance Index among the three different countries (Germany, UK and USA). This variable is Share Prices, with 79.77% average of CI. This means that de-trended Share Prices are relatively more correlated across countries compared to the other variables. This result makes sense because it points to the existence of a globalized equity market where price dynamics are largely driven by a single "risk appetite" factor. Remember that the countries under study are known by their systemically importance, i.e., they have a high capacity to influence and impact the behavior of the world economy and finance. For this reason, the economy and finance of each of these countries are highly correlated between them, meaning that the respective cycles must be also highly synchronized. Also, if the goal is to find an universal measure to be used as a proxy for financial cycles (like GDP for economic cycles), then we should be looking for the one with the highest correlation across countries. Having this in mind, it makes total sense to select the financial variable that has the greater Concordance Index (among these countries) to represent financial cycles. Nonetheless, other tests and methods are used next for the same purpose.

Please remember that the objective in this paper is not the same as the most of the literature cited in Section 2.2.. While the literature focus on identifying country-specific financial cycles, the current study focuses on identifying the most reliable measure of the financial cycle. There is a vast literature analysing financial cycles, but there is no consensus on which variable better characterizes them. This is where our research comes in.

2.5.3. Granger Causality test

The Granger Causality Test is an approach developed by Granger (1969) to help answering the question whether a specific time series causes the other (whether one time series is useful in forecasting another) or vice-versa. In other words, it helps to see the ability to predict the future values of a time series using prior values of another time series.

A time series x is said to Granger-cause y if there is evidence, through a series of F-tests on lagged l values of x (and with lagged values of y also included), that those x values provide statistically significant information about y future values.[8]

In EViews, the following generic bivariate regressions are run:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \cdots + \beta_l x_{t-l} + \epsilon_t, \qquad (2.5.)$$

and

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \cdots + \beta_l y_{t-l} + u_t. \qquad (2.6.)$$

The outputs are grouped in Table 2.3.. The joint null hypothesis of the reported F-statistics, for each equation, is the following one:

$$\beta_1 = \beta_2 = \cdots = \beta_l = 0.$$

If the null hypothesis is not rejected, then x does not Granger-cause y (in the case of the first equation) or y does not Granger-cause x (in the case of the second equation).

The purpose of this test is to help in the identification of the most suitable variable to measure and be a proxy for financial cycles. The variable that will be chosen must be as much independent as possible, i.e., it should be the leading one among the variables under study. Therefore, when performing the Granger Causality test between two variables, the one (X) that presents the highest F-statistic (rejecting the null hypothesis that X does not Granger-cause Y) is chosen over the other one (Y). Performing this method for all variables in a specific country will give us a leading variable for each of the possible combinations. Afterwards, the variable selected is the one considered leading more times. Given the results presented in Table 2.3., we verify that, among the three countries, Share Prices is the most leading variable (with the only exception of the United States of America). Even though this conclusion cannot be achieved for the United States of America, our final conclusion concerning which variable is more accurate to measure Financial Cycles will depend on the combination of the three methods: the Concordance Index; the Granger Causality test and the AUROC test. By

[8] An assumption of the Granger Causality test is that the time series must be stationary. Unit Root tests were performed (Augmented Dickey Fuller test) to the cycles time series and all the null hypothesis that there is a Unit Root were rejected (see Appendix C).

analyzing the results from these three tests, the variable that is more frequently predominant is chosen. Additionally, robustness tests, namely using different filtering procedures, are performed in Section 2.7. to validate our main conclusions.

Notice that Table 2.3. does not indicate any reference to the time series #CreditAllSectors neither #InterestRateFRED. Since #CreditBanks and #CreditAllSectors were both representing the Credit variable and #InterestRateOECD and #InterestRateFRED were both representing the Interest Rate variable, an analysis was performed (explained next) to select only one time series to represent the respective variable.

Table 2.3.
Granger Causality test results

This Table reports the results from the Granger Causality test. These results are separated by country: Germany, UK and USA. For each country, the null hypothesis that variable X does not Granger Cause Y is tested for each pair combination of the four variables under study. In each pair combination, the X variable from the null hypothesis rejected with the highest F-statistic is chosen as the leading variable for that pair combination in that specific country. *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	184.15***	#HousePrices
#CreditBanks	#HousePrices	165.87***	
#SharePrices	#CreditBanks	5.33***	#SharePrices
#CreditBanks	#SharePrices	2.86**	
#SharePrices	#HousePrices	2.74**	#SharePrices
#HousePrices	#SharePrices	1.87	
#InterestRateOECD	#CreditBanks	9.66***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	4.52***	
#InterestRateOECD	#HousePrices	5.44***	#InterestRateOECD
#HousePrices	#InterestRateOECD	1.59	
#InterestRateOECD	#SharePrices	204.35***	#SharePrices
#SharePrices	#InterestRateOECD	204.36***	
Most Leading Variable			**#SharePrices**

(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	118.95***	#HousePrices
#CreditBanks	#HousePrices	80.31***	
#SharePrices	#CreditBanks	45.97***	#SharePrices
#CreditBanks	#SharePrices	38.61***	
#SharePrices	#HousePrices	82.47***	#SharePrices
#HousePrices	#SharePrices	67.10***	
#InterestRateOECD	#CreditBanks	27.95***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	18.55***	
#InterestRateOECD	#HousePrices	54.35***	#InterestRateOECD
#HousePrices	#InterestRateOECD	44.89***	
#InterestRateOECD	#SharePrices	237.61***	#SharePrices
#SharePrices	#InterestRateOECD	414.07***	
Most Leading Variable			**#SharePrices**

(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	33.16***	#CreditBanks
#CreditBanks	#HousePrices	37.19***	
#SharePrices	#CreditBanks	16.26***	#CreditBanks
#CreditBanks	#SharePrices	31.09***	
#SharePrices	#HousePrices	29.29***	#SharePrices
#HousePrices	#SharePrices	23.90***	
#InterestRateOECD	#CreditBanks	42.62***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	39.19***	
#InterestRateOECD	#HousePrices	0.01	#HousePrices
#HousePrices	#InterestRateOECD	0.03	
#InterestRateOECD	#SharePrices	57.22***	#InterestRateOECD
#SharePrices	#InterestRateOECD	49.60***	
Most Leading Variable			**#CreditBanks or #InterestRateOECD**

2.5.4. Choice between time series of the same variable

Following the explanation above, in this study there are two time series (#CreditBanks and #CreditAllSectors) that are representing the same variable (Credit) and other two time series (#InterestRateOECD and #InterestRateFRED) representing the Interest Rate variable. In order to select only one time series to represent the respective variable, the following two methods were used:

1. Analyze the F-statistic obtained in Granger Causality test;
2. Analyze the Adjusted R-square in OLS regression estimation.

The first method is similar to the one explained and performed in the previous section. It consists on choosing the leading time series (between #CreditBanks and #CreditAllSectors for the Credit variable and between #InterestRateOECD and #InterestRateFRED for the Interest Rate variable) by analyzing the F-statistic obtained when applying the Granger Causality test. The F-statistic results are shown in Table 2.4..

Table 2.4.
Granger Causality test results for different time series of the same variable
The Granger Causality test is applied to pairs of time series that represent the same variable. The goal is to verify which is the leading time series that should be chosen to represent the respective variable. For Credit, the time series are CreditAllSectors and CreditBanks. For Interest Rate, the time series are InterestRateFRED and InterestRateOECD. For each pair of time series from the same variable, two Granger Causality tests are performed: one assuming a specific time series as X (Leading) variable and another assuming the other times series as X (Leading) variable. The X (Leading) time series from the null hypothesis rejected (meaning that X Granger-causes Y) with the highest F-statistic is chosen to represent the respective variable. This methodology is applied for each country under study (Germany, UK and USA). *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#CreditAllSectors	#CreditBanks	118.65***	#CreditBanks
#CreditBanks	#CreditAllSectors	135.81***	
#InterestRateFRED	#InterestRateOECD	195.25***	#InterestRateOECD
#InterestRateOECD	#InterestRateFRED	215.21***	

(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#CreditAllSectors	#CreditBanks	30.18***	#CreditAllSectors
#CreditBanks	#CreditAllSectors	29.04***	
#InterestRateFRED	#InterestRateOECD	104.13***	#InterestRateFRED
#InterestRateOECD	#InterestRateFRED	102.00***	

(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#CreditAllSectors	#CreditBanks	49.63***	#CreditBanks
#CreditBanks	#CreditAllSectors	84.64***	
#InterestRateFRED	#InterestRateOECD	47.28***	#InterestRateOECD
#InterestRateOECD	#InterestRateFRED	49.33***	

Table 2.4. reveals that the time series #CreditBanks is more frequently the leading one over the #CreditAllSectors time series and, therefore, it must be chosen to represent the Credit

variable. Similarly, the #InterestRateOECD time series leads the #InterestRateFRED time series and, consequently, it is chosen to represent the Interest Rate variable.

The second method consists on estimating an Ordinary Least Square (OLS) regression where one time series is the dependent variable y_t and the lagged values of the other time series (of the same variable) is the independent variable x_{t-l}, that is

$$y_t = \alpha_0 + \beta_1 x_{t-1} + \cdots + \beta_l x_{t-l} + \epsilon_t. \tag{2.7.}$$

This is another method that allows to verify which time series is the leading one (between time series #CreditBanks and #CreditAllSectors for Credit and between #InterestRateOECD and #InterestRateFRED for Interest Rates). Since the results show that the independent variable is always significant to explain the behavior of the dependent variable, two methods are used to decide which one should be selected as the leading one: one method is to choose the independent variable that presented the highest t-statistic; another method consists on analyzing the Adjusted R-square, i.e., the proportion of the variance for a dependent variable that is explained by an independent variable. The chosen leading variable will be the independent variable of the regression with the highest t-statistic and Adjusted R-square.

The outputs are gathered in Table 2.5. and the reported t-statistics are for the following joint null hypothesis:

$$\beta_1 = \beta_2 = \cdots = \beta_l = 0.$$

According to Table 2.5., the time series #CreditBanks is chosen to represent the Credit variable and the time series #InterestRateOECD to represent the Interest Rate variable. From now on, the time series #CreditAllSectors and #InterestRateFRED are excluded from the study.

Table 2.5.
OLS estimation results

The estimation results of equation (2.7.) are shown in this table. This is another method to choose which time series should represent the corresponding variable. For each pair of time series from the same variable, two OLS estimations are performed: one assuming a specific time series as X (Leading) variable and another assuming the other times series as X (Leading) variable. The X (Leading) time series from the OLS estimation with the highest t-statistic and Adjusted R-square is chosen to represent the respective variable. This methodology is applied for each country under study (Germany, UK and USA). *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

(Germany) Null Hypothesis: X is not significant

X (Leading)	Y (Dependent)	t-statistic	Adj. R-square	Leading Variable
#CreditAllSectors	#CreditBanks	41.1939***	88.11%	#CreditBanks
#CreditBanks	#CreditAllSectors	58.3030***	93.66%	
#InterestRateFRED	#InterestRateOECD	61.9968***	94.28%	#InterestRateOECD
#InterestRateOECD	#InterestRateFRED	147.1627***	98.94%	

(UK) Null Hypothesis: X is not significant

X (Leading)	Y (Dependent)	t-statistic	Adj. R-square	Leading Variable
#CreditAllSectors	#CreditBanks	61.2767***	94.49%	#CreditAllSectors
#CreditBanks	#CreditAllSectors	25.3859***	75.05%	
#InterestRateFRED	#InterestRateOECD	106.7737***	98.00%	#InterestRateOECD
#InterestRateOECD	#InterestRateFRED	171.4962***	99.21%	

(USA) Null Hypothesis: X is not significant

X (Leading)	Y (Dependent)	t-statistic	Adj. R-square	Leading Variable
#CreditAllSectors	#CreditBanks	30.4229***	80.03%	#CreditBanks
#CreditBanks	#CreditAllSectors	41.1835***	88.80%	
#InterestRateFRED	#InterestRateOECD	153.6470***	99.02%	#InterestRateFRED
#InterestRateOECD	#InterestRateFRED	107.8755***	98.03%	

2.5.5. AUROC test

The third (and last) method used to select the best financial variable to represent Financial Cycles consists on studying which variable is more capable to predict financial crisis. As stated previously, there is an increasingly interest on studying financial cycles with the purpose of defining macroprudential policies. One of the main goals of most of the literature on financial cycles is to be able to predict Financial Crises. For this reason, the variable selected as proxy for Financial Cycles should be the one that has the highest predictable power of financial crises. By applying the current methodology, we evaluate how informative and explanatory the financial variable is to explain crises. It can be seen as a "coincident indicator" since the peak of a cycle should be coincident with the onset of a crisis. Then, we can simply assume that the variable with the highest explanatory and informative power is also the one with the highest predictable power. To do that, historical events of worldwide financial and economic crises from 1960 to 2018 were gathered and transformed in a dummy variable where:

$$Crises_t = \begin{cases} 0, if\ there\ is\ no\ worldwide\ economic/financial\ crises\ going\ on \\ 1, if\ there\ is\ a\ worldwide\ economic/financial\ crises\ going\ on \end{cases}.$$

Then, the following simplistic univariate logistic model is considered:

$$Crises_t = Constant + \ Financial\ Cycle_{i,t}. \tag{2.8.}$$

In order to assess the goodness of fit of each financial variable to explain events of financial crises, the "Area Under the Receiver Operating Characteristic" (AUROC)[9] measure is used. When applying this technique, an AUROC value between 0 and 1 is obtained, where the higher the AUROC value, the more informative the financial variable is. The value of 1 represents a

[9] For more details regarding the AUROC measure see Bush et al. (2014), Detken et al. (2014) and Giese et al. (2014).

perfect fit, while values below 0.50 means that the independent variable gives no information to explain the behavior of the dependent variable.

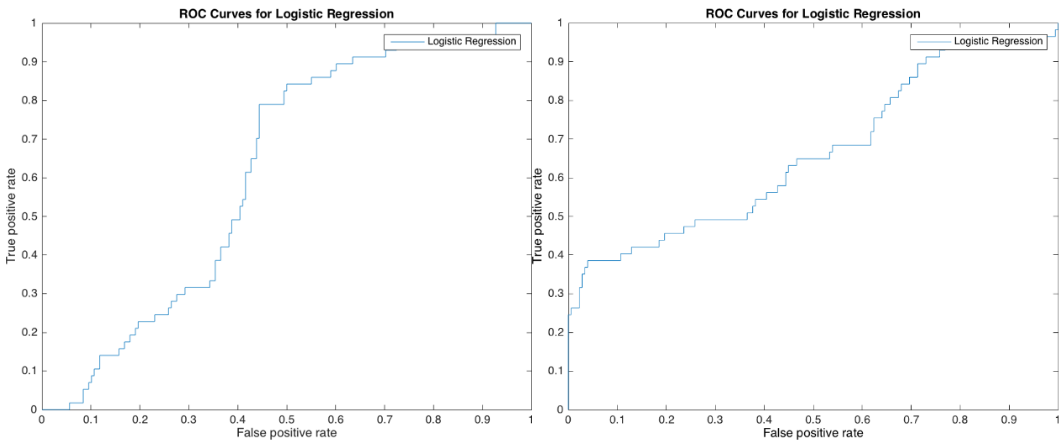
In order to perform this method, the Matlab software was used.[10] The results obtained are shown in Table 2.6.:

Table 2.6.
AUROC test results
This table shows the AUROC test results obtained after applying this method to the time series of each variable, for each country under study. The time series/variable with the highest AUROC results average (among countries) should be considered as the one more capable to explain events of financial crises.

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
Germany	0.6335	0.5848	0.6172	0.7034
UK	0.5375	0.5729	0.6643	0.6252
USA	0.4587	0.5928	0.6568	0.5869
Average	**0.5432**	**0.5835**	**0.6461**	**0.6385**

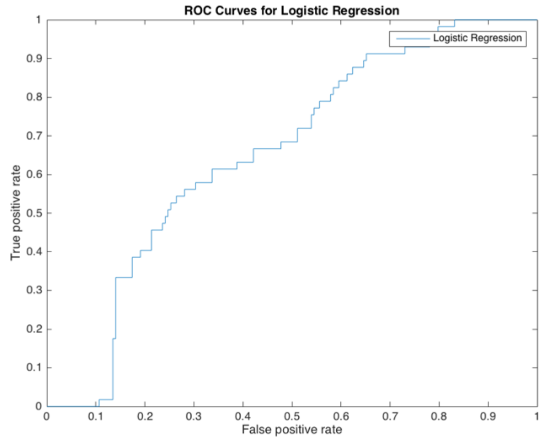
The results in Table 2.6. show that the variable Share Prices is the one, on average, with the best predictive power of financial crises, meaning that, considering this method, Share Prices variable should be selected to measure Financial Cycles. Even though Share Prices is the variable with the highest predictive power for the United Kingdom and for the United States of America, the same is not verified for Germany. However, as explained earlier, our goal is to identify the variable that is more frequently predominant among the three methods, with the final results being re-validated in the robustness tests section.

Figure 2.2. presents a graphical analysis on this issue for the Share Prices variable. The higher the AUROC curve, the better is the model's performance. The rest of the graphs are shown in Appendix D.



(a) Germany (b) UK

[10] To have access to the Matlab code, please contact the corresponding author of the current paper.



(c) USA

Figure 2.2.
AUROC curve
AUROC curve for the variable Share Prices in Germany, UK and USA, respectively.

2.5.6. Final results

In the Methodology section, three methods (Concordance Index, Granger Causality test and AUROC test) were used to conclude which of the four financial variables under study (Credit, House Prices, Share Prices and Interest Rates) is the most accurate proxy for financial cycles. Table 2.7. summarizes all the results obtained for each variable and test.

Table 2.7.
Summary table
This table shows the results from all methods used to decide which variable should be chosen to represent financial cycles. The best results for each method are in bold.

References	Variable	Concordance Index	Granger Causality Rank	AUROC value
CreditBanks	Credit	54.39%	4th	0.543
HousePrices	House Prices	56.25%	3rd	0.584
SharePrices	SharePrices	79.77%	1st	0.646
InterestRateOECD	Interest Rate	58.40%	2nd	0.639

All the three methods used lead to the same conclusion, i.e., the Share Prices variable (a country's stock market index) is the most accurate proxy to measure financial cycles.

Given the ongoing discussion on the importance of Business Cycles (GDP) compared to Financial Cycles (Share Prices), namely which one is the leading one, a brief analysis between both cycles (financial and business) is presented next.

2.6. Share Prices (Financial Cycles) vs. GDP (Business Cycles)

In this section, a brief analysis and comparison is performed to the estimated cycles of Share Prices (Financial Cycles) and the estimated cycles of GDP (Business Cycles). The methods applied are the same three used in the Methodology section, i.e., the Concordance Index, the Granger Causality test and the AUROC test.

Starting with the Concordance Index analysis, Table 2.8. shows that the Share Prices variable has a much greater Concordance Index value (between Germany, UK and USA) than the GDP variable. In other words, there is a greater correlation among the stock indices of each country than among the GDP of the same countries.

Table 2.8.
Concordance Index results for Share Prices and GDP

Variable	SharePrices	GDP
CI Germany-UK	82.48%	61.64%
CI Germany-USA	74.79%	62.50%
CI UK-USA	82.05%	64.66%
Average	**79.77%**	**62.93%**

Regarding the Granger Causality test (see Appendix E), both null hypothesis (Share Prices does not Granger cause GDP and GDP does not Granger cause Share Prices) are not rejected. Therefore, no further analyses and conclusions were taken from this method.

Finally, when applying the AUROC technique to access which variable has the highest power to predict financial crises, the results in Table 2.9. show an average AUROC value of 0.6461 for the Share Prices variable and 0.5749 for the GDP variable. Appendix F depicts such results. This means that the cycle (Financial Cycle) of a country's stock index is more reliable to predict financial crises than the cycle of a country's GDP (Business Cycle).

Table 2.9.
AUROC test results for Share Prices and GDP

Variable	SharePrices	GDP
Germany	0.6172	0.6242
UK	0.6643	0.5372
USA	0.6568	0.5632
Average	**0.6461**	**0.5749**

In both methods (Concordance Index and AUROC test) the results are similar, giving a superior importance to Share Prices variable over the GDP variable in predicting financial and economic crisis.

2.7. Robustness tests

In this Section, we perform three additional tests to verify the robustness of the main results.

2.7.1. Testing different time periods

The first robustness check consists of splitting the sample into two different time periods and applying the three tests performed in the Methodology Section to each subsample: before and after the 2008 financial crisis. The results obtained from the Concordance Index test, for both periods, corroborate the conclusion that Share Prices is the most synchronized variable. Regarding the Granger Causality test, there are divergent conclusions. In the pre-crisis period, Interest Rate is the most leading variable while in the post-crisis period the most leading variable is the Shares Prices. Finally, in what concerns the AUROC test, it was only possible to obtain results to the pre-crisis time period. For this period, the variable that showed more capacity to predict financial crisis was Share Prices, in accordance with the conclusions achieved for the whole sample. Regarding the post-crisis period, since the length of the sample is smaller, the iterations limit when running the AUROC test code was reached before achieving any result.

The results of the Concordance Index test and for the Granger Causality test, for both pre-crisis period and post-crisis period, are reported in Table 2.10. and Table 2.11., respectively. The results of the AUROC test applied to the post-crisis time series are presented in Table 2.12..

Table 2.10.
Concordance Index test results for pre-crisis and post-crisis periods
Same procedure applied in Table 2.2., but now distinguishing between pre-crisis and post-crisis periods.

Pre-crisis

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
CI Germany-UK	40.78%	33.77%	82.72%	64.40%
CI Germany-USA	38.83%	36.42%	71.73%	59.69%
CI UK-USA	73.74%	74.83%	80.63%	59.69%
Average	**51.12%**	**48.34%**	**78.36%**	**61.26%**

Post-crisis

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
CI Germany-UK	82.50%	77.50%	80.95%	40.48%
CI Germany-USA	72.50%	82.50%	90.48%	61.90%
CI UK-USA	55.00%	95.00%	90.48%	61.90%
Average	**70.00%**	**85.00%**	**87.30%**	**54.76%**

Table 2.11.
Granger Causality test results for pre-crisis and post-crisis periods

Same procedure applied in Table 2.3., but now distinguishing between pre-crisis and post-crisis periods. *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

Pre-crisis
(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	209.00***	#HousePrices
#CreditBanks	#HousePrices	106.90***	
#SharePrices	#CreditBanks	3.89***	#SharePrices
#CreditBanks	#SharePrices	1.63	
#SharePrices	#HousePrices	1.57	#SharePrices
#HousePrices	#SharePrices	1.66	
#InterestRateOECD	#CreditBanks	6.91***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	2.92***	
#InterestRateOECD	#HousePrices	9.82***	#InterestRateOECD
#HousePrices	#InterestRateOECD	2.58**	
#InterestRateOECD	#SharePrices	195.08***	#SharePrices
#SharePrices	#InterestRateOECD	189.36***	
Most Leading Variable			**#SharePrices**

Pre-crisis
(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	78.71***	#HousePrices
#CreditBanks	#HousePrices	50.46***	
#SharePrices	#CreditBanks	33.72***	#SharePrices
#CreditBanks	#SharePrices	26.02***	
#SharePrices	#HousePrices	65.60***	#SharePrices
#HousePrices	#SharePrices	48.53***	
#InterestRateOECD	#CreditBanks	43.81***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	29.71***	
#InterestRateOECD	#HousePrices	52.08***	#InterestRateOECD
#HousePrices	#InterestRateOECD	32.30***	
#InterestRateOECD	#SharePrices	202.51***	#SharePrices
#SharePrices	#InterestRateOECD	380.55***	
Most Leading Variable			**#SharePrices**

Pre-crisis

(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	4.28***	#CreditBanks
#CreditBanks	#HousePrices	1.34	
#SharePrices	#CreditBanks	0.33	#CreditBanks
#CreditBanks	#SharePrices	6.61***	
#SharePrices	#HousePrices	12.63***	#SharePrices
#HousePrices	#SharePrices	9.16***	
#InterestRateOECD	#CreditBanks	57.18***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	46.19***	
#InterestRateOECD	#HousePrices	1.29	#HousePrices
#HousePrices	#InterestRateOECD	0.01	
#InterestRateOECD	#SharePrices	66.18***	#InterestRateOECD
#SharePrices	#InterestRateOECD	58.37***	
Most Leading Variable			**#CreditBanks or #InterestRateOECD**

Post-crisis

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	264.66***	#HousePrices
#CreditBanks	#HousePrices	166.85***	
#SharePrices	#CreditBanks	319.76***	#SharePrices
#CreditBanks	#SharePrices	187.05***	
#SharePrices	#HousePrices	0.01	#SharePrices
#HousePrices	#SharePrices	0.45	
#InterestRateOECD	#CreditBanks	10.78***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	10.25***	
#InterestRateOECD	#HousePrices	75.68***	#InterestRateOECD
#HousePrices	#InterestRateOECD	6.94***	
#InterestRateOECD	#SharePrices	3.41***	#SharePrices
#SharePrices	#InterestRateOECD	19.82***	
Most Leading Variable			**#SharePrices**

Post-crisis
(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	502.65***	#HousePrices
#CreditBanks	#HousePrices	283.58***	
#SharePrices	#CreditBanks	436.74***	#SharePrices
#CreditBanks	#SharePrices	231.88***	
#SharePrices	#HousePrices	55.94***	#SharePrices
#HousePrices	#SharePrices	28.15***	
#InterestRateOECD	#CreditBanks	12.74***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	17.92***	
#InterestRateOECD	#HousePrices	806.54***	#InterestRateOECD
#HousePrices	#InterestRateOECD	95.44***	
#InterestRateOECD	#SharePrices	35661.20***	#SharePrices
#SharePrices	#InterestRateOECD	193.36***	
Most Leading Variable			**#SharePrices**

Post-crisis
(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	703.49***	#CreditBanks
#CreditBanks	#HousePrices	3619.46***	
#SharePrices	#CreditBanks	347.30***	#CreditBanks
#CreditBanks	#SharePrices	324.77***	
#SharePrices	#HousePrices	647.06***	#SharePrices
#HousePrices	#SharePrices	177.45***	
#InterestRateOECD	#CreditBanks	1.21	#InterestRateOECD
#CreditBanks	#InterestRateOECD	3.92**	
#InterestRateOECD	#HousePrices	11.32***	#HousePrices
#HousePrices	#InterestRateOECD	43.98***	
#InterestRateOECD	#SharePrices	91.50***	#InterestRateOECD
#SharePrices	#InterestRateOECD	3.06**	
Most Leading Variable			**#CreditBanks or #InterestRateOECD**

Table 2.12.

AUROC test results for pre-crisis period

Same procedure applied in Table 2.6., but for only the pre-crisis period.

Pre-crisis

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
Germany	0.6275	0.6086	0.6034	0.7369
UK	0.4879	0.4862	0.6825	0.6177
USA	0.6580	0.5265	0.6984	0.5891
Average	**0.5911**	**0.5404**	**0.6614**	**0.6479**

2.7.2. Testing different band pass filters

Secondly, and following Canova (2020), we use an alternative version of the band pass filter implementation of Christiano and Fitzgerald (2003), namely the Baxter and King (1999)'s filter, to corroborate our main conclusions. Instead of using the Christiano and Fitzgerald (2003)'s filter to extract the cycles from the original time series, now we use the Baxter and King (1999)'s filter. Then, we re-apply the three tests performed in the Methodology Section: The Concordance Index, the Granger Causality test and the AUROC test. Table 2.13. shows the results obtained from the Concordance Index test and, once again, we find that Share Prices is the most synchronized variable among the four financial variables under study. Regarding the Granger Causality test, the results from Table 2.14. show that the most leading variable is the Shares Prices for all the three countries. In what concerns the AUROC test, with the results reported in Table 2.15., the cycle that showed more capacity to predict financial crisis was the one from Share Prices.

Table 2.13.
Concordance Index Results for cycles extracted with Baxter and King (1999)'s filter
Same procedure applied in Table 2.2., but now for cycles obtained using the Baxter and King (1999)'s filter.

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
CI Germany-UK	59.18%	55.36%	79.05%	58.57%
CI Germany-USA	48.78%	66.07%	84.76%	55.71%
CI UK-USA	61.22%	71.43%	74.29%	64.76%
Average	**56.40%**	**64.29%**	**79.40%**	**59.68%**

Table 2.14.
Granger Causality test Results for cycles extracted with Baxter and King (1999)'s filter
Same procedure applied in Table 2.3., but now for cycles obtained using the Baxter and King (1999)'s filter. *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	0.03	#CreditBanks
#CreditBanks	#HousePrices	0.22	
#SharePrices	#CreditBanks	10.99***	#SharePrices
#CreditBanks	#SharePrices	6.50***	
#SharePrices	#HousePrices	34.58***	#SharePrices
#HousePrices	#SharePrices	34.31***	
#InterestRateOECD	#CreditBanks	8.72***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	3.42**	
#InterestRateOECD	#HousePrices	0.16	#InterestRateOECD
#HousePrices	#InterestRateOECD	0.02	
#InterestRateOECD	#SharePrices	0.43	#SharePrices
#SharePrices	#InterestRateOECD	0.81	
Most Leading Variable			**#SharePrices**

(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	21.08***	#HousePrices
#CreditBanks	#HousePrices	18.63***	
#SharePrices	#CreditBanks	1.92	#SharePrices
#CreditBanks	#SharePrices	1.83	
#SharePrices	#HousePrices	4.72***	#SharePrices
#HousePrices	#SharePrices	3.83**	
#InterestRateOECD	#CreditBanks	39.83***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	31.42***	
#InterestRateOECD	#HousePrices	90.72***	#InterestRateOECD
#HousePrices	#InterestRateOECD	43.96***	
#InterestRateOECD	#SharePrices	0.95	#SharePrices
#SharePrices	#InterestRateOECD	1.10	
Most Leading Variable			**#SharePrices**

(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	36.19***	#CreditBanks
#CreditBanks	#HousePrices	43.44***	
#SharePrices	#CreditBanks	58.28***	#SharePrices
#CreditBanks	#SharePrices	24.55***	
#SharePrices	#HousePrices	10.88***	#SharePrices
#HousePrices	#SharePrices	6.57***	
#InterestRateOECD	#CreditBanks	28.67***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	13.36***	
#InterestRateOECD	#HousePrices	0.01	#HousePrices
#HousePrices	#InterestRateOECD	0.03	
#InterestRateOECD	#SharePrices	6.61***	#SharePrices
#SharePrices	#InterestRateOECD	7.78***	
Most Leading Variable			**#SharePrices**

Table 2.15.
AUROC test results for cycles extracted using the Baxter and King (1999)'s filter
Same procedure applied in Table 2.6., but now for cycles obtained using the Baxter and King (1999)'s filter.

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
Germany	0.5503	0.5835	0.7500	0.6221
UK	0.6070	0.5781	0.6419	0.5347
USA	0.5910	0.5853	0.5827	0.5900
Average	**0.5828**	**0.5823**	**0.6582**	**0.5823**

In summary, all the three tests applied to the cycles extracted using the Baxter and King (1999)'s filter lead to the same conclusions previously achieved (when using the Christiano and Fitzgerald (2003)'s filter), i.e., Share Prices is the most accurate variable to measure financial cycles.

2.7.3. Testing different filtering procedures

Finally, our last robustness test consists of applying a different filtering procedure to extract the cyclical component from our time series. This procedure consists of running a quadratic polynomial regression to each variable. Each regression is assumed to have a polynomial trend and the cycle is obtained as the residual of this same regression (see Canova, 2020). Then, the Concordance Index, the Granger Causality test and the AUROC test are performed, with the corresponding results displayed in Tables 2.16., 2.17. and 2.18., respectively. Considering these results, we re-validate our initial conclusions, i.e., Share Prices is, among the financial variables under study, the one with the highest Concordance Index, the most leading variable (with the only exception of Germany) and the one with the most predictable power of financial crisis. Therefore, one may conclude that Share Prices is an accurate variable to measure financial cycles.

Table 2.16.
Concordance Index Results for cycles extracted using polynomial detrending
Same procedure applied in Table 2.2., but now for cycles obtained through polynomial detrending.

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
CI Germany-UK	47.27%	46.35%	73.93%	64.96%
CI Germany-USA	58.95%	55.73%	73.50%	61.97%
CI UK-USA	50.45%	66.67%	68.80%	62.82%
Average	**52.23%**	**56.25%**	**72.08%**	**63.25%**

Table 2.17.
Granger Causality Test Results for cycles extracted using polynomial detrending
Same procedure applied in Table 2.3., but now for cycles obtained through polynomial detrending. *, ** and *** indicate statistical significance at the 15%, 10% and 5% levels, respectively.

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	29. 80***	#CreditBanks
#CreditBanks	#HousePrices	31.39***	
#SharePrices	#CreditBanks	8.58***	#SharePrices
#CreditBanks	#SharePrices	0.63	
#SharePrices	#HousePrices	2.53*	#SharePrices
#HousePrices	#SharePrices	0.36	
#InterestRateOECD	#CreditBanks	5.70***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	0.18	
#InterestRateOECD	#HousePrices	12.53	#InterestRateOECD
#HousePrices	#InterestRateOECD	0.31	
#InterestRateOECD	#SharePrices	9.03	#InterestRateOECD
#SharePrices	#InterestRateOECD	1.22	
Most Leading Variable			**#InterestRateOECD**

(UK) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	1.67	#HousePrices
#CreditBanks	#HousePrices	1.49	
#SharePrices	#CreditBanks	2.30	#SharePrices
#CreditBanks	#SharePrices	0.15	
#SharePrices	#HousePrices	6.74***	#SharePrices
#HousePrices	#SharePrices	4.78**	
#InterestRateOECD	#CreditBanks	20.63***	#InterestRateOECD
#CreditBanks	#InterestRateOECD	0.68	
#InterestRateOECD	#HousePrices	14.49***	#InterestRateOECD
#HousePrices	#InterestRateOECD	7.34***	
#InterestRateOECD	#SharePrices	3.77***	#SharePrices
#SharePrices	#InterestRateOECD	3.91**	
Most Leading Variable			**#SharePrices**

(USA) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Leading Variable
#HousePrices	#CreditBanks	14.69***	#CreditBanks
#CreditBanks	#HousePrices	15.68***	
#SharePrices	#CreditBanks	11.83***	#SharePrices
#CreditBanks	#SharePrices	10.60***	
#SharePrices	#HousePrices	7.68***	#SharePrices
#HousePrices	#SharePrices	1.95***	
#InterestRateOECD	#CreditBanks	0.87	#InterestRateOECD
#CreditBanks	#InterestRateOECD	0.12	
#InterestRateOECD	#HousePrices	1.11	#HousePrices
#HousePrices	#InterestRateOECD	1.79	
#InterestRateOECD	#SharePrices	5.68***	#SharePrices
#SharePrices	#InterestRateOECD	6.86***	
Most Leading Variable			**#SharePrices**

Table 2.18.
AUROC test results for cycles extracted using polynomial detrending

Same procedure applied in Table 2.6., but now for cycles obtained through polynomial detrending.

Variable	CreditBanks	HousePrices	SharePrices	InterestRateOECD
Germany	0.6358	0.6339	0.6019	0.5324
UK	0.5085	0.5317	0.7787	0.5123
USA	0.7175	0.6109	0.7601	0.4926
Average	**0.6206**	**0.5922**	**0.7136**	**0.5124**

2.8. Conclusions

This study aims to fill a gap in the literature by identifying the most suitable and appropriate measure to represent Financial Cycles (similar to GDP for Business Cycles). To do this, four financial variables identified by the existing literature were included in the study: Credit, House Prices, Share Prices and Interest Rates. The method used to estimate and ex- tract the cycles from the original time series was the Christiano and Fitzgerald (2003) filter. Then, three methods were used (Concordance Index, Granger Causality Test and AUROC Test) to identify which of the four variables is the best proxy for financial cycles. In all of them, the results pointed to the same variable: Share Prices. Our results are robust to different filtering procedures.

The first test, the Concordance Index, identifies the variable which presents the most similar behavior between the different countries, being an important indicator given the systemically effect and impact that these cycles represent in the economies around the world. The second test, the Granger Causality test, choses the variable that presents more evidence of being the leading one, which helps in the prediction-making process. Finally, the third test, the AUROC test, selects the variable with the highest predictive power of financial crises, which is a fundamental tool for macroprudential policymakers.

After identifying the variable to measure Financial Cycles (Share Prices), a comparison between this variable and GDP was performed. The results show that the financial variable has a higher capacity to predict financial and economic crises than GDP, which justifies the recent increasing interest of macroprudential policymakers on Financial Cycles.

Our conclusions contribute to the literature in the selection of the best variable to measure financial cycles and predict financial and economic crises.

As recommendations for future work on this matter, it would be interesting to:

- Extend this study for China and Japan, which nowadays are also systemically important countries, i.e., they have a high capacity to influence and impact the behavior of the world economy/finance;
- Include synthetic variables (combination of different variables in one synthetic variable) on this study and verify if they present better results than Share Prices alone;
- Perform a complete analysis of the features of the estimated Financial Cycle (persistence; magnitude; slope; severity; cycle length, spectrum, covariance, etc.) and compare to Business Cycles.

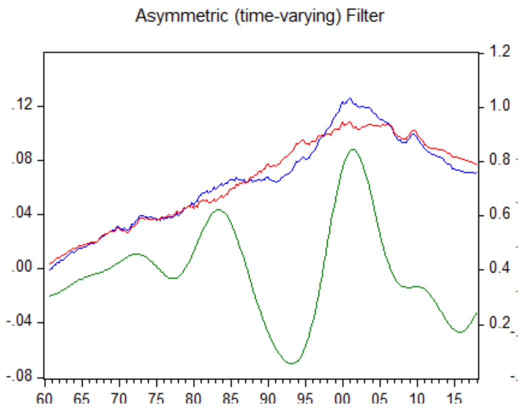
2.9. Appendices

Appendix A
Augmented Dickey-Fuller test
Augmented Dickey-Fuller test for the presence of Unit Roots in the Original Time Series.
Null Hypothesis: Variable has a Unit Root.

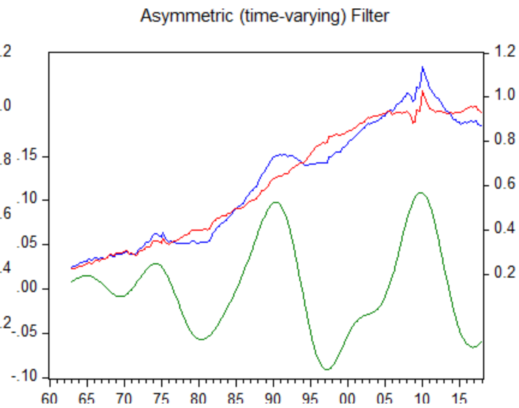
Variable	Country	t-statistic	p-value
#CreditBanks	Germany	-2.637623	0.0869
#CreditBanks	UK	-1.219681	0.6662
#CreditBanks	USA	-2.781400	0.0625
#CreditAllSectors	Germany	-2.601596	0.0941
#CreditAllSectors	UK	-0.116090	0.9451
#CreditAllSectors	USA	-1.033053	0.7417
#HousePrices	Germany	-1.789946	0.3847
#HousePrices	UK	-1.233629	0.6598
#HousePrices	USA	-1.294326	0.6321
#SharePrices	Germany	-0.979016	0.7609
#SharePrices	UK	-2.525212	0.1108
#SharePrices	USA	-0.712719	0.8402
#InterestRateOECD	Germany	-1.529888	0.5168
#InterestRateOECD	UK	-4.365597	0.0004
#InterestRateOECD	USA	-3.225463	0.0198
#InterestRateFRED	Germany	-2.136678	0.2306
#InterestRateFRED	UK	-4.732938	0.0001
#InterestRateFRED	USA	-3.581933	0.0068
#GDP	Germany	-2.998134	0.0365
#GDP	UK	-1.485815	0.5392
#GDP	USA	-2.700601	0.0754

Appendix B
Graphical output from the CF filter

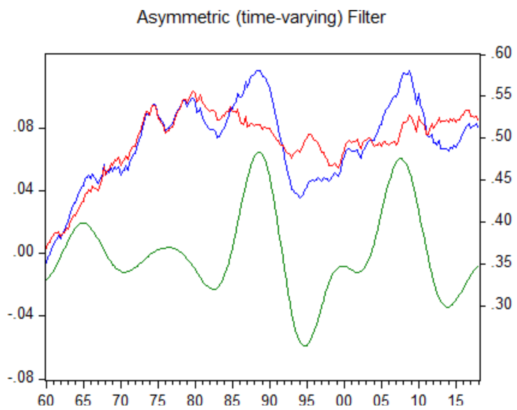
Variable: Credit from Banks



(a) Germany

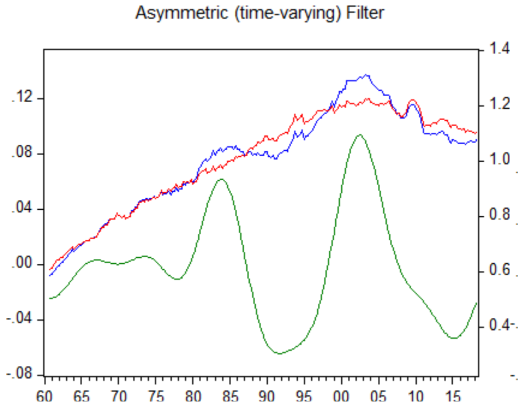


(b) UK

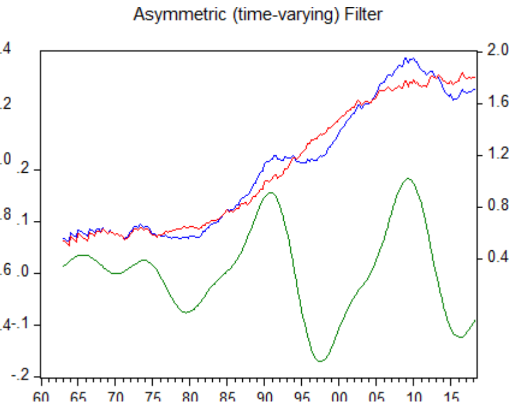


(c) USA

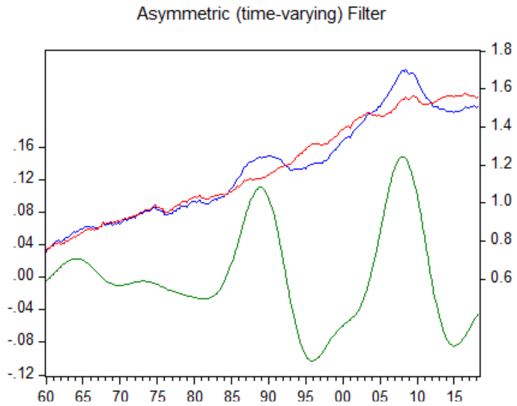
Variable: Credit from all Sectors



(a) Germany

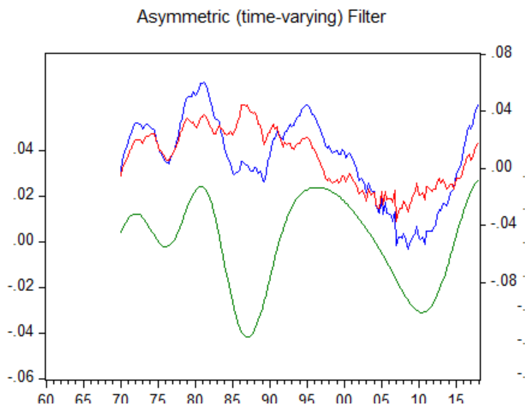


(b) UK

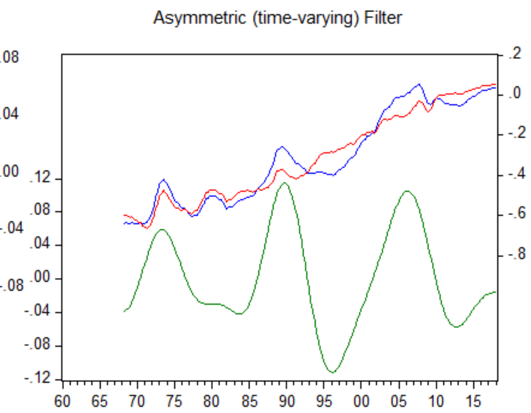


(c) USA

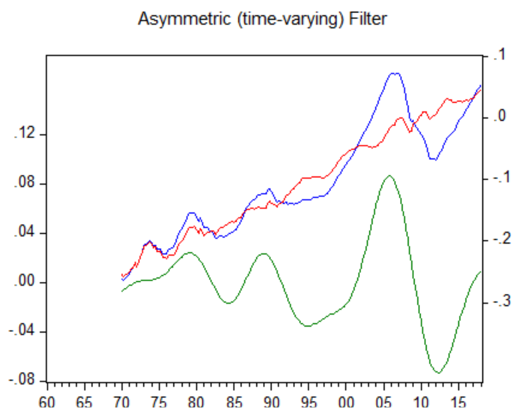
Variable: House Prices



(a) Germany

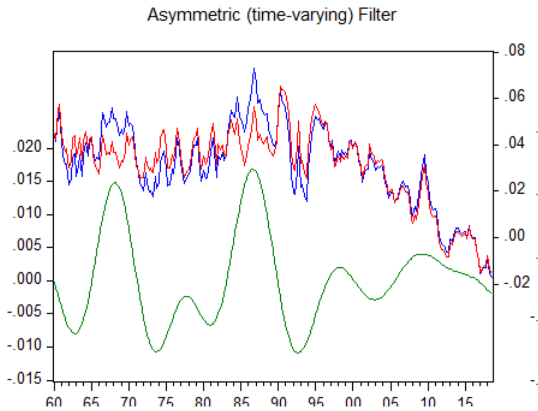


(b) UK

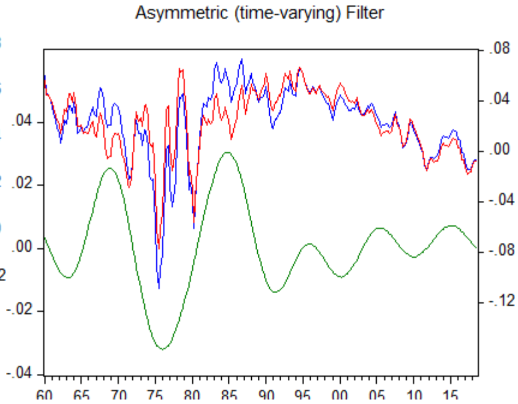


(c) USA

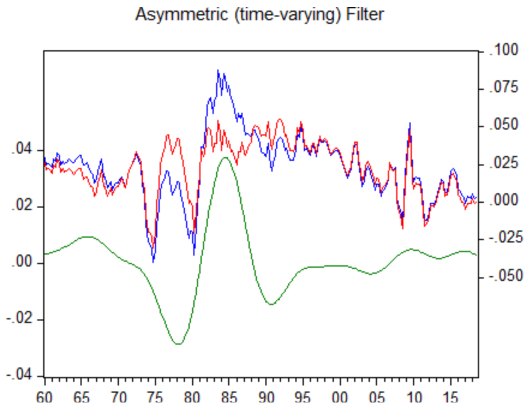
Variable: Interest Rate OECD



(a) Germany

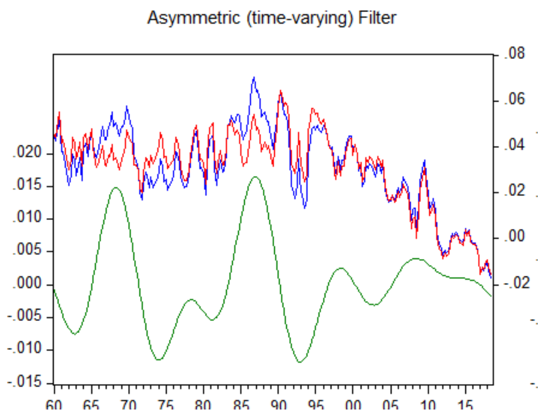


(b) UK

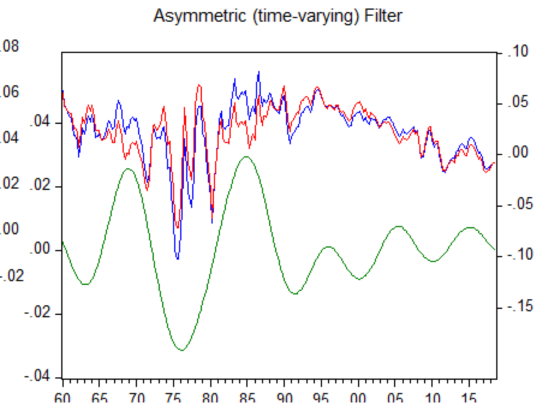


(c) USA

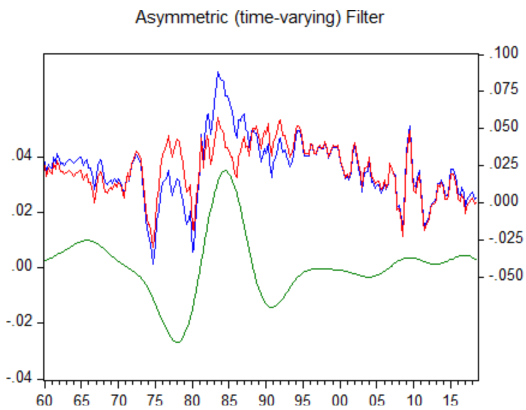
Variable: Interest Rate FRED



(a) Germany

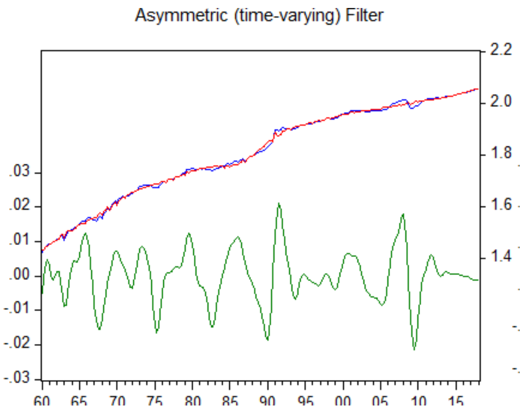


(b) UK

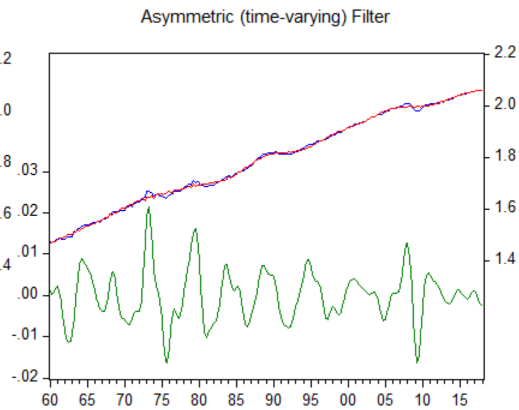


(c) USA

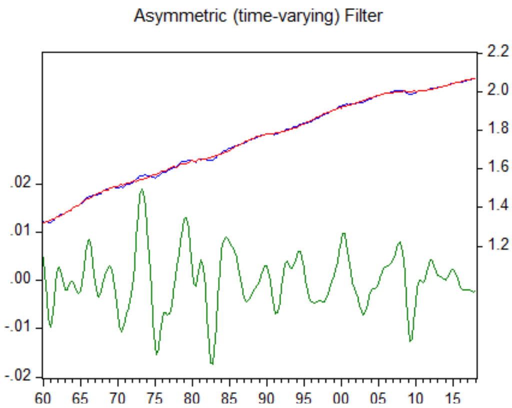
Variable: GDP



(a) Germany



(b) UK



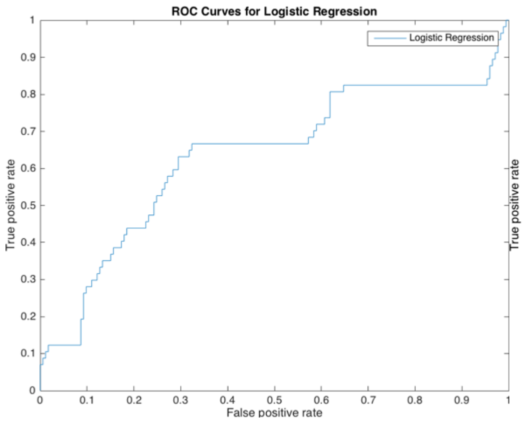
(c) USA

Appendix C
Augmented Dickey-Fuller test for cycles
Augmented Dickey-Fuller test for the presence of Unit Roots in the Cycles Time Series.
Null Hypothesis: Cycle has a Unit Root.

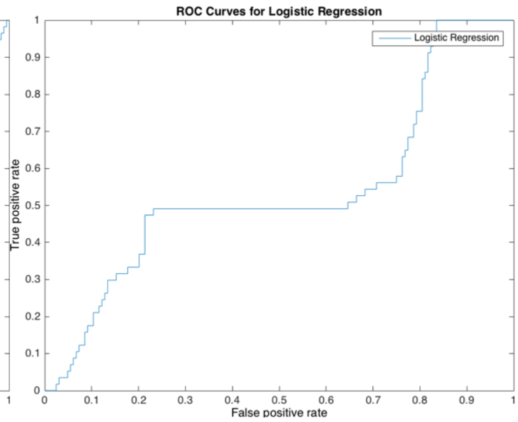
Variable	Country	t-statistic	p-value
#CreditBanks	Germany	-22.03378	0.0000
#CreditBanks	UK	-34.88339	0.0001
#CreditBanks	USA	-27.41230	0.0000
#CreditAllSectors	Germany	-28.28985	0.0000
#CreditAllSectors	UK	-43.61111	0.0001
#CreditAllSectors	USA	-37.52733	0.0001
#HousePrices	Germany	-24.34845	0.0000
#HousePrices	UK	-37.65290	0.0001
#HousePrices	USA	-26.84162	0.0000
#SharePrices	Germany	-26.06248	0.0000
#SharePrices	UK	-21.03773	0.0000
#SharePrices	USA	-22.43866	0.0000
#InterestRateOECD	Germany	-28.11390	0.0000
#InterestRateOECD	UK	-21.73355	0.0000
#InterestRateOECD	USA	-20.52049	0.0000
#InterestRateFRED	Germany	-30.88085	0.0000
#InterestRateFRED	UK	-22.20538	0.0000
#InterestRateFRED	USA	-20.61638	0.0000
#GDP	Germany	-15.43140	0.0000
#GDP	UK	-16.53720	0.0000
#GDP	USA	-15.04341	0.0000

Appendix D
AUROC curve

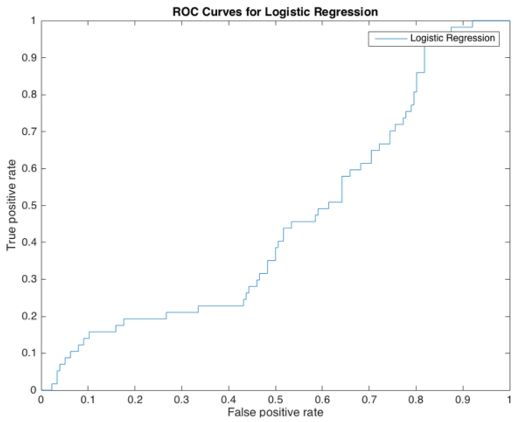
Variable: Credit from Banks



(a) Germany

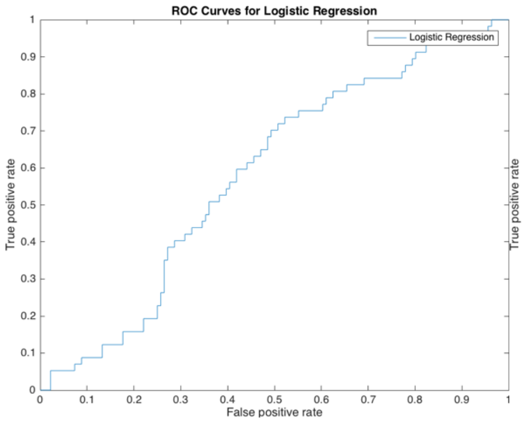


(b) UK

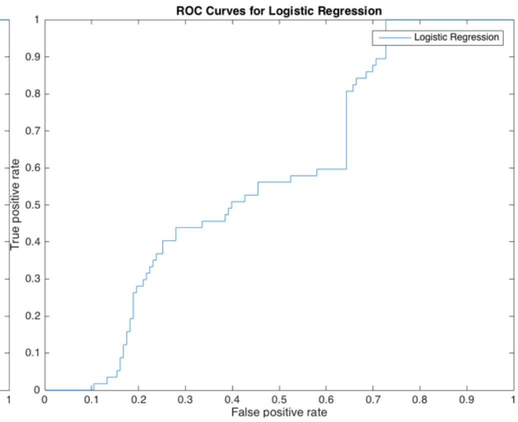


(c) USA

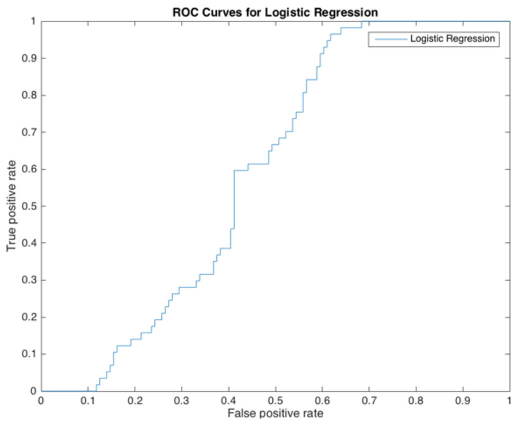
Variable: House Prices



(a) Germany

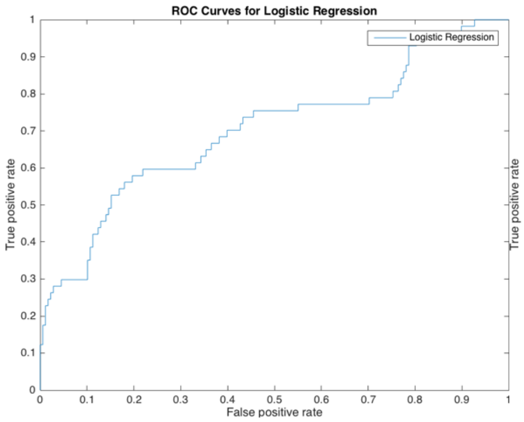


(b) UK

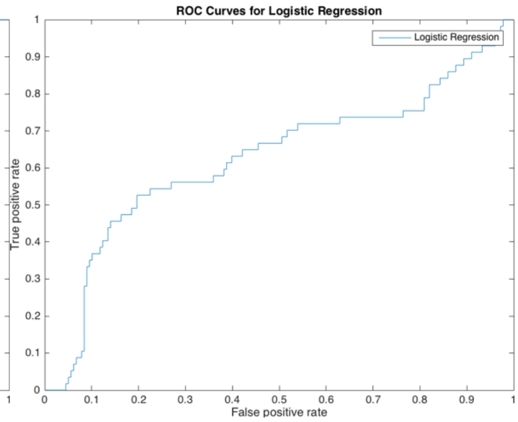


(c) USA

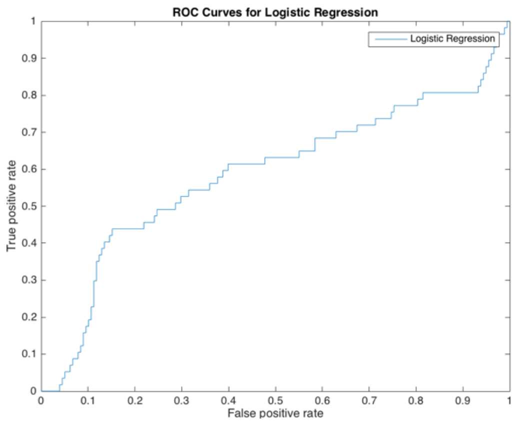
Variable: Interest Rate OECD



(a) Germany



(b) UK



(c) USA

Appendix E
Granger Causality test between Share Prices and GDP

(Germany) Null Hypothesis: X does not Granger Cause Y

X (Leading)	Y (Dependent)	F-statistic	Null Hypotheses
#GDP	#SharePrices	0.0041	Not rejected
#SharePrices	#GDP	0.0016	Not rejected

(UK) Null Hypothesis: X does not Granger Cause Y

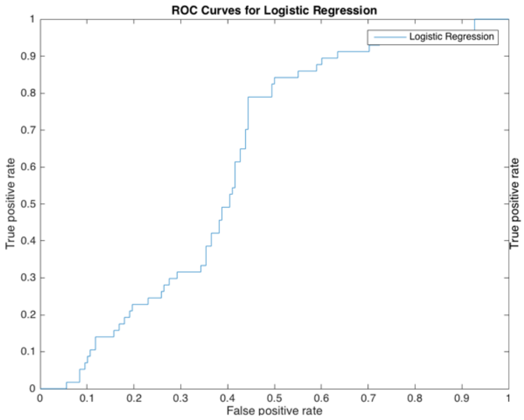
X (Leading)	Y (Dependent)	F-statistic	Null Hypothesis
#GDP	#SharePrices	0.0092	Not rejected
#SharePrices	#GDP	0.0234	Not rejected

(USA) Null Hypothesis: X does not Granger Cause Y

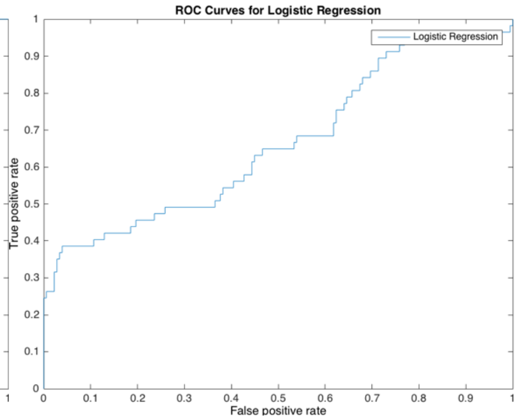
X (Leading)	Y (Dependent)	F-statistic	Null Hypothesis
#GDP	#SharePrices	0.0488	Not rejected
#SharePrices	#GDP	0.0131	Not rejected

Appendix F
AUROC curve for Share Prices and GDP

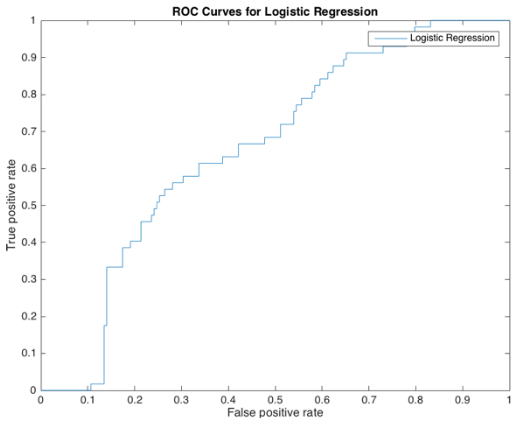
Variable: Share Prices



(a) Germany

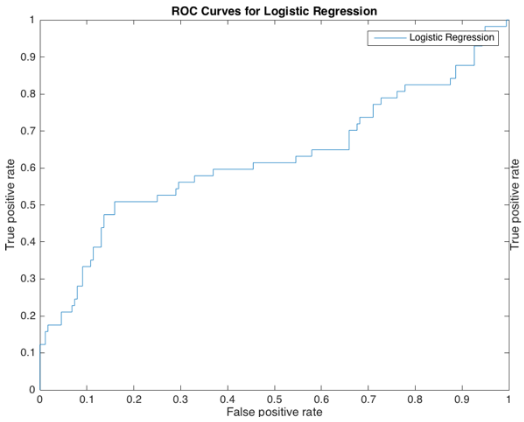


(b) UK

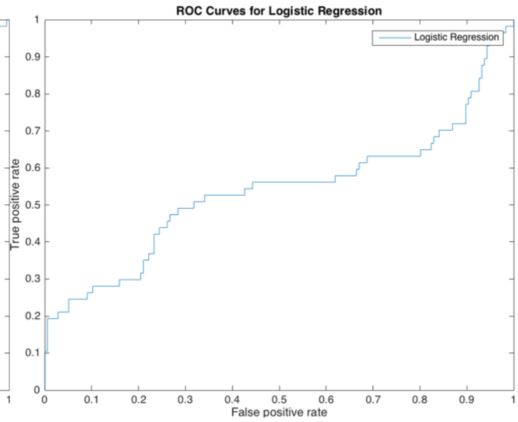


(c) USA

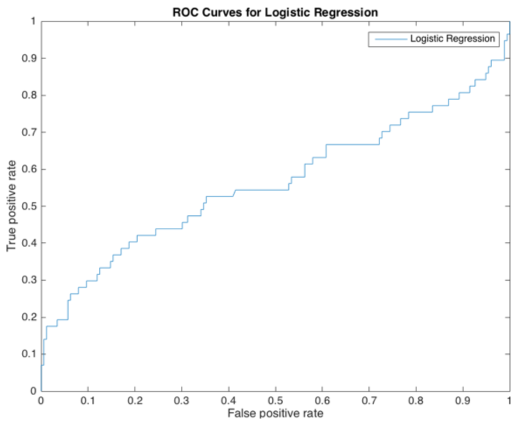
Variable: GDP



(a) Germany



(b) UK



(c) USA

3. Banking regulation and banks' risk-taking behavior: The role of political institutions

Abstract

This paper examines whether the influence of banking regulation on banks' risk is channeled through the quality of political institutions, using panel data from a sample of 535 banks from OECD countries, for the 2004–2016 period. As banking regulatory factors, we consider capital stringency, activity restrictions and supervisory power. We find that the overall effect of banking regulation on banks' risk is conditional on the quality of political institutions. Activity restrictions and capital stringency have a statistically significant positive effect on banks' risk and this effect is mitigated by better political institutions. On the contrary, stringent supervisory power tends to reduce banks' risk and better political institutions reinforce this effect. The results are robust across different measures of political institutions, banks' risk and estimation methods.

Keywords: Banks' risk, Banking regulation, Political institutions

JEL Classification: G10, G21, G28, G32, G38

3.1. Introduction

The 2008-09 global financial crisis that started in the United States led to profound and structural reforms of the financial system. This new regulatory environment potentially affected banks' risk and, consequently, their sustainability. At the same time, the quality of political institutions or the institutional environment where banks operate may have influence on bank's risk, as it also has on the risk of non-financial firms. Understanding how the quality of political institutions may influence the overall effect of banking regulation on banks' risk is a topic that still deserves a thorough investigation.

There is a comprehensive literature studying the effect of several regulatory factors on banks' risk, namely restrictions on banks' activities, capital stringency and supervisory power, with mixed empirical evidence. For instance, Barth et al. (2004), Laeven and Levine (2009), Ashraf (2017), Wu et al. (2017, 2019), Li (2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020) report that financial systems with more restrictions on banks' activities are less stable, while Fernandez and Gonzalez (2005), Pasiouras et al. (2006), Agoraki et al. (2011), Wang and Sui (2019) and Teixeira et al. (2020a) show that banks' risk is lower when activity restrictions are stricter. Similarly, while Besanko and Kanatas (1996), Blum (1999), Calem and Rob (1999), Ashraf (2017), Li (2019) and Al-Shboul et al. (2020) find a positive relationship between capital stringency and banks' risk, Barth et al. (2004), Beltratti and Stulz (2012), Agoraki et al. (2011), Wu et al. (2017, 2019) and Danisman and Demirel (2019) reveal evidence of a negative association between regulation and risk. Finally, concerning supervisory power, Stigler (1971), Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018) and Al-Shboul et al. (2020) argue that as the power of supervisory authorities increase banks become less stable, whereas Shleifer and Vishny (1998), Wu et al. (2017, 2019) and Danisman and Demirel (2019) conclude that higher levels of supervisory power lead to an increase of banks' risk.

In parallel, the literature documents empirical evidence that banks' risk-taking behavior is affected by the quality of political institutions and this relationship became even more important after the global financial crisis. In fact, Ashraf (2017) and Wang and Sui (2019) find empirical evidence that political institutions are predictors of banks' risk-taking behavior. Nevertheless, the literature is not consistent over the signal and magnitude of this effect. On the one hand, Ashraf (2017) and Wand and Sui (2019) point out that sound political institutions may reduce banks' risk-taking by lowering the government expropriation of banks, improving the information environment that weakens the information asymmetries between banks and borrowers and reducing operating costs. On the other hand, as better political institutions promote the competition in credit markets, reducing financing costs, banks are encouraged to take more risk in order to compensate for the spread reduction and try to regain market share. Moreover, Ashraf (2017) and Wand and Sui (2019) further state that sound political institutions may increase banks' risk by generating moral hazard problems through the expectation that a government will bailout the banks if economic conditions deteriorate.

Even though the extant literature relating both banking regulation and political institutions with bank risk-taking behavior, there are still important questions that deserve further research: is the effect of banking regulation on banks' risk contingent on the quality of political institutions? If so, can the quality of political institutions mitigate or reinforce the overall effect of banking regulation on banks' risk? The existing literature on this subject has studied the direct effect of each of the aforementioned factors on banks' risk and, in some cases, the indirect effect through other factors (e.g., through market power, Agoraki et al., 2011, and Danisman and Demirel, 2019; through deposit insurance, Ashraf et al., 2020; through investor protection, Teixeira et al., 2020a; through taxation, Horvath, 2020; and through banks' ownership, Mohsni and Otchere, 2014 and Boubakri et al., 2020), but, to the best of our knowledge, none of them has investigated how the overall effect of banking regulation on banks' risk depends on the quality of political institutions. The goal of this paper it to fill this gap in the literature by studying how the effect of banking regulation (activity restriction, capital stringency and supervisory power) on banks' risk is conditional on political institutions.

The empirical analysis is conducted based on a sample of 535 banks from Organisation for Economic Co-operation and Development (OECD) countries for the period of 2004-2016. The results show that while stricter capital stringency and activity restriction tend to increase banks' risk, higher levels of supervisory power tend to reduce this risk. Moreover, in countries with better political institutions banks' risk tend to be lower. Focusing on the interplay between banking regulation, political institutions and banks' risk, we find that political institutions mitigate the positive effect of activity restriction and capital stringency on banks' risk and reinforce the negative effect of supervisory power on it. These results are robust to a different estimation method and distinct measures of banks' risk and political institutions.

We contribute to the literature in at least five important ways. First, we add to the regulation and finance literature by providing further evidence of the direct effect of banking regulation on banks' risk, in particular the effects of activity restrictions, capital stringency and supervisory power. Second, we further explore the direct effect of the quality of political institutions on banks' risk, either measured through democratic accountability or political constraints, adding to the literature on the institutions-risk nexus. Third, and more important due to its novelty, we show that the overall effect of banking regulation on banks' risk is conditional on the quality of political institutions where banks have their headquarters. Fourth, our paper contributes to the literature that studies the determinants of banks' risk, such as Laeven and Levine (2009), Houston et al. (2010), Anginer et al. (2014), Haq et al. (2014), Fang et al. (2014), Luo et al. (2016), Ashraf (2017), Wang and Sui (2019) and Teixeira et al. (2020a), among others. Finally, this paper adds to the literature that investigates the influence of political institutions on firms' behavior.

The rest of the paper is organized as follows. Section 3.2. hypothesizes the various channels through which banking regulation and political institutions influence banks' risk-taking behavior. Section 3.3. introduces data and variables and presents the methodology. Section 3.4. reports empirical results and the robustness checks. Section 3.5. presents the conclusion.

3.2. Literature review and hypotheses development

3.2.1. The effect of banking regulation on banks' risk-taking behavior

3.2.1.1. Activity restrictions and banks' risk

The economic theory that provides predictions about the effect of activity restrictions on banks' risk is uncertain (Barth et al., 2004). For instance, Boyd et al. (1998) argue that since moral hazard encourages risk-taking, banks that are allowed to engage in more activities have, naturally, more opportunities to take risk. This means that higher levels of activity restrictions reduce banks' risk. By contrast, Hellmann et al. (2000) and Gonzalez (2005) argue that as regulation on banks' activities becomes more restrictive, banks may lose profitability, incentivizing banks' managers to invest on risky projects. Moreover, less activity restrictions allow banks to diversify their income sources and, therefore, reduce risk. Under this view, higher levels of activity restrictions increase banks' risk.

There is empirical evidence for both effects of activity restrictions on banks' risk. For instance, Fernandez and Gonzalez (2005), Pasiouras et al. (2006), Agoraki et al. (2011), Wang and Sui (2019) and Teixeira et al. (2020a) conclude that as restrictions on banks' activities become more stricter, banks' risk diminishes, whereas Barth et al. (2004), Laeven and Levine (2009), Li (2019), Ashraf (2017), Wu et al. (2017, 2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020) provide empirical evidence that more restrictions on banks' activities lead to less stable financial systems, i.e., higher banks' risk.

Therefore, we test the following hypothesis:

H1: Activity restrictions have a positive or negative effect on banks' risk.

3.2.1.2. Capital stringency and banks' risk

The economic theory also provides mixed predictions on the effect of capital stringency on banks' risk (Santos, 2001). On the one hand, Koehn and Santomero (1980), Kim and Santomero (1988) and Blum (1999) posit that banks' risk increases as capital requirements augments. If it is too costly for banks to fulfill higher capital requirements in the near future, they will try to meet this goal by taking more risk today. On the other hand, Dewatripont and Tirole (1994) argue that capital stringency has a negative effect on banks' risk since as capital requirements increase banks benefit from a buffer against losses, reducing their risk. Additionally, as capital requirements become stricter, the propensity to engage in new risky investments that demands larger amounts of capital at risk is reduced (lower risk).

The empirical evidence that relates capital stringency and banks' risk supports both effects (positive and negative). While Barth et al. (2004), Agoraki et al. (2011), Beltratti and Stulz (2012), Wu et al. (2017, 2019), Danisman and Demirel (2019) and Teixeira et al. (2020a) find evidence of a negative effect of capital stringency on risk, Besanko and Kanatas (1996), Blum (1999), Calem and Rob (1999), Ashraf (2017), Li (2019) and Al-Shboul et al. (2020) show that higher capital requirements increase banks' risk.

Based on the above arguments, we test the following hypothesis:

H2: Capital stringency has a positive or negative effect on banks' risk.

3.2.1.3. Supervisory power and banks' risk

Supervisory power captures the power that supervisory authorities and agencies have over banks and their management, controlling and closely following banks' activity and restricting their risk-taking actions if needed (Barth et al., 2004). There are two theoretical views on how supervisory power affects banks' risk: the public interest view and the private interest view. The former view finds advantages of powerful supervisors, assuming that high levels of supervisory power encourage the improvement of the banking system and the fix and correction of banking market failures, such as information asymmetry (Stigler, 1971; Barth et al., 2004). Under this view, more power given to supervisory authorities reduces banks' risk. Conversely, the private interest view argues that supervisory authorities and agencies may not have the right incentives to perform these improvements and corrections. When the focus of the supervisory agents is on using their power to maximize their own welfare instead of correctly supervising banks, mistakes that affect the banking industry are made. In this case, supervisory agencies failures may be so significant that they lead to counterproductive results such as intensified corruption, reduced banks' efficiency and increased banks' risk (Boot and Thakor, 1993;

Shleifer and Vishny, 1998; Quintyn and Taylor, 2002). In this case, higher levels of supervisory power increase banks' risk.

Once again, the existing empirical evidence supports both effects: a positive and a negative effect of supervisory power on banks' risk. On the one hand, Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018) and Al-Shboul et al. (2020) find that strong supervisory power reduces excessive banks' risk-taking. On the other hand, Pasiouras et al. (2009), Wu et al. (2017, 2019) and Danisman and Demirel (2019) show that greater supervisory power increases banks' risk.

Taking into account this exposition, we test the following hypothesis:

H3: Supervisory power has a positive or negative effect on banks' risk.

3.2.2. The effect of the quality of political institutions on banks' risk-taking behavior

According to the economic theory, there are four main channels through which political institutions can have an effect on banks' risk. The first one is the 'government expropriation risk'. The conflict of interest that exists between the banking industry and governments makes the first one vulnerable to government expropriation. While governments are responsible for regulating the banking industry, they also depend on this industry to survive, meaning that an expropriation decision is always a possibility (Haber et al., 2008). This expropriation may take different forms. Governments can regulate with the goal of achieving a bank monopoly and, therefore, taking advantage from the only bank in the market. They can also grant licenses or benefits to their favored banks; favor banks with the goal of getting a board position in these banks later; influence and encourage deals for the interest of the government; encourage banks to grant loans to firms that are politically connected with the government, among other expropriation forms. This way of government expropriation risk may lead to higher banks' risk due to the inefficiencies related to the monopoly, deals with government's favored groups, loans granted to politically connected firms, among other situations. Even though countries with strong political institutions, such as the United States, are not immune from the government expropriation risk, this risk is expected to be lower in democratic regimes compared to authoritarian regimes (Liu and Ngo, 2014). Therefore, better political institutions should translate into lower banks' risk.

The second channel relates to how political institutions react to negative shocks in the financial and banking industry. For instance, moral hazard problems tend to occur when governments provide bailouts in order to avoid firms and banks to fail. This also happens when governments are members of a deposit insurance scheme with the intention of protecting the depositors' interests and avoiding depositor runs in worst case scenarios. According to Dam and Koetter (2012) and Antzoulatos and Tsoumas (2014), this behavior of governments encourages banks to take on more risk in expansion periods. Since democratic governments are more likely to provide bailouts when a negative shock affects the banking industry, keeping depositors and masses by their side, the 'bailout expectation' increases in the presence of better political institutions. Hence, in countries with better political institutions (which generate moral hazard due to the 'bailout expectation') we should expect lower levels of banks' risk.

The third channel is through adverse selection. Adverse selection happens when riskier firms have more probability to obtain loans from banks than less risky firms. This normally happens due to the information asymmetry between banks and borrowers, leading to severe problems in credit markets (Stiglitz and Weiss, 1981). The asymmetric information can be reduced through better political institutions. As shown by Bushman et al. (2004), firms tend to disclose more information as political institutions become stronger. The probability of adverse selection occurring is naturally reduced in transparent environments, where creditworthiness of borrowers is easily verified by banks. Also, there are more firms' investments and, consequently, a higher demand for bank credit in countries with stronger political institutions (Boubakri et al., 2013), which decreases adverse selection. If banks have more borrowers looking for loans, they are able to select the less risky ones, reducing the probability of non-performing loans. Hence, according to this view, better political institutions should lead to a reduction on banks' risk.

Finally, a fourth channel is through the credit market competition. In countries with political constraints, the access of firms to alternative sources of financing is reduced. According to Qi et al. (2010), financing costs of firms are lower in countries with better political institutions. This means that banks, in addition to losing some market share, have to reduce interest rates in the loans conceded to firms. To compensate both these challenges, banks tend to take more risk by granting loans to risky firms. Therefore, a positive influence of better political institutions and banks' risk is expected.

All in all, the effect of political institutions on banks' risk can be mixed. On the one hand, better political institutions may increase banks' risk by promoting moral hazard problems ('bailout expectation') and intensifying the competition on credit markets. On the other hand, better political institutions may decrease banks' risk by reducing information asymmetry and government expropriation. While Bui and Bui (2019) and Al-Shboul et al. (2020) find empirical evidence of a positive effect of the quality of political institutions on banks' risk, Ashraf (2017), Wang and Sui (2019), Rezgallah et al. (2019) and Uddin et al. (2020) report an opposite effect.

Based on the above arguments, we test the following hypothesis:

H4: The quality of political institutions has a positive or negative effect on banks' risk.

3.2.3. The interplay between banking regulation and political institutions

The literature about the determinants of banks' risk fails to investigate whether the effect of banking regulation on banks' risk is contingent on the quality of political institutions. An important and related literature has focused, instead, on other channels of the regulation-risk nexus. Laeven and Levine (2009) study the interplay between banking regulation (activity restriction and capital stringency) and the ownership structure of each bank as determinants of banks' risk. Houston et al. (2010) further include financial transparency, information sharing and creditors' rights on this analysis. More recently, Danisman and Demirel (2019) study the role of market power, Ashraf et al. (2020) examine the importance of deposit insurance and Teixeira et al. (2020a) consider whether investors' protection mitigates or reinforces the effect of banking regulation on risk.

According to Fang et al. (2014), a sound institutional environment encourages banks' financial information disclosure, transparency, valuation of their clients' risk and so on, which will ultimately reduce the risk taken by banks. They argue that if there is any banking regulatory reform that reduces banks' risk, this reduction should be greater in the presence of better institutional environments. Following their conclusion, one might think that the effect of an increase of some banking regulatory reform (capital stringency, activity restrictions or supervisory power) on banks' risk will also depend on the respective country's level of political institutions. In other words, political institutions may have a reinforcing or a mitigating effect on the overall effect that each banking regulation factor has on banks' risk. If the banking regulation and political institutions factors have similar direct effects (same direction) on banks' risk, then, when accounting for the interplay, we should expect a reinforcing effect of political institutions on the overall effect of the banking regulatory factor on banks' risk. By contrast, if the banking regulation and political institutions factors have opposite direct effects (inverse direction) on banks' risk, we should expect a mitigating effect of political institutions on the overall effect of the banking regulatory factor on banks' risk.

To summarize, we test the following hypothesis:

H5: The effect of banking regulation on banks' risk is reinforced or mitigated by the quality of political institutions.

3.3. Data and methodology

3.3.1. Data and sample

The data used in this study was collected from various sources. Bank-level accounting data were collected from the Bureau van Dijk's Bankscope database. This database is extensively used by researchers in the banking literature (see for instance Gropp and Heider, 2010; Ashraf, 2017; Wang and Sui, 2019; among others), given the standardized and universal format in which banks' financial information is presented, allowing comparisons between banks from different countries (Pasiouras et al., 2006). Data on stock prices were downloaded from Thompson Reuters Datastream. Macroeconomic data are from the International Monetary Fund (IMF)'s World Economic Outlook database, World Development Indicators (WDI) of World Bank and OECD database. Data on banking regulation variables (activity restrictions, capital stringency and supervisory power) is taken from the World Bank's Bank Regulation and Supervision Survey (BRSS). These surveys were conducted by Barth et al. (2008, 2013) and Anginer et al. (2019) and provide a unique source of comparable economy-level data on how banks are regulated and supervised around the world. Like the Bureau van Dijk's Bankscope database, the World Bank's Bank Regulation and Supervision Survey database is also widely used by researchers in the banking literature. Following similar studies by Ashraf (2017) and Wang and Sui (2019), we use the information from the survey conducted in 2007 by Barth et al. (2008) for bank observations over the period 2004-2007, from the 2012 survey by Barth et al. (2013) for bank observations over the period 2008-2011, and from the 2019 survey by Anginer et al. (2019) for bank observations over the period 2012-2016. Finally, the data collected to construct the dummy variable that identifies the crisis periods is from the Leaven and Valencia (2018)'s systemic banking crises database. Data on political institutions was gathered from the International Country Risk Guide (ICRG) for the democratic accountability variable, and from Henisz (2010) for the political constraints variable (used in the robustness tests).

Our data is organized in a panel format, starting in 2004 and ending in 2016. The final sample consists on 535 publicly traded commercial banks and bank-holding companies from OECD countries. Banks with negative equity were excluded in the corresponding year. Finally, all bank-level variables were winsorized at the 1% and 99% levels to ensure that the results are not driven by outliers. Since not all banks were active for the sample period, the panel data is unbalanced.

3.3.2. Model specification, variables and descriptive statistics

3.3.2.1. Estimation model

Following Lee et al. (2014) and Pascual et al. (2015), our model to investigate the determinants of banks' risk is constructed based on a basic risk model where the dependent variable is a function of bank-specific, macroeconomic and external variables. Then, extra variables related to our research focus are included in the model, such as banking regulation and political institutions variables.

The model is described as follows:

$$\begin{aligned} Risk_{i,j,t} &= \beta_0 + \beta_1 Risk_{i,t-1} + \beta_2 BankSpecific_{i,t} + \beta_3 External_{j,t} \\ &\quad + \beta_4 BankingRegul_{j,t} + \beta_5 PoliticalInst_{j,t} \\ &\quad + \beta_6 (BankingRegul \times PoliticalInst)_{j,t} + Year_t + \varepsilon_{i,j,t}\ , \end{aligned} \tag{3.1.}$$

where i, j, t stand for bank i, in country j at year t. $Risk$ is the bank's risk measure and $BankSpecific$ is the vector of bank-specific variables. $External$ is the vector of macroeconomic and external variables. $BankingRegul$ is the vector of banking regulation variables, while $PoliticalInst$ stands for the political institutions variable. The interaction between both variables is represented by the $(BankingRegul \times PoliticalInst)$ term. Following Ashraf (2018), Alraheb et al. (2019) and Rezgallah et al. (2019), time dummies ($Year$) are included in the model, guaranteeing robustness and capturing the influence of aggregate (time-series) trends. The last term, ε, stands for the stochastic error.

As shown by Delis and Kouretas (2011), Louzis et al. (2012), Castro (2013) and Pascual et al. (2015), banks' risk tends to persist over time due to sensitivity to macroeconomic shocks and informational opacity. For this reason, the one-period lagged value of the dependent variable is included in the model, making it dynamic (Teixeira et al., 2020a).

Regarding the $(BankingRegul \times PoliticalInst)$ term, a total of three interactions are considered, since there are three banking regulation variables (activity restrictions, capital stringency and supervisory power) and one political institution variable. The study of these interactions allows us to better understand the nonlinear effect of banking regulation on banks' risk through political institutions. Recent studies such as Li and Tanna (2019) and Teixeira et al. (2020a) perform similar analysis but for different variables and interactions. The overall effect of banking regulation on banks' risk is given by the sum of its individual effect and the indirect effect through the interaction term with political institutions. This overall effect (individual + indirect) might be positive and/or negative, depending on the level of political institutions, which influences the indirect effect (interaction term).

The overall effect of banking regulation on banks' risk is given by the following equation:

$$\frac{\partial Risk_{i,j,t}}{\partial BankingRegul_{j,t,m}} = \beta_{4,m} + \beta_{6,m} PoliticalInst_{j,t} \,, \qquad (3.2.)$$

where m assumes value 1 if the banking regulatory variable is activity restrictions, 2 for capital stringency and 3 for supervisory power.

Equation (3.2.) allows us to conclude that the individual effect is given by the coefficient estimate β_4, while the indirect effect is determined by the coefficient and interaction estimate β_6, conditional on the value of $PoliticalInst$. Depending on the magnitude and sign of β_4 and β_6 and on the range of $PoliticalInst$, the overall effect of banking regulation on banks' risk, i.e. ($\beta_{4,m} + \beta_6 PoliticalInst_{j,t}$), may be positive and/or negative.

Considering the presence of a dynamic panel data model, where a lagged dependent variable is included as a regressor in the model, the strict exogeneity assumption is likely to be violated (the probability of the lagged dependent variable being correlated with the error term is high), which makes the estimates from methods such as OLS, Random Effects and/or Fixed Effects inconsistent and biased. Therefore, and following recent studies by Alessandri and Nelson (2015), Luo et al. (2016), Borio et al. (2017), Qian et al. (2019) and Stef and Dimelis (2020), the two-step System Generalized Method of Moments (System GMM) suggested by Arellano and Bover (1995) and Blundell and Bond (1998) must be used, especially in panel data sets with a small time dimension and a large number of countries, as in our study (Roodman, 2009). This method is particularly well suited to handle the inconsistency caused by endogeneity, autocorrelation and heterogeneity in panel data as well as in dealing with the bias produced by omitted variables in cross-sectional estimations (Bond et al., 2001). Additionally, according to Blundell and Bond (1998), the system GMM outperforms the Standard/Difference-GMM from Arellano and Bover (1995), providing stronger instruments.

The decision on which variables should be considered as exogenous or endogenous is driven by the economic theory and existing literature. A variable x should be considered endogenous if it is correlated with past, contemporaneous or future error terms. If x is uncorrelated with the error terms, then it must be considered exogenous. Therefore, all the macroeconomic and external variables (vector $External$) of our sample are considered exogenous (as well as the time dummy variable) and all the other variables (the lag value of banks' risk, the bank-specific variables, the banking regulation and the political institutions variables) are considered endogenous.

The system GMM estimation has two main concerns: the serial autocorrelation of errors and the proliferation of instruments. These two concerns are more relevant when the panel used is made up by a sample with a reduced number of individuals and a longer period. The proliferation of instruments refers to the existence of a higher level of instruments, which causes overidentification in the model due to the generation of instrumental variables. To check if the number of instruments is adequate and it does not produce overidentification, we use the Hansen test. Regarding the serial autocorrelation of errors, we use the autoregressive (Arellano and Bond) test.

In summary, there are two methods to detect the effectiveness of the instruments: the Hansen test of overidentifying restrictions and the autoregressive (AR) test. The former allows us to verify the justness of the instruments and if they are statistically valid. If the null hypothesis of the Hansen test of over-identifying restrictions is not rejected, then the instrumental variables are valid.[11] The latter tests the hypothesis of existing first/second-order serial correlation in the error term in both the difference regression and the system difference-level regression (the differenced error term is permitted to be first-order serially correlated, but the error term in the second-order serial correlation will break the assumption of the GMM measure). The null hypothesis of the absence of the second-order serial correlation should not be rejected (Arellano and Bond, 1991).

3.3.2.2. Risk, banking regulatory and political institutions variables

To measure banks' risk, we use the annualized standard deviation of daily stock price returns times the market value of equity, divided by the market value of the bank, in line with Gropp and Heider (2010), Teixeira et al. (2014) and Teixeira et al. (2020a). Our choice on this risk proxy relies on the fact that it is a market-based measure instead of an accounting-based one. It incorporates information of the banks' stock price volatility, capturing the banks' total risk: the idiosyncratic risk and the market risk. Alternative measures considered in the literature include the non-performing loans (Agoraki et al., 2011; Danisman and Demirel, 2019), the Z-score (Laeven and Levine, 2009; Houston et al., 2010; Ashraf, 2017, 2020; Biswas, 2019; Li, 2019; among others), and banks' beta (Schuermann and Stiroh, 2006). In the robustness tests' section, we use the Z-score variable as an alternative measure for banks' risk.

To capture banking regulation, in particular activity restrictions, capital stringency and supervisory power, we use three of the most important measures from the World Bank's Bank

[11] The null hypothesis states that all instruments are jointly exogenous and that the instruments used are not correlated with residuals.

Regulation and Supervision Survey (BRSS) dataset.

Activity restrictions is measured by the overall restrictiveness index from the database, as in Wu et al. (2017, 2019), Danisman and Demirel (2019), Li (2019), Ashraf et. al (2020), Teixeira et al. (2020a) and Al-Shboul et al. (2020). It reflects the extent to which banks are restricted to engage in the following non-lending activities: insurance (e.g., insurance underwriting and selling), securities market (e.g., underwriting, brokering, dealing, and all aspects of the mutual fund industry), real estate (e.g., real estate investment, development, and management) and/or owning non-financial firms. Each of these activities originates a separate index that ranges from 1 to 4, where 1 means that there is no restriction on banks to operate the respective activity and 4 means that the activity cannot be developed by banks at all. Consequently, the overall index takes values between 4 and 16, with higher values of this variable meaning higher activity restrictions.

Capital stringency is measured by the sum of two sub-indices: the initial capital stringency index and the overall capital stringency index, as in Wu et al. (2017, 2019), Danisman and Demirel (2019), Li (2019), Ashraf et. al (2020), Teixeira et al. (2020a) and Al-Shboul et al. (2020). While the first sub-index includes information on whether the source of funds that count as regulatory capital can include assets other than cash, government securities, or borrowed funds, and whether the authorities verify these sources of capital, the second sub-index (the overall capital stringency sub-index) examines whether the capital requirements incorporate certain risk elements, such as credit and market risks, and whether certain market losses are extracted before calculating the minimum amount of capital. In addition to taking into account the minimum capital that a bank should maintain (capital requirement), this variable also captures regulatory requirements on the various components of this capital (nature and sources). The capital requirements index ranges from 0 to 10, where higher scores indicate greater capital stringency.

Finally, the power of supervisory agencies is represented by the supervisory power index of the World Bank's Bank Regulation and Supervision Survey (BRSS), as in Wu et al. (2017, 2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020). This index measures the rights of the supervisory agencies to meet with auditors, demand information, and take legal action against them; to force a bank to change its internal organizational structure, management and/or directors; to oblige the bank to provision against potential losses and suspend dividends, bonuses, and management fees; and to supersede the rights of shareholders and intervene in a bank and/or declare a bank insolvent. It captures the power that supervisory authorities have to take actions to prevent and correct problems in the banking industry, even against the banks' management decisions. The index ranges from 0 to 14, where higher values indicate more powerful supervisors.

The quality of political institutions is proxied by the democratic accountability index from the International Country Risk Guide (ICRG), as in Ashraf (2017) and Wang and Sui (2019). This index measures the type of the government in a country (i.e., alternative democracy, dominated democracy, de-facto one-party state, de-jure one-party state and autarchies) and responsiveness of the government to its people. It ranges from 1 to 6, where higher values of this measure represent forms of government closer to democratic regimes (alternative democracies) and lower values represent forms of government closer to autarchies. Since a higher degree of democracy promotes political competitiveness, it stands for better political institutions. As a robustness test, we use the political constraints index of Henisz (2010) as an alternative measure of political institutions.

3.3.2.3. Control variables

Seven bank-level factors, namely Profitability, Leverage, Size, Operational Efficiency (inverse of Cost-Income ratio), Asset Diversity, Income Diversity and Credit Risk (inverse of Credit Quality) are used to control for bank-specific characteristics. These factors are identified by the banking literature (Laeven and Levine, 2009; Pascual et al., 2015; Ashraf, 2017; Wand and Sui, 2019; Teixeira et al., 2020a; among others) as significant determinants of banks' risk. Given the differences in the samples (e.g., countries and time periods considered) of each of these studies, the empirical evidence of the effect of each of these factors on banks' risk is mixed.

Starting with profitability, most of the existing literature, as Biase and Apolito (2012) and Pascual et al. (2015), find a negative effect of this variable on banks' risk, arguing that banks with high profits are better prepared and protected against unexpected and undesirable market events.

Regarding leverage, the empirical literature finds mixed results. One the one hand, banks with higher capital ratios feel more comfortable to take riskier investments (Mercieca et al., 2007; Uhde and Heimeshoff, 2009). On the other hand, more debt may represent more volatility of banks' profitability and a higher default probability, i.e., more risk (Biase and Apolito, 2012).

In what concerns size, the empirical results from the existing literature are also mixed. Some authors like Biase and Apolito (2012) and Pascual et al. (2015) argue that due to the "too big to fail" hypothesis, larger banks have an extra government guarantee which gives them a greater competitive advantage compared to smaller banks. Additionally, larger banks are usually armed with rich funding sources and diversified investment channels (Afonso et al., 2014). Other authors such as Jonghe (2009) and Altunbas et al. (2011) show that greater banks are naturally more exposed to market deteriorations and, therefore, have more risk.

Operational efficiency, measured by the inverse of the cost-to-income ratio, typically has a positive effect on banks' risk. Banks that are more operationally efficient, i.e., that have lower cost-to-income ratios, become more optimistic with improved operational efficiency, lessening their risk aversion (they feel more comfortable to assume risky investments). Therefore, as Louzis et al. (2012), Pascual et al. (2015) and Wand and Sui (2019) show, greater cost-to-income ratios have a negative effect on banks' risk.

The recent banking literature also identifies the business model as an important determinant of banks' risk. Following Luo et al. (2016), the banks' business model is proxied by the income and asset diversity variables. While income diversity measures the diversification across different sources of income, asset diversity measures the diversification across different types of assets. According to the empirical literature, the diversification effect on banks' risk can be mixed. On the one hand, if we consider the portfolio theory, a firm's risk is lower if it has access to different sources of revenue (Demirguc-Kunt and Huizinga, 2010; Biase and Apolito, 2012). On the other hand, Jonghe (2009) argues that diversification may increase banks' risk since they lose focus on their traditional and core activity, leading to unstable financial systems.

The last bank-level variable considered in our study is the credit risk (inverse of credit quality) of banks. This variable is measured by the ratio of provisions for loan loss to total loans, where higher values of this ratio mean lower credit quality. Intuitively, an increase on credit quality (lower values of the variable) should represent a decrease in banks' risk (Lee et al., 2014).

In addition to the bank-level variables, we control for market concentration and the systemic banking crisis periods. The market concentration variable measures the level of market competition in the banking sector. Following Agoraki et al. (2011) and Luo et al. (2016), this variable is the ratio of total assets of the three largest commercial banks to total assets of all commercial banks of a country, capturing the effect of industry structure on bank risk-taking. As highlighted by Agoraki et al. (2011), the effect that market competition has on banks' risk depends on the market power (market share) of each bank. Markets with low competition usually mean less risk to banks with more market power (they do not have to take risks to gain market share and improve their results) and more risk to banks with less market power (they have to assume more risks to gain market share and improve their results). Regarding the systemic banking crisis period, it is an indicator variable that equals 1 in the years of systemic banking crisis and 0 otherwise, in line with the crisis periods defined by Laeven and Valencia (2018). This variable is generally accepted among researchers of the banking literature, since during crisis periods the uncertainty and volatility of the market conditions increase and, consequently, banks' risk increases.

Finally, we control for four macroeconomic variables given the high exposure of banks to the economy: inflation, GDP growth, the level of interest rates and the slope of interest rates.

The effect of inflation on banks' risk can be mixed. For instance, Caglayan and Xu (2016) provide empirical evidence that inflation volatility affects the allocation of bank loans and therefore its risk, regardless of inflation being positive or negative. Uhde and Heimeshoff (2009) argue that the effect of inflation on banks' risk depends on whether the banks were expecting it or not and how they pass this inflation to its customers. Furthermore, Teixeira et al. (2020a) provide evidence of a negative effect of inflation on banks' risk.

Regarding GDP growth, it captures the effect of business cycles on banks' risk. Most of the literature argues that when a country is not growing (in what concerns GDP), the economic conditions become weak and the economic environment unstable, leading to poor loan quality, credit losses and reduced profits, which represent an increase in banks' risk (Pascual et al., 2015).

The level of interest rates is also recognized by the literature as a significant determinant of banks' risk. On the one hand, there is evidence that in a financial environment of low interest rates, banks face pressure to obtain higher yields and, therefore, tend to assume more risks through risky investments (Castro, 2013). On the other hand, the value of a bank is higher in an environment of low interest rates, which means that they will not assume too much risk in order to preserve its value (Gizycki, 2001).

Finally, regarding the slope of interest rates, the existing literature about its effect on banks' risk is scarce. An exception is Foos et al. (2017), who show that banks' risk tends to increase as the yield curve gets steeper, although this effect is conditional on other bank-level characteristics.

The model also incorporates a time dummy ($Year$) variable, as in Ashraf (2018), Alraheb et al. (2019) and Rezgallah et al. (2019), guaranteeing robustness and capturing the influence of aggregate (time-series) trends.

Table 3.1. summarizes the definition of the variables.

Table 3.1.
Variables definitions

Variable	Description	Source
Banks' risk		
Asset Risk	Annualized standard deviation of daily stock price returns times the market value of equity over the market value of the bank.	Thompson Reuters Datastream, Bankscope database and authors' calculations
Z-score	Natural logarithm of (ROA + E/A)/σ(ROA). ROA represents the rate of return on assets, E/A is the equity-to-assets ratio and σ(ROA) is the standard deviation of the rate of return on assets. A higher score suggests a lower probability of bank insolvency and, therefore, less risk.	Bankscope database and authors' calculations
Banking regulatory variables		
Activity restriction	Overall Restrictiveness Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures the extent to which banks are restricted to engage in the following non-lending activities: insurance activities, securities market activities, real estate activities and/or owning non-financial firms. Each of the previous activities originates an individual index that ranges from 1 to 4, where 1 means that there is no restriction on banks to operate the respective activity and 4 means that the activity cannot be developed by banks at all. The overall index takes values between 4 and 16, with higher values of this variables meaning higher activity restrictions.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Capital stringency	Capital Stringency Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures whether regulatory capital requirements for banks in a country respect Basel accords. The capital requirements index ranges from 0 to 10, where higher scores reflect greater capital stringency.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Supervisory power	Supervisory Power Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures the rights of the supervisory agencies to meet with auditors, demand information, and take legal action against them; to force a bank to change its internal organizational structure, management and/or directors; to oblige the bank to provision against potential losses and suspend dividends, bonuses, and management fees; and to supersede the rights of shareholders and intervene in a bank and/or declare a bank insolvent. The index ranges from 0 to 14, where higher values indicate more powerful supervisors.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Political institutions variables		
Democratic accountability	Democratic accountability index from the International Country Right Guide database. This index measures the type of the government in a country (*i.e.*, alternative democracy, dominated democracy, de-facto one-party state, de-jure one-party state and autarchies) and responsiveness of the government to its people. This index ranges from 1 to 6, where higher values represent democratic forms of government (alternative democracies) and lower values represent autarchies.	International Country Right Guide database
Political constraints	POLCONV index from Henisz (2010) database. This index measures the degree of constraints that any branch of the government can face, when making a policy change decision, from other branches of the government, through interventions and vetoes. This index ranges from 0 to 1, with higher values representing a higher level of political constraints, *i.e.*, stronger political institutions.	Henisz (2010)
Bank specific variables		
Profitability	Profit after interest expenses over the book value of assets.	Bankscope database and authors' calculations
Leverage	Book value of total liabilities over total assets, measured in market terms, *i.e.*, as the sum of the market value of equity and the book value of total liabilities.	Bankscope database and authors' calculations
Size	Natural logarithm of the book value of total assets.	Bankscope database and authors' calculations
Cost-income ratio	Operating costs or non-interest costs over net operating income.	Bankscope database and authors' calculations
Asset diversity	Measures the diversification across different types of assets and is given by 1-[(net loans-other earnings assets)⁄(total earnings assets)].	Bankscope database and authors' calculations
Income diversity	Measures the diversification across different sources of income and is given by 1-[(net interest income-other operating income)⁄(total operating income)]	Bankscope database and authors' calculations
Credit risk	Provisions for loan losses to total loans.	Bankscope database and authors' calculations
External variables		
GDP growth	Annual percentage change of Gross Domestic Product (GDP).	IMF's database
Inflation	Annual percentage change in the Consumer Price Index (CPI).	IMF's database
Level of interest rates	10-year yield rate on government bonds.	OECD database
Slope of interest rates	Difference between the 10-year yield rate and the 1-year yield rate on government bonds.	OECD database
Concentration	Measures the level of market competition in the banking sector and is given by the fraction of the assets of the three largest banks over the assets of all commercial banks in a country.	World Bank database
Crisis	Dummy variable that assumes the value 1 in the years of systemic banking crisis and 0 otherwise.	Laeven and Valencia (2018)

3.3.2.4. Descriptive statistics

Table 3.2. shows the descriptive statistics, whereas Figure 3.1. depicts the distribution of the dependent variable. Banks' risk has an annual mean value of 3.64% and an annual standard deviation of 2.51%. These values are lower than those reported by Teixeira et al. (2020a), whose sample is from 2004-2014. This happens because, when adding banks' data of 2015 and 2016 (period characterized by more stability in the financial and banking sectors) to the sample, a natural decrease of banks' risk and its fluctuation is expected.

The results show that the mean values of the banking regulation variables and the political institutions variables are relatively high. Democratic accountability reveals a relatively low dispersion across banks (homogeneity). These results are expected since our sample consists only of banks from OECD countries (developed countries).

Regarding banks' profitability, the mean value of 1.19% is in line with the one of similar samples by Teixeira et al. (2020a, 2020b). Additionally, as in Gropp and Heider (2010), most banks exhibit high leverage ratios, with a mean value of 88.20%. In what concerns the macroeconomic variables, the GDP has growth on average at 1.89% per year, from 2004 to 2016. This value is comparable to the mean value of inflation during the same period.

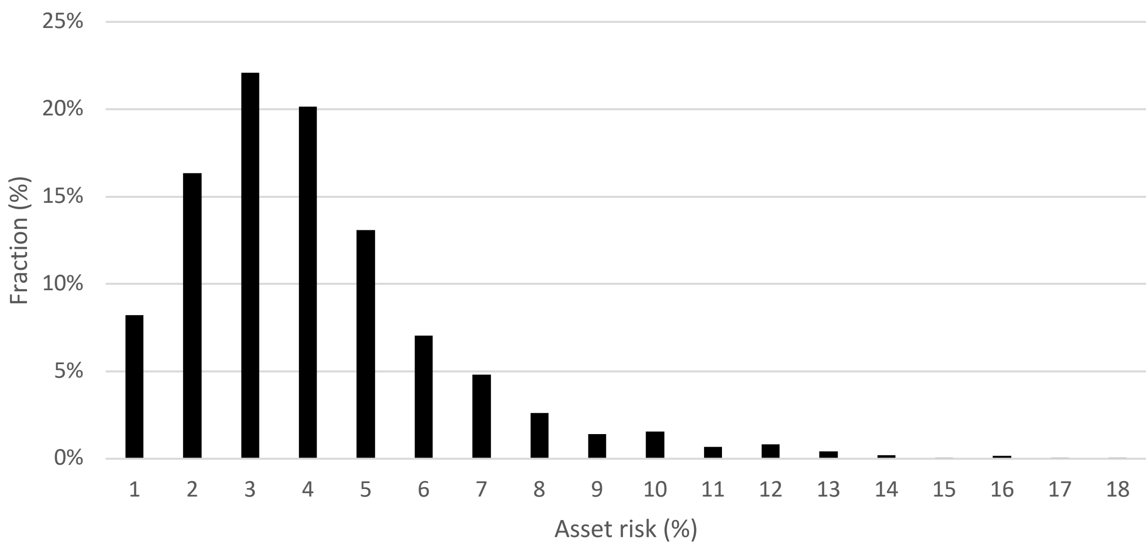


Fig. 3.1.
Distribution of banks' risk

Table 3.2.
Summary statistics

	N	Mean	St. Dev.	Min.	Max.	Distribution 10th	50th	90th
Banks' risk								
Asset risk (%)	4230	3.644	2.509	0.000	26.393	1.161	3.150	6.526
Z-score	4230	1.856	1.350	-5.540	8.031	0.063	1.937	3.432
Banking regulatory variables								
Activity restriction	4230	9.822	2.416	4.000	14.000	6.000	9.000	13.000
Capital stringency	4230	7.013	1.139	3.000	10.000	6.000	7.000	8.889
Supervisory power	4230	12.212	1.755	5.000	14.500	10.000	12.000	14.500
Political institution variable								
Democratic accountability	4230	5.936	0.280	3.708	6.000	6.000	6.000	6.000
Political constraints	4230	0.827	0.078	0.226	0.893	0.761	0.852	0.854
Bank specific variables								
Profitability (%)	4230	1.190	0.685	-6.008	7.277	0.394	1.154	2.002
Leverage (%)	4230	88.199	6.101	53.477	99.867	80.412	88.539	85.817
LOG Size	4230	8.397	2.149	4.281	14.733	6.089	7.936	11.489
Cost-income ratio	4230	33.489	7.651	5.638	87.705	23.678	33.768	41.932
Asset diversity	4230	0.576	0.294	0.022	1.931	0.271	0.518	0.964
Income diversity	4230	0.914	0.325	0.041	1.907	0.515	0.891	1.367
Credit risk	4230	0.517	1.150	-2.134	56.848	0.017	0.295	1.278
External variables								
GDP growth (%)	4230	1.885	1.950	-8.075	25.163	-0.137	1.967	3.513
Inflation (%)	4230	1.948	1.634	-2.097	11.874	0.038	1.640	3.515
Level of interest rates (%)	4230	3.067	1.381	-0.362	10.054	1.803	2.786	4.629
Slope of interest rates (%)	4230	1.530	1.154	-2.074	9.834	-0.362	1.520	2.711
Concentration	4230	43.750	17.913	28.060	98.627	32.796	35.120	75.571
Crisis	4230	0.306	0.461	0	1	0	0	1

3.4. Empirical results

3.4.1. System GMM estimation

We estimate two different models to investigate the effect of banking regulation and political institutions on banks' risk. Model 3.1. contains the linear and direct effects of political institutions and banking regulation on the dependent variable (banks' risk), whereas Model 3.2. includes the non-linear and indirect effects of banking regulation on banks' risk through interaction terms with the political institutions' variable.

The method used to estimate the models is the System GMM suggested by Arellano and Bover (1995) and Blundell and Bond (1998), which guarantees consistency and efficiency, as explained in section 3.3.2.1.. The estimation results are reported in Table 3.3..

Table 3.3.
Banks' risk model with banking regulatory and political institutions variables
The dependent variable, bank's asset risk, is given by the annualized standard deviation of daily stock price returns times the market value of equity over the market value of the bank. Model 3.1. is given by Equation (3.1.) with $\beta_6 = 0$, *i.e.* with no interaction terms between banking regulation and political institutions, whereas Model 3.2. expands Model 3.1. by including the interactions terms. The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) two-step System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. The null hypothesis of the Hansen test states that all instruments are jointly exogenous and that the instruments used are not correlated with residuals. The null hypothesis of the autoregressive (AR) test states that there is not second-order serial correlation in the error term.

Dependent variable: asset risk	**Model 3.1.**	**Model 3.2.**
Lagged dependent variable	0.226*** (0.001)	0.228*** (0.001)
Banking regulatory variables		
Activity restriction	0.072*** (0.002)	0.411*** (0.058)
Capital stringency	0.043*** (0.003)	0.646*** (0.033)
Supervisory power	-0.039*** (0.002)	0.443*** (0.043)
Political institution variable		
Democratic accountability	-0.233*** (0.012)	2.097*** (0.146)
Interaction variables		
Activity restriction x Democratic accountability		-0.056*** (0.010)
Capital stringency x Democratic accountability		-0.105*** (0.006)
Supervisory power x Democratic accountability		-0.080*** (0.007)
Bank specific variables		
Profitability	-0.259*** (0.008)	-0.258*** (0.006)
Leverage	-0.287*** (0.001)	-0.283*** (0.001)
LOG Size	-0.075*** (0.002)	-0.076*** (0.001)
Cost-income ratio	-0.006*** (0.001)	-0.008*** (0.000)
Asset diversity	-0.028 (0.021)	0.056*** (0.016)
Income diversity	0.881*** (0.020)	0.908*** (0.016)
Credit risk	0.464*** (0.009)	0.461*** (0.006)
External variables		
GDP growth	0.061*** (0.002)	0.062*** (0.001)
Inflation	0.075*** (0.004)	0.066*** (0.002)
Level of interest rates	-0.188*** (0.004)	-0.182*** (0.003)
Slope of interest rates	0.168*** (0.005)	0.177*** (0.003)
Concentration	0.005*** (0.000)	0.004*** (0.000)
Crisis	0.509*** (0.009)	0.503*** (0.007)
Year dummies	Yes	Yes
p-value of AR(2) test	0.147	0.146
p-value of Hansen test	0.154	0.845

Across these two estimations, there is a high persistence degree of banks' risk, since the coefficient of the lagged dependent variable is statistically significant at the 1% level. This result is in line with the previous evidence of Delis and Kouretas (2011), Louzis et al. (2012), Castro (2013), Lee et al. (2014), Pascual et al. (2015) and Teixeira et al. (2020a), thus corroborating the choice of a dynamic model instead of a static one.

The results of Model 3.1. reveal that the direct effect of each of the banking regulation variables (activity restrictions, capital stringency and supervisory power) is statistically significant in explaining banks' risk. Activity restrictions have a positive effect on banks' risk. This result is in line with Barth et al. (2004), Laeven and Levine (2009), Ashraf (2017), Li (2019), Wu et al. (2017, 2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020), suggesting that more restrictions on banks' activity leads to moral hazard, which motivates banks' risk-taking. Alternatively, this result can also mean the loss of profitability motivated by the restrictiveness of banks' activities, which incentivizes banks' managers to invest on risky projects, in line with Hellmann et al. (2000) and Gonzalez (2005). Moreover, less activity restrictions allow banks to diversify their income sources and, therefore, reduce risk. Regarding capital stringency, the effect on banks' risk is also positive, supporting the evidence of Ashraf (2017), Li (2019) and Al-Shboul et al. (2020). Banks' risk increases as capital requirements increase (Koehn and Santomero, 1980; Kim and Santomero, 1988; Blum, 1999). If it is too costly for banks to fulfill the higher capital requirements in the near future, they will try to meet this goal by taking more risk today. Finally, the negative coefficient of the supervisory power variable is aligned with the empirical evidence of Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018) and Al-Shboul et al. (2020), supporting the public interest view theory that high levels of supervisory power encourage the fix and correction of banking market failures (e.g., information asymmetry) and the improvement of the banking system.

Additionally, we find that the quality of political institutions has a negative direct effect on banks' risk. This negative effect supports the hypothesis that better political institutions (democratic regimes) reduces the government expropriation risk (Liu and Ngo, 2014) and, therefore, banks' risk-taking behavior. Moreover, in the presence of stronger political institutions, firms tend to disclose more information (Bushman et al., 2004), encouraging transparent environments and avoiding asymmetric information, which naturally leads to lower banks' risk. Our results are consistent with the ones from Bui and Bui (2019) and Al-Shboul et al. (2020).

Now, regarding Model 3.2., the results show that both constitutive and interaction coefficient terms are statistically significant, meaning that the overall effect of banking regulation on banks' risk is conditional on political institutions. In this model, we find that the estimated coefficients of the individual effect of activity restrictions, capital stringency, supervisory power and democratic accountability on banks' risk is positive. However, these coefficient signs must be analyzed jointly with the estimated coefficient of the interaction terms, giving us the overall effect. For a better understanding, a graphical illustration of the marginal effects of banking regulation and political institutions variables are presented in Figure 3.2.

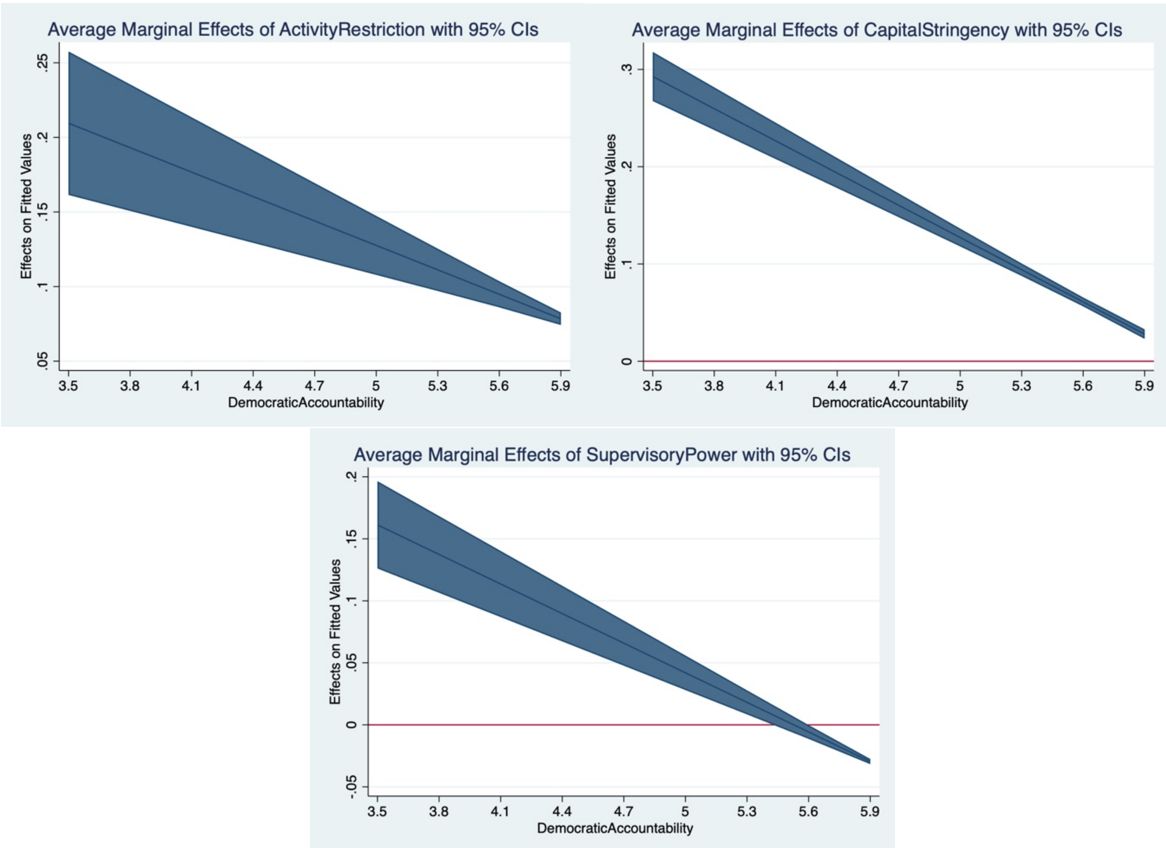


Fig. 3.2.
Marginal effects of banking regulation variables
Marginal effects of activity restrictions, capital stringency and supervisory power on banks' risk, evaluated at all values of the political institutions' variables, democratic accountability. These marginal effects are calculated based on the results of Model 3.2., using the method of Brambor et al. (2006) and Berry et al. (2012), *i.e.*, using the Equation (3.2.) evaluated at all values of the democratic accountability variable. $\beta_{4,m}$ stands for the estimated coefficient of the constitutive term and $\beta_{6,m}$ for the estimated coefficient of the interaction term with political institutions. m assumes value 1 if the banking regulatory variable is activity restriction, 2 for capital stringency and 3 for supervisory power. The dashes lines provide the 95% confidence intervals.

Following Li and Tanna (2019), these graphical illustrations of the marginal effects were generated using the method of Brambor et al. (2006) and Berry et al. (2012), based on Equation

(3.2.). For instance, the marginal effect of capital stringency on banks' risk is calculated using:

$$\frac{\partial Risk_{i,j,t}}{\partial CapitalStringency_{j,t}} = \beta_{4,2} + \beta_{6,2} DemocAccount_{j,t} \,, \tag{3.3.}$$

evaluated at all values of the democratic accountability variable, where $\beta_{4,2}$ stands for the estimated coefficient of the constitutive term of capital stringency and $\beta_{6,2}$ for the estimated coefficient of the interaction term between capital stringency and democratic accountability.

Regarding activity restrictions and capital stringency, although the overall effect of these variables is always positive for the whole amplitude of democratic accountability, it becomes lower as the latter assumes higher values, as shown in Figure 3.2.. This means that better political institutions mitigate the positive effect of activity restrictions and capital stringency on banks' risk. This effect was expected since, in Model 3.1., the effect of activity restrictions and capital stringency on banks' risk is positive and the effect of democratic accountability is negative (opposite effects). Relating these results with the theory, we conclude that when taking into account the interplay between banking regulation and political institutions, activity restrictions and capital stringency in fact increase the risk of banks due to the cost of fulfilling higher capital requirements, moral hazard, loss of profitability (which encourages investments on risky projects) and lower diversification of banks' income sources, but this increase is mitigated by more transparent environments and lower government expropriation risk associated with better political institutions.

Model 3.2. also reveals that the overall effect of supervisory power on banks' risk is negative for the mean value of the democratic accountability variable. Interestingly, this effect assumes different signs depending on the magnitude of the democratic accountability variable (see Figure 3.2.), which ranges between 3.7 and 6 and where higher values represent better political institutions. For sound political institutions, the overall effect of supervisory power on banks' risk is negative. As political institutions deteriorate, the overall effect of supervisory power on banks' risk increases, achieving positive values in extreme cases (banks from countries with worse political institutions). This turning point happens when the democratic accountability variable assumes the value of 5.53. In our sample, 94% of the banks are from countries with a democratic accountability variable greater than 5.53, which leads to a negative overall effect of supervisory power on banks' risk. This result was expected given that our sample consists only of OECD countries, which are considered developed countries and, consequently, have relatively sound political institutions.

Based on this analysis, we conclude that political institutions reinforce the negative effect of supervisory power on the risk-taking behavior of banks. This result is in line with Model 3.1., where the direct effect of both variables (supervisory power and democratic accountability) is negative. Relating these results with the theory, we conclude that the effect of supervisory agencies on controlling banks' activities and fixing market failures is intensified in the presence of lower government expropriation risks and more transparent environments associated to better political institutions. In the opposite situation, where banks operate in countries with weak political institutions (when the democratic accountability variable assumes values lower than 5.53), banks' risk tends to increase as supervisory agencies have more power. In other words, for weak political institutions, the supervisory power has a positive effect on banks' risk. Based on the theory, weak political institutions lead to less transparent environments, more corruption and moral hazard. With this scenario, supervisory authorities may not have the right incentives to perform improvements and corrections on the banking industry but, instead, they are looking for the maximization of their welfare. In this environment of corruption, moral hazard and wrong incentives of the supervisory agencies, it is expected that higher supervisory power leads to an increase in banks' risk.

Although the democratic accountability index ranges from 1 to 6, the lowest value that this variable assumes in our sample is 3.70. This happens because our sample is composed only by banks from OECD countries, which are considered developed countries and, consequently, tend to have strong political institutions. Nevertheless, the political institutions variable is statistically significant in both estimations, confirming its importance in explaining banks' risk and in conditioning the effect of banking regulatory variables.

In what concerns bank-specific variables, we find a statistically significant positive relation between income diversity, credit risk and banks' risk, and a negative relation between profitability, leverage, size and cost-income ratio. Asset diversity has a positive and statistically significant effect on risk in Model 3.1.. Overall, these estimating results are aligned with the existing literature.

The estimated coefficients associated with the country-specific variables reveal that banks' risk increases in countries with higher concentration levels in the banking industry, more inflation, higher GDP growth and steeper interest rates curve, whereas higher interest rates lead to a decrease in banks' risk.

Finally, the positive sign of the estimated coefficient of the systemic banking crisis variable suggests that during the periods of banking crisis there is an intensification of banks' risk-taking behavior. Regarding the time dummy variable, it has been found jointly statistically significant in all equations. Due to space constraints they are not reported here but are available upon request.

The Hansen test confirms the validity of instruments and the AR(2) test confirms the absence of second-order serial correlation in each model, meaning that the system GMM estimation is correctly utilized.

3.4.2. Robustness tests

In this section we carry out three robustness tests to further validate our results. First, we estimate the risk model using the one-step system GMM estimator instead of the two-step system GMM estimator. As it is generally accepted, the two-step system GMM estimator performs at least as well as the one-step estimator, since the latter is usually asymptotically inefficient (Hwang and Sun, 2018). Nevertheless, we report in Table 3.4. the estimation results with the one-step system GMM (Model 3.3.).

Second, we use the Political Constraints Index of Henisz (2010) as an alternative measure of the quality of political institutions, leading to Model 3.4. in Table 3.4.. This index measures the degree of constraints that any branch of the government can face from other branches of the government, when making a policy change decision. These constraints can assume the form of interventions and vetoes. To determine this index, Henisz (2010) uses data on the number of independent government departments (executive, administrative, legislative, judicial and sub-federal branches) with veto power within and outside these sectors. It ranges from 0 to 1, with higher values representing a higher level of political constraints, i.e., stronger political institutions. Even though this measure is widely used in the literature (Stulz, 2005; Boubakri et al., 2013, 2015; among others), one drawback is identified by Ashraf (2017): it will be difficult to change ineffective policies if the government faces more restrictions. For this reason, this index is not used as the main measure of political institutions but as an alternative measure for robustness tests.

At last, we use the Z-Score variable as a proxy for banks' risk instead of the standard deviation of return on assets (Laeven and Levine, 2009; Cubillas and Gonzalez, 2014; Luo et al., 2016). It is computed as the logarithm of $(ROA + E/A)/\sigma(ROA)$, where ROA stands for the rate of return on assets, E for equity, A for assets and $\sigma(ROA)$ for the standard deviation of the rate of return on assets of the last three years. The Z-score variable must be analyzed inversely to the standard deviation of return on assets, i.e., higher values of Z-score represent a lower probability of banks' default and, consequently, lower risk. For this robustness test we estimate Model 3.5. in Table 3.4..

Table 3.4.
Robustness tests

Robustness tests: a different estimation method (Model 3.3.), an alternative proxy for political institutions (Model 3.4.) and an alternative proxy for banks' risk (Model 3.5.). In Model 3.3., the one-step System GMM estimator is used instead of the two-step System GMM estimator. In Model 3.4. the Political Constraints Index of Henisz (2010) is used as an alternative measure for political institutions. In Model 3.5., the Z-score is used as an alternative measure of banks' risk. All models are given by Equation (3.1.). The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent variable: banks' risk	**Model 3.3.**	**Model 3.4.**	**Model 3.5.**
Lagged dependent variable (asset risk)	0.228*** (0.014)	0.243*** (0.001)	
Lagged dependent variable (Z-score)			0.517*** (0.002)
Banking regulatory variables			
Activity restriction	0.424 (0.779)	0.084*** (0.008)	-0.308*** (0.032)
Capital stringency	0.660 (0.579)	0.002 (0.012)	0.252*** (0.026)
Supervisory power	0.443 (0.867)	0.264*** (0.011)	-0.733*** (0.030)
Political institution variables			
Democratic accountability	2.139 (2.520)		-1.641*** (0.103)
Political constraints		3.760*** (0.160)	
Interaction variables			
Activity restriction x Democratic accountability	-0.058 (0.130)		0.043*** (0.005)
Capital stringency x Democratic accountability	-0.107 (0.099)		-0.043*** (0.005)
Supervisory power x Democratic accountability	-0.080 (0.146)		0.126*** (0.005)
Activity restriction x Political constraints		-0.032*** (0.010)	
Capital stringency x Political constraints		0.026* (0.015)	
Supervisory power x Political constraints		-0.375*** (0.014)	
Bank specific variables			
Profitability	-0.251*** (0.060)	-0.198*** (0.003)	0.501*** (0.004)
Leverage	-0.282*** (0.007)	-0.281*** (0.000)	0.000 (0.001)
LOG Size	-0.076*** (0.017)	-0.081*** (0.002)	-0.021*** (0.001)
Cost-income ratio	-0.007 (0.005)	-0.004*** (0.000)	-0.014*** 0.000
Asset diversity	0.034 (0.121)	0.091*** (0.014)	0.225*** (0.010)
Income diversity	0.893*** (0.152)	0.924*** (0.013)	-0.092*** (0.012)
Credit risk	0.468*** (0.045)	0.431*** (0.004)	-0.304*** (0.003
External variables			
GDP growth	0.063*** (0.002)	0.066*** (0.001)	-0.016*** (0.002)
Inflation	0.067** (0.031)	0.092*** (0.002)	-0.034*** (0.001)
Level of interest rates	-0.183*** (0.034)	-0.188*** (0.002)	-0.125*** (0.002)
Slope of interest rates	0.179*** (0.041)	0.149*** (0.002)	-0.011*** (0.001)
Concentration	0.004 (0.002)	0.003*** (0.000)	-0.002*** (0.000)
Crisis	0.501*** (0.116)	0.582*** (0.006)	-0.078*** (0.006)
Year dummies	Yes	Yes	Yes

We find that the main results of Model 3.2. do not change comparatively to the ones obtained in Models 3.3. and 3.4.: the lagged dependent variable is statistically significant, validating the persistence of banks' risk, and the overall effect of both activity restrictions and capital stringency on banks' risk is always positive for the whole amplitude of the political institutions variable. As far as concerns supervisory power, the overall effect is negative assuming the mean value of the proxy of political institutions and it then becomes positive for low values of the proxy of political institutions. The overall effect of political institutions on banks' risk is negative when assuming the mean values of activity restrictions, capital stringency and supervisory power. As in Model 3.2., the overall effect of political institutions on banks' risk becomes positive for lower values of banking regulation variables. Model 3.5. provides similar results to Models 3.2., 3.3. and 3.4., except for the overall effect of capital stringency on banks' risk. Although the effect is positive (higher capital stringency, higher banks' risk, i.e., lower values of Z-score) around the mean value of the political institutions' variable, it becomes negative for lower values of democratic accountability.

3.5. Conclusion

Despite the vast literature examining the effect of banking regulation and the quality of political institutions on banks' risk-taking behavior, it still remains unexplored how the effect of banking regulation variables on banks' risk depends on the quality of political institutions. Our study fills this gap in the literature by investigating the interplay between banking regulation, political institutions and banks' risk.

A model of the determinants of banks' risk is estimated using the system GMM method, based on data of OECD publicly traded banks, organized in a panel format, during the period between 2004 and 2016.

We provide statistically significant evidence of a positive direct effect of activity restrictions and capital stringency on banks' risk, and a rather negative direct effect of supervisory power. Moreover, we show that sound political institutions contribute to reduce banks' risk. When accounting for the interplay between banking regulation and political institutions, we conclude that the overall effect of banking regulation on banks' risk is conditional on political institutions. We show that activity restrictions and capital stringency maintain its statistically significant positive effect on banks' risk and that this effect is mitigated by better political institutions. The inverse happens with supervisory power, i.e., its negative effect on banks' risk is reinforced by better political institutions.

Our results are robust to several tests such as a different estimation method, an alternative proxy for political institutions and an alternative proxy for banks' risk.

It is our belief that the empirical evidence and findings achieved in this study are an interesting tool for banks' managers, regulatory agencies and political institutions. For banks' managers, we provide information related to the determinants of banks' risk, which is useful when making decisions related to the financing structure, business models and capital ratios. In what concerns regulatory agencies and political institutions, our paper provides important conclusions that will help government, regulatory and political authorities in their structural decisions with impact on the financial and banking industries.

As recommendations for future work on this matter, it would be interesting to perform this study on emerging markets, where banking regulation and political institutions variables vary more than in developed countries; to analyse the interplay between banking regulation and financial freedom in explaining banks' risk; and to investigate the interaction between banking regulation and political institutions on banks' profitability.

4. Banking regulation and banks' risk-taking behavior: The role of investors' protection

Abstract

This paper examines whether the influence of banking regulation on banks' risk is channeled through the level of investors' protection, using panel data from a sample of 535 banks from OECD countries, for the 2004–2016 period. As banking regulatory factors, we consider activity restrictions, capital stringency and supervisory power. We find that the overall effect of banking regulation on banks' risk is conditional on the level of investors' protection, with investor protection playing the role of reinforcing each of these individual effects. Investor protection reinforces the positive effect of activity restrictions and capital stringency on banks' risk and reinforces the negative effect of supervisory power on this risk. These results are robust to a different estimation method and a different proxy for banks' risk. Additional robustness tests reveal that some of the banking regulation effects are contingent on banks' size and the systemic banking crisis period.

Keywords: Banks' risk, Banking regulation, Investors' protection

JEL Classification: G01, G21, G28, G32, G38, P26

4.1. Introduction

The international financial system faced profound and structural reforms after the 2008-09 global financial crisis. The banking industry was one of the most affected with this new regulatory environment, especially in what concerns banks' risk. The existing literature shows that, in addition to banking regulation, the level of investors' protection is also a determinant of banks' risk-taking behaviour. Going one step further, this paper focus on how the protection of investors' rights (shareholders' and creditors' protection) shape the effect of banking regulation on banks' risk.

Following this context, there is an extant literature studying the effect of several regulatory adjustments on banks' risk, namely restrictions on banks' activities, capital stringency and supervisory power, with mixed empirical evidence. For instance, while Barth et al. (2004), Laeven and Levine (2009), Ashraf (2017), Wu et al. (2017, 2019), Li (2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020) show that financial systems become less stable in the presence of more restrictions on banks' activities, Fernandez and Gonzalez (2005), Pasiouras et al. (2006), Agoraki et al. (2011), Wang and Sui (2019) and Teixeira et al. (2020a) find a negative relationship between activity restrictions and banks' risk. Regarding capital stringency, Besanko and Kanatas (1996), Blum (1999), Calem and Rob (1999), Ashraf (2017), Li (2019) and Al-Shboul et al. (2020) reveal evidence that banks' risk increases as the regulatory capital becomes more stringent. On the contrary, Barth et al. (2004), Beltratti and Stulz (2012), Agoraki et al. (2011), Wu et al. (2017, 2019) and Danisman and Demirel (2019) argue that capital stringency has a negative effect on banks' risk. Finally, Stigler (1971), Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018) and Al-Shboul et al. (2020) show that banks become less stable as the supervisory power of authorities increases, while Wu et al. (2017, 2019) and Danisman and Demirel (2019) argue that banks' risk increases as the power given to supervisory authorities also increases.

Another strand of the literature studies the effect of the institutional environment, namely the level of investors' protection (shareholders' and creditors' protection) on banks' risk, following the foundations of the law and finance literature (La Porta et al., 1998). On the one hand, Laeven and Levine (2009) argue that banks assume more risks when shareholders benefit from a higher level of protection. On the other hand, there is a mixed evidence regarding the effect that creditors' protection has on banks' risk. While Acharya et al. (2011) document that firms' risk-taking is reduced when creditors' rights are stronger, Fang et al. (2014) find that banks stability increases as creditors' rights become stronger.

The study of the direct effect of banking regulation and investors' protection on banks' risk-taking behavior, as discussed above, is then complemented with another strand of literature that recognizes the existence of important channels through which banking regulation influences risk: market power (Agoraki et al., 2011, and Danisman and Demirel, 2019); deposit insurance (Ashraf et al., 2020), banks' ownership (Laeven and Levine, 2009, and Boubakri et al., 2020), financial transparency (Houston et al., 2010) and political institutions (Dutra et al. 2020).

This literature lacks, however, on providing a comprehensive investigation on whether investors' protection plays a role on shaping the effect of banking regulation on banks' risk. Although Teixeira et al. (2020a) provide some hints on this interplay, we believe this topic deserves further investigation. It is important to further examine the possible reinforcing or mitigating effect of investors' protection when analyzing the effect of restrictions on banks' activities, capital stringency and supervisory power on banks' risk-taking behavior. We aim to fill this gap in the literature.

Based on a sample of 535 banks from Organisation for Economic Co-operation and Development (OECD) countries for the period of 2004-2016, we find that while activity restrictions and stricter capital stringency tend to increase banks' risk, more supervisory power tends to reduce this risk. Furthermore, we conclude that banks' risk increases in countries with high levels of shareholders' protection and decreases in countries with high levels of creditors' rights. Regarding the interplay between banking regulation, investors' protection and banks' risk, we find that investors' protection (shareholders' rights and creditors' rights) reinforces both the positive effect of activity restrictions and capital stringency on banks' risk and the negative effect of supervisory power on banks' risk.

These results are robust to a different estimation method and a different proxy for banks' risk. Further analysis reveals that the effect of banking regulation on banks' risk is contingent on banks' size and the systemic banking crisis reinforces (mitigates) the positive (negative) effect of regulation on banks' risk.

This study contributes to the literature in at least four important ways. First, we add to the literature that considers important channels through which banking regulation (activity restrictions, capital stringency and supervisory power) affects banks' risk. We document that investors' protection reinforces the effect of banking regulation on banks' risk. Second, we contribute to the law and finance literature by providing further evidence of the direct effect of banking and investors' protection on banks' risk. Third, we contribute to the existing literature on the determinants of banks' risk, as Laeven and Levine (2009), Houston et al. (2010), Anginer et al. (2014), Haq et al. (2014), Fang et al. (2014), Luo et al. (2016), Ashraf (2017), Wang and Sui (2019), Teixeira et al. (2020a) and Dutra et al. (2020). Finally, we perform additional tests to understand how the effect of banking regulation through investors' protection on banks' risk changes during the systemic banking crisis period and whether this effect is different for larger banks compared to smaller ones.

The remainder of the paper is structured as follows. Section 4.2. presents the various channels through which banking regulation and investors' protection influence banks' risk. Section 4.3. describes the data, sample and variables and explains the empirical analysis. Section 4.4. displays the empirical results and the robustness checks. Section 4.5. presents the concluding remarks.

4.2. Literature review and hypotheses development

4.2.1. The effect of banking regulation on banks' risk-taking behavior

4.2.1.1. Activity restrictions and banks' risk

According to Barth et al. (2004), the economic theory provides mixed predictions about the relationship between the restrictions on banks' activities and their risk. For instance, Hellmann et al. (2000) and Gonzalez (2005) claim that as the restrictions on banks' activities increase, they lose profitability, making pressure on banks' managers to invest on risky projects. Moreover, banks are able to diversify their sources of income and reduce their risk when facing less activity restrictions. This means that, under this view, banks' risk increases for higher levels of activity restrictions. By contrast, Boyd et al. (1998) argue that when banks are allowed to engage in more activities, they have naturally more opportunities to take risk. Due to moral hazard problems, the effect of less activity restrictions on increasing banks' risk is magnified. According to this theory, banks' risk should decrease for higher levels of activity restrictions.

The empirical evidence that relates activity restrictions and banks' risk supports both effects (positive and negative). While Barth et al. (2004), Laeven and Levine (2009), Li (2019), Ashraf (2017), Wu et al. (2017, 2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020) document that financial systems become less stable in the presence of more restrictions on banks' activities, Fernandez and Gonzalez (2005), Pasiouras et al. (2006), Agoraki et al. (2011), Wang and Sui (2019) and Teixeira et al. (2020a) provide evidence that as activity restrictions increase, banks' risk decreases.

Based on the above arguments, we test the following hypothesis:

H1: Activity restrictions have a positive or negative effect on banks' risk.

4.2.1.2. *Capital stringency and banks' risk*

As reviewed by Santos (2001), the economic also provides conflicting predictions about the relationship between capital stringency and banks' risk. On the one hand, Dewatripont and Tirole (1994) posit that the effect of capital stringency on banks' risk is negative since with higher regulatory capital requirements banks are more comfortable and solid, with a greater buffer against losses, which contributes to reduce their risk. Moreover, the propensity of banks to engage in new and riskier investments is lower if they have to fulfill higher levels of capital requirements. On the other hand, Koehn and Santomero (1980), Kim and Santomero (1988) and Blum (1999) argue that capital stringency has a positive effect on banks' risk. If the cost of fulfilling higher capital requirements is high, banks are forced to invest on risky projects today in order to increase their profitability.

There is empirical evidence aligned with both these theoretical effects of capital stringency on banks' risk. While Besanko and Kanatas (1996), Blum (1999), Calem and Rob (1999), Ashraf (2017), Li (2019) and Al-Shboul et al. (2020) find evidence of a positive effect of capital stringency on banks' risk, Barth et al. (2004), Agoraki et al. (2011), Beltratti and Stulz (2012), Wu et al. (2017, 2019), Danisman and Demirel (2019) and Teixeira et al. (2020a) show that higher capital requirements decrease banks' risk.

Considering this exposition, we test the following hypothesis:

H2: Capital stringency has a positive or negative effect on banks' risk.

4.2.1.3. *Supervisory power and banks' risk*

As pointed out by Barth et al. (2004), the supervisory power is given by the power that supervisory authorities have over banks, namely on controlling their activity and restricting their risk-taking decisions if needed. On this dimension of banking regulation, two theoretical views on the effect of supervisory power on banks' risk are presented by the literature: the private interest and the public interest view. Boot and Thakor (1993) and Quintyn and Taylor (2002) argue that supervisory agents may not have the right incentives when performing their duty. When facing the wrong incentives, such as using their power to maximize their own welfare instead of correctly supervising banks, supervisory agents tend to make mistakes and take bad decisions, leading to corruption, reduced banks' efficiency and, consequently, increased banks' risk. Under this view, banks' risk increases as supervisory power increases. Conversely, the public interest view, aligned with Stigler (1971) and Barth et al. (2004), states that supervisory power leads to the improvement of the banking system and to the correction of banking market failures, like information asymmetry. In this case, banks' risk is lower as more power is given to the supervisory authorities.

Given these two distinct views, there is empirical evidence supporting both a negative and a positive effect of supervisory power on banks' risk. On the one hand, Pasiouras et al. (2009), Wu et al. (2017, 2019) and Danisman and Demirel (2019) find that strong supervisory power encourages excessive banks' risk-taking. On the other hand, Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018) and Al-Shboul et al. (2020) show that greater supervisory power decreases banks' risk.

Therefore, we test the following hypothesis:

H3: Supervisory power has a positive or negative effect on banks' risk.

4.2.2. The effect of shareholders' and creditors' protection on banks' risk

The law and finance literature, which grew out of the seminal work of La Porta et al. (1997, 1998), had demonstrated that differences in the legal protection of investors (shareholders' and creditors' rights) are important for the financial development of a country through better contracting and enforcement mechanisms. Following this literature, several studies have related investors' protection to bank risk-tasking behavior. Consistent with this view, we conjecture that the degree of protection of shareholders' and creditors' rights may play an important role in determining bank risk-taking behavior through different channels.

The economic theory suggests a positive effect of shareholder protection on banks' risk based on the argument that the amount of corporate resources diverted by corporate insiders or executives on a firm is reduced with better investors' protection (Shleifer and Wolfenzon, 2002). The executives of a firm may choose to pursue their self-interest, possibly by diverting corporate resources for personal benefits, at the expense of shareholders. Given that the amount of cash flow diversion is reduced when a company's cash flow is low, executives may even avoid some value-enhancing risky projects as a way to preserve their private benefits. Nevertheless, the amount of corporate resources diverted depends on the level of shareholders' protection, as a smaller diversion is expected with stronger investors' protection. Thus, with stronger shareholder protection the executives tend to make investment choices closer to the optimal choices. Supporting this theory, studying nonfinancial firms, John et al. (2008) find a positive association between shareholder protection and managers' incentives to undertake riskier but possibly more value-enhancing investments, while, for banks, Laeven and Levine (2009) show that banks with more powerful shareholders have a tendency to undertake more risks.

Concerning the effect of creditors' protection (rights) on banks' risk-taking behavior, there are at least two opposite channels discussed in the literature. On the one hand, Acharya et al. (2011) propose a "dark side" to stronger creditors' rights, whereby these rights lead managers to reduce corporate risk-taking. This theory posits that with stronger creditors' rights there is a higher chance for the lender to grab collateral or force repayment of the debtor that is in financial distress or even to force changes in the management of the debtor during a reorganization process, suggesting that borrowers are less willing to take risks when creditors are better protected. For nonfinancial firms, Acharya et al. (2011) provide consistent international empirical evidence supporting this theory. As for banks, the theory is supported by the empirical evidence of Fang et al. (2014), who find that strengthened creditors' rights are likely to promote a higher degree of banking stability, Cole and Turk-Ariss (2018), who document that banks reduce their loan positions and consequently take on less risk when creditors' rights are stronger, and Biswas (2019), who show empirical evidence that stronger creditors' rights enhance bank stability, through the market power channel. On the other hand, the "bright side" literature, proposed by Houston et al. (2010), argues that strengthened creditors' rights can enhance greater bank risk, as stronger legal protections foster the confidence to lend to risky enterprises with poorer credit ratings. This relation finds support in the empirical evidence of Houston et al. (2010) and Teixeira et al. (2020a).

Based on the above arguments, we expect a positive relation between the level of shareholders' protection and banks' risk, and an either positive or negative relation between the level of creditors' protection and banks' risk.

Therefore, the following hypotheses are tested:

H4: The level of shareholders' protection has a positive or negative effect on banks' risk.

H5: The level of creditors' protection has a positive or negative effect on banks' risk.

4.2.3. The interplay between banking regulation and investors' protection

As stated by Fang et al. (2014), the way banks disclosure their financial information (transparency), monitor their borrowers' management, evaluate the risk of their clients, and so on, is conditional on the institutional environment where they operate. One strand of the institutional environment is the level of protection that investors (shareholders and creditors) benefit in each country, meaning that the effect of banking regulation reforms on banks' risk may be conditional on the level of investors' protection, namely shareholders' and creditors' protection. In fact, although Teixeira et al. (2020a) document the importance of investors' protection on the bank regulation-risk channel, it is still pertinent to investigate whether investors' protection have a reinforcing or a mitigating effect on the overall effect that each banking regulation factor has on banks' risk.

The economic theory supports both effects (reinforcing and mitigating). On the one hand, a strand of the literature (e.g. Fang et al., 2014) defends that good institutional environments motivates financial stability and, consequently, a reduction on banks' risk. Since higher levels of investors' protection is perceived to contribute to better institutional environments, if banking regulation is efficient in reducing banks' risk, higher levels of investors' protection will reinforce this effect. Inversely, if banking regulation increases the risk of banks, the level of investors' protection is expected to mitigate this effect. On the other hand, high levels of investors' protection may be a limited downside of shareholders and creditors, motivating overconfidence and a willing to invest in riskier projects. Therefore, if the banking regulation in a specific country is being efficient in reducing banks' risk, this effect may become less efficient if the level of investors' protection on that country increases. In other words, shareholders' and creditors' protection may mitigate the negative effect of banking regulation on banks' risk. On the other side, if banking regulation is motivating an increase in banks' risk, this effect may be reinforced in environments of strongly protected investors.

To summarize, we test the following hypotheses:

H6: The effect of banking regulation on banks' risk is reinforced or mitigated by the level of shareholders' protection.

H7: The effect of banking regulation on banks' risk is reinforced or mitigated by the level of creditors' protection.

4.3. Data and methodology

4.3.1. Data and sample

The sample is organized in an unbalanced panel data since not all banks were active for the sample period. It is composed by 535 publicly traded commercial banks and bank-holding companies from OECD countries over the period 2004-2016. Banks with negative equity were excluded in the corresponding year. To ensure that results are not driven by outliers, we winsorize all bank-level variables at the 1% and 99% levels.

Different sources of data are used to build our sample. Banks' accounting data is obtained from the Bureau van Dijk's Bankscope database, which provides information in a standardized format, allowing comparisons between banks from different countries (Pasiouras et al., 2006). For this reason, this database is widely used in banking related literature (Gropp and Heider, 2010; Ashraf, 2017; Wang and Sui, 2019; among others). Banks' historical stock prices are from Thompson Reuters Datastream, while external and macroeconomic data comes from the

OECD database, World Development Indicators (WDI) of World Bank and International Monetary Fund (IMF)'s World Economic Outlook database. Data for the quality of political institutions, measured by the democratic accountability variable (Dutra et al., 2020), is collected from the International Country Risk Guide (ICRG). Systemic banking crises data is collected from Leaven and Valencia (2018). We gather the data for the three banking regulation variables (activity restrictions, capital stringency and supervisory power), from the World Bank's Bank Regulation and Supervision Survey (BRSS). This banking regulation data is based on surveys conducted by Barth et al. (2008, 2013) and Anginer et al. (2019). They require information on how banks are regulated and supervised around the world, providing a unique source of comparable economy-level data. As in Ashraf (2017) and Wang and Sui (2019), the results from the survey conducted by Barth et al. (2008) in 2007 and by Barth et al. (2013) in 2012 are considered for the periods 2004-2007 and 2008-2011, respectively. For the period 2012-2016, we consider the results from Anginer et al. (2019)'s survey conducted in 2019. Finally, the source of investors' protection variables is the World Bank's Doing Business Data Set and are described and explained in Caprio et al. (2007).

4.3.2. Model specification, variables and descriptive statistics

4.3.2.1. Estimation model

The model to empirically estimate the determinants of banks' risk follows the basic risk model of Lee et al. (2014), Pascual et al. (2015) and Dutra et al. (2020), where the dependent variable is a function of bank-specific, macroeconomic and external variables. As in Dutra et al. (2020), we add to the model extra variables related to our research focus, namely banking regulation and investors' protection variables.

The model is described as follows:

$$\begin{aligned} Risk_{i,j,t} = \beta_0 + \beta_1 Risk_{i,t-1} + \beta_2 BankSpecific_{i,t} + \beta_3 External_{j,t} \\ + \beta_4 BankingRegul_{j,t} + \beta_5 InvestProtect_{j,t} \\ + \beta_6 (BankingRegul \times InvestProtect)_{j,t} + Year_t + \varepsilon_{i,j,t}, \end{aligned} \qquad (4.1.)$$

where i, j, t stand for bank i, in country j at year t. $Risk$ is the bank's risk measure and $BankSpecific$ is the vector of bank-specific variables. $External$ is the vector of macroeconomic and external variables. $BankingRegul$ is the vector of banking regulation variables, while $InvestProtect$ stands for the vector of investors' protection variables. The interaction between both variables is represented by the $(BankingRegul \times InvestProtect)$ term. To guarantee robustness (Baltagi, 2001) and capture the influence of aggregate (time-series) trends, time dummies ($Year$) are included in the model, as in Ashraff (2018), Alraheb et al. (2019) and Rezgallah (2019). The stochastic error is represented by ε.

We use a dynamic model with the one-period lagged value of the dependent variable as an explanatory variable because, as shown by Delis and Kouretas (2011), Louzis et al. (2012), Castro (2013) and Pascual et al. (2015), banks' risk tends to persist over time due to sensitivity to macroeconomic shocks and informational opacity.

The ($BankingRegul \times InvestProtect$) term incorporates a total of six interactions, since there are three banking regulation variables (activity restriction, capital stringency and supervisory power) and two investors' protection variables (shareholders' and creditors' protection/rights). These interaction terms capture the nonlinear effect of banking regulation on banks' risk through investors' protection. The overall effect of banking regulation on banks' risk is given by the sum of its individual effect and the indirect effect through the interaction term with investors' protection. This overall effect (individual + indirect) might be positive and/or negative, depending on the level of investors' protection, which influences the indirect effect (interaction term).

The overall effect of banking regulation on banks' risk is given by the following equation:

$$\frac{\partial Risk_{i,j,t}}{\partial BankingRegul_{j,t,m}} = \beta_{4,m} + \beta_{6,m,n} InvestProtect_{j,t,n}, \quad (4.2.)$$

where m equals 1, 2 or 3 if the banking regulatory variable is activity restriction, capital stringency and supervisory power, respectively. The parameter n takes the value of 1 or 2 depending on whether the investors' protection variable is shareholders' protection or creditors' protection.

The individual effect of banking regulation on banks' risk is given by the coefficient estimate β_4, while the indirect effect is given by the coefficient and interaction estimate β_6, conditional on the value of $InvestProtect$. Depending on the magnitude and sign of β_4 and β_6 and on the range of $InvestProtect$, the overall effect of banking regulation on banks' risk, i.e. ($\beta_{4,m} + \beta_{6,m,n} InvestProtect_{j,t,n}$), may be positive and/or negative.

The model is estimated using a two-step System Generalized Method of Moments (System GMM), suggested by Arellano and Bover (1995) and Blundell and Bond (1998), following recent studies by Liu et al. (2015), Alessandri and Nelson (2015), Luo et al. (2016), Borio et al. (2017), Quian et al. (2019) and Stef and Dimelis (2020). This estimation method is advisable for panel data sets with a small time dimension and a large number of countries (Roodman, 2009), as in our study. Also, this model is particularly well suited to handle autocorrelation and heterogeneity in panel data, the inconsistency caused by endogeneity, as well as in dealing with the bias produced by omitted variables in cross-sectional estimations (Bond et al., 2001). Furthermore, the system GMM provides stronger instruments and outperforms the Standard/Difference-GMM from Arellano and Bover (1995), according to Blundell and Bond (1998).[12]

For the system GMM estimation method, exogenous and endogenous variables have to be identified. This identification is driven by the existing literature and economic theory. If a variable x is correlated with past, contemporaneous or future error terms, then it should be considered endogenous. Instead, a variable x should be considered exogenous if it is uncorrelated with the error terms. Therefore, all the macroeconomic and external variables (vector $External$) of our sample are considered exogenous (as well as the time dummy variable) and all the other variables of our sample (the lag value of banks' risk, the bank-specific variables, the banking regulation and the investors' protection variables) are considered endogenous.

The system GMM estimation has two main concerns known as the proliferation of instruments and the serial autocorrelation of errors. Therefore, two diagnostic tests are executed to check the fitness of the estimated model. The first one is the Hansen test which tests if all instruments are jointly exogenous, i.e., the instruments used are not correlated with residuals. This null hypothesis should not be rejected. The second diagnostic test is the Arellano and Bond (1991) test for the second-order serial correlation in the error term, known as AR(2) test. The null hypothesis reflects the absence of the second-order serial correlation and should not be rejected.

4.3.2.2. Risk, banking regulation and investors' protection variables

Following Gropp and Heider (2010), Teixeira et al. (2014) and Teixeira et al. (2020a), we measure banks' risk by the standard deviation of asset returns, computed as the annualized standard deviation of daily stock price returns times the market value of equity, divided by the market value of the bank. This is a market-based measure instead of an accounting-based one, which means that it incorporates information of the banks' stock price volatility and, therefore, captures the total risk of the bank: idiosyncratic and market risk. There are alternative measures of banks' risk in the literature. For instance, Agoraki et al. (2011) and Danisman and Demirel

[12] In dynamic panel data models, the probability of the lagged dependent variable being correlated with the error term is high, which means that the strict exogeneity assumption may be violated. Then, methods such as OLS, Random Effects and/or Fixed Effects give inconsistent and biased estimations.

(2019) use the non-performing loans, Laeven and Levine (2009), Houston et al. (2010), Ashraf (2017), Biswas (2019), Li (2019) and Ashraf et al. (2020) use the Z-score and Schuermann and Stiroh (2006) use banks' beta. To verify the robustness of our results, we decide to use the Z-score variable as an alternative measure of banks' risk. The results are analyzed in the robustness tests' section.

Regarding banking regulation, we use the well-known indices from BRSS dataset that are commonly used to capture information about banks' activity restrictions, banks' capital stringency and the power of supervisory agencies over banks in a specific country.

The overall restrictiveness index from the BRSS database is used as a measure for the restrictions on banks' activities, as in Wu et al. (2017, 2019), Danisman and Demirel (2019), Li (2019), Ashraf et. al (2020), Teixeira et al. (2020a) and Al-Shboul et al. (2020). This index assumes values between 4 and 16 as a result from the sum of four different sub-indexes. Each sub-index takes values between 1 and 4, measuring how restrictive a bank is to operate in the respective activity: insurance (e.g., insurance underwriting and selling), securities market (e.g., underwriting, brokering, dealing, and all aspects of the mutual fund industry), real estate (e.g., real estate investment, development, and management) and owning non-financial firms.

The sum of the initial capital stringency index and the overall capital stringency index is used as a measure of banks' capital stringency, following Wu et al. (2017, 2019), Danisman and Demirel (2019), Li (2019), Ashraf et. al (2020), Teixeira et al. (2020a) and Al-Shboul et al. (2020). On the one hand, the initial capital stringency index provides information on whether the regulatory capital of banks can include assets other than cash, government securities, or borrowed funds, and whether the authorities verify the sources of these funds. One the other hand, the overall capital stringency index provides information on whether banks' regulatory capital incorporates certain risk elements, such as credit and market risks, and whether the calculation of the minimum amount of capital (regulatory capital requirements) considers or not certain market losses. In sum, the measure used for capital requirements takes into account not only the minimum capital that a bank should maintain (regulatory capital requirement), but also the regulatory requirements on the various components of this capital (nature and sources). It ranges from 0 to 10, with higher scores indicating greater capital stringency.

Finally, the supervisory power index of the BRSS is used to measure the power of supervisory agencies over banks, following Wu et al. (2017, 2019), Danisman and Demirel (2019) and Al-Shboul et al. (2020). It reflects the rights of supervisory agents to meet with auditors, demand information, and take legal action against them; to force a bank to change its internal organizational structure, management and/or directors; to oblige the bank to provision against potential losses and suspend dividends, bonuses, and management fees; and to supersede the rights of shareholders and intervene in a bank and/or declare a bank insolvent. Overall, it reflects the authorities' supervisory power to take actions in order to prevent and correct inefficiencies in the banking industry, even against banks' decisions. Higher values of this index indicate more powerful supervisors, ranging from 0 to 14.

The investors' protection variables are proxied by two indexes from the World Bank Doing Business Data Set, as in Caprio et al. (2007) and Teixeira et al. (2020a). The shareholders' rights variable is proxied by the score-ease of shareholders suits index, while the creditors' rights variable is proxied by the score-strength of legal rights index. The former index measures how likely shareholders plaintiffs are to access internal corporate evidence and recover legal expenses, ranging on a scale from 0 to 100, where 0 represents the worst regulatory performance and 100 the best regulatory performance, i.e., stronger shareholders' rights and protection. The latter index measures whether certain features that facilitate lending exist within the applicable collateral and bankruptcy laws, also ranging on a scale from 0 to 100, where 0 represents the worst regulatory performance and 100 the best regulatory performance, i.e., stronger creditors' rights and protection.

4.3.2.3. Control variables

A set of bank-specific, macroeconomic and external variables are identified by the banking literature as determinants of banks' risk. We follow this literature, in particular Laeven and Levine (2009), Albertazzi and Gambacorta (2009), Pascual et al. (2015), Ashraf (2017), Wand and Sui (2019), Teixeira et al. (2020a), among others, in order to identify the controls variables of the risk model.

The bank-level factors that are included in our model to control for bank-specific characteristics are Leverage, Size, Profitability, Operational Efficiency (inverse of Cost-Income ratio), Credit Risk (inverse of Credit Quality), Income Diversity and Asset Diversity.

Even though most of the literature on banks' risk has identified these factors as statistically significant in explaining banks' risk-taking behavior, due to the differences in datasets, countries and time periods, their results on the sign of these effects are mixed.

Starting with leverage, the empirical results from the existing literature are mixed. Some authors, as Biase and Apolito (2012), argue that higher levels of debt are associated with more volatility of banks' profitability, higher default probability and, consequently, more risk. Other authors, like Mercieca et al. (2007) and Uhde and Heimeshoff (2009), show that banks feel more comfortable to take riskier investments when their capital ratios are high.

Regarding size, the empirical literature also finds mixed results. On the one hand, due to the "too big to fail" hypothesis (which provides extra government guarantees), larger banks have a greater competitive advantage compared to smaller banks (Pascual et al., 2015; Biase and Apolito, 2015). Moreover, larger banks have access to better funding sources and diversified investment channels (Afonso et al., 2014). On the other hand, banks of greater dimension are naturally more exposed to market deteriorations, assuming more risk (Jonghe, 2009; Altunbas et al., 2011).

In what concerns profitability, its effect on banks' risk is negative, as shown by most of the existing literature, as Biase and Apolito (2012) and Pascual et al. (2015), who argue that profits make banks more prepared to face unexpected events and market deteriorations.

The operational efficiency tends to have a positive effect on bank's risk. This variable is measured by the inverse of the cost-to-income ratio. Banks with low cost-to-income ratios, i.e., with high operational efficiency, become more optimistic and less risk averse, assuming risky investments. Consequently, and as shown by Louzis et al. (2012), Pascual et al. (2015) and Wand and Sui (2019), greater cost-to-income ratios/lower operational efficiency have a negative effect on banks' risk.

Regarding the credit quality of banks, it is measured by the inverse of credit risk. Credit risk is proxied by the ratio of provisions for loan loss to total loans, where higher values of this ratio stand for lower credit quality. Intuitively, higher values of credit quality (lower values of the variable credit risk) represent a decrease in banks' risk (Lee et al., 2014).

The last two bank-level variables considered in our study are related to the bank's business model, which are proxied by the income and asset diversity variables (Luo et al, 2016). The former measures the diversification across different sources of income, while the latter measures the diversification across different types of assets. These two diversification effects on banks' risk can be mixed, according to the existing literature. While the portfolio theory states that diversifying the sources of revenue allow firms to reduce their risk (Demirguç-Kunt and Huizinga, 2010; Biase and Apolito, 2012), this diversification may provoke a focus dispersion of firms on their core activity, leading to unstable and inefficient financial systems (in the case of banks).

The macroeconomic and external factors included in our model as control variables are the GDP growth, the inflation rate, the level of interest rates, the slope of interest rates, the quality of political institutions, the market concentration and the systemic banking crisis period.

Starting with GDP growth, it captures the effect of business cycles on banks' risk. An increase in banks' risk happens if a country is not growing in what concerns GDP, as shown by most of the literature, like Albertazzi and Gambacorta (2009) and Pascual et al. (2015). Negative values of GDP growth lead to the deterioration of economic conditions and environment, affecting the loan quality and promoting credit losses and reduced profits.

The level of inflation is also recognized by the existing literature as an important determinant of banks' risk, with mixed effects. For instance, Uhde and Heimeshoff (2009) argue that the effect of inflation on banks' risk-taking behavior depends on how banks pass this inflation to its customers and whether they were expecting it or not. Caglayan and Xu (2016) show evidence that the allocation of bank loans and therefore its risk are affected by inflation volatility, regardless of inflation being positive or negative. Other authors like Teixeira et al. (2020a) provide empirical evidence of a negative relationship between inflation and banks' risk.

Regarding the level of interest rates, the existing literature show mixed empirical evidence of its effect on banks' risk. On the one hand, banks' value is higher in low interest rates' environments, meaning that they prefer to avoid too much risk in order to preserve its value (Gizycki, 2001). On the other hand, when interest rates are low banks tend to make risky investments in order to obtain higher yields (Castro, 2013).

The last macroeconomic variable included in our model is the slope of interest rates. Even though the existing literature about the effect of this variable on banks' risk is scarce, Foos et al. (2017) and Teixeira et al. (2020a) show that banks' risk tends to increase as the yield curve gets steeper, although this effect is conditional on other bank-level characteristics.

According to Dutra et al. (2020), the quality of political institutions is statistically significant in explaining banks' risk. Therefore, in our model we control for the quality of political institutions across countries, proxied by the democratic accountability index from the International Country Risk Guide (ICRG), as in Ashraf (2017) and Wang and Sui (2019). This index measures the degree of democracy in a country, where higher scores stand for greater political competitiveness, leading to better political institutions. Nevertheless, there is mixed evidence on the effect of political institutions on banks' risk. While Ashraf (2017), Wang and Sui (2019), Rezgallah et al. (2019) and Udinn et al. (2020) find empirical evidence of a negative effect of the quality of political institutions on banks' risk, Bui and Bui (2019) and Al-Shboul et al. (2020) report an opposite effect.

Finally, we also control for market concentration and for the periods of systemic banking crisis. The primer reflects the level of competition in the banking industry and it is measured by the ratio of total assets of the three largest commercial banks to total assets of all commercial banks of a country, as in Agoraki et al. (2011) and Luo et al. (2016). According to Agoraki et al. (2011), depending on the market power (market share) of each bank, the effect that market competition has on banks' risk varies. While banks with more market power do not need to take risks in order to gain market share and improve profits, the same does not happen with banks with less market power. Therefore, lower levels of competition usually mean less risk to banks with high levels of market share and more risk to banks with less market power. The latter is a dummy variable that equals 1 during the years of the systemic banking crisis and 0 otherwise, following Laeven and Valencia (2018). This is a generally accepted variable in the banking related literature, given that banks' risk tends to increase during the systemic banking crisis period when the uncertainty and volatility of the market conditions are higher.

A time dummy ($Year$) variable is also included in the model, guaranteeing robustness (see Baltagi, 2001) and capturing the influence of aggregate (time-series) trends.

Table 4.1. summarizes the definition of the variables.

Table 4.1.
Variable sources and definitions

Variable	Description	Source
Banks' risk		
Asset Risk	Annualized standard deviation of daily stock price returns times the market value of equity over the market value of the bank.	Thompson Reuters Datastream, Bankscope database and authors' calculations
Z-score	Natural logarithm of (ROA + E/A)/σ(ROA). ROA represents the rate of return on assets, E/A is the equity-to-assets ratio and σ(ROA) is the standard deviation of the rate of return on assets. A higher score suggests a lower probability of bank insolvency and, therefore, less risk.	Bankscope database and authors' calculations
Banking regulatory variables		
Activity restrictions	Overall Restrictiveness Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures the extent to which banks are restricted to engage in the following non-lending activities: insurance activities, securities market activities, real estate activities and/or owning non-financial firms. Each of the previous activities originates an individual index that ranges from 1 to 4, where 1 means that there is no restriction on banks to operate the respective activity and 4 means that the activity cannot be developed by banks at all. The overall index takes values between 4 and 16, with higher values of this variables meaning higher activity restrictions.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Capital stringency	Capital Stringency Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures whether regulatory capital requirements for banks in a country respect Basel accords. The capital requirements index ranges from 0 to 10, where higher scores reflect greater capital stringency.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Supervisory power	Supervisory Power Index from the World Bank's Bank Regulation and Supervision Survey (BRSS) database. This index measures the rights of the supervisory agencies to meet with, demand information from, and take legal action against auditors; to force a bank to change its internal organizational structure, management, directors, etc.; to oblige the bank to provision against potential losses and suspend dividends, bonuses, and management fees; and to supersede the rights of shareholders and intervene in a bank and/or declare a bank insolvent. The index ranges from 0 to 14, where higher values indicate more powerful supervisors.	World Bank's Bank Regulation and Supervision Survey (BRSS) database
Investors' protection variables		
Shareholders' rights	Score-Ease of shareholder suits index from the World Bank Doing Business Data Set. The ease of shareholder suits index measures how likely shareholders plaintiffs are to access internal corporate evidence and recover legal expenses. It ranges from 0 to 100, where 0 represents the worst regulatory performance and 100 the best regulatory performance, *i.e.*, stronger shareholders' rights and protection.	World Bank Doing Business Data Set
Creditors' rights	Score-Strength of legal rights index from the World Bank Doing Business Data Set. The strength of legal rights index measures whether certain features that facilitate lending exist within the applicable collateral and bankruptcy laws. It ranges from 0 to 100, where 0 represents the worst regulatory performance and 100 the best regulatory performance, *i.e.*, stronger creditor's rights and protection.	World Bank Doing Business Data Set

Bank specific variables		
Leverage	Book value of total liabilities over total assets, measured in market terms, *i.e.*, as the sum of the market value of equity and the book value of total liabilities.	Bankscope database and authors' calculations
Size	Natural logarithm of the book value of total assets.	Bankscope database and authors' calculations
Profitability	Profit after interest expenses over the book value of assets.	Bankscope database and authors' calculations
Cost-income ratio	Operating costs or non-interest costs over net operating income.	Bankscope database and authors' calculations
Credit risk	Provisions for loan losses to total loans.	Bankscope database and authors' calculations
Income diversity	Measures the diversification across different sources of income and is given by 1-[(net interest income-other operating income)⁄(total operating income)]	Bankscope database and authors' calculations
Asset diversity	Measures the diversification across different types of assets and is given by 1-[(net loans-other earnings assets)⁄(total earnings assets)].	Bankscope database and authors' calculations
External variables		
GDP growth	Annual percentage change of Gross Domestic Product (GDP).	IMF’s database
Inflation	Annual percentage change in the Consumer Price Index (CPI).	IMF’s database
Level of interest rates	10-year yield rate on government bonds.	OECD database
Slope of interest rates	Difference between the 10-year yield rate and the 1-year yield rate on government bonds.	OECD database
Democratic accountability	Democratic accountability index from International Country Right Guide database. This index measures the type of the government in a country (*i.e.*, alternative democracy, dominated democracy, de-facto one-party state, de-jure one-party state and autarchies) and responsiveness of the government to its people. This index ranges from 1 to 6, where higher values represent democratic forms of government (alternative democracies) and lower values represent autarchies.	International Country Right Guide database
Concentration	Measures the level of market competition in the banking sector and is given by the fraction of the assets of the three largest banks over the assets of all commercial banks in a country.	World Bank database
Crisis	Dummy variable that assumes the value 1 in the years of systemic banking crisis and 0 otherwise.	Laeven and Valencia (2018)

4.3.2.4. Descriptive statistics

The sample descriptive statistics are reported in Table 4.2.. The distribution of the dependent variable, graphically represented in Figure 4.1., has an annual mean value of 3.64% and an annual standard deviation of 2.51%, which shows variations in the level of risk across banks. Comparing these results with the ones reported by Teixeira et al. (2020a), we conclude that the banks of our sample have lower risk and lower standard deviation than their sample. From our analysis, we can justify this phenomenon by the fact that our sample is longer (2004-2016) than the one from Teixeira et al. (2020a), with two more years of data, (2004-2014), and that since 2015 and 2016 were years characterized by more stability in the banking sector, which means lower levels of banks’ risk and less volatility.

Regarding banking regulation and investors’ protection variables, the results show relatively high mean values and low dispersion across countries (homogeneity), which is expected since only banks from OECD countries (developed countries) are considered in our sample. Interestingly, Turkey is the country from our sample that has the worst performance in what concerns investors' protection, while the United States of America is the country with the best performance in this field.

The annual mean value of banks' leverage is 88.20%, a relatively high leverage ratio, as in Gropp and Heider (2010). In what concerns banks' profitability, we report a mean value in line with Teixeira et al. (2020a, 2020b), rounding 1.19%. Regarding macroeconomic and external variables, we find that countries have grown (in terms of GDP) 1.89% per year, on average, from 2004 to 2016. This growth is followed by the inflation rate, with an annual mean of 1.95%. At last, the democratic accountability variable, which measures the quality of political institutions across countries, has a relatively high mean value and low standard deviation. Again, this happens because our sample is composed only by banks from OECD countries (developed countries).

Table 4.2.
Descriptive statistics

						Distribution		
	N	Mean	St. Dev.	Min.	Max.	10th	50th	90th
Banks' risk								
Asset risk (%)	4230	3.644	2.509	0.000	26.393	1.161	3.150	6.526
Z-score	4230	1.856	1.350	-5.540	8.031	0.063	1.937	3.432
Banking regulatory variables								
Activity restrictions	4230	9.822	2.416	4.000	14.000	6.000	9.000	13.000
Capital stringency	4230	7.013	1.139	3.000	10.000	6.000	7.000	8.889
Supervisory power	4230	12.212	1.755	5.000	14.500	10.000	12.000	14.500
Investors' protection variables								
Shareholders' rights	4230	77.292	24.313	16.667	91.667	33.333	91.667	91.667
Creditors' rights	4230	85.162	14.634	40.000	94.186	60.000	94.186	94.186
Bank specific variables								
Leverage (%)	4230	88.199	6.101	53.477	99.867	80.412	88.539	85.817
LOG Size	4230	8.397	2.149	4.281	14.733	6.089	7.936	11.489
Profitability (%)	4230	1.190	0.685	-6.008	7.277	0.394	1.154	2.002
Cost-income ratio	4230	33.489	7.651	5.638	87.705	23.678	33.768	41.932
Credit risk	4230	0.517	1.150	-2.134	56.848	0.017	0.295	1.278
Income diversity	4230	0.914	0.325	0.041	1.907	0.515	0.891	1.367
Asset diversity	4230	0.576	0.294	0.022	1.931	0.271	0.518	0.964
External variables								
GDP growth (%)	4230	1.885	1.950	-8.075	25.163	-0.137	1.967	3.513
Inflation (%)	4230	1.948	1.634	-2.097	11.874	0.038	1.640	3.515
Level of interest rates (%)	4230	3.067	1.381	-0.362	10.054	1.803	2.786	4.629
Slope of interest rates (%)	4230	1.530	1.154	-2.074	9.834	-0.362	1.520	2.711
Democratic accountability	4230	5.936	0.280	3.708	6.000	6.000	6.000	6.000
Concentration	4230	43.750	17.913	28.060	98.627	32.796	35.120	75.571
Crisis	4230	0.306	0.461	0	1	0	0	1

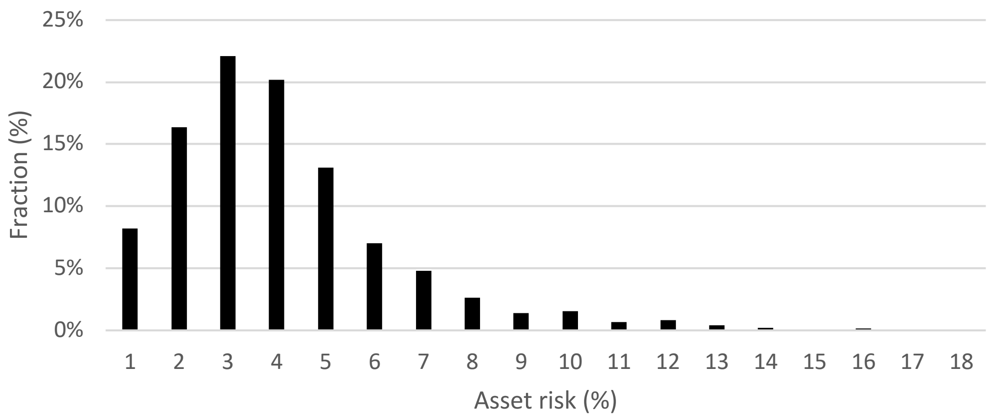


Fig. 4.1.
Distribution of the dependent variable (banks' risk).

4.4. Empirical results

4.4.1. System GMM estimation

The estimation method used in our model is the two-step System GMM suggested by Arellano and Bover (1995) and Blundell and Bond (1998). As explained in section 4.3.2.1., this method guarantees consistency and efficiency of the results.

Three models are estimated to investigate the effect of banking regulation and investors' protection on banks' risk. In Model 4.1., we only examine the direct and linear effects of banking regulation and investors' protection on bank's risk-taking behavior. In Models 4.2. and 3, we include the non-linear and indirect effects of banking regulation on banks' risk through interaction terms with the investors' protection variables. The interaction between banking regulation and shareholders' protection is estimated in Model 4.2., while the interaction between banking regulation and creditors' protection is estimated in Model 4.3..

The estimation results are reported in Table 4.3..

We find that the coefficient of the lagged dependent variable is statistically significant at the 1% level across the three models. This means that there is a high persistence degree of banks' risk, justifying the choice of a dynamic model, as in Delis and Kouretas (2011), Louzis et al. (2012), Castro (2013), Lee et al. (2014), Pascual et al. (2015) and Teixeira et al. (2020a).

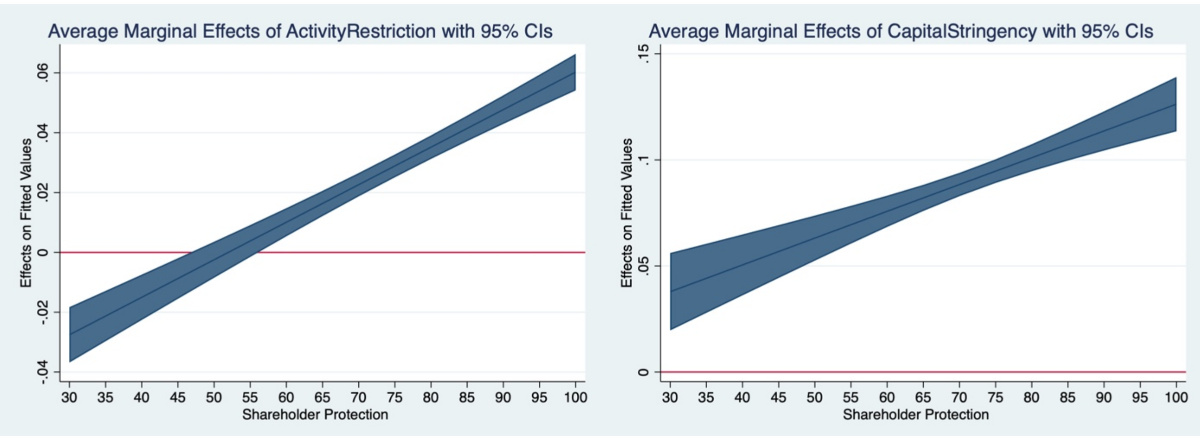
Table 4.3. Banks' risk model with banking regulatory and investors' protection variables. The dependent variable is given by the annualized standard deviation of daily stock price returns times the market value of equity over the market value of the bank. Model 4.1. is given by Equation (4.1.) with $\beta_6 = 0$, *i.e.* with no interaction terms between banking regulation and investors' protection variables, whereas Model 4.2. and Model 4.3. expand Model 4.1. by including the interactions terms between banking regulation and shareholders' and creditors' protection, respectively. The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) two-step System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively. The null hypothesis of the Hansen test states that all instruments are jointly exogenous and that the instruments used are not correlated with residuals. The null hypothesis of the autoregressive (AR) test states that there is not second-order serial correlation in the error term.

Dependent variable: asset risk	**Model 4.1.**	**Model 4.2.**	**Model 4.3.**
Lagged dependent variable	0.226*** (0.001)	0.221*** (0.002)	0.220*** (0.002)
Banking regulatory variables			
Activity restriction	0.037*** (0.001)	-0.065*** (0.007)	-0.247*** (0.005)
Capital stringency	0.059*** (0.002)	0.000*** (0.015)	-0.059*** (0.006)
Supervisory power	-0.031*** (0.002)	0.218*** (0.007)	0.002*** (0.006)
Investors' protection variables			
Shareholders' rights	0.005*** (0.000)	0.031*** (0.002)	0.001*** (0.000)
Creditors' rights	-0.003*** (0.000)	-0.002*** 0.000	-0.041*** (0.001)
Interaction variables			
Activity restriction x Shareholders' rights		0.001*** (0.000)	
Capital stringency x Shareholders' rights		0.001*** (0.000)	
Supervisory power x Shareholders' rights		-0.004*** (0.000)	
Activity restriction x Creditors' rights			0.005*** (0.000)
Capital stringency x Creditors' rights			0.001*** (0.000)
Supervisory power x Creditors' rights			-0.002*** (0.000)
Bank specific variables			
Leverage	-0.288*** (0.001)	-0.284*** (0.001)	-0.279*** (0.001)
LOG Size	-0.083*** (0.002)	-0.076*** (0.003)	-0.051*** (0.002)
Profitability	-0.260*** (0.006)	-0.228*** (0.008)	-0.219*** (0.005)
Cost-income ratio	-0.014*** (0.001)	-0.013*** (0.001)	-0.012*** (0.001)
Credit risk	0.434*** (0.005)	0.439*** (0.008)	0.419*** (0.006)
Income diversity	0.938*** (0.020)	0.953*** (0.023)	0.591*** (0.024)
Asset diversity	-0.090*** (0.015)	-0.096*** (0.023)	-0.008 (0.022)
External variables			
GDP growth	0.069*** (0.002)	0.060*** (0.002)	0.071*** (0.001)
Inflation	0.072*** (0.002)	0.069*** (0.003)	0.105*** (0.003)
Level of interest rates	-0.188*** (0.004)	-0.171*** (0.005)	-0.105*** (0.004)
Slope of interest rates	0.192*** (0.004)	0.218*** (0.004)	0.155*** (0.003)
Democratic Accountability	-0.181*** (0.009)	-0.257*** (0.010)	0.026*** (0.011)
Concentration	0.003*** (0.000)	0.002*** (0.000)	0.000 (0.000)
Crisis	0.499*** (0.009)	0.420*** (0.010)	0.011*** (0.009)
Year dummies	Yes	Yes	Yes
p-value of AR(2) test	0.157	0.160	0.149

Focusing on Model 4.1., we find that the three banking regulation variables (activity restrictions, capital stringency and supervisory power) are statistically significant in explaining banks' risk. While activity restrictions and capital stringency have a positive effect on banks' risk, supervisory power has a negative effect. The positive effect of activity restrictions is in line with Barth et al. (2004), Laeven and Levine (2009), Ashraf (2017), Li (2019), Wu et al. (2017, 2019), Danisman and Demirel (2019), Al-Shboul et al. (2020) and Dutra et al. (2020), corroborating the theory that more restrictions on banks' activity leads to moral hazard and, consequently, to an increase in banks' risk. Moreover, as banks face less restrictions on the activities they can operate, it is possible to diversify their income sources and reduce risk. On the contrary, as activity restrictions increase, banks are forced to choose riskier projects and loan operations (related to the banks' main activity) in order to maintain their profitability levels. Regarding the positive effect of capital stringency on banks' risk, it is aligned with the empirical evidence of Ashraf (2017), Li (2019), Al-Shboul et al. (2020) and Dutra et al. (2020). Since it is costly for banks to fulfill increases in the minimum regulatory capital, they will tend to assume more risk today with the goal of being capable to meet this requirement (Koehn and Santomero, 1980; Kim and Santomero, 1988; Blum, 1999). Finally, the negative effect of supervisory power on banks' risk is in line with the empirical evidence of Anginer et al. (2014), Garcia-Kuhnert et al. (2015), Mohsni and Otchere (2018), Clark et al. (2018), Al-Shboul et al. (2020) and Dutra et al. (2020), supporting the public interest view theory which states that as supervisory agencies have more power, the correction and improvement of banking market failures (e.g., information asymmetry) are more efficient.

Regarding the investors' protection variables, we document that both shareholders' and creditors' rights are statistically significant in explaining banks' risk. As expected, shareholders' protection has a positive effect on banks' risk, suggesting that the amount of corporate resources diverted by corporate insiders or executives on a firm is reduced with better investors' protection (Shleifer and Wolfenzon, 2002). With stronger shareholders' protection the executives tend to make investment choices closer to the optimal choices, undertaking riskier but possibly more value-enhancing investments. Our results are in line with the ones reported by John et al. (2008), Laeven and Levine (2009) and Teixeira et al. (2020a). On the contrary, we find a negative effect of creditors' protection on banks' risk, corroborating the "dark side" theory of Acharya et al. (2011). This theory posits that with stronger creditors' rights there is a higher chance for the lender to grab collateral or force repayment of the debtor that is in financial distress or even to force changes in the management of the debtor during a reorganization process, suggesting that borrowers are less willing to take risks when creditors are better protected. Our results are aligned with the ones of Fang et al. (2014), Cole and Turk-Ariss (2018) and Biswas (2019).

Now, focusing in Model 4.2., we report statistically significant constitutive and interaction (with shareholders' protection) coefficient terms of the banking regulation variables, which allow us to conclude that the overall effect of activity restrictions, capital stringency and supervisory power on banks' risk is conditional on shareholders' protection. The reported individual effect of activity restrictions on banks' risk is negative while the individual effects of capital stringency and supervisory power are positive. Regarding the individual effect of shareholders' and creditors' protection, it is positive for the former and negative for the latter. Regarding the individual effects of the banking regulation variables, we document that some of these effects have different signs than the ones reported in Model 4.1., which is the case of activity restrictions and supervisory power. However, the individual coefficient signs should not be analyzed separately but jointly with the estimated coefficient of the interaction terms (interactions between the banking regulation variables and the shareholders' protection variable), giving us the overall effect. The overall effect of each banking regulation variable should be compared (instead of the individual effect) with the effects estimated in Model 4.1.. For a better understanding, a graphical illustration of the marginal effects of banking regulation and shareholders' protection variables is presented in Figure 4.2..



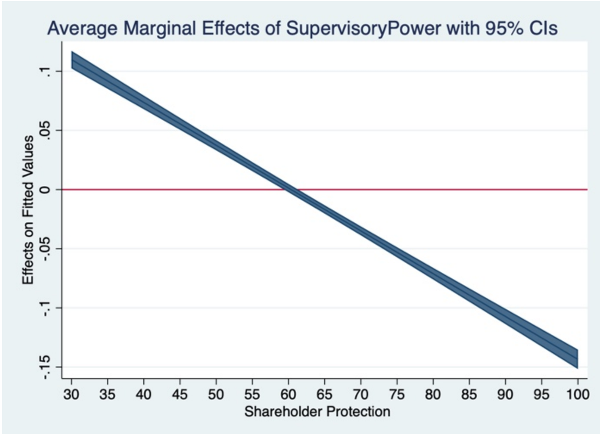


Fig. 4.2.
Marginal effects of banking regulation variables on shareholders' protection
Marginal effects of activity restrictions, capital stringency and supervisory power on banks' risk, evaluated at all values of the shareholders' protection variable. These marginal effects are calculated based on the results of Model 4.2., using the method of Brambor et al. (2006) and Berry et al. (2012), *i.e.*, using Equation (4.2.) evaluated at all values of the shareholders' protection variable. $\beta_{4,m}$ stands for the estimated coefficient of the constitutive term and $\beta_{6,m,n}$ for the estimated coefficient of the interaction term with investors' protection. m assumes value 1 if the banking regulatory variable is activity restriction, 2 for capital stringency and 3 for supervisory power and n assumes the value 1 if the investors' protection variables is the shareholders' protection and 2 for the creditors' protection. The dashes lines provide the 95% confidence intervals.

These graphical illustrations of the marginal effects were generated following Li and Tanna (2019), using the method of Brambor et al. (2006) and Berry et al. (2012), based on Equation (4.2.). For instance, the marginal effect of activity restrictions on banks' risk is calculated using:

$$\frac{\partial Risk_{i,j,t}}{\partial ActivityRestrict_{j,t}} = \beta_{4,1} + \beta_{6,1,1} ShareholdersProtect_{j,t}\ , \qquad (4.3.)$$

evaluated at all values of the shareholders' protection variable, where $\beta_{4,1}$ stands for the estimated coefficient of the constitutive term of activity restrictions and $\beta_{6,1,1}$ for the estimated coefficient of the interaction term between activity restrictions and shareholders' protection.

Starting with activity restrictions, the overall effect of this variable on banks' risk is positive for the mean value (85.16) of the shareholders' protection variable. Interestingly, this effect assumes different signs depending on the magnitude of the shareholders' protection variable (see Figure 4.2.), which ranges between 40 and 94.19 and where higher values represent greater protection and rights for shareholders. For high levels of shareholders' protection, the overall effect of activity restrictions on banks' risk is positive. As shareholders' rights deteriorate, the overall effect of activity restrictions on banks' risk decreases, achieving negative values in extreme cases (banks from countries with worse shareholders' rights). This turning point happens when the shareholders' protection variable assumes the value of 51.93. In our sample, 92.70% of the banks are from countries with a shareholders' protection variable greater than 51.93, which leads to a positive overall effect of activity restrictions on banks' risk. This result was expected given that our sample consists only of OECD countries, which are considered developed countries and, consequently, have relatively sound protection for shareholders. Based on this analysis, we conclude that shareholders' protection reinforces the positive effect of activity restrictions on the risk-taking behavior of banks. Relating these results with the theory, we conclude that the problems from restrictions on banks' activities, like moral hazard, loss of profitability (which encourages investments on risky projects) and lower diversification of banks' income sources, are magnified as the protection of shareholders increases. In other words, better shareholders' protection leads to less resources diverted by banks' insiders or executives and, consequently, to an increase in the amount of banks' resources available to invest. This increase in the banks' available resources to invest, combined with high levels of activity restrictions, forces banks to make riskier investments.

Regarding capital stringency, the overall effect of this variable is always positive for the whole amplitude of shareholders' protection and it becomes higher as the latter assumes greater values, as shown in Figure 4.2.. This means that environments of high levels of shareholders' protection reinforces the positive effect of capital stringency on banks' risk. Relating these results with the theory, we conclude that when taking into account the interplay between banking regulation and shareholders' protection, capital stringency in fact increases the risk of banks due to the cost of fulfilling higher capital requirements, being this effect reinforced by the managers' incentives to undertake riskier investments, associated with higher levels of shareholders' protection.

Finally, the overall effect of supervisory power on banks' risk is negative for the mean value of the shareholders' protection variable. Like activity restrictions, this effect also assumes different signs depending on the magnitude of the shareholders' protection variable (see Figure 4.2.). For higher levels of shareholders' protection, the overall effect of supervisory power on banks' risk is negative. As shareholders' protection deteriorate, the overall effect of supervisory power on banks' risk increases, achieving positive values in extreme cases (banks from countries with worse shareholders' rights). This turning point happens when the shareholders' protection variable assumes the value of 60.35. In our sample, 83% of the banks are from countries with a shareholders' protection variable greater than 60.35, which leads to a negative overall effect of supervisory power on banks' risk. Based on this analysis, we conclude that shareholders' protection reinforces the negative effect of supervisory power on the risk-taking behavior of banks. Relating these results with the theory, we conclude that the effect of supervisory agencies on controlling banks' activities and fixing market failures is intensified in the presence of higher levels of shareholders' protection (less corruption and diversion of banks' resources). In the opposite situation, where banks operate in countries with weak shareholders' rights (when the shareholders' protection variable assumes values lower than 60.35), banks' risk tends to increase as supervisory agencies have more power. In other words, for weak shareholders' protection, the supervisory power has a positive effect on banks' risk. Based on the theory, the weak protection of shareholders lead to diversion of banks' resources and corruption by banks' insiders and executives. With this scenario, supervisory authorities may have the wrong incentives to perform improvements and corrections on the banking industry but, instead, they are looking for the maximization of their welfare. In this environment of corruption and wrong incentives of the supervisory agencies, it is expected that higher supervisory power leads to an increase in banks' risk.

Regarding Model 4.3., both constitutive and interaction (with creditors' protection) coefficient terms of banking regulation variables are also statistically significant, meaning that the overall effect of activity restrictions, capital stringency and supervisory power on banks' risk is conditional on creditors' protection. The reported individual effects of activity restrictions and capital stringency on banks' risk are negative while the individual effect of supervisory power is positive. Regarding the individual effect of shareholders' and creditors' protection, it is positive for the former and negative for the latter, as in Model 4.2.. While in Model 4.2. the sign of the individual effects of activity restrictions and supervisory power is different than the ones reported in Model 4.1., in Model 4.3. all the individual effects of the three banking regulation variables (activity restrictions, capital stringency and supervisory power) have different signs compared to the ones estimated in Model 4.1.. Once again, the individual coefficient signs should not be analyzed separately but jointly with the estimated coefficient of the interaction terms (interactions between the banking regulation variables and the creditors' protection variable), giving us the overall effect. It is the overall effect of each banking regulation variable that should be compared (instead of the individual effect) with the effects estimated in Model 4.1.. The graphical illustration of the marginal effects of banking regulation and creditors' protection variables is presented in Figure 4.3..

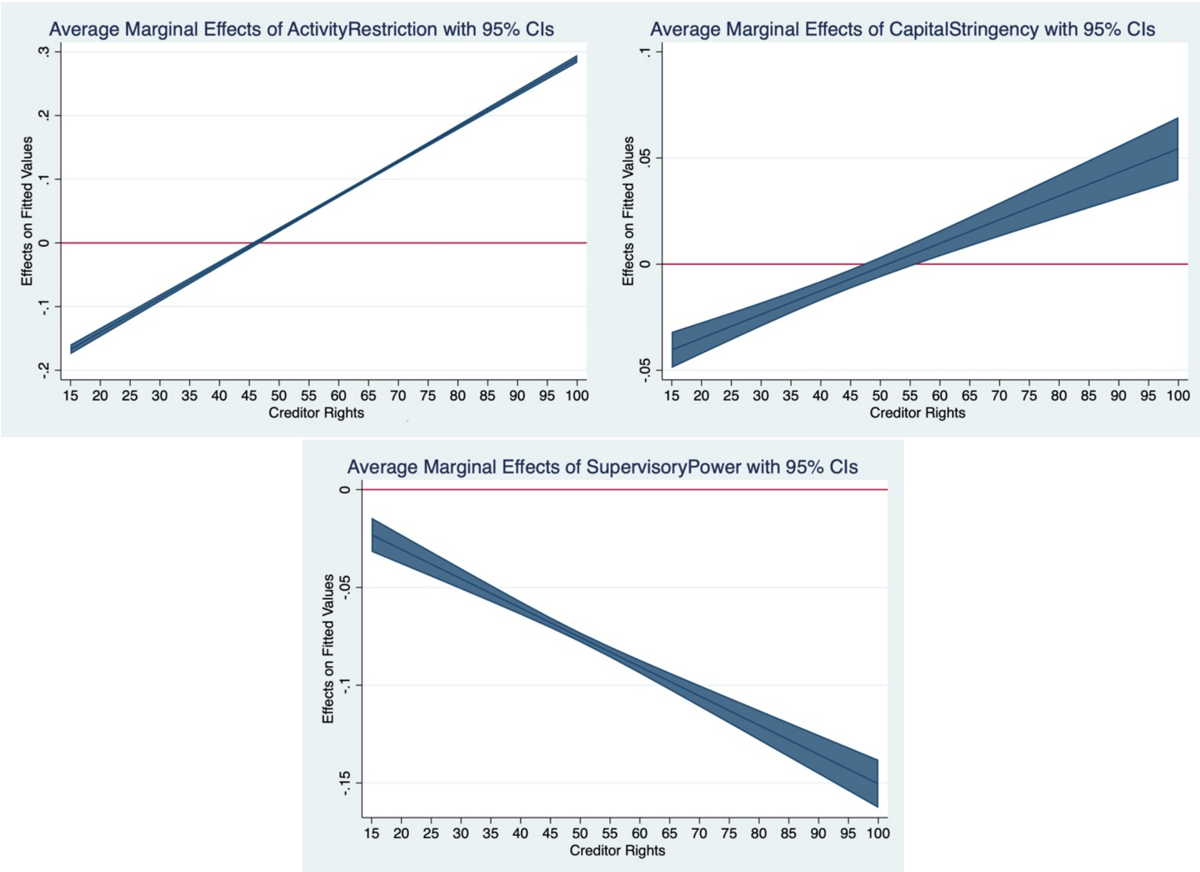


Fig. 4.3.
Marginal effects of banking regulation variables on creditors' protection
Marginal effects of activity restrictions, capital stringency and supervisory power on banks' risk, evaluated at all values of the creditors' protection variable. These marginal effects are calculated based on the results of Model 4.2., using the method of Brambor et al. (2006) and Berry et al. (2012), *i.e.*, using Equation (4.2.) evaluated at all values of the creditors' protection variable. $\beta_{4,m}$ stands for the estimated coefficient of the constitutive term and $\beta_{6,m,n}$ for the estimated coefficient of the interaction term with investors' protection. m assumes value 1 if the banking regulatory variable is activity restriction, 2 for capital stringency and 3 for supervisory power and n assumes the value 1 if the investors' protection variables is the shareholders' protection and 2 for the creditors' protection. The dashes lines provide the 95% confidence intervals.

These marginal effects are calculated based on Equation (4.2.). As an example, the marginal effect of activity restrictions on banks' risk is calculated using:

$$\frac{\partial Risk_{i,j,t}}{\partial ActivityRestrict_{j,t}} = \beta_{4,1} + \beta_{6,1,2} CreditorsProtect_{j,t}\ , \qquad (4.4.)$$

evaluated at all values of the shareholders' protection variable, where $\beta_{4,1}$ stands for the estimated coefficient of the constitutive term of activity restrictions and $\beta_{6,1,2}$ for the estimated coefficient of the interaction term between activity restrictions and creditors' protection.

Regarding activity restrictions and capital stringency, the overall effect of these variables on banks' risk is positive for the mean value (77.29) of the creditors' protection variable. Remarkably, these effects assume different signs depending on the magnitude of the creditors' protection variable (see Figure 4.3.), which ranges between 16.67 and 91.67 and where higher values represent greater protection and rights for creditors. For high levels of creditors' protection, the overall effect of activity restrictions and capital stringency on banks' risk is positive. As creditors' rights deteriorate, the overall effect of activity restrictions and capital stringency on banks' risk decrease, achieving negative values in extreme cases (banks from countries with worse creditors' rights). This turning point happens when the creditors' protection variable assumes the value of 46.08, in the case of activity restrictions, and the value of 50.92, in the case of capital stringency. In our sample, 84.44% of the banks are from countries with a creditors' protection variable greater than 46.08, which leads to a positive overall effect of activity restrictions on banks' risk. Regarding capital stringency, 79.34% of the banks are from countries with a creditors' protection variable greater than 50.92, leading to a positive overall effect of capital stringency on banks' risk. As in Model 4.2., these results were expected given that our sample consists only of OECD countries, which are considered developed countries and, consequently, have relatively sound protection for creditors. Based on this analysis, we conclude that creditors' protection reinforces the positive effect of activity restrictions and capital stringency on the risk-taking behavior of banks. This suggests that the problems from restrictions on banks' activities and stringency on banks' regulatory capital, like the cost of fulfilling higher capital requirements, moral hazard, loss of profitability (which encourages investments on risky projects) and lower diversification of banks' income sources, are magnified as the protection of creditors increase. In other words, in environments of strong creditors' rights and legal protections, where banks are encouraged to lend to risky enterprises with poorer credit ratings, combined with high levels of activity restrictions and capital stringency which also motivates risky decisions, banks' risk tend to increase.

Finally, although the overall effect of supervisory power is always negative for the whole amplitude of creditors' protection, it becomes even more negative as the latter assumes higher values, as shown in Figure 4.3.. This means that stronger legal protection to creditors reinforces the negative effect of supervisory power on banks' risk. This result leads to the conclusion that the effect of supervisory agencies on controlling banks' activities and fixing market failures is intensified in the presence of high levels of creditors' protection, which reflects more rights for creditors to grab collateral or force repayment of the debtor that is in financial distress or even to force changes in the management of the debtor during a reorganization process. With a close monitoring of both supervisory agencies and creditors over banks' activities, they are naturally less willing to take risks.

Both investors' protection variables, shareholders' and creditors' protection, are statistically significant in all three estimations (Model 4.1., 4.2. and 4.3.), confirming their importance in explaining banks' risk and in conditioning the effect of banking regulatory variables. Although the shareholders' protection variable and the creditors' protection variable ranges from 40 to 94.19 and from 16.67 to 91.67, respectively, the corresponding average in our sample is 85.16 and 77.30, respectively. This happens because our sample includes only banks from OECD countries, which are considered developed countries and, consequently, tend to present higher levels of investors' protection.

The estimated coefficients associated with the bank-specific variables reveal that leverage, size, profitability and cost-income ratio have a statistically significant negative effect on banks' risk. Regarding credit risk and income diversity, their effect on banks risk is positive and statistically significant. Finally, asset diversity has a negative effect on banks' risk, but it is statistically significant only in Models 4.1. and 4.2.. Overall, these estimating results are aligned with the existing literature.

In what concerns country-specific variables, we find that banks' risk increases in countries with higher GDP growth, more inflation, steeper interest rates curve, better political institutions and higher concentration levels in the banking industry, whereas higher interest rates lead to a decrease in banks' risk. Note, however, that the estimated coefficient of concentration is not statistically significant at a 10% level in Model 4.3..

Finally, the estimated coefficient of the systemic banking crisis variable is positive, suggesting that during the period of the banking crisis there is an intensification of banks' risk-taking behavior. The time dummy variable has been found jointly statistically significant in all three estimations. Due to space constraints, they are not reported here but are available upon request.

The two-step system GMM estimation is correctly utilized since the Hansen test confirms the validity of instruments and the AR(2) test confirms the absence of second-order serial correlation in each model.

4.4.2. Additional tests and robustness checks

In this section, in addition to the robustness checks that validate the main results, we perform further tests that provide additional and interesting results on the effect of banking regulation on banks' risk.

First, we use an alternative estimation method, namely the one-step system GMM estimator, to validate the first order effects of the banking regulatory and investors' protection variables on banks' risk.[13] Model 4.4. re-estimates Model 4.1. but using the one-step system GMM estimator instead of the two-step system GMM estimator. The estimation results are reported in Table 4.4. and show that the main results of Model 4.1. do not change comparatively to the ones obtained in Model 4.4., documenting our initial conclusions about the direct effects of banking regulation and investors' protection on banks' risk.

Second, we use an alternative measure of banks' risk, namely the Z-Score to validate the results obtained in Models 4.2. and 4.3., i.e., whether the effect of banking regulation on banks' risk is reinforced or mitigated by the level of investors' protection.[14] The corresponding results, from Models 4.5. and 4.6., are reported in Table 4.4.. As in Models 4.2. and 4.3., activity restrictions and capital stringency have a positive effect on banks' risk (negative effect on Z-score) and supervisory power a negative effect on banks' risk (positive effect on Z-score). These effects are reinforced by higher levels of shareholders' and creditors' protection. All the remaining variables, both bank specific and macroeconomic/external variables, have the same effect on banks' risk as in Models 4.2. and 4.3., except for the level of interest rates. In Models 4.5. and 4.6., where the Z-score is used as a proxy for banks' risk, the level of interest rates has a positive effect on the risk taken by banks. Nevertheless, the economic theory supports both effects, as shown in section 4.3.2..

Third, an interesting analysis is to verify whether the effect of banking regulation on banks' risk channeled through investors' protection is similar in large banks compared to the smaller ones. Therefore, we split our sample into two halves, sorted by banks' size, based on the median of this variable. The first half has the largest banks of the original sample and the second half has the smallest ones. Then we re-estimate Models 4.2. and 4.3. for each subsample, generating Models 4.7., 4.8., 4.9. and 4.10. with the corresponding results presented in Table 4.5..

Models 4.7. and 4.8. stands for the re-estimation of Models 4.2. and 4.3., respectively, but only considering the subsample of the largest banks. We conclude that our main initial results hold for largest banks, i.e., there is a positive effect of activity restrictions and capital stringency and a negative effect of supervisory power on the risk of the largest banks, and these effects are reinforced by higher levels of shareholders' and creditors' protection.

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[13] According to Hwang and Sun (2018), the two-step system GMM estimator performs at least as well as the one-step estimator, since the latter is usually asymptotically inefficient.

[14] This measure is used by Laeven and Levine (2009), Cubillas and González (2014) and Luo et al. (2016) and it is calculated as the natural logarithm of $(ROA + E/A)/\sigma(ROA)$, where ROA represents the rate of return on assets, E stands for equity, A for assets and $\sigma(ROA)$ is the respective standard deviation of ROA. Z-score behaves inversely to the standard deviation of return on assets, i.e., lower values of Z-score represent a higher probability of banks' default and, consequently, higher banks' risk.

Table 4.4.
Robustness checks
Robustness tests: a different estimation method (Model 4.4.) and an alternative proxy for banks' risk (Models 4.5. and 4.6.). In Model 4.4., we re-estimate Model 4.1. but using the one-step System GMM estimator instead of the two-step System GMM estimator. In Models 4.5. and 4.6. we re-estimate Models 4.2. and 4.3. but using the Z-score as proxy for banks' risk. The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent variable: asset risk	**Model 4.4.**	**Model 4.5.**	**Model 4.6.**
Lagged dependent variable	0.225*** (0.014)		
Lagged dependent variable (Z-Score)		0.518*** (0.003)	0.525*** (0.002)
Banking regulatory variables			
Activity restriction	0.037** (0.021)	0.051*** (0.006)	0.022*** (0.003)
Capital stringency	0.062** (0.027)	0.134*** (0.012)	0.037*** (0.006)
Supervisory power	-0.032** (0.020)	-0.051*** (0.007)	-0.047*** (0.003)
Investors protection variables			
Shareholders rights	0.006 (0.005)	-0.017*** (0.001)	-0.011*** (0.000)
Creditors rights	-0.002 (0.003)	0.004*** 0.000	0.008*** (0.001)
Interaction variables			
Activity restriction x Shareholders rights		-0.001*** (0.000)	
Capital stringency x Shareholders rights		-0.002*** (0.000)	
Supervisory power x Shareholders rights		0.001*** (0.000)	
Activity restriction x Creditors rights			-0.001*** (0.000)
Capital stringency x Creditors rights			-0.000*** (0.000)
Supervisory power x Creditors rights			0.001*** (0.000)
Bank specific variables			
Leverage	-0.288*** (0.008)	0.004*** (0.001)	0.003*** (0.001)
LOG Size	-0.081*** (0.018)	0.013*** (0.001)	0.021*** (0.002)
Profitability	-0.263*** (0.062)	0.544*** (0.007)	0.518*** (0.008)
Cost-income ratio	-0.015*** (0.005)	0.012*** (0.001)	0.013*** (0.000)
Credit risk	0.438*** (0.046)	-0.294*** (0.004)	-0.296*** (0.005)
Income diversity	0.946*** (0.164)	-.117*** (0.020)	-0.089*** (0.019)
Asset diversity	-0.103 (0.124)	0.273*** (0.013)	0.235*** (0.012)
External variables			
GDP growth	0.071*** (0.020)	-.018*** (0.001)	-0.018*** (0.001)
Inflation	0.072** (0.030)	-0.034*** (0.002)	-0.038*** (0.002)
Level of interest rates	-0.188*** (0.033)	-0.115*** (0.003)	-0.120*** (0.003)
Slope of interest rates	0.192*** (0.041)	-.047*** (0.003)	-0.047*** (0.003)
Democratic Accountability	-0.180 (0.154)	0.052*** (0.007)	0.014* (0.008)
Concentration	0.003 (0.003)	-0.004*** (0.000)	-0.005*** (0.000)
Crisis	0.499*** (0.116)	-0.139*** (0.010)	-0.115*** (0.009)
Year dummies	Yes	Yes	Yes

Models 4.9. and 4.10. correspond to the re-estimation of Models 4.2. and 4.3., respectively, but now considering the subsample of the smallest banks of our original sample. Interestingly, we obtain distinct results compared to the ones from Models 4.2., 4.3., 4.7. and 4.8., particularly in what concerns activity restrictions and supervisory power.

Regarding activity restrictions, as it becomes stricter, the risk of the smaller banks decreases, contrarily to what happens with larger banks. This positive effect between supervisory power and (smaller) banks' risk corroborates the theory of Boyd et al. (1998), who argue that banks have more opportunities to take more risk if they are allowed to engage in more activities, and validates the empirical evidence of Fernandez and Gonzalez (2005), Pasiouras et al. (2006), Agoraki et al. (2011), Wang and Sui (2019) and Teixeira et al. (2020a). These results suggest that activity restrictions have different effects on banks' risk, depending on the level of banks' size. On the one hand, since larger banks have already invested much more on their core activity than smaller banks, they face pressure to invest their available funds on different activities, in order to diversify their risk, obtain different income sources, increase profitability and reduce risk. Therefore, any increase on activity restrictions leads to an increase in the risk of the largest banks. On the other hand, since smaller banks still have space to invest and grow on the banking activity, they must concentrate on their core business rather than incurring in more risk by investing in different activities where banks' managers are not expert.

The results of the interaction effect between activity restrictions and investors' protection of the smaller banks show that the negative effect of activity restrictions on banks' risk is mitigated by the level of shareholders' protection (Model 4.9.) and reinforced by the level of creditors' protection (Model 4.10.).

According to the economic theory, the mitigating effect of shareholders' rights on the negative relationship between activity restrictions and banks' risk can be explained by the fact that higher levels of shareholders' protection originates overconfidence and an increasing willing to invest on risky projects, since the downside for shareholders of a bad investment is limited. This means that if the regulation in a specific country is being effective in reducing banks' risk by restricting the range of activities they can operate, this effectiveness is mitigated by an increasing willing to invest in risky projects.

In what concerns the reinforcing effect of creditors' rights on the negative relationship between activity restrictions and banks' risk, it is justified by the fact that banking regulatory policies are more efficient in reducing banks' risk in the presence of good institutional environments. Since high levels of creditors' protection promote better institutional environments, a reinforcing effect on reducing banks' risk by restricting their activities should be expected.

As far as supervisory power is concerned, as it becomes stronger, the risk of the smaller banks' also increases, in line with the private interest view. This view, supported by Boot and Thakor (1993) and Quintyn and Taylor (2002), suggests that supervisory agents may not have the right incentives when performing their duty, increasing the probability of mistakes and bad decisions with a negative impact on banks' risk. Pasiouras et al. (2009), Wu et al. (2017, 2019) and Danisman and Demirel (2019) present empirical evidence with similar results. From these results it follows that supervisory power has different effects on banks' risk, depending on the level of banks' size. On the one hand, since supervisory agencies are more worried on the risk taken by larger banks, which have a greater impact in the economy, it is normal that the effectiveness of their supervisory work on reducing the risk of these banks is higher. On the other hand, when dealing with smaller banks with a lower preponderance in the economy and financial system, the probability of not correctly supervising these banks is higher. According to Boot and Thakor (1993) and Quintyn and Taylor (2002), supervisory agents may not have the right incentives when performing their duty, but instead the intention of using their power to maximize their own welfare, leading to mistakes, bad decisions, corruption and, consequently, higher levels of smaller banks' risk.

The aforementioned positive effect of supervisory power on (smaller) banks' risk is reinforced by higher levels of shareholders' and creditors' protection. This interception effect is justified by the fact that high levels of investors' protection may be seen as a limited downside of shareholders and creditors, motivating overconfidence and a willing to invest on riskier projects. Therefore, if supervisory power is leading to an increase in banks' risk, it is expected that this positive effect is reinforced in environments of highly protected investors with a limited downside and an increasing willing to make risky investments.

At last, we investigate whether the direct effects of banking regulation on banks' risk were more or less intense during the systemic banking crisis period. According to Beltratti and Stulz (2012), changes in the banking regulatory environment are more likely to happen during the systemic banking crisis period. In Model 4.11., we re-estimate Model 4.1. but now including interaction terms between the three banking regulatory variables and the systemic banking crisis dummy variable. The corresponding results are depicted in Table 4.6. and show that the positive effects of activity restrictions and capital stringency on banks' risk are magnified during the systemic banking crisis period, corroborating the evidence of Beltratti and Stulz (2012).

Table 4.5.
Additional tests
Additional tests: the original sample is divided into two subsamples by banks' size. The subsample of the largest banks is used to estimate Models 4.7. and 4.8., whereas the subsample of the smallest banks is used to estimate Models 4.9. and 4.10.. Models 4.7. and 4.9. re-estimate Model 4.2., whereas Models 4.8. and 4.10. re-estimate Model 4.3.. All models are given by Equation (4.1.) and estimated using two-step System GMM. The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent variable: asset risk	**Model 4.7.**	**Model 4.8.**	**Model 4.9.**	**Model 4.10.**
Lagged dependent variable	0.224*** (0.001)	0.215*** (0.001)	0.260*** (0.001)	0.257*** (0.001)
Banking regulatory variables				
Activity restriction	-0.159*** (0.007)	-0.284*** (0.006)	-0.978*** (0.140)	-0.170 (0.162)
Capital stringency	0.045*** (0.005)	-0.104*** (0.006)	-1.013*** (0.234)	-0.742*** (0.161)
Supervisory power	0.394*** (0.009)	0.092*** (0.005)	-0.828*** (0.117)	-0.921*** (0.092)
Investors protection variables				
Shareholders rights	0.057*** (0.002)	-0.004*** (0.000)	-0.179*** (0.034)	0.062*** (0.006)
Creditors rights	-0.007*** (0.001)	-0.044*** 0.001	0.004* (0.002)	-0.192*** (0.020)
Interaction variables				
Activity restriction x Shareholders rights	0.003*** (0.000)		0.007*** (0.002)	
Capital stringency x Shareholders rights	0.001*** (0.000)		0.014*** (0.004)	
Supervisory power x Shareholders rights	-0.006*** (0.000)		0.009*** (0.002)	
Activity restriction x Creditors rights		0.007*** (0.000)		-0.006** (0.003)
Capital stringency x Creditors rights		0.002*** (0.000)		0.012*** (0.003)
Supervisory power x Creditors rights		-0.003*** (0.000)		0.014*** (0.002)
Bank specific variables				
Leverage	-0.281*** (0.001)	-0.278*** (0.001)	-0.269*** (0.002)	-0.272*** (0.003)
LOG Size	-0.032*** (0.005)	-0.006* (0.003)	0.155*** (0.011)	0.158*** (0.014)
Profitability	-0.345*** (0.009)	-0.316*** (0.008)	-0.213*** (0.014)	-0.212*** (0.015)
Cost-income ratio	-0.022*** (0.001)	-0.021*** (0.001)	-0.012*** (0.002)	-0.011*** (0.002)
Credit risk	0.249*** (0.006)	0.201*** (0.008)	0.375*** (0.012)	0.389*** (0.015)
Income diversity	0.614*** (0.024)	0.366*** (0.024)	0.781*** (0.057)	0.855*** (0.058)
Asset diversity	0.210*** (0.028)	0.168*** (0.022)	-0.323*** (0.041)	-0.309*** (0.042)
External variables				
GDP growth	0.062*** (0.001)	0.078*** (0.001)	-0.028*** (0.008)	-0.011 (0.009)
Inflation	0.117*** (0.003)	0.166*** (0.002)	-0.127*** (0.010)	-0.128*** (0.009)
Level of interest rates	-0.142*** (0.003)	-0.064*** (0.003)	0.462*** (0.024)	0.188*** (0.029)
Slope of interest rates	0.197*** (0.004)	0.117*** (0.004)	0.270*** (0.024)	0.495*** (0.028)
Democratic Accountability	-0.033*** (0.012)	0.308*** (0.009)	-2.781*** (0.102)	-2.890*** (0.140)
Concentration	0.004*** (0.000)	0.002*** (0.000)	0.031*** (0.002)	0.018*** (0.002)
Crisis	0.660*** (0.008)	0.156*** (0.013)	2.181*** (0.252)	3.021*** (0.302)
Year dummies	Yes	Yes	Yes	Yes

Regarding supervisory power, we document that its effect on reducing banks' risk is less efficient during the systemic banking crisis period. In sum, if the regulatory variable generally leads to an increase in banks' risk, this effect is magnified during the systemic banking crisis period, whereas if the regulatory variable generally leads to a decrease in banks' risk, this effect is less efficient during the systemic banking crisis period.

Table 4.6.
Additional tests

Additional test: risk model with interaction between banking regulation variables and crisis dummy variable. The reported coefficients and their robust standard errors (in parentheses) clustered at country levels are obtained using the Arellano and Bover (1995) and Blundell and Bond (1998) System GMM estimator. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Dependent variable: asset risk	**Model 4.11.**
Lagged dependent variable	0.218*** (0.002)
Banking regulatory variables	
Activity restriction	0.041*** (0.002)
Capital stringency	0.012*** (0.002)
Supervisory power	-0.066*** (0.002)
Investors protection variables	
Shareholders rights	0.008*** (0.000)
Creditors rights	-0.004*** (0.000)
Interaction variables	
Activity restriction x Crisis	0.156*** (0.003)
Capital stringency x Crisis	0.004 (0.003)
Supervisory power x Crisis	0.026*** (0.003)
Bank specific variables	
Leverage	-0.286*** (0.001)
LOG Size	-0.059*** (0.003)
Profitability	-0.203*** (0.008)
Cost-income ratio	-0.006*** (0.001)
Credit risk	0.489*** (0.006)
Income diversity	0.717*** (0.024)
Asset diversity	-0.058*** (0.022)
External variables	
GDP growth	0.079*** (0.002)
Inflation	0.119*** (0.003)
Level of interest rates	-0.126*** (0.004)
Slope of interest rates	0.191*** (0.003)
Democratic Accountability	-0.024* (0.012)
Concentration	0.003*** (0.000)
Crisis	-1.812*** (0.043)
Year dummies	Yes

4.5. Conclusion

In this study we analyze the effect of banking regulation and investors' protection on banks' risk-taking behavior and whether the overall effect of banking regulation on banks' risk is channeled through investors' protection. As banking regulatory factors we consider activity restrictions, capital stringency and supervisory power, whereas investors' protection is measured by shareholders' and creditors' rights. The paper aims to investigate whether shareholders' and creditors' rights reinforce or mitigate the effect of each banking regulatory factor on banks' risk. We also examine how the effect of banking regulation on banks' risk is intensified during the systemic banking crisis period and whether this effect is different for larger banks compared to smaller ones.

This paper uses annual data for a sample of 535 OECD publicly traded banks, organized in a panel format, over the 2004-2016 period, and all models are estimated using the two-step system GMM.

The results indicate that the three banking regulation variables (activity restrictions, capital stringency and supervisory power) are statistically significant in explaining banks' risk, with a positive effect of activity restrictions and capital stringency, and a negative effect of supervisory power. Moreover, we argue that the individual effect of shareholders' protection on banks' risk is positive, whereas higher levels of creditors' protection lead to lower values of banks' risk. More importantly, when accounting for the interplay between banking regulation and investors' protection, we find that both shareholders' and creditors' rights reinforce each individual effect of the banking regulation variables on banks' risk. It reinforces the positive effect of activity restrictions and capital stringency and the negative effect of supervisory power. These results are robust to an alternative estimation method and to an alternative measure of banks' risk.

Additional robustness tests reveal that the main results hold for the largest banks, i.e., there is a positive effect of activity restrictions and capital stringency and a negative effect of supervisory power on the risk of the largest banks, and these effects are reinforced by higher levels of shareholders' and creditors' protection. However, when considering smaller banks, we find distinct results, particularly in what concerns activity restrictions and supervisory power. For smaller banks, their risk decreases as activity restrictions become stricter, with this effect being mitigated by higher levels of shareholders' protection and reinforced by higher levels of creditors' protection. Regarding supervisory power, the empirical evidence shows a positive effect of supervisory power on banks' risk, with this effect being reinforced by higher levels of both shareholders' and creditors' protection. Finally, when analyzing how banking regulation impacts banks' risk during the systemic banking crisis period, we show that the positive effects of activity restrictions and capital stringency on banks' risk are magnified during this period, whereas the negative effect of supervisory power on banks' risk is less pronounced in this period.

The results have potential banking regulatory, policy and management implications. In addition to provide to regulatory and political entities information on how banking regulation influences banks' risk, our results also provide a set of factors that determine banks' risk, helping banks' managers in their strategic decisions.

Finally, we believe that further work on this matter should focus on emerging markets, where banking regulation and investors' protection variables vary more than in developed countries; analyse the interplay between banking regulation and financial freedom in explaining banks' risk; and to investigate the interaction between banking regulation and investors' protection on banks' profitability.

5. Conclusion

This thesis provides important results that allow to fill some gaps in the literature.

The first article concludes that Share Prices is, among the four financial variables under study, the most suitable and appropriate measure to represent Financial Cycles, similar to GDP for Business Cycles. We use the Christiano and Fitzgerald (2003) filter to estimate and extract the cycles from the original time series of four different variables (Credit, House Prices, Share Prices and Interest Rates) and then apply three methods/tests: Concordance Index, Granger Causality Test and AUROC Test. The first one identifies which variable has the most similar behavior between the different countries, being an important indicator given the systemically effect and impact that these cycles originate in the economies around the world. The Granger Causality test selects the variable that presents more evidence of being the leading one, which is important and useful for the prediction-making process. Finally, the AUROC test finds the variable with the highest predictive power of financial crises, which is a fundamental tool for macroprudential policymakers. Among these three methods, Share Prices is found to be the variable more frequently chosen to represent and measure Financial Cycles. Then, an additional conclusion is achieved when comparing this variable with GDP: the financial variable shows a higher capacity to predict financial and economic crises than GDP, which justifies the recent increasing interest of macroprudential policymakers on Financial Cycles.

The second article contributes to the banking regulation – risk literature by examining how the effect of banking regulation on banks' risk depends on the quality of political institutions. We show that activity restrictions and capital stringency have a statistically significant positive effect on banks' risk and that this effect is mitigated by better political institutions, whereas the negative effect of supervisory power on banks' risk is reinforced by better political institutions.

Regarding the third article, we find that both shareholders' and creditors' rights reinforce each individual effect of the banking regulation variables on banks' risk. In other words, higher levels of investors' protection in a country reinforce the positive effect of activity restrictions and capital stringency and the negative effect of supervisory power on banks' risk. Further tests show that these results hold for the largest banks, but, when considering smaller banks, distinct results are obtained in what concerns activity restrictions and supervisory power. The results suggest that smaller banks' risk decreases as activity restrictions become stricter, with this effect being mitigated by higher levels of shareholders' protection and reinforced by higher levels of creditors' protection. For higher levels of supervisory power, smaller banks' risk increases with this effect being reinforced by higher levels of both shareholders' and creditors' protection. Finally, when investigating how banking regulation impacts banks' risk during the systemic banking crisis period, we conclude that the positive effect of activity restrictions and capital stringency on banks' risk is magnified during this period, whereas the negative effect of supervisory power on banks' risk is less pronounced in the same period.

The empirical evidence and findings achieved in this study have potential banking regulatory, policy and management implications, being an interesting tool for banks' managers, regulatory agencies and political institutions. First of all, given the increasing interest on financial cycles, academics, policymakers and banks' managers can now consider Share Prices as a feasible and accurate variable to measure financial cycles, and use it to predict financial and economic crises. Secondly, we provide information related to the determinants of banks' risk, which is useful for banks' managers when making strategic decisions related to the financing structure, business models and capital ratios. Finally, this thesis provides important conclusions that will help government, regulatory and political authorities in their structural decisions with impact on the financial and banking industries.

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