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Banks' Systemic Risk, Household, and Mortgage Credit: Evidence from Europe

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“A good Scientist has freed himself of concepts and keeps his mind open to what is.”

Lao Tzu, Tao Te Ching, (6th century B.C.)

Abstract

This dissertation aims to contribute to the debate on the determinants of banks' systemic risk by studying the relationship between household credit and banks' systemic risk, and the relationship between mortgage credit and banks' systemic risk. For this purpose, it is estimated the effect of household and mortgage credit growth on banks' systemic risk and the effect of the share of the household and mortgage credit on banks' systemic risk.

The sample includes forty-two banks from twelve European countries during the years 2004-2009. System Generalised Method of Moments (GMM) estimation technique is used, which accommodates constant unobserved heterogeneity and endogeneity.

After controlling for banks characteristics, our results show a negative effect of household and mortgage credit growth on banks' systemic risk. Also, they show a negative effect of the share of household and mortgage credit on banks' systemic risk. The former result is inconsistent with the literature and can be attributed to the different independent variables used. The latter result is consistent with the literature on mortgage credit with respect to its characteristics that promote diversification in banks' portfolios. Moreover, no statistically significant result is found for the relationship between banks' systemic risk and household and mortgage credit in a crisis period. In addition, our results show a U-shaped relationship between banks' systemic risk and the share of household and mortgage credit. The result is consistent with previous evidence showing that asset diversification increases financial stability, while asset concentration increases financial fragility and banks risk.

JEL classification: G20; G21.

Keywords: Banks' systemic risk; Household credit; Mortgage credit.

Resumo

Esta dissertação visa contribuir para o debate sobre os determinantes do risco sistémico dos bancos através do estudo da relação entre o crédito às famílias o risco sistémico dos bancos e, a relação entre o crédito à habitação e o risco sistémico dos bancos. Para isso, estimou-se o efeito do crescimento do crédito às famílias e à habitação no risco sistémico dos bancos e o efeito da percentagem de crédito às famílias e à habitação no risco sistémico dos bancos.

A amostra utilizada inclui quarenta e dois bancos de doze países europeus durante os anos 2004-2009. É utilizada a técnica de estimação System Generalised Method of Moments (GMM), que acomoda a constante heterogeneidade não observada e endogeneidade.

Após o controlo das características dos bancos, os nossos resultados mostram uma relação negativa entre o crescimento do crédito às famílias e à habitação com o risco sistémico dos bancos. Além disso, os resultados mostram uma relação negativa entre a percentagem do crédito às famílias e à habitação com o risco sistémico dos bancos. O primeiro resultado é inconsistente com a literatura e pode ser atribuído às diferentes variáveis independentes utilizadas. Este último resultado é consistente com a literatura sobre crédito hipotecário no que diz respeito às suas características que promovem diversificação no portefólio dos bancos. Além disso, não encontramos resultados estatisticamente significativos para a relação entre o risco sistémico dos bancos com o crédito das famílias e da habitação num período de crise. Por fim, os resultados demonstram também uma relação com a forma de U entre o risco sistémico dos bancos com a percentagem do crédito às famílias e à habitação. Este resultado está de acordo com a evidência de que a diversificação de ativos aumenta a estabilidade financeira, enquanto a concentração de ativos aumenta a fragilidade financeira e o risco dos bancos.

Palavras-Chave: Risco sistémico dos bancos; Crédito habitação; Crédito às famílias.

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1. Introduction

Despite a formally accepted definition of systemic risk remains missing (Billio et al., 2012), there is common ground between the literature and regulators regarding its definition, with the systemic risk being consistently linked to events where financial institutions fail due to a shock and a simultaneous propagation process (De Bandt et al., 2000). After the financial crisis of 2007-09, the literature on systemic risk gained new momentum due to a reflexive process among regulators and policymakers, with its prevention being one of the main tasks of the central bank (Soros, 2013; Dow, 2000). The focus has been acute due to the tremendous high costs of systemic events for taxpayers, as governments tend to bail out financial institutions to ensure the survival of the financial system, as was the case in the last Global Financial Crisis (Bougheas et al., 2015). As a result, the literature has been puzzled by what impact banks' systemic risk.

The ongoing debate on the determinants of a banks' systemic risk continues to grow in size and scope. In the literature, there has been a particular focus on the components of banks' balance sheets (e.g. non-performing loans, leverage ratio, bank capital, derivative holdings) and from their income statement (e.g. non-interest income) as a relevant explanatory variables of banks' systemic risk (Mayordomo et al., 2014; De Jonghe et al., 2015; Laeven et al. 2016). Recently, the literature has expanded with studies relating banks' systemic risk to corporate governance (Díez-Esteban et al., 2022), Environmental, Social and Governance (Aevoae et al., 2022), and banks' business model choices (Marques et al., 2021)

This dissertation follows the former studies on the relationship with the components of banks' balance sheets, focusing on household and mortgage credit as possible relevant variable to explain banks' systemic risk. The relationship is studied by estimating the effect of household and mortgage credit growth on banks' systemic risk and the effect of the share of household and mortgage credit on banks' systemic risk.

The study of these types of credit is relevant because of the increasing share of total bank credit flowing to household and mortgage credit and due to their high growth rates observed before the Global Financial Crisis (Mian et al., 2009; Mian et al., 2010; Schularick et al., 2012; Jordà et al., 2013). This "debt shift " has potential impacts on economic growth and financial stability, raising concerns for policymakers (Taylor et al., 2015; Bezemer et al., 2020). Empirically, there are extensive studies that corroborate the impact of debt change on economic growth (Jappelli et al., 1994; Büyükkarabacak et al., 2010; Werner, 2012; Samatas

et al., 2019; Müller et al., 2021). Besides this impact, different types of credit may also have different effects on financial stability (Büyükkarabacak et al., 2010; Werner, 2012; Müller et al., 2021).

The dissertation contributes to the existing literature by simultaneously studying the relationship of growth and the share of these types of credit with the banks' systemic risk. As the number of studies that have studied the impact of the household credit on the bank is limited (Le et al., 2021). And in the literature on systemic risk, the only type of credit addressed was foreign currency credit, where Yesin et al. (2013) found evidence that such type of credit increases systemic risk.

Systemic risk has been associated with two relevant theoretical dimensions: cross-section and procyclicality, where credit and banks' systemic risk may have an inherent theoretical relationship. For instance, an increasing share of the same type of credit can increase banks' systemic risk via propagation, through the cross-sectional dimension, as it increases the degree of correlation of banks' financial holdings, and because they share the same type of credit risk (Billio et. al, 2012; Smaga, 2014; Benoit et al., 2017). Moreover, the procyclical dimension of banks' systemic risk comes from the positive relationship between overall credit growth and the economic environment, which has been corroborated by supply-side explanations (Bikker et al., 2002; Berger et al., 2004; Smaga, 2014; Mian et al., 2017, 2017).

Empirically, for the relationship between overall credit and banks' systemic risk. Soedarmono et al. (2017) found that abnormal credit growth leads to higher banks' systemic risk. A sizable amount of literature supports this finding by linking credit growth to financial fragility and as a predictor of a financial crisis (Honohan, 1997; Rousseau et al., 2011; Reinhart et al., 2011; Schularick et al., 2012; Jordà et al., 2013).

As for the empirical relationship of household credit with financial fragility, it is mainly studied through the growth of household leverage, where there is consistent evidence of a positive relationship (Schneider et al., 2004; Mian, 2010; Büyükkarabacak et al., 2010; Sutherland et al., 2012; Zabai et al., 2017; Mian et al., 2017, 2017). However, the literature is absent on the relationship between the share of household credit and financial fragility.

Furthermore, the literature on the relationship between mortgage credit (the main component of household credit) and financial fragility is more diverse and mixed (Le al., 2021). The mortgage credit growth is consistently associated with financial instability, while the quantities and share of mortgage credit are associated with financial stability (Cacnio,

2014; Hsu et al., 2014; Jordà et al., 2015, 2016; Morgan et al., 2017, 2018; Muller et al. 2021). Moreover, a few studies show a different relationship between the share of mortgage credit and financial stability in a crisis period (Morgan et al., 2017, 2018). Besides being variable and time-dependent, according to the same limited literature, the relationship between the share of mortgage credit and financial stability appears to be non-linear (Morgan et al., 2017, 2018).

The sample comprises forty-two European banks representing twelve different European countries. The sample period used to study the relationships is between 2004 and 2009 because it was a period of the accumulation where the imbalances that preceded the financial crisis in 2007-2009 were formed due to the high credit growth rate, according to Brunnermeier et al. (2020). Also, according to the literature, the high credit growth is what precedes financial fragility (Honohan, 1997; Rousseau et al., 2011; Reinhart et al., 2011; Jordà et al., 2013; Schularick et al., 2012). The main credit variables used in this study are at the country level due to inconsistency in banks' financial statements.

In this dissertation, the database structure of the database combines time series with cross-sectional data, leading to panel data formation. To accommodate constant unobserved heterogeneity and endogeneity, the Generalised System Method of Moments (GMM) is applied, which is in line with previous literature. Additionally, banks' CAMEL variables are added to the model to control the effects.

Our results suggest a negative effect of household and mortgage credit growth on banks' systemic risk. In addition, they show a negative effect of the share of household and mortgage credit on banks' systemic risk. Moreover, our results show a U-shaped relationship between banks' systemic risk and the share of household and mortgage credit. Lastly, no statistically relevant result is found for the relationship between banks' systemic risk and household and mortgage credit in a crisis period.

The remainder of this dissertation is organised as follows. Chapter 2 covers the definition of systemic risk, how to measure it, and the theoretical background between credit and banks' systemic risk relationship. Also, it presents evidence of the relationship between overall credit and financial fragility. In addition, it documents the evidence of the effects of household and mortgage credit on financial fragility. Chapter 3 describes the hypothesis that will be tested. Chapter 4 presents the data, the variables, and the methodology employed. Chapter 5 contains a discussion of the empirical results. Chapter 6 comprises robustness tests. Lastly, conclusions and limitations from the study are drawn in Chapter 7.

2. Literature Review

2.1 Systemic Risk

The absence of a formally accepted definition of systemic risk coupled with a rapidly evolving area of research makes a comprehensive literature review challenging (Billio et al., 2012). Nevertheless, systemic risk has consistently been linked to events where financial institutions fail due to a shock and a propagation process, also known as contagion in the literature (De Bandt et al., 2000).

Moreover, international regulators have provided some definitions. In collaboration with the Bank of International Settlements (BIS) and the Financial Stability Board (FSB), the International Monetary Fund (IMF) defines systemic risk as the risk that disrupts financial intuitions due to impairments throughout the financial system and may produce adverse consequences for the real economy (Caruana, 2010). This definition seems consensual between the Basel Committee Banking Supervision (BCBS) and the European Central Bank (ECB). The BCBS stated that "...systemic importance should be measured in terms of the impact that a bank failure may have on the overall financial system and the wider economy, rather than the risk that a failure may occur." (BCBS, p. 4, 2018). The ECB defined systemic risk as "The risk that the inability of one institution to meet its obligations when due will cause other institutions to be unable to meet their obligations. Such a failure may cause significant liquidity or credit problems and, as a result, could threaten the stability of or confidence in markets." (ECB, p. 226, 2004).

Further, defining systemic risk as the risk that many market participants simultaneously face severe losses, which are then spread through the system, is presented accord 220 papers published over the past 35 years (Benoit et al., 2017). In other words, the literature associates the systemic risk with a state of financial vulnerability, where suddenly a shock occurs, amplified by market participants' endogenous response (Borio, 2003). The shock can be idiosyncratic or systematic, where idiosyncratic is related to the individual wealth of the financial institution, and systematic is when it affects all financial institutions simultaneously (De Bandt et al., 2000). Moreover, the origins of this shock may be in the financial sphere (e.g. asset price correction) or in the real economy (e.g. spontaneous reduction in investment) (Borio, 2003). Based on these definitions, the consistency in the literature about the relevance of the propagation can be highlighted.

Propagation is the crucial component of systemic risk being at the heart of its analysis, as the propagation dynamics makes an initial shock truly systemic (Martínez-Jaramillo et al., 2010). Propagation is characterized by the distress of a single bank harming another bank, also known as the domino effect (Allen et al., 2012; Borio, 2003). The banking system tends to be inherently more vulnerable to propagation due to the close connection between financial institutions and the rest of the economy (Billio et al., 2012). In addition, the significant growth of shadow banking, high levels of leverage, risk of loss of confidence, and an aggressive liquidity management strategy have increased its vulnerability (Smaga, 2014).

A. Measurement of Systemic Risk

Since the introduction of Basel II, risk measures at the individual level of financial institutions have increased. For example, Value at Risk (VaR) and expected shortfall are the most common measures of financial institution risk. Although, they only focus on the risk of financial institutions in isolation (Brunnermeier et al., 2013). However, if there is some consensus on these types of risk measure, in the case of measuring bank' systemic risk, there is an open debate with different metrics used in the literature. The most relevant measure with a growing body in the literature is the one proposed by Acharya, Engle, and Richardson (2012). Also, other pertinent measures are proposed by Adrian and Brunnermeier (2011) and Huang, Zhou, and Zhu (2012).

Adrian and Brunnermeier (2011) propose a co-risk measure that captures the propagation process, such as liquidity spirals and externalities. First, the Var_q^i is implicitly defined as the q quantile, i.e., where X^i is the variable of institutions i for which the Var_q^i is defined and is typical a positive number when $q > 50$ (Equation 2.1). While the CoVar, which stands for conditional, contagion, or co-movement is the "Var of the institutions j (or financial system) conditional on some event $C(X_i)$, which is implicitly defined by the q -quantile of conditional probability distribution." (Adrian et al., pg. 7, 2011) (Equation 2.2). The institution's contribution to systemic risks defines as the difference between CoVaR conditional on the institution being under distress, and the CoVaR in the median state of the institution. In other words, $\Delta\text{CoVar}_{q^{j|i}}$ is the difference between the Var of the institutional j conditional on the distress of the institutions i and the VaR of the institutional j conditional on the median state of the institution i (Equation 2.3). Based on this conditionality, we can observe that this measure $\Delta\text{CoVar}_{q^{j|i}}$ can capture the spillover effects across the financial network. In the case where i is equal to the system, then $\Delta\text{CoVar}_{q^{j|i}=\text{system}}$, it can provide information about which institutions have a higher risk if the financial crisis occurs (Equation 2.3).

$$2.1 \Pr(X^i \leq \text{Var}_q^i) = q\%.$$

$$2.2 \Pr(X^j | C(X_i) \leq \text{CoVar}_q^{j|C(X_i)}) = q\%.$$

$$2.3 \Delta\text{CoVar}_q^{j|i} = \text{CoVar}_q^{j|X^i=\text{Var}_q^i} - \text{CoVar}_q^{j|X^i=\text{Var}_{50}^i}.$$

Huang, Zhou, and Zhu (2012) proposed a systemic risk measure based on insurance prices against systemic financial distress. The methodology is based on two key components: the bank's probability of default and the correlation of asset returns between banks. Both features are extracted from the financial market. The probability of default is estimated from the spread of credit default swaps (CDS), and the co-movements of equity prices are used for the correlation.

As mentioned above, the most relevant measure is provided by Acharya, Engle, and Richardson (2012), which captures the question of how much capital a financial institution will need to raise to function normally if we have another financial crisis. This question arises from the authors' definition of systemic risk as the overall contribution of a firm to the failure of the whole system and is not in terms of the failure of a financial firm itself. The rationale goes as follows: if only the capital of an individual financial firm is low, the firm can no longer be financially intermediate. However, this has low consequences because other financial firms can fill the void of the failing firm. Thus, systemic bank risk emerges when capital is low in the aggregate because other financial firms cannot step in to inject capital. The definition is represented by Equation 2.4, where systemic risk is composed of the real social cost per dollar of the capital shortfall, the probability of a crisis and the expected capital shortfall of the firm in a crisis. The authors focus on the expected capital shortfall as it captures relevant characteristics such as leverage, size, and interconnectedness.

$$\begin{aligned}
 2.4 \text{ Real systemic risk of a firm} = & \\
 & \text{Real social cost of a crisis per dollar of shortage} \times \\
 & \text{Probability of a crisis (i.e. an aggregate capital shortfall)} \times \\
 & \text{Expected capital shortfall of the firm in crisis.}
 \end{aligned}$$

The presentation of calculation of the systemic risk variable according to the methodology of Acharya, Engle and Richardson (2012) is extensively presented in the methodology section (Chapter 4.3) because it is the measure of bank systemic risk used as the dependent variable in our models.

2.2 Systemic Risk and Credit: Cross-sectional and Procyclicality dimension

A. Cross-sectional

The propagation of systemic risk is associated in the literature with the cross-sectional dimension, which increases the propagation of the system due to the common exposures of the financial system and interconnection channels (Caruana, 2010). Common exposure is a propagation channel associated with the degree of correlation between financial institutions' holdings (Billio et al., 2012), which tends to create a crisis with lasting costs (Borio, 2003). At the same time, the main interconnection channels are the interbank market (Rochet et al., 1996), the interbank payment system (Rochet et al., 1996), and the settlement payment system (Borio et al., 1993), which leads to broad transmission across international borders (Bougheas et al., 2015). Although there is no consensus in the literature on the positive relationship between interconnectedness and systemic risk. Allen et al. (2000) and Freixas et al. (2000) suggest that as a system has a complete structure, it has a more robust way of dealing with shocks since the losses of a distressed bank are divided and transferred among more creditors and between banks through the interbank agreements.

Different types of credit can impact the cross-sectional dimension of systemic risk as it represents a common exposure that banks hold on the asset side, thus increasing their interconnectedness across the bank's balance sheet (Billio et al., 2012; Benoit et al., 2017). Therefore, it can be argued that an increasing share in the same type of credit will result in a higher degree of correlation between the bank's balance sheets. Further, as they have the same type of credit risk, theoretically, it may also increase the banks' systemic risk (Smaga, 2014).

B. Procyclicality

Procyclicality is a relevant dimension of systemic risk, with its adverse effects on systemic risk attracting researchers (Smaga, 2014). It relates to how systemic risk behaves over time and is one of the main problems of the current financial system, as it destabilises the whole system through the amplification of financial shocks (Borio, 2003; Schwerter, 2011). Procyclicality is characterised by a build-up of financial fragility when systemic risk appears lower (Caruana, 2010). This build-up of financial fragility is a result of benign risk assessments when we are in a booming economic environment, which leads to a lower external financing constraint, resulting in increase of leverage (Borio, 2003). However, the real and financial imbalances generated in this period are hardly considered, leading to the overstretching of the system (Borio, 2003; Smaga, 2014). Then, the process reverses, where financial institutions "overreact" with high deleveraging, increasing the impact of the financial shock (Smaga, 2014). Thus, the procyclicality of banks' systemic risk comes from the positive relationship between leverage and the economic environment. Moreover, the regulator has recognised the procyclical dimension of systemic risk by addressing it with the countercyclical capital buffer. As implemented in Basel III, they are used to build an additional capital buffer to prevent excessive credit growth (Schwerter, 2011).

Although, the procyclicality of credit growth with economic growth is debatable in the literature. The supply-side explanation argues that credit has a procyclical effect and is supply-driven. In contrast, the demand-side argues that credit is demand-driven and hence countercyclical. According to the supply-side explanation, credit has a procyclical effect with a crucial role in the business cycle (Bikker et al., 2002). As mentioned in the procyclical dynamics of banks' systemic risk, banks tend to underestimate credit risk and lose lending standards during periods of economic expansion, making them willing to provide more credit at cheaper terms, while overestimating credit risk in periods of economic recession, imposing greater restrictions on the credit concession (Berger et al., 2004; Mian et al., 2017, 2017). On the demand side, Bernanke and Gertler (1995) stated that credit demand behaves countercyclically, deriving from the need of firms and households to smooth the impact of their change on output or income. The evidence supports the supply-side explanation and, consequently, the idea of credit being procyclical with economic growth, with extensive empirical evidence showing a positive relationship between credit growth and economic growth (Cappiello et al., 2010; Beck et al., 2012; Werner, 2012; Sassi et al., 2014).

2.3 Overall Credit and Financial Fragility Relationship: Evidence

Since the 18th and 19th centuries, British scholars have emphasised the role of paper credit in a private banking system and its potentially destabilising effects, even in a gold standard regime, which implies a more inelastic monetary regime (Taylor et al. 2015). Thus, the idea that financial fragility and the subsequent financial crisis are a consequence of a credit boom that goes wrong is widely documented in the literature. However, the 2008-09 financial crisis played a special role, reigniting the understanding of the crucial role of credit fluctuations in amplifying, propagating, and generating shocks both in normal times and especially during a financial crisis (Schularick et al., 2012).

Furthermore, the literature is especially focused on credit growth, which has been linked to financial fragility, with aggregate lending considered a classic indicator of failures of individual banks and the banking systems themselves (Honohan, 1997). Also, in the literature, despite of the relationship with the share of credit being scarce, there is evidence of a higher ratio of credit to GDP increasing the financial instability (Gadanecz et al., 2008). Finally, regarding the literature on banks' systemic risk, the only study that tests the relationship between credit and banks' systemic risk is provided by Soedarmono et al. (2017). They found that higher abnormal loan growth leads to higher systemic risk one year ahead, based on a sample containing 161 listed banks in Asia from 1998 to 2012.

In addition, some extensive literature studies are addressed by Rousseau et al. (2011), who provided evidence of credit growth leading to inflation and weakened the banking systems resulting in financial crises, using panel data from 84 countries from 1960 to 2004. Also, Reinhart et al. (2011), with panel data from 70 advanced and emerging economies from 1800-2009, including 290 banking crises, support that private debt increased as an antecedent of banking crises. Moreover, Jordà et al. (2013), with a dataset of 14 advanced countries between 1870 and 2008, documented that deeper recessions are preceded by credit-intensive expansion. Moreover, Schularick et al. (2012), with the same dataset, showed that credit growth is a powerful predictor of financial crises. Although, this view is not consensual with Bernanke and Gertler (1995) stating that credit aggregates are not driving forces affecting the economy. They argue that still, credit conditions are the best measures of the external finance premium and not the aggregate amount of credit. However, the previous idea is further supported by the literature that links credit growth with future non-performing loans (NPL), lower relative income, and lower capital ratio, making credit growth a key driver of bank risk (Hess et al. 2009; Foos et al., 2010; Festić et al., 2011).

2.4 The “Debt Shift”: Implication for Economic Growth and Financial Stability

Since the 1990s, an increase in the share of total bank credit has been flowing to households, real estate and financial assets. For example, the share of credit to households in both the developed and developing world accounted for more than 40 per cent of total bank lending in 2007 (Beck et al., 2012). Moreover, there was a rapid acceleration in household and mortgage debt relative to other types of credit between 2002 and 2006, suggesting that both the timing and severity of the economic recession from 2007 to 2009 were related to this acceleration (Mian et al., 2009; Mian et al., 2010). This "debt shift" taking place has potential impacts on economic growth and financial stability, raising concerns for policymakers (Taylor et al., 2015; Bezemer et al., 2020).

Empirically, some studies in the macroeconomic literature corroborate the impact of debt shifting on economic growth, with credit to firms being associated with higher economic growth (Gourinchas et al., 2001; Oikarinen, 2009; Beck et al., 2012; Werner, 2012; Jordà et al., 2013; Sassi et al., 2014). While credit to non-corporate entities, such as credit to households and mortgage credit, is associated with lower economic growth and productivity (Jappelli et al., 1994; Büyükkarabacak et al., 2010; Werner, 2012; Bezemer et al., 2016; Samatas et al., 2019; Müller et al., 2021).

Besides the different types of credit having different effects on economic growth, they can also have different effects on financial stability (Büyükkarabacak et al., 2010; Werner, 2012; Müller et al., 2021).

2.5 Household and Mortgage Credit Relationship with Financial Fragility

The relationship of household credit with financial fragility is mainly studied using household leverage growth, where there is consistent evidence of a positive relationship, especially when it is at high levels (Zabai et al., 2017). However, the literature is absent on the relationship between the share of household credit with financial fragility. According to Muller et al. (2021) and Schneider et al. (2004), household credit fragility comes from sensitivity to changes in credit supply, contributing disproportionately to the build-up of financial fragility.

Büyükkarabacak et al. (2010) provide evidence that household credit expansions are statistically and economically significant predictors of banking crises, using the growth of credit to GDP and a dataset with 37 developed and emerging economies from 1990 to 2007. Moreover, Mian (2010) presented evidence that growth in household debt, defined as the debt-to-income ratio, in 2006 is a statistically significant predictor of the severity of the recession from 2007 to 2009 in all U.S. counties.

Also, Sutherland et al. (2012) gather evidence on the likelihood of an increase in recession when household debt to GDP is above trend. In the same line, Mian et al. (2017) showed that the global household debt cycle, as measured by the growth of household credit to GDP, partially predicts the severity of the global recession from 2007 to 2012, using a panel data of 30 countries from 1960 to 2012.

The literature on the relationship between mortgage credit (the main component of household credit) and financial fragility is more diverse and mixed (Le al., 2021). The mortgage credit growth is consistently associated with financial instability. In contrast, the quantities and share of mortgage credit are associated with financial stability. Moreover, a few studies show a different relationship between the share of mortgage credit with financial stability depending on the selected period (crisis and non-crisis periods). Besides being variable and time-dependent, according to the same limited literature, the relationship between the share of mortgage credit with financial stability is non-linear.

Over the last two decades, a boom-bust cycle in house prices has been an experience in several different developed countries, e.g. Spain, Ireland, the United States and the United Kingdom, with a severe consequence for financial stability (Jordà et al., 2015). Also, this period of the boom-bust cycles is associated with the main causes of the banking crisis, with the interaction between credit and asset prices being a key factor in the financial instability

(Allen et al., 2013; Jordà et al., 2015). The boom-bust cycle as the procyclicality dimension of systemic risk has a positive relationship with credit growth and can be characterized by two distinct moments. First, in a boom, the mortgage credit and housing collateral feed into each other, increasing the homeowner's ability to borrow more. Then, in a bust, the relationship is still positive. Still, the feedback is reversed, with homeowners having credit constraints, resulting in fire sales of assets, leading to a deterioration in collateral prices and further credit tightening (Jeanne et al., 2010, Mian et al., 2016).

Empirically, Jordà et al. (2015, 2016), with a dataset of 17 countries over the past 140 years, showed that excessive mortgage credit growth is a key source of financial instability, especially when fueled by asset price bubbles, resulting in deeper recessions. Moreover, Muller et al. (2021), with a dataset of 117 countries between 1940 and 2014, show that growth in the ratio of household credit to GDP, especially mortgage credit, contributes to macroeconomic boom and bust cycles, increasing financial fragility. Regulators have recognized the adverse effects of mortgage credit growth with macroeconomic prudential regulations such as loan-to-value (LTV) and loan-to-interest (LTI), which appear to be effective in preventing credit growth and future non-performing loans (Lim, et al., 2011; Ahuja et al., 2011).

On the other hand, mortgage credit can contribute to financial stability as it tends to be smaller, more predictable, and promotes portfolio diversification due to its different risk properties and the fact that it exhibits greater financial stability than corporate lending as the risk of individual households is lower than that of corporate loans (Morgan et al., 2017). Empirically, Cacnio (2014), in a research project conducted by the SEACEN Centre comprising 13 countries located in South and Southeast Asia, showed that the amount of mortgage credit does not threaten the financial stability of banks. For example, Hsu et al. (2014), using a dataset composed of Tapei, China between 1998 and 2012, found a non-significant long-term relationship and a negative and significant short-term relationship between the amount of mortgage credit with NPL. In addition, the share of mortgage credit also has a positive relationship with financial stability. Morgan et al. (2017, 2018), in two different studies with a sample consisting of 397 banks in 19 emerging Asian economies from 2003 to 2014 and, 1889 banks in 65 advanced and emerging economies for the period 1987-2014, found a positive relationship between the share of mortgage credit in total outstanding loans with financial stability, defined as bank Z-score and the NPL ratio.

Moreover, in the same two studies, Morgan et al. (2017, 2018) showed that the relationship between the share of mortgage credit and NPL has a U-shaped relationship, meaning that an increase in the share of mortgage credit tends to be positive for financial stability, reducing the NPL ratio, until it exceeds a critical level of 49-63% of total loans, where the incremental impact on financial stability becomes negative. This evidence is consistent with the literature that found both a positive and negative effect of loan diversification on bank financial strength and bank risk, respectively (Rossi et al., 2009; Shim, 2019).

Furthermore, some literature suggests that the share of mortgage credit does not contribute to systemic risk and increases financial stability, except in periods of housing bubbles and financial crisis, because the risk of individual mortgage credit becomes highly correlated in this period, resulting in a higher risk to financial stability (Morgan et al., 2017, 2018). IMF (2011) found a positive relationship between mortgage credit to GDP in 2004-2007 with NPL during 2007-2008 for a dataset with 36 advanced and emerging economies over the period 2004-2009. However, the relationship is negative and insignificant relative to the overall effect in the whole sample. Furthermore, Morgan et al. (2017, 2018), in both the previously mentioned studies, also found differences between non-crisis and crisis periods. In the non-crisis period, the bank's financial stability is positively affected by a higher share of mortgages, while in a crisis period it is negatively impacted.

3. Hypothesis Development

The empirical research focuses on the relationship between banks' systemic risk and household and mortgage credit for European banks. Also, it uses CAMEL variables to control this relationship. Following this literature review, the following hypotheses can be tested:

Hypotheses 1.

- a) *There is a positive effect of household and mortgage credit growth on banks' systemic risk.*
- b) *There is a negative effect of the share of household and mortgage credit on banks' systemic risk.*

The procyclical dimension of banks' systemic risk comes from the positive relationship between the overall credit growth and the economic environment, which supply-side explanations have corroborated. Also, extensive literature has documented a positive relationship between overall credit growth and financial fragility, with findings of a positive relationship between banks' systemic risk and abnormal credit growth (Soedarmono, 2017). Moreover, besides the relationship with overall credit growth, the literature has consistently found a positive relationship between the household and mortgage credit growth with financial instability due to its sensitivity to changes in credit supply and the connection with boom-bust cycles that originates the build-up of the financial fragility (Schneider et al, 2004; Mian, 2010; Büyükkarabacak et al., 2010; Sutherland et al., 2012; Jordà et al., 2015, 2016; Mian et al., 2017, 2017; Muller et al., 2021).

Theoretically, it can be argued that the share of household and mortgage credit is positively associated with banks' systemic risk through its cross-sectional dimension based on the notion that it increases the correlation of banks' assets as they also share the same type of credit risk (Billio et al., 2012; Smaga, 2014; Benoit et al., 2017). Although, the empirical literature has found a positive relationship between the share of mortgage credit with bank stability, which is attributed to mortgage characteristics that increase portfolio diversification (Cacnio 2014; Hsu et al., 2014; Morgan et al., 2017, 2018). This possibility of a negative relationship with banks' systemic risk is propagated to the share of household credit because mortgage credit is the biggest component of household credit and, in our sample, mortgage credit accounts for more than 70% of total credit to households.

Hypotheses 2.

- a) *There is a positive effect of the share of household and mortgage credit on banks' systemic risk in a crisis period.*
- b) *There is a positive effect of household and mortgage credit growth on banks' systemic risk in a crisis period.*

Some literature suggests that the share of mortgage credit does not contribute to systemic risk and enhances financial stability, except in periods of housing bubbles, because mortgage credit risk becomes significantly correlated in these periods. (IMF, 2011; Morgan et al., 2017, 2018).

Moreover, the mortgage credit growth is positively associated with boom-and-bust cycles. This connection comes from the relationship between the mortgage credit growth and mortgage collateral prices, as they feed back on each other, contributing to boom-and-bust cycles that result in an increase in financial fragility. In a period of crisis, the relationship is still positive, but the feedback is reversed, with credit constraints leading to a deterioration in collateral prices, which leads to further credit tightening (Jeanne et al., 2010; Mian et al., 2016; Muller et al., 2021).

Based on the above rationale, the relationship between mortgage credit and banks' systemic risk is propagated in both hypotheses for credit to household.

Hypothesis 3. *There is a non-linear effect of the share of household and mortgage credit on banks' systemic risk.*

In two different studies, Morgan et al. (2017, 2018) found a U-shaped relationship between the share of mortgage credit and financial stability, where an increase in the share of mortgage credit tends to be favorable to financial stability until it exceeds a critical level, where the incremental impact on financial stability becomes negative. This non-linearity is consistent with the literature that found both a positive and negative effect of loan diversification on bank financial strength and bank risk, respectively (Rossi et al., 2009; Shim, 2019). As mentioned above, the hypothesis is propagated to the share of household credit.

Table 3.1. Summary of Variables and Hypothesis

Variables definition, notation, and expected effect of the explanatory variables.

Variables	Construction	Expected sign
<i>A. Dependent variables</i>		
SRISK/LRMES		Dependent variables
<i>B. Key independent variables</i>		
Growth of Household Credit (C.H.G.)	Chapter 4.3., section B.	H1. a) Positive
Growth of Mortgage Credit (C.M.G.)	Chapter 4.3., section B.	H1. a) Positive
Share of Household Credit (C.H.)	Chapter 4.3., section B.	H1. b) Negative
Share of Mortgage Credit (C.M.)	Chapter 4.3., section B.	H1. b) Negative
Crisis	Dummy coded 1 in years of the GFC (2007-2009)	H2. Positive
Square Root of Household Credit (C.H. ²)	-	H3. Positive
Square Root of Household Credit (C.M. ²)	-	H3. Positive
<i>C. Control variables</i>		
TIER 1 Capital	Equity capital (TIER1) / Total Risk Weighted Assets (RWA)	Negative
Loan to Assets (L.T.O.A)	Total Loans / Total Assets	Negative
Business management (N.I.I)	Non-interest income / Total Income	Positive
Return on Assets	EBIT / Total Assets	Positive
Cash	Cash / Total Assets	Negative
Size	Logarithm of Total Assets	Positive

4. Data and methodology

4.1 Data

A. Number of Banks

The sample includes forty-two banks from twelve different European countries. The criteria for choosing these forty-two banks were the data available in the Leonard N. Stern School of Business (New York University) V-Lab for this period, as the banks' systemic risk variable in this database follows the methodology of Acharya, Engle, and Richardson (2012). Table A.2 shows the breakdown of the number of banks by country.

B. Time Period

The sample period from 2004 to 2009 is used based on the period's relevance according to some authors and the characteristics of this period. According to Brunnermeier et al. (2020), this period was an accumulation phase in which the imbalances that preceded the financial crisis in 2007-2009 were formed due to the high credit growth rate. In addition, on graph A.1, the average growth of household mortgage credit was substantially high before 2009. According to the literature, high credit growth precedes financial fragility (Honohan, 1997; Rousseau et al., 2011; Reinhart et al., 2011; Jordà et al., 2013; Schularick et al., 2012). In another view, graph A.2 shows that the share of household and mortgage credit in total credit was stable throughout the period between 2004 and 2021.

C. Data Sources

The main independent variables used to represent the banks' systemic risk are SRISK and LRMES, following Acharya, Engle, and Richardson (2012) methodology. SRISK is the expected capital that the firm will need in the case of a financial crisis, and LRMES is the long marginal expected shortfall. Both are drawn from the Leonard N. Stern School of Business (New York University) V-Lab, which follows the Acharya, Engle, and Richardson (2012) methodology. The credit variables are composed of proxy data due to the inconsistency and lack of reporting in Banks' financial statements on the type of credit they hold during the selected period. Thus, credit variables are used from the country where the banks are headquartered. Credit data are extracted from the country of each bank, provided by the ECB and the Swiss National Bank (SNB). Control variables were extracted from the banks' financial statements and using the Orbis database.

4.2 Variables

A. Systemic Risk

The measure provided by Acharya, Engle, and Richardson (2012) focuses on the expected capital shortfall of a firm in a crisis period, which captures the firm's overall contribution to systemwide failure. The variable that captures it is SRISK, which is defined as the expected capital that the firm i will need in the case of a financial crisis, in a time period (t) (Equation 4.1). It can be estimated using a bivariate daily time series model of equity return of financial firm i and a market index (or can be only the financial sector) (Equation 4.2).

The long marginal expected shortfall (LRMES) is an average of the fractional returns of the firm's equity in a crisis scenario, where the crisis scenario is given by a fall of a broad index (e.g S&P 500) of 40 percent over the following six months. The LRMES is obtained by using the marginal expected shortfall (MES) to extrapolate in scenarios of crisis, where MES is the expected equity loss per euro invested in a bank if the overall market declines by a given amount, and it is calculated using the average return of each bank during 5% of the worst days of the market. The LRMES is more severe and has a longer duration with multiplication for 18 of MES (Equation 4.3). Given this parameter, the SRISK is calculated by assuming that the debt's book value will not change during the next sixth month and the equity value will fall by the LRMES amount. The prudential capital ratio (k) is assumed to be 8% during the period (Equation 4.4).

$$4.1 \text{ SRISK}_{i,t} = E_{t-1}(\text{Capital Shortfall}_i | \text{Crisis})$$

$$4.2 \text{ Rm}_{m,t} = \sigma_{m,t} \varepsilon_{m,t}$$

$$4.3 \text{ LRMES}_{i,t} = 1 - \exp(-18 * \text{MES}_{i,t})$$

$$4.4 \text{ SRISK}_{i,t} = E((K(\text{Debt} + \text{Equity}) - \text{Equity}) | \text{Crisis}) = \\ = K\text{Debt}_{i,t} - (1 - k)(1 - \text{LRMES}_{i,t}) \times \text{Equity}_{i,t}$$

B. Country Level Variables

The effect of household and mortgage credit on the banks' systemic risk is captured through the growth and the share of these types of credit at the country level. Accordingly, the following variables are created:

1. Share of Household Credit (C.H.):

$$4.5 \text{ CH of Country}_{i,t} = \frac{\text{Household credit}_{i,t}}{\text{Total Loans}_{i,t}}$$

2. Share of Mortgage Credit Share (C.M.):

$$4.6 \text{ CM of Country}_{i,t} = \frac{\text{Mortgage Credit}_{i,t}}{\text{Total Loans}_{i,t}}$$

3. Growth of Household Credit (C.H.G.):

$$4.7 \text{ CHG of Country}_{i,t} = \frac{\text{Household credit}_{i,t} - \text{Household credit}_{i,t-1}}{\text{Household credit}_{i,t-1}}$$

4. Growth of Mortgage Credit (C.M.G.):

$$4.8 \text{ CMG of Country}_{i,t} = \frac{\text{Mortgage credit}_{i,t} - \text{Mortgage credit}_{i,t-1}}{\text{Mortgage credit}_{i,t-1}}$$

C. Control Variables

To control the specific financial situation of each bank, the literature adds control variables that capture the individual financial condition of financial institutions. This dissertation follows this approach and uses the CAMEL rating system. CAMEL variables evaluate critical dimensions of banks, such as capital adequacy, asset quality, business management, earning quality, and liquidity (Hirtle et al., 1999; Ferrouhi, 2014). The variables used are the TIER 1, which captures the capital adequacy, since it is the ratio of a bank's core equity capital to its total risk-weighted assets (RWA); Loans to assets (L.T.O.A), which measures the asset quality; Non-interest income to total income (N.I.I), which represents the management quality; Return on Assets (R.O.A) evaluates the earning quality; Cash capture the liquidity and Size through the log of assets control the size component. The expected sign of these variables is presented in table 3.1., which is consensual in the literature (Laeven et al., 2016; Arena, 2008; Jin et al., 2011; Distinguin et al., 2006; Galán, J., 2021).

4.3. Methodology

A. Model

The main objective is empirically to study the relationship between banks' systemic risk with household and mortgage credit. This relationship is examined by creating two models to prevent collinearity problems since credit growth of mortgage credit and household have a higher correlation. Also, the credit share of mortgage and household have a higher correlation.

The first one examines the relationship between banks' systemic risk and household credit growth and the share of household credit through the CHG and CH, respectively. The second studied the link of banks' systemic risk with the mortgage credit growth and the share of mortgage credit through the CMG and CM, respectively. In addition, to study the possibility of non-linearity of the share of household and mortgage credit, it is added the CH² and CM² to both models, respectively. Also, the dummy Crisis is created and multiplied by the relevant key independent variables to study the relation in the crisis period. Both models include the control variables (CAMEL variables). For this purpose, it leads to a formulation of two empirical models that are expressed as follows:

$$\begin{aligned} 4.9 \quad \text{Systemaric risk}_{i,t} = & \beta + \beta_1 CH_i + \beta_2 CHG_i + \beta_3 CH_i^2 + \\ & \beta_4 Crisis + \beta_5 CH_i * Crisis + \beta_6 CHG_i * Crisis + \beta_7 TIER1_i + \\ & \beta_8 LTOA_i + \beta_9 BM_i + \beta_{10} ROA_i + \beta_{11} Cash_i + \beta_{12} Size_i + \varepsilon_{i,t} \end{aligned}$$

$$\begin{aligned} 4.10 \quad \text{Systemaric risk}_{i,t} = & \beta + \beta_1 CM_i + \beta_2 CMG_i + \beta_3 CM_i^2 + \\ & \beta_4 Crisis + \beta_5 CM_i * Crisis + \beta_6 CMG_i * Crisis + \beta_7 TIER1_i + \\ & \beta_8 LTOA_i + \beta_9 BM_i + \beta_{10} ROA_i + \beta_{11} Cash_i + \beta_{12} Size_i + \varepsilon_{i,t} \end{aligned}$$

The i denotes the banks, the t is the time, ε_i and η_i are the stochastic errors. The variables CHG, CMG, CH, and CM are lagged one year, following previous literature (Soedarmono, 2017). Although, this lag is only introduced when the SRISK is the dependent variable because LRMES is already a variable's expected value for 18 months. Moreover, table 3.1 presents the definitions of variables and their expected sign.

B. Econometric Model

In this dissertation, the database structure combines time series with cross-sectional data, leading to the formation of panel data. Thus, the methodology applied is in concurrence with the data structure. Following the literature (Battaglia et al., 2013; Soedarmono et al., 2017; Díez-Esteban et al., 2022), it is employed a Generalised System Method of Moments (GMM).

The Generalized System Method of Moments (GMM) was proposed by Arellano and Bond (1991) and Blundell and Bond (1998). This methodology is dynamic, with its estimator accommodating constant unobserved heterogeneity and endogeneity issues by employing lagged dependent variable as a regressor (Blundell and Bond, 2000; Blundell et al., 2000). The generalized two-step method of moments (GMM) is used since it produces a more efficient output than the one-step GMM (Roodman, 2009).

The consistency of the GMN estimators is accessed through the three robustness test: Wald test, Hansen-J test, and Arellano-Bond autocorrelation tests. The Wald test access the global significance of the explanatory variables. To validate the number of lags and the variables presented in the model, it is resorted to the Hansen-J test and to Arellano-Bond autocorrelation test (Arellano and Bond, 1991). The Hansen-J test identifies restrictions in a dynamic panel data model (Hansen, 1982). The Arellano-Bond indicates if exists a second-order autocorrelation between residuals in a first-differenced equation (Arellano and Bond, 1991). Overall, estimators are valid if the Hansen-J test and the Arellano-Bond autocorrelation tests are not statistically significant. And if the Wald test is statistically significant to reject the null hypothesis of joint insignificance of our explanatory variables.

5. Empirical Results

5.1 Descriptive Statistics and Correlation Structure

Table 5.1 presents descriptive statistics (mean, median, standard deviation, maximum and minimum) of all variables used in this study. Also, the pairwise correlation coefficients with all the variables are reported in Table 5.2.

Panel A shows the key independent where SRISK has a mean of 1 and LRMES has a mean of 32. BNP Paribas had a maximum SRISK of 8 in 2006, and the Bank of Ireland had a maximum LRMES of 70 in 2009. For this sample period, LRMES had higher volatility than SRISK.

The key independent variables are present in Panel B. The credit to the household has an average share of 48% and the mortgage credit of 34%, meaning that on average, 72% of the credit to households is mortgage credit. As a result, the average annual growth of both types of credit is identical (12%), with mortgage credit slightly more volatile. The country with a higher credit share of households and mortgage credit was Germany with 64% and 53% in 2004, respectively, while with a lower share was Italy with 30% and 17% in 2004, respectively. Regarding credit growth, Spain had the higher growth rate of mortgage credit (34%) in 2005, while the lower growth rate (29%) occurred in Belgium in 2009. Also, Belgium had the slower household growth (23%) in 2009, while Austria's had the maximum growth rate (35%) in 2005.

The control variables in Panel C are not described for simplicity and lower contribution to the results.

The results of the correlation matrix show a positive correlation between SRISK and the share of household and mortgage credit. However, SRISK and household and mortgage credit growth have a lower negative correlation. Further, LRMES has a negative correlation with the share of household and mortgage credit and a lower negative correlation with the household and mortgage credit growth.

Table 5.1 Descriptive Statistics

Variables	Mean	Std. Dev.	Median	Minimum	Maximum
Panel A: <i>Dependent Variables</i>					
SRISK	0.835	1.975	0.065	0.000	8.140
LRMES	32.104	15.009	34.705	1.080	69.630
Panel B: <i>Key Independent variables</i>					
CM	0.343	0.105	0.352	0.165	0.534
CH	0.476	0.095	0.483	0.296	0.629
CMG	0.116	0.091	0.114	-0.289	0.344
CHG	0.116	0.094	0.106	-0.229	0.382
Panel C: <i>Control variables</i>					
TIER1	0.086	0.034	0.079	0.001	0.184
LTOA	0.661	0.202	0.676	0.187	1.000
NII	0.016	0.017	0.011	-0.012	0.949
ROA	0.013	0.012	0.008	-0.004	0.050
CASH	0.020	0.013	0.017	0.001	0.068
SIZE	17.463	1.689	17.698	12.956	21.453

Table 5.2 Correlation Matrix

	SRISK	LRMES	CH	CM	CHG	CMG	TIER1	LTOA	NII	ROA	CASH	SIZE
SRISK	1.000											
LRMES	0.459	1.000										
CH	0.0283	-0.371	1.000									
CM	0.109	-0.444	0.904	1.000								
CHG	-0.128	-0.024	0.039	-0.095	1.000							
CMG	-0.070	-0.095	0.256	-0.072	0.795	1.000						
TIER1	-0.396	-0.415	0.438	0.474	-0.035	-0.072	1.000					
LTOA	-0.714	-0.445	-0.011	0.084	0.020	-0.024	0.283	1.000				
NII	-0.362	0.206	-0.304	-0.296	-0.082	-0.094	-0.138	-0.298	1.000			
ROA	-0.253	-0.199	0.090	0.232	0.064	0.090	0.003	0.020	-0.264	1.000		
CASH	-0.182	0.390	-0.350	-0.325	0.068	-0.061	-0.194	0.013	-0.266	0.226	1.000	
SIZE	-0.171	0.282	-0.353	-0.241	0.063	0.024	-0.055	0.098	-0.221	0.267	0.542	1.000

5.2 System Generalized Method of Moments (GMM)

Table 5.3 Result of Estimation 1 (Equation 4.9)

	SRISK			LRMES		
	Household Credit	Crisis Period	Full model	Household Credit	Crisis Period	Full model
Lag Independent Variable	0.463*** (0.120)	0.479*** (0.117)	0.419*** (0.007)	-0.197 (0.188)	-0.619*** (0.093)	-0.692** (0.373)
CH				-408.355*** (138.629)	-462.638*** (198.500)	-573.211*** (218.713)
CHG				-29.650*** (6.964)	-42.846*** (15.646)	-34.483** (17.850)
CH ²					353.175** (187.385)	410.172** (191.559)
CH(-1)	3.589 (2.899)	1.155*** (3.835)	-0.595** (3.046)			
CHG(-1)	-0.353* (0.193)	-0.320* (0.219)	-0.401** (0.190)			
CH ² (-1)	-3.695 (3.467)	-1.732 (4.582)	0.011 (3.397)			
Crisis		0.270* (0.152)	0.143 (0.095)		2.050 (6.541)	4.225 (10.924)
CH*Crisis					-8.202 (10.762)	-12.483 (18.773)
CHG*Crisis					12.449 (16.027)	13.171 (20.781)
CH(-1)*Crisis		-0.585** (0.803)	-0.352 (0.295)			
CHG(-1)*Crisis		0.593 (0.370)	0.455 (0.476)			
TIER1			-0.010** (0.005)			0.200 (0.353)
LTOA			0.298 (0.265)			39.828** (20.517)
NII			-0.014*** (0.001)			-0.013 (0.850)
ROA			-6.666*** (2.544)			-8.622 (13.52)
Cash			-4.560*** (1.609)			-139.981 (144.309)
Size			0.023*** (0.006)			1.060** (0.421)
Wald test	25.098***	87.843***	9468.183***	88.381***	90.440***	357.592***
AR(1)	-2.179***	-3.815***	-0.069	-2.048***	-0.344	0.667
AR(2)	-0.289	0.398	0.094	-0.425**	-1.632	-0.270
Hansen-J	8.950	13.139	8.313	11.032***	30.520***	10.178
No. Banks	42	42	23	42	42	23

Note: *** significant at 99% confidence level; ** 95%; * 90%. Values in parentheses are the standard deviations. See Table 3.1 for variable definitions.

Table 5.4 Result of Estimation 1 (Equation 4.10)

	SRISK			LRMES		
	Mortgage Credit	Crisis Period	Full model	Mortgage Credit	Crisis Period	Full model
Lag Independent Variable	0.144*** (0.031)	0.086*** (0.033)	0.415*** (0.016)	-0.326*** (0.059)	0.147* (-0.088)	0.072 (0.107)
CM				-98.047 (171.553)	-528.974** (216.527)	-321.128** (148.837)
CMG				-38.1223*** (5.146)	-44.245*** (8.808)	-59.001*** (13.381)
CM ²				149.367 (241.844)	656.353*** (280.203)	474.295*** (220.252)
CM(-1)	12.418*** (3.987)	4.059* (4.793)	-2.730* (1.593)			
CMG(-1)	-0.793*** (0.189)	-1.727*** (0.300)	-0.792*** (0.234)			
CM ² (-1)	-19.327*** (5.799)	-4.804 (7.669)	5.375*** (1.933)			
Crisis		0.311* (0.172)	-0.159 (0.084)		-1.612 (3.674)	-9.741* (3.830)
CM*Crisis					-1.510 (-0.197)	2.045 (7.695)
CMG*Crisis					9.481 (12.649)	32.386* (14.400)
CM(-1)*Crisis		-1.826** (0.384)	-0.505* (0.203)			
CMG(-1)*Crisis		0.974** (0.402)	0.570* (0.191)			
TIER1			-0.009* (0.006)			0.158 (0.345)
LTOA			0.461 (0.302)			37.010* (20.274)
NII			-0.013*** (0.001)			-0.101*** (0.030)
ROA			-7.305*** (1.363)			-379.314*** (45.892)
Cash			-3.611 (2.448)			-22.894 (90.164)
Size			0.032*** (0.010)			0.885*** (0.249)
Wald test	103.991***	147.498***	371.168***	155.325***	160.523***	361.960***
AR(1)	-1.598	-3.216***	-1.860*	-2.088***	-3.216***	-1.914*
AR(2)	-0.324	-0.621	1.547	-2.090***	-0.621	1.093
Hansen-J	17.383	24.979**	15.263	31.533***	26.698***	13.171
No. Banks	44	44	23	44	44	23

Note: *** significant at 99% confidence level; ** 95%; * 90%. Values in parentheses are the standard deviations. See Table 3.1 for variable definitions.

Tables 5.3 and 5.4 present the full models, where the effects of household and mortgage credit on banks' systemic risk are studied. SRISK and LRME are used as a proxy of banks' systemic risk, which captures short-term systemic risk (SRISK) and long-term systemic risk (LRMES).

From the GMM regressions, consistent evidence of a negative effect of household and mortgage credit growth on banks' systemic risk in both the short and long term rejects our hypothesis. This result is inconsistent with previous literature (Schneider et al., 2004; Mian, 2010; Büyükkarabacak et al., 2010; Sutherland et al., 2012; Jordà et al., 2015, 2016; Mian et al., 2017, 2017; Muller et al., 2021). The different results can be attributed to the different independent variables used, since, in this study, a simple credit growth variable is used and not the growth of credit to GDP as in previous literature mentioned.

Furthermore, consistent evidence of a negative effect of the share of household and mortgage credit on bank's systemic risk in both the short and long term confirms our hypothesis. This result is consistent with the notion that mortgage characteristics increase portfolio diversification and is in line with previous findings (Cacnio 2014; Hsu et al., 2014; Morgan et al., 2017, 2018).

Regarding the second hypotheses, the coefficients of crisis are not statistically significant, even for a 10 percent significance level in any model. Therefore, it cannot be concluded whether the above results are the same or different depending on the presence of a crisis period.

Our third hypothesis is accepted, since our result shows a U-shaped relationship (positive and statistically significant coefficients CM^2 and CH^2) between the banks' systemic risk with the share of the household and mortgage credit, in line with previous literature (Morgan et al., 2017, 2018). Thus, this means that until a certain point, an increase in the share of the mortgage and household credit tends to negatively affect banks' systemic risk. In contrast, after a certain point, this relationship becomes positive. This result is in line with previous evidence that asset diversification increases financial stability, while asset concentration is negative for financial stability and increases bank risk (Rossi et al., 2009; Morgan et al., 2017, 2018; Shim, 2019).

Furthermore, according to previous literature, the breakpoint can be obtained by calculating $-(\beta_1/2\beta_2)$ (De Miguel et al., 2004; Morgan et al., 2017, 2018; Díez-Esteban et al., 2022). The results show a statistically significant household breakpoint of 70% in the case of LRMEs. For mortgage credit, we find a breakpoint of 25% in the case of SRISK and 34%

in the case of LRMES. Based on these results, it can be argued that mortgage credit tends to have a positive relationship with banks' systemic risk because the average of breakpoints is below the average share (34%), while household credit tends to have a negative relationship as its breakpoint is above the average (48%). Although, this result on mortgage credit should be carefully assessed because Morgan et al. (2017) found a breakpoint between 49–63% for mortgage credit in relation to non-performing loans.

Overall, these empirical results of the four full regression models are valid because the Hanse-J test and the Arellano-Bond autocorrelation test for second order are not statistically significant, at least at the 1 per cent level. Also, the Wald test rejects the null hypothesis of joint insignificance of our explanatory variables in both regressions for a significance level of 1 per cent. In addition, the relationships obtained between CAMEL variables and banks' systemic risk are to some extent consistent with previous literature.

6. Additional Robustness Tests

To ensure consistency of the results, it is employed the robustness test. A GMN estimation regression is employed with a two-year lag, as performed by Soedarmono et al. (2017), to ensure consistency in the results, following the same reasoning presented in the chapter 4.3, section A. The results presented in the Appendix C are overall weak. The two full models that have SRISK as dependent variable, are invalid to draw a conclusion, given that both shows a statistically significant 10 percent significance level for the Hanse-J test. In addition, the two other full models with LRMES as dependent variable partially corroborated the previous results. However, most of the independent variables presented in these two models are not statistically significant.

The Durbin-Wu-Hausman augmented-regression test is used to test for endogeneity, which is associated with the correlation between the explanatory variables and the error term that can cause bias and inconsistency in the estimation. Table C.3. shows that there is no endogeneity, by rejecting the null hypothesis for 1% significance level for the four models.

Furthermore, to test for heteroskedasticity of all the variables, the Augmented Dickey-Fuller test is applied, where constant and trend terms with a lag length of 1 are included. In Table C.4., the results show no presence of heteroskedasticity in our key and control variables used in the model, by rejecting the null hypothesis for 1% significance level for the four models.

7. Conclusion and Limitations

The last GFC of 2007-09 was a catalyst for the literature on bank systemic risk due to the high cost incurred in rescuing important systemic financial intuitions. Consequently, central banks and policymakers have introduced measures to prevent banks' systemic risk as their primary mission is to ensure financial stability. Therefore, the debate on the determinants of a banks' systemic risk has grown in size and scope.

This dissertation contributes to this debate by studying the relationship between banks' systemic risk and household and mortgage credit. The importance of studying these types of credit is due to the increasing share of total bank credit flowing into household and mortgage credit and high growth rates of these types of credit observed prior to the Global Financial Crisis. This "debt shift" has potential implications for financial stability and, consequently, for banks' systemic risk.

Overall, the results suggest a negative effect of household and mortgage credit growth on banks' systemic risk. This result is inconsistent with previous literature (Schneider et al., 2004; Mian, 2010; Büyükkarabacak et al., 2010; Sutherland et al., 2012; Jordà et al., 2015, 2016; Mian et al., 2017, 2017; Muller et al., 2021) and with our hypothesis, which can be attributed to the different independent variable used. In addition, as our hypothesis suggested, the results show a negative effect of the share of household and mortgage credit on banks' systemic risk. This result is consistent with previous findings and the notion that mortgage credit characteristics enhance portfolio diversification (Cacnio 2014; Hsu et al., 2014; Morgan et al., 2017, 2018).

In addition, our results show a U-shaped relationship between the share of household and mortgage credit with banks' systemic risk, corroborating our hypothesis of a non-linear relationship. The result is also in line with previous evidence showing that asset diversification increases financial stability, while asset concentration increases financial fragility and banks risk. (Rossi et al., 2009; Morgan et al., 2017, 2018; Shim, 2019). The household breakpoint found was 70% in the case of LRMES. For mortgage credit, a breakpoint of 21% is found in the case of SRISK, and 34% for LRMES. However, the results of these breakpoints results should be accessed carefully. Furthermore, no statistically relevant result can be found for the relationship between banks' systemic risk and household and mortgage credit in a crisis period.

The results demonstrated that the debt shifting that has occurred to household and mortgage credit has positive effects on banks' systemic risk, given the characteristics of mortgage credit: been smaller; more predictable; lower risk of the individual household, appear to have positive effects on enhancing portfolio diversification and exhibiting greater financial stability than firm credit, resulting in lower banks' systemic risk (Morgan et al., 2017, 2018). Moreover, these characteristics of this type of credit seem to offset the theoretical implications regarding the increase of banks' systemic risk via propagation, since this debt shift increases the correlation of banks assets. And it also goes against the theoretical dimension of the procyclicality of banks' systemic risk. Nevertheless, the results presented, and their practical implications should also be carefully accessed as the robustness tests are weak.

This dissertation may motivate further studies of mortgage and household credit due to mixed evidence given the different studies on the share and growth of these types of credit. In addition, it may motivate research on other types of credit (e.g., firm credit), given that there is already strong evidence of a positive relationship with economic growth. Moreover, based on current literature, future research on banks' systemic risk may be more focused on other growing topics of the banks' systemic risk literature, such as banks' business model choices (Marques et al., 2021), corporate governance (Díez-Esteban et al., 2022) and Environmental, Social, and Governance (Aevoae et al., 2022).

The present study presents several limitations. First, country-level data rather than individual bank data are used for the main independent variables. Second, the period is relatively short compared to the literature standards. Third, it is used for the credit growth variable, a simple credit growth variable, and not the growth of credit to GDP as some literature uses. Finally, it focuses mainly on the eurozone with a relatively smaller number of banks compared to the literature standards (e.g. 95 banks in Mayordomo et al., 2014; 161 banks in Soedarmono et al., 2017; 87 banks in Díez-Esteban et al., 2022).

8. Appendix

Appendix A. Data Set Descriptions

Table A.1 Banks List

1	Alandsbanken Abp
2	Alpha Bank SA
3	Attica Bank SA
4	Banca Carige SpA
5	Banca Monte dei Paschi di Siena SpA
6	Banca Popolare di Milano Scarl
7	Banco Bilbao Vizcaya Argentaria SA
8	Banco Bpi SA
9	Banco Comercial Portugues SA
10	Banco de Sabadell SA
11	Banco de Valencia SA
12	Banco Espirito Santo SA
13	Banco Popular Español SA
14	Banco Santander SA
15	Bank of Ireland
16	Bankinter SA
17	Berner Kantonalbank AG
18	BNP Paribas SA
19	Comdirect Bank AG
20	Commerzbank AG
21	Credit Agricole Atlantique Vendee
22	Credit Agricole SA
23	Credit Suisse Group AG
24	Credito Emiliano SpA
25	Deutsche Bank AG
26	Edmond de Rothschild Suisse SA
27	Erste Group Bank AG
28	Eurobank Ergasias SA
29	HSBC Trinkaus & Burkhardt AG
30	ING Groep NV
31	Intesa Sanpaolo SpA

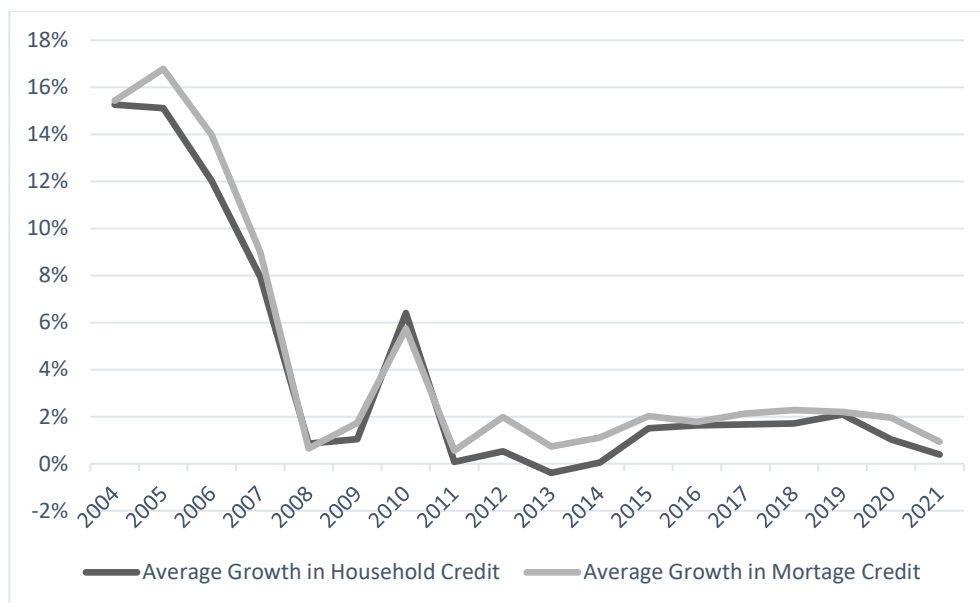
32	KBC Groep NV
33	Luzerner Kantonalbank AG
34	Mediobanca SpA
35	National Bank of Greece SA
36	Oberbank AG
37	Permanent TSB Group Holdings PLC
38	Societe Generale SA
39	UBS Group AG
40	UniCredit SpA
41	Valiant Holding AG
42	Van Lanschot NV

Table A.2 Composition of the sample by countries

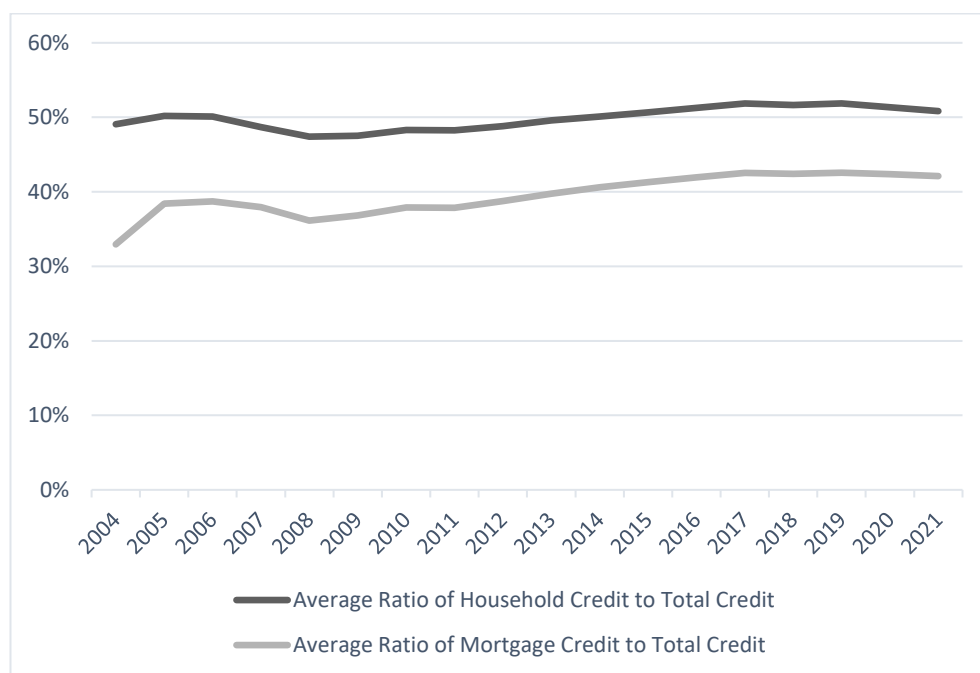
Country	Number of Banks	Number of observations
Austria	2	10
Belgium	2	10
Finland	1	5
France	4	20
Germany	4	20
Greece	4	20
Ireland	2	10
Italy	7	35
Netherlands	2	10
Portugal	3	15
Spain	6	30
Switzerland	7	35

Appendix B. Evolution of Household and Mortgage Credit

Graph B.1 Average Household and Mortgage Credit between 2004 and 2021.



Graph B.2 Average Household and mortgage credit share between 2004 and 2021.



Appendix C. Robustness Test

Table C.1 Result of Estimation 2 (Equation 4.9)

	SRISK			LRMES		
	Household Credit	Crisis Period	Full model	Household Credit	Crisis Period	Full model
Lag Independent Variable	0.506*** (0.007)	0.231*** (0.077)	0.276*** (0.109)	-0.167* (0.095)	-0.261*** (0.098)	-0.211 (0.159)
CH (-1)				181.591** (102.831)	9.549 (115.34)	-272.352* (161.217)
CHG (-1)				-42.650*** (9.249)	-15.409*** (11.288)	1.019 (14.430)
CH ² (-1)				-251.015*** (95.768)	-54.784** (107.424)	230.160 (148.855)
CH(-2)	17.622 (12.354)	-4.786*** (5.878)	-9.555 (8.828)			
CHG(-2)	5.727* (3.196)	-0.183 (0.977)	-0.624 (1.326)			
CHG ² (-2)	-16.976 (11.591)	4.498 (5.404)	8.832 (7.727)			
Crisis		0.592* (0.335)	0.314 (0.389)		22.329*** (4.734)	2.903*** (7.470)
CH(-1)*Crisis					-30.630*** (8.424)	-25.616*** (12.621)
CHG(-1)*Crisis					-35.410*** (14.199)	13.171*** (20.781)
CH(-2)*Crisis		-1.058* (0.624)	-1.329** (0.678)			
CHG(-2)*Crisis		0.338 (0.897)	1.291 (1.305)			
TIER1			-0.033 (0.024)			0.109 (0.460)
LTOA			1.503 (1.388)			35.324 (26.202)
NII			-1.739*** (0.463)			-3.483 (10.901)
ROA			-11.409 (7.272)			-292.744** (147.454)
Cash			-5.342 (5.829)			-86.317 (124.226)
Size			0.555 (0.372)			0.475** (1.153)
Wald test	32.716***	32.824***	47.754***	48.615***	63.83***	45.327***
AR(1)	-2.021***	-3.184***	-2.300***	-2.803*	-3.529***	-1.941
AR(2)	-0.650	-0.259	0.319	-0.0815	-1.255	-0.031
Hansen-J	12.163	22.056	45.512***	83.028***	75.401***	19.546
No. Banks	42	42	23	42	42	23

Note: *** significant at 99% confidence level; ** 95%; * 90%. Values in parenthesis are the standard deviations. See Table 3.1 for variable definitions.

Table C.2 Result of Estimation 2 (Equation 4.10)

	SRISK			LRMES		
	Mortgage Credit	Crisis Period	Full model	Mortgage Credit	Crisis Period	Full model
Lag Independent Variable	0.128*** (0.088)	0.086*** (0.033)	0.259*** (0.107)	-0.409*** (0.090)	-0.391*** (0.090)	-0.302** (0.158)
CM(-1)				-173.198 (186.737)	-235.368 (190.068)	-472.966 (332.912)
CMG(-1)				-47.496*** (5.146)	-39.776*** (9.211)	-31.916*** (14.580)
CM ² (-1)				147.249 (281.996)	253.668 (283.667)	596.417 (516.870)
CM(-2)	-65.486*** (70.099)	4.059 (4.793)	-25.881* (26.193)			
CMG(-2)	-1.664*** (1.450)	-1.727*** (0.300)	-3.185*** (1.115)			
CMG ² (-2)	-107.726*** (108.605)	-4.804 (7.669)	45.833 (1.933)			
Crisis		0.311* (0.172)	-0.340 (0.514)		13.063 (5.431)	22.319*** (8.211)
CM(-1)*Crisis					-19.042 (9.388)	-33.800*** (14.324)
CMG(-1)*Crisis					-27.665 (11.186)	-35.366** (18.707)
CM(-2)*Crisis		-1.826*** (0.384)	-0.844 (1.503)			
CMG(-2)*Crisis		0.974*** (0.402)	2.088*** (0.923)			
TIER1			-5.219*** (2.289)			5.383 (46.019)
LTOA			1.216 (1.178)			35.293* (25.113)
NII			1.622*** (0.441)			1.537 (10.552)
ROA			-3.481*** (7.608)			-116.470*** (146.720)
Cash			-0.106 (5.197)			-103.463 (119.479)
Size			0.605* (0.326)			1.002 (1.115)
Wald test	6.765***	147.498***	48.889***	88.151***	102.718***	58.59***
AR(1)	-2.633**	-3.216***	-2.189*	-2.592***	-2.821***	-1.349
AR(2)	-1.370	-0.621	0.424	-2.310***	-2.089***	0.255
Hansen-J	76.433	24.979**	44.639***	61.288***	58.829***	14.506
No. Banks	42	42	23	42	42	23

Note: *** significant at 99% confidence level; ** 95%; * 90%. Values in parenthesis are the standard deviations.

See Table 3.1 for variable definitions.

Table C.3 Endogeneity Results

	DWH Statistic	P-value
Equation 13	39.257	0.000
Equation 14	18.481	0.010
Equation 13 (2)	25.983	0.000
Equation 14 (2)	20.403	0.0048

Table C.4 Unit root test Results

Variables	χ^2	P-Value
CM	97.331	0.000
CMG	149.717	0.000
CH	128.127	0.000
CHG	202.925	0.000
Tier1	330.476	0.000
LTOA	531.791	0.000
NII	202.087	0.000
ROA	196.694	0.000
CASH	417.291	0.000
SIZE	528.377	0.000

9. References

- Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, 102(3), 59-64.
- Adrian, T., & Brunnermeier, M. K. (2011). *CoVaR* (No. w17454). *National Bureau of Economic Research*.
- Aevoae, G. M., Andries, A. M., Ongena, S., & Sprincean, N. (2022). ESG and Systemic Risk (No. 22-25). *Swiss Finance Institute*. Research Paper, No. 22-25.
- Ahuja, A., & Nabar, M. (2011). Safeguarding banks and containing property booms: Cross-country evidence on macroprudential policies and lessons from Hong Kong SAR. *IMF Working Paper*, No. 11/284.
- Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, 108(1), 1-33.
- Allen, F., Babus, A., & Carletti, E. (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics*, 104(3), 519-534.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297.
- Arena, M. (2008). Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data. *Journal of Banking & Finance*, 32(2), 299-310.
- Battaglia, F., & Gallo, A. (2013). Securitisation and systemic risk: An empirical investigation on Italian banks over the financial crisis. *International Review of Financial Analysis*, 30, 274-286.
- Beck, T., Büyükkarabacak, B., Rioja, F., Valev, N., (2012). Who gets the credit? And does it matter? Household vs. Firm lending across countries. *The B.E. Journal Macroeconomic*, 12(1), 1-46.
- Benoit, S., Colliard, J. E., Hurlin, C., & Pérignon, C. (2017). Where the risks lie: A survey on systemic risk. *Review of Finance*, 21(1), 109-152.
- Berger, Allen N., and Gregory F. Udell (2004). "The institutional memory hypothesis and the procyclicality of bank lending behavior." *Journal of Financial Intermediation*, 13(4), 458-495.
- Bernanke, B. S., & Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4), 27-48.
- Bezemer, D., Grydaki, M., & Zhang, L. (2016). More mortgages, lower growth?. *Economic Inquiry*, 54(1), 652-674.
- Bezemer, D., Samarina, A., & Zhang, L. (2020). Does mortgage lending impact business credit? Evidence from a new disaggregated bank credit data set. *Journal of Banking & Finance*, 113, 105760.

- Bikker, J. A., & Hu, H. (2002). Cyclical patterns in profits, provisioning and lending of banks and procyclicality of the new Basel capital requirements. *Banca Nazionale del Lavoro Quarterly Review*, 55(221), 143-175.
- Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3), 535-559.
- BIS (2018). Global systemically important banks: revised assessment methodology and the higher loss absorbency requirement. Available at <https://www.bis.org/bcbs/publ/d445.htm>.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.
- Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: an application to production functions. *Econometric Reviews*, 19(3), 321-340.
- Borio, C. (2003). Towards a macroprudential framework for financial supervision and regulation?. *CEifo Economic Studies*, 49(2), 181-215.
- Borio, C. E., & Van den Bergh, P. (1993). The nature and management of payment system risks: an international perspective. *Basel: Bank for International Settlements*. No. 36.
- Bougheas, S., & Kirman, A. (2015). Complex financial networks and systemic risk: A review. *Complexity and Geographical Economics*, 19(1), 115-139.
- Brunnermeier, M. K., & Oehmke, M. (2013). Bubbles, financial crises, and systemic risk. *Handbook of the Economics of Finance*, 2, 1221-1288.
- Brunnermeier, M., Rother, S., & Schnabel, I. (2020). Asset price bubbles and systemic risk. *The Review of Financial Studies*, 33(9), 4272-4317.
- Büyükkarabacak, B., & Valev, N. T. (2010). The role of household and business credit in banking crises. *Journal of Banking & Finance*, 34(6), 1247-1256.
- Cacnio F. (2014). Mortgage finance and consumer credit: implications on financial stability in SEACEN economies. *SEACEN Centre*, Kuala Lumpur.
- Capiello, L., Kadareja, A., Kok, C., & Protopapa, M. (2010). Do bank loans and credit standards have an effect on output? A panel approach for the euro area. *European Central Bank*. Working Paper No. 1150.
- Caruana, J. (2010). Systemic risk: how to deal with it?. *Bank of International Settlements*, 1-21. Available at <https://www.bis.org/publ/othp08.htm>.
- Cipollini, A., & Fiordelisi, F. (2012). Economic value, competition and financial distress in the European banking system. *Journal of Banking & Finance*, 36(11), 3101-3109.
- De Bandt, O., & Hartmann, P. (2000). Systemic risk: a survey. *European Central Bank*. Working Paper No.35.

- De Jonghe, O., Diepstraten, M., & Schepens, G. (2015). Banks' size, scope and systemic risk: What role for conflicts of interest?. *Journal of Banking & Finance*, 61, S3-S13.
- De Miguel, A., Pindado, J., & De La Torre, C. (2004). Ownership structure and firm value: New evidence from Spain. *Strategic Management Journal*, 25(12), 1199-1207.
- Díez-Esteban, J. M., Farinha, J. B., García-Gómez, C. D., & Mateus, C. (2022). Does board composition and ownership structure affect banks' systemic risk? European evidence. *Journal of Banking Regulation*, 23(2), 155-172.
- Distinguin, I., Rous, P., & Tarazi, A. (2006). Market discipline and the use of stock market data to predict bank financial distress. *Journal of Financial Services Research*, 30(2), 151-176.
- Dow, J. (2000). What Is Systemic Risk? Moral Hazard, Initial Shocks, and Propagation. *Monetary and Economic Studies*, 18(2), 1-24.
- ECB (2004). Annual Report of 2003. Available at <https://www.ecb.europa.eu/pub/pdf/annrep/ar2004en.pdf?4cc01c9b5ba4f31492c002bd7b5c954e>.
- Ferrouhi, E. M. (2014). Moroccan Banks analysis using camel model. *International Journal of Economics and Financial Issues*, 4(3), 622-627.
- Festić, M., Kavkler, A., & Repina, S. (2011). The macroeconomic sources of systemic risk in the banking sectors of five new E.U. member states. *Journal of Banking & Finance*, 35(2), 310-322.
- Foos, D., Norden, L., & Weber, M. (2010). Loan growth and riskiness of banks. *Journal of Banking & Finance*, 34(12), 2929-2940.
- Freixas, X., Parigi, B. M., & Rochet, J. C. (2000). Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of Money, Credit and Banking*, 611-638.
- Gadanecz, B., & Jayaram, K. (2008). Measures of financial stability-a review. *Irving Fisher Committee Bulletin*, 31(1), 365-383.
- Galán, J. (2021). CREWS: a CAMELS-based early warning system of systemic risk in the banking sector. *Banco de España Occasional Paper*, (2132).
- Gourinchas, P. O., Valdés, R., Landerretche, O., Talvi, E., & Banerjee, A. V. (2001). Lending Booms: Latin America and the World. *Economía*, 1(2), 47-99.
- Hansen, L. P. (1982). Large sample properties of generalised method of moments estimators. *Econometrica*, 50(4), 1029-1054.
- Hess, K., Grimes, A., & Holmes, M. (2009). Credit losses in Australasian banking. *Economic Record*, 85(270), 331-343.
- Hirtle, B., & Lopez, J. A. (1999). Supervisory information and the frequency of bank examinations. *Economic Policy Review*, 5(1), 1-20.
- Honohan, P. (1997). Banking system failures in developing and transition countries: Diagnosis and predictions. *BIS Working Paper No.39*.

Hsu P-C, Yu Y (2014). Mortgage finance and consumer credit: implications for financial stability in Chinese Taipei. In: Cacic F. Mortgage finance and consumer credit: implications on financial stability in SEACEN economies. *SEACEN Centre, Kuala Lumpur*.

Huang, X., Zhou, H., & Zhu, H. (2012). Systemic risk contributions. *Journal of Financial Services Research*, 42(1), 55-83.

International Monetary Fund (2011). Housing finance and financial stability—back to basics? In global financial stability report. International Monetary Fund. April, Washington, DC. Available at <http://www.imf.org/external/pubs/ft/gfsr/2011/01/pdf/chap3.pdf>.

Jappelli, T., & Pagano, M. (1994). Saving, growth, and liquidity constraints. *The Quarterly Journal of Economics*, 109(1), 83-109.

Jeanne, O., & Korinek, A. (2010). Excessive volatility in capital flows: A pigouvian taxation approach. *American Economic Review*, 100(2), 403-07.

Jin, J. Y., Kanagaretnam, K., & Lobo, G. J. (2011). Ability of accounting and audit quality variables to predict bank failure during the financial crisis. *Journal of Banking & Finance*, 35(11), 2811-2819.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2013). When credit bites back. *Journal of Money, Credit and Banking*, 45(s2), 3-28.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). Leveraged bubbles. *Journal of Monetary Economics*, 76, S1-S20.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2016). The great mortgaging: housing finance, crises and business cycles. *Economic Policy*, 31(85), 107-152.

Kiyotaki, N., & Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2), 211-248.

Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance*, 69, S25-S34.

Le, T.D.Q. and Nguyen, D.T. (2021), Bank stability, credit information sharing and a shift toward households' lending: international evidence, *International Journal of Managerial Finance*, ahead-of-print.

Lim, C. H., A. Costa, F. Columba, P. Kongsamut, A. Otani, M. Saiyid, T. Wezel, and X. Wu (2011): "Macroprudential policy: What instruments and how to use them? Lessons from country experiences." *IMF Working Paper No. 13/166*.

Marques, B. P., & Alves, C. F. (2021). The profitability and distance to distress of European banks: do business choices matter?. *The European Journal of Finance*, 27(15), 1553-1580.

Martínez-Jaramillo, S., Pérez, O. P., Embriz, F. A., & Dey, F. L. G. (2010). Systemic risk, financial contagion and financial fragility. *Journal of Economic Dynamics and Control*, 34(11), 2358-2374.

- Mayordomo, S., Rodriguez-Moreno, M., & Peña, J. I. (2014). Derivatives holdings and systemic risk in the U.S. banking sector. *Journal of Banking & Finance*, 45, 84-104.
- Mian, A., & Sufi, A. (2009). The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *The Quarterly Journal of Economics*, 124(4), 1449-1496.
- Mian, A., & Sufi, A. (2010). Household Leverage and the Recession of 2007–09. *IMF Economic Review*, 58(1), 74-117.
- Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4), 1755-1817.
- Mian, A., Sufi, A., & Verner, E. (2017). How do credit supply shocks affect the real economy? Evidence from the United States in the 1980s (No. w23802). *National Bureau of Economic Research*.
- Morgan, P. J., & Zhang, Y. (2017). Mortgage lending, banking crises, and financial stability in Asia and Europe. *Asia Europe Journal*, 15(4), 463-482.
- Morgan, P. J., & Zhang, Y. (2018). Mortgage lending and financial stability in Asia. *The Singapore Economic Review*, 63(01), 125-146.
- Müller, K., & Verner, E. (2021). Credit allocation and macroeconomic fluctuations. Available at SSRN 3781981.
- Oikarinen, E. (2009). Interaction between housing prices and household borrowing: The Finnish case. *Journal of Banking & Finance*, 33(4), 747-756.
- Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American Economic Review*, 101(5), 1676-1706.
- Rochet, J. C., & Tirole, J. (1996). Controlling risk in payment systems. *Journal of Money, Credit and Banking*, 28(4), 832-862.
- Rochet, J. C., & Tirole, J. (1996). Interbank lending and systemic risk. *Journal of Money, credit and Banking*, 28(4), 733-762.
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71(1), 135-158.
- Rossi, S. P., Schwaiger, M. S., & Winkler, G. (2009). How loan portfolio diversification affects risk, efficiency and capitalization: A managerial behavior model for Austrian banks. *Journal of Banking & Finance*, 33(12), 2218-2226.
- Rousseau, P. L., & Wachtel, P. (2011). What is happening to the impact of financial deepening on economic growth?. *Economic Inquiry*, 49(1), 276-288.
- Samatas, A., Makrominas, M., & Moro, A. (2019). Financial intermediation, capital composition and income stagnation: The case of Europe. *Journal of Economic Behavior & Organization*, 162, 273-289.
- Sassi, S., & Gasmi, A. (2014). The effect of enterprise and household credit on economic growth: New evidence from European Union countries. *Journal of Macroeconomics*, 39, 226-231.

- Schneider, M., & Tornell, A. (2004). Balance sheet effects, bailout guarantees and financial crises. *The Review of Economic Studies*, 71(3), 883-913.
- Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, 102(2), 1029-61.
- Schwerter, S. (2011). Basel III's ability to mitigate systemic risk. *Journal of Financial Regulation and Compliance*, 19(4), 337-354.
- Shim, J. (2019). Loan portfolio diversification, market structure and bank stability. *Journal of Banking & Finance*, 104, 103-115.
- Smaga, P. (2014). The concept of systemic risk. *Systemic Risk Centre Special Paper*, (5). *The London School of Economics and Political Science*.
- Soedarmono, W., Sitorus, D., & Tarazi, A. (2017). Abnormal loan growth, credit information sharing and systemic risk in Asian banks. *Research in International Business and Finance*, 42, 1208-1218.
- Soros, G. (2013). Fallibility, reflexivity, and the human uncertainty principle. *Journal of Economic Methodology*, 20(4), 309-329.
- Sutherland, D., & Hoeller, P. (2012). Debt and Macroeconomic Stability: An Overview of the Literature and Some Empirics. *OECD Economics Department*. Working Papers No. 1006.
- Taylor, A. M. (2015). Credit, financial stability, and the macroeconomy. *Annu. Rev. Econ.*, 7(1), 309-339.
- Werner, R. A. (2012). Towards a new research programme on 'banking and the economy'—Implications of the quantity theory of credit for the prevention and resolution of banking and debt crises. *International Review of Financial Analysis*, 25, 1-17.
- Yesin, P. (2013). Foreign currency loans and systemic risk in Europe. *Swiss National Bank*. Working Paper No. 13.06.
- Zabai, A. (2017). Household debt: recent developments and challenges. *BIS Quarterly Review*, December.