Bakkar, Yassine

Thesis

Systemic risk, bank charter value, capital structure and international complexity : evidence from developed countries

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ECOLE DOCTORALE Sociétés et organisations n°526

FACULTE de Droit et des Sciences Economiques

Laboratoire d'Analyse et de Prospective Economiques (LAPE) EA1088

Thèse

pour obtenir le grade de

Docteur de l'Université de Limoges

Discipline / Spécialité : Sciences Economiques

présentée et soutenue par

Yassine BAKKAR

le 15 Janvier 2018

"Systemic risk, bank charter value, capital structure and international complexity: Evidence from developed countries"

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GENERAL INTRODUCTION

The global financial crisis of 2007–2009 has highlighted the importance of promoting financial stability across the world through better risk management and adequate regulation and supervision of financial firms that are "too-big-to fail" and systemically important[1]. This global crisis has clearly demonstrated that the entire financial system was overextended, owing to a combination of weak internal risk management and institutional framework for overseeing the stability of financial systems. *Lehman Brothers*, *Bear* Stearns or *Merill Lynch* were simply examples of the weakest links in a long chain of fragile financial firms[2]. Thus, as contagion fears spread to all financial institutions around the world, market participants began to consider the worst-case scenarios. Immediately after the crisis erupted, it was followed by a wave of public support for reform, which crested in 2010–2011 with the Dodd-Frank Act, Liikanen proposals and the Basel III standards on leverage, funding and liquidity.

The global financial crisis as well as European sovereign debt crisis (in late 2011) have also shown that even though idiosyncratic risks may be diversified and limited, financial shocks to a single institution can quickly spread across a large number of firms and markets, threatening the whole system, imposing significant negative externalities and leading to severe economic contagion. If such financial shocks were to lead to a failure of a systemically-important bank, the resulting financial instability could be disastrous. This type of scenario highlights the need for

[1] This notion refers to largest firms in financial sector, whose failure would have major negative spillover effects for the rest of the financial system and for the real economy. Bank's size and scope made financial firm systemically more important leading to "too big to fail" or "too-complex-to-unwind" paradigm.

[2] According to a 2012 study by Andrew G. Haldane of the Bank of England, the global financial crisis caused failures in around half of the 101 banks with balance sheets larger than U.S.$ 100 billion as of 2006. The vast majority of these banks, including Lehman Brothers in the U.S., had not breached any of the prudential regulations already in place before the crisis (particularly capital requirements). Moreover, 11 had already met the capital requirements that are currently being introduced as part of the new Basel III regulations, Dodd–Frank Act in the U.S. or Liikanen proposals in Europe. And yet four of those 11 still failed. (See: http://www.bis.org/review/r120905a.pdf).

identifying and understanding the contribution of banks to systemic risk in the financial system. One of the greatest concerns was the systemic risk of the banking system.

Against this backdrop, key aspects of recent regulatory reforms and academic researches include measuring and regulating systemic risk, and designing macroprudential approach to bank regulation[3]. Systemic risk is of the essence here. Thus, this dissertation develops different systemic risk measures that are theoretically sound (Brownlees and Engle, 2012; Adrian and Brunnermeier, 2011; Acharya et al., 2010; among others) as well as idiosyncratic risk measures using publicly available financial information and stock market data.

With regards to the importance of financial sectors in leading economies, particularly the banking industry, this dissertation contributes to the most recent efforts of quantifying systemic risk by shedding light on three important concerns associated with systemically important institutions: bank market valuation (charter value), bank capital structure and bank complexity (internationalization and organization) as vital aspects for financial stability. The main findings provide a number of insights into the nature of banks' systemic risk, point to important policy implications and highlight micro/macroprudential regulation introduced by Basel guidelines especially for systemically important and complex banks.

This thesis comprises three research papers that I wrote during the Ph.D. program. The second paper was written as a part of Europlace Institute of Finance research project. Each chapter is self-contained and can be read individually. While they cover rather different topics, they are all primarily empirical in nature and largely share empirical methods. The outcomes of the three included papers give support to the authorities to enact comprehensive micro- and macroprudential regulation schemes.

[3] This has been a focus of institutions such as the European Systemic Risk Board (in the Europe), the Financial Stability Oversight Council (in the U.S., as well as at the global level) and the Basel-based Financial Stability Board (FSB)– which monitors regulatory practices around the world to ensure that they meet globally-agreed standards.

The *first paper* (Bakkar, Rugemintwari and Tarazi "*Charter Value and Bank Stability Before and After the Global Financial Crisis of 2007–2008"*), considers how bank charter value (franchise value) affects risk-taking and systemic risk before the financial crisis (2000–2006), during the financial crisis years (2007–2009) and after the financial crisis (2010–2013). The recent global financial crisis has triggered several debates on bank size as one of the main specific determinant of systemic risk. This paper goes beyond the crude measure of bank size and apply a forward-looking measure of bank performance (i.e. charter value, which denotes the present value of the bank's expected income stream). Particularly, it examines the extent to which bank charter value (reflected in Tobin's q) has impacted risk-taking behavior as well as banks' exposures to idiosyncratic and systemic risks in good economic times and the crisis period. This question is based on prior literature documenting that bank charter value is a protection volume from bankruptcy (i.e. absorbing capacity that would be lost in case of bankruptcy) and a bank's self-imposed risk discipline device that advocates the co-called "*charter value*" hypothesis, i.e. high charter value incentives banks to avoid high-risk choices that may trigger a drop in its charter value, (Jones et al., 2011; González, 2005; Keeley, 1990; among others). This paper utilizes individual bank market and accounting data for the OECD listed banks over the period from 2000 to 2013 to empirically revisit the charter value hypothesis before, during and after the global financial crisis of 2007–2008. We calculate measures of idiosyncratic risk (systematic risk and total risk), systemic risk (systemic risk exposure (the MES, Acharya et al., 2010) and contagion risks (ΔCoVaR, Adrian and Brunnermeier, 2011))[4] and default risk (MZ-score, Lepetit et al., 2008) for each bank and each year. These measures of risk are then related to bank charter value and other bank-level and country-level figures. The findings show that, prior the financial crisis (2000–2006), the relation between charter value and risk-taking and systemic risk is sensitive to market conditions: i.e. charter value provides incentives to accumulate risk which in turn contributes to higher systemic risk during expansions (see Saunders and Wilson, 2001). Therefore, bank charter value is positively associated with both standalone and systemic risks that undermines financial stability. Thus, results before the financial crisis are in striking contradiction of the charter value

[4] These components capture the main characteristics of systemic risk—default risk, interconnectedness, and bank size. For an overview of methodologies in systemic risk analysis (see: Bertay et al. (2013), Acharya et al. (2012), Adrian and Brunnermeier (2011), Acharya et al., (2010)). These systemic risk measures are useful complements to balance sheet information.

hypothesis. Inversely, after the financial crisis (2010–2013), empirical results corroborate a negative relation between charter value and bank risks, consistent with the charter value hypothesis[5]. Whereas, we do not find that the charter value holds an effect on bank risks over the financial crisis years (2007–2009). Subsequently, this paper examines effects of differences in risk taking cultures, bank size, growth strategy and business model before the financial crisis (2000–2006), so to explain this positive evidence between charter value and risk. It thereby demonstrates that such relationship is relevant for U.S. and European banks; particularly, for very large (or "*too big to fail*") and large banks with high growth strategies, and for those large with a focused business model. Hence, these results lend support to the views that conservation buffers introduced by Basel III may not be enough to guarantee bank stability. Therefore, the capital conservation buffers should not only be based on the business cycle, but also on the state of the financial system and the potential effects of market conditions on such a complex relation between valuable bank charters and both risk-taking incentives and systemic risk.

In the *second paper* (Bakkar, De Jonghe and Tarazi "*Does banks' systemic importance affect their capital structure and balance sheet adjustment processes?"*), we investigate if the Basel III more stringent capital requirements, specifically for systemic institutions, affect banks' capital structure adjustment and contribution to the real economy. This paper contributes to the bank capital structure adjustment literature (De Jonghe and Öztekin, 2015; Lepetit, et al., 2015; Flannery and Hankins, 2013; Berger et al., 2008; among others) by looking at possible conflicts between regulatory and non-regulatory optimal capital structure and differences for systemically important financial institutions–SIFIs in terms of adjustment mechanisms (i.e. balance sheet reshuffling) and adjustment speed. Addressing this issue is paramount to draw effective regulatory and policy implications regarding SIFIs. The dataset consists of all the OECD listed in the period from 2000 to 2012. In a first step, we implement a general partial adjustment model (for both leverage and risk-weighted capital ratios) to model and estimate the target capital ratios (Flannery and Rangan, 2006; Gropp and Heider, 2010; De Jonghe and Öztekin, 2015 and Lepetit et al., 2015). Then, we look into unconditional adjustment mechanisms when banks (i.e. broad bank sample)

[5] After the financial crisis (2010–2013), results are consistent with bank's self-imposed discipline device that advocates the so-called "charter value" hypothesis; i.e. high charter value incentives banks to avoid high-risk choices that may trigger a drop in their charter value (see Jones et al., 2011; González, 2005; Keeley, 1990; among others).

are either above or below their target capital ratios (i.e. capital gap), by investigating growth rates in assets (specifically lending), liability and equity classes. In a second step, we allow for time-varying speed of adjustment, specified by various measures of bank systemic importance that could affect the adjustment speed and the adjustment mechanisms. For that, we implement two systemic risk measures (exposure to systemic risk and contagion risk), two systemic size measures (crude size and systemic size, see Bertay et al., 2013 and Barth and Schnabel, 2013) as well as an aggregated systemic risk index based on the quintiles of the four aforementioned measures. On an aggregate level, the analysis provides interesting insights in the mechanisms and the relative dominance of leverage vis-à-vis risk-weighted capital ratios. They hence show that the sign of the leverage and risk-weighted capital ratio gap determines whether equity is adjusted via earnings retention (leverage dominates regulatory capital) or externally raised equity (regulatory stance matters), or by asset side adjustments via loans and risky assets (regulatory gap matters). Besides the signs of capital gaps, the findings also reveal that the speed at which banks adjust and the way they adjust show large differences between large, systemic and complex banks versus small banks. The results thereby show that systemic risk and size measures affect the extent to which banks adjust their capital ratios, and play an opposite role (on the speed of adjustment) for leverage ratio vis-à-vis regulatory capital ratios. They indicate that SIFIs are slower than other small banks in adjusting to their target leverage ratio but quicker in reaching to their target regulatory ratios. Moreover, analysis demonstrates that SIFIs are reluctant to change their capital base by either issuing or repurchasing equity and prefer sharper downsizing and/or faster expansion. They also provide evidence that balance sheet adjustment processes are more procyclical for SIFIs. These results have implications for policy makers, who are currently seeking ways to accurately reinvigorate the implementation of new (systemic risk-based) capital requirements and assessing their impacts for the economy as a whole. In this sense, findings also provide useful insights for supervisors when they gauge the specific capital requirement they can impose on each bank (through Pillar 2 of the Basel III Accord).

The *third paper* (Bakkar and Pamen-Nyola "*Internationalization and systemic risk: Evidence from a sample of European listed banks*") contributes to the literature by empirically investigating whether internationalization, organizational structures and geographical complexity affect bank systemic risk with regards to economic conditions, and questions how the 2007–2008 financial crisis and the 2009–2010 sovereign debt crisis might have impacted the existing relationship. It seeks to extend the previous studies on bank organizational complexity and standalone risk (Goetz et al., 2016; Gropp et al., 2010; Dell'Ariccia and Marquez, 2010). For this purpose, we construct a data set on internationalization and foreign complexity of European banks based in 15 Western European countries during the 2002–2013 period. The dataset covers a panel data of 105 listed banks that have networks of affiliates around the world. Complexity measures are collected to reflect bank organization and level of internationalization (number of foreign subsidiaries and number of host countries) and geographical complexity of affiliate locations (span of all the subsidiaries across different regions or countries around the world)[6]. Systemic risk measures are calculated for each bank and each year to capture different aspects: bank systemic exposure (the MES), capital shortfall (SRisk, Brownlees and Engle, 2012) and contagion risks (ΔCoVaR). Results highlight the existence of a reversed effect of internationalization and foreign complexity on systemic risk measures, internationalization and geographical complexity indicators are important drivers of bank systemic risk during the financial distress period (2008–2011) and later (2012–2013), and no longer affect systemic risk before financial crisis period (2005–2007). Then, the paper further investigates different aspects of foreign organizational complexity (both worldwide networks of foreign subsidiaries and foreign branches) on bank systemic risk over 2011–2013 period. A close look into the impact of the foreign organizational choice of affiliates (incorporated subsidiaries and legally integrated branches) indicates that having a network of branches contributes to reduce the systemic risk exposure (the MES) and thus enhancing stability; while owning a foreign subsidiaries network is ineffective on the bank MES, albeit slightly negatively affects SRisk. Overall, this paper contributes to the literature on global bank complexity and systemic risk. It carries various policy implications. Results contribute to the ongoing debate on the merits of imposing systemic risk-based capital requirements and capital surcharges on too-complex banks, as outlined in the proposals regarding the reform of the Basel Accord.

[6] Previous studies on bank organizational complexity document different aspects of bank organizational and geographic complexity that are relevant factors affecting banks' standalone risk (Goetz et al., 2016; Gropp et al., 2010; Dell'Ariccia and Marquez, 2010; Carmassi and Herring, 2016).

Chapter 1

Charter Value and Bank Stability Before and After the Global Financial Crisis of 2007–2008*

Abstract. We investigate how bank charter value affects risk for a sample of OECD banks by using standalone and systemic risk measures before, during, and after the global financial crisis of 2007-2008. Prior to the crisis, bank charter value is positively associated with risk-taking and systemic risk for very large "too-big-too-fail" banks and large U.S. and European banks but such a relationship is inverted during and after the crisis. A deeper investigation shows that such a behavior before the crisis is mostly relevant for very large banks and large banks with high growth strategies. Banks' business models also influence this relationship. We find that for banks following a focus strategy, higher charter value amplifies both standalone and systemic risk for large U.S. and European banks. Our findings have important policy implications and cast doubts on the relevance of the uniform more stringent capital requirements introduced by Basel III.

* This chapter draws from the working paper (Bakkar, Rugemintwari and Tarazi "Charter Value and Bank Stability Before and After the Global Financial Crisis of 2007–2008") co-authored with Clovis Rugemintwari, from Université de Limoges–LAPE, and Amine Tarazi, from Université de Limoges–LAPE. I am grateful to my supervisors Amine Tarazi and Clovis Rugemintwari for guidance, advice and encouragement during the writing of this paper. An earlier version of this paper has been presented at (1) Portsmouth-Fordham Conference on Banking and Finance, September 24–25, 2016, Portsmouth, United-Kingdom; (2) 33rd International Symposium on Money, Banking and Finance, July 7–8, 2016, Clermont-Ferrand, France; (3) LAPE Finest Workshop, June 9, 2015, Limoges, France; (4) PhD seminar and LAPE summer meeting June 2015. I have also received very helpful comments from John Finnerty (discussant), Iftekhar Hasan, Kose John, Ion Lapteacru (discussant), Phillipe Rous; as well as conferences and workshop participants.

1. Introduction

This paper revisits the charter value hypothesis (CVH) in banking and the effectiveness of its risk-disciplining impact in the light of the major transformations of the banking industry before and after the global financial crisis of 2007–2008 (GFC). Worldwide, in the years preceding the GFC, banks experienced tremendous changes. Specifically, value enhancing mergers and acquisitions (M&A) arrangements led banks to grow in size, become larger and more powerful by increasing their market shares, and yet, riskier (Anginer et al., 2014; Martinez-Miera and Repullo, 2010; De Jonghe and Vennet, 2008). Mechanically, banks gained competitive advantage and an increase in their charter value, backed by size, operational complexity and higher profit expectations driven by more aggressive risk-taking policies (Jones et al., 2011; Furlong and Kwan, 2006; Stiroh, 2004)[7]. Such operations had altered bank charter value but also the importance of large "too-big-to-fail" (TBTF) banks and institutions which were later recognized as "systemically important financial institutions" (SIFIs) or "too-complex-to-unwind" banks[8]. These banks were at the heart of the GFC. They were deeply involved in complex activities and tended to accumulate less capital and less stable funds before the crisis while regulators, by focusing on microprudential regulation, did little to prevent the resulting build-up of systemic risk (Bostandzic and Weiss, 2016; Laeven et al., 2015; Brunnermeier et al., 2012).

It is widely recognized that charter value (or franchise value, proxied by Tobin's q) self-disciplines bank risk-taking, the so-called charter value hypothesis (CVH), and provides banks with a valuable source of monopoly power (Jones et al., 2011; Ghosh, 2009; González, 2005; Gan, 2004; Demsetz et al., 1996; Keeley, 1990). Higher charter value is expected to lower risk-taking incentives and increase capital because of the higher bankruptcy costs that banks could endure if they fail. Nevertheless, banks have systematically looked for higher profitability, more returns and higher margins, by increasing their exposure to new market-based instruments and by extensively

[7] Jones et al. (2011) emphasize three factors to explain the increase in charter value during the 1988-2008 period: a rise in banks' noninterest income, a run-up in the stock market, potentially "irrational exuberance", and a strong economic growth.

[8] M&A operations have significantly reduced the degree of competition and have positively affected prices and margins. They were achieved for strategic reasons, such as improving market share, profitability, or efficiency (Jones et al., 2011; De Jonghe and Vennet, 2008).

relying on short-term debt (Martynova et al., 2015). This shift towards new financial instruments at a large scale and riskier business models is puzzling for banks with high charter value.

Meanwhile, systemic risk has considerably increased in the banking industry with a higher threat posed by very large banks, including those with high charter values which pursued riskier policies prior the GFC. Market imperfections and system vulnerability to contagion have also enhanced systemic risk (Hartmann, 2009). Also, banks had benefited from implicit guarantees and deposit insurance, particularly for SIFIs, which allowed them to gain competitive advantages and to change their growth strategy and business model and therefore to take more risk (Jones et al. (2011)). Another factor that has received less attention, before the GFC, is the increase in bank charter value. This leads us to adopt a different view on the disciplining role of charter value in such a risk-accumulating period (before the GFC).

The perception of bank risk has also changed, based not only on its individual dimension (idiosyncratic risk and individual default risk), but also more and more on the vulnerability of banks and their contribution to systemic risk. Hence, throughout this paper, we look at both risk dimensions and consider standalone alongside systemic risk measures. We go beyond the literature addressing the nexus between bank charter value and risk by considering systemic risk indicators (Anginer et al., 2014; Hovakimian et al., 2015; Jones et al., 2011; Soedarmono et al., 2015) along the traditional standalone proxies (Niu, 2012; Jones et al., 2011; González, 2005).

Large banks, TBTF banks and SIFIs, have a natural tendency to grow further, change their business model and hence follow high risk strategies presumably above the socially optimal levels (Acharya et al., 2012). Their failure propagates contagion across the system and could also trigger the default of other banks and degenerate into global financial distress[9]. Although there is no unique definition of systemic risk, wherein the entire financial system is distressed, it is commonly accepted that a bank's systemic risk exposure refers to the comovement of individual bank risk and sensitivity to an extreme shock (Haq and Heaney, 2012; Weiß et al., 2014; Laeven et al., 2015). Various measures have been proposed in the literature to capture bank systemic risk. Adrian and Brunnermeier (2011) have introduced a comovement measure (ΔCoVaR) of financial system value

[9] Laeven and Levine (2007) argue that SIFIs engaged in multiple activities (charter-gain-enhancing) suffer from increased agency problems and poor corporate governance that could be reflected in systemic risk. Demirgüç-Kunt and Huizinga (2010) find that banks that rely to a larger extent on non-deposit funding and non-interest income are more profitable but also riskier.

at risk (VaR) conditionally on banks' VaR; Acharya (2009) considers the sensitivity of bank equity losses to market crashes (MES); while, the tail-beta used among others by Campbell et al. (2008) and Anginer et al. (2014) captures the sensitivity of systematic risk to extreme events (tail risk). The inherent unstable nature of risk (pre and post GFC), suggests that the relationship between charter value and risk may possibly change depending on the opportunities and constraints that banks face in different environments. Typically, the acute GFC period (2007–2009) is a period of high volatility and sharp decrease in the stock prices of most listed banks. To study to what extent charter value impacts risk taking behavior and stability in such circumstances, we build our analysis not only on standalone risk measures but also on systemic risk indicators which capture different risk dimensions and specifically, either the contribution of an individual bank's collapse to systemic risk or the exposure of a given institution to a major shortfall in the financial system as a whole.

Although there is a broad literature looking at the impact of charter value on bank individual risk (Niu, 2012; Jones et al., 2011; González, 2005; Konishi and Yasuda, 2004; Demsetz et al., 1996; Keeley, 1990) there is no clear-cut consensus on the effect of bank charter value on banks' standalone risk and systemic risk in normal versus abnormal economic conditions (i.e. pre and post the GFC). Hence, this paper examines the stability of the relationship between charter value and risk to track possible changes before the crisis (2000-2006), during the crisis (2007-2009), and after (2010-2013). It also looks into possible differences for U.S. banks, European banks and the more conservative banks in the rest of OECD countries which rely on a more traditional banking model[10]. It also considers possibly different impacts of charter value on standalone and systemic bank risk measures. To the best of our knowledge, this is the first study that investigates the charter value hypothesis by considering both standalone and systemic risk measures of bank risk by further differentiating the exceptional risk-building period prior to the GFC from the acute crisis and post-crisis periods.

We use a sample, spanning from 2000 to 2013, of 853 banks established in OECD countries. The results show that prior to the GFC charter value positively impacts both standalone

[10] Banks in these three geographical areas have very different business models and operate in differently organized banking systems. U.S. and European banks are more market-oriented; whereas, Australian, Canadian and Japanese banks are more reliant on traditional intermediation activities. Haq et al. (2016) argue that Australian and Canadian banks appear to pursue safer policies, even before the GFC (1995-2006), hence preserving financial stability.

and systemic bank risk measures but such a relationship is inverted during and after the crisis. A deeper investigation shows that such a behavior before the crisis is mostly relevant for very large banks and large banks with high growth strategies. Banks' business models also influence this relationship. In presence of strong diversification strategies, charter value has no impact on both standalone and systemic risks. Conversely, for banks following a focus strategy, higher charter value amplifies systemic risk for very large banks and both standalone and systemic risk for large U.S. and European banks.

The remainder of the chapter is organized as follows. Section 2 presents the data and variables used in this paper. In section 3, we present the empirical specifications. In section 4, we present the results of the econometric investigation. Section 5 reports robustness checks and concludes.

2. Data and variables

2.1. Sample selection

The sample comprises publicly traded OECD banks for which stock price information and accounting data are available in both the Bloomberg and Thomson-Reuters databases. To ensure that we use the most informative risk indicators, we delete banks with missing historical stock prices or infrequently traded stocks. We disregard stocks if daily returns are zero during at least 30% of the whole trading period. Hence, we only consider bank stocks that are very liquid, i.e. those that are most likely to reflect important extreme events in their movements. Subsequently, we retrieve accounting data and filter out bank year observations by dropping the top and bottom 1 percent level to eliminate the adverse effects of outliers and misreported data. Due to the delisting of many banks, mainly due to mergers and acquisitions, we end up with an unbalanced panel dataset of 853 commercial, cooperatives and savings banks, from the 28 major advanced OECD economies, among which 22 are European[11] (Table 1.1.). Our sample period runs from January 03, 2000 to December 31, 2013 (Table 1.2.). The sample is dominated by commercial banks and by U.S. banks. It consists of 500 U.S. banks and 353 non-U.S. banks (of which 245 are European and 84 are Japanese). Taken together, listed banks account for more than 55% of the total assets of the European banking industry and 77% in the U.S.. For the other OECD countries, the coverage varies between 9% for Mexico to 31% for Japan.

[11] From 988 banks, we end up with 853 banks due to our data cleaning process as well as the data availability that varies depending on the combination of variables used in regressions. Our sample consists of 22 European countries, three Americas countries (U.S., Canada and Mexico) and three Asian-Pacific countries (Japan, South Korea, Australia). Iceland and New Zealand were dropped because of insufficient liquid stocks (see Table 1.1.).

Table 1. 1. Sample composition

Table shows the sample country composition. It presents the distribution of 853 listed banks in 28 OECD countries: Australia, Austria, Belgium, Britain, Canada, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Luxembourg, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, Turkey and United-States. Sample is dominated by U.S. banks with 506 banks; whereas, number of European banks stands at 245 banks.

Country	Banks	N	Country	Banks	N
Australia	6	83	Luxembourg	1	10
Austria	7	61	Mexico	3	32
Belgium	3	31	Netherlands	3	36
Canada	11	128	Norway	17	205
Czech	1	13	Poland	12	140
Denmark	40	458	Portugal	3	39
Finland	2	25	Slovakia	2	20
France	21	255	South Korea	7	57
Germany	18	201	Spain	15	159
Greece	12	128	Sweden	4	49
Hungary	1	13	Switzerland	24	261
Ireland	2	20	Turkey	16	159
Italy	25	292	United-Kingdom	13	128
Japan	84	1077	United-States	500	5411

Table 1.2. Sample distribution by calendar year

Table shows the sample distribution by calendar year. The sample spans 14 years, from 2000 to 2013. Bank-year observations vary between 459 and 735 observations.

Year	Freq.	Percent
2000	608	6.41
2001	639	6.73
2002	674	7.1
2003	675	7.11
2004	695	7.32
2005	715	7.53
2006	754	7.94
2007	784	8.26
2008	768	8.09
2009	577	6.08
2010	735	7.74
2011	717	7.55
2012	691	7.28
2013	459	4.84

Data on individual bank daily stock prices, stock market indexes, as well as generic government bond yields, implicit volatility indexes and three-month LIBOR and Overnight Indexed Swap (OIS) spreads were collected from Bloomberg. Annual income statement and balance sheet data are obtained from Thomson Reuters whereas the OECD Metadata statistics provide yearly macroeconomic data: inflation and gross domestic product growth rates.

In line with previous research, we define very large “too-big-too-fail” banks institutions with total assets above $20 billion, large banks as those with total assets ranging from $1 billion to $20 billion and small banks as those with assets between $500 million and $1 billion (Köhler, 2015; Laeven et al., 2015; Barry et al., 2011; Lepetit et al., 2008). Because of their specific business models, we exclude banks with less than $500 million of total assets (Distinguin et al., 2013)[12].

2.2. Standalone risk variables

We consider four standalone risk indicators that are equity based risk measures: total risk, bank-specific risk, systematic risk and a market based z-score. Total risk is computed as a moving standard deviation of bank stock daily returns. This is calculated each day for each bank using a moving window of 252 daily return observations. Similarly, we estimate the rest of the standalone risk measures with the following single index rolling market model[13]:

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \varepsilon_{i,t}, \quad (1)$$

Where $R_{i,t}$ is the daily (t) stock return of bank i, $R_{M,t}$ the daily return on the market index of the country where the bank is located and $\varepsilon_{i,t}$ is the residual term. With this, $\beta_{i,M}$, the equity market

[12] We exclude community banks, those with total assets less than $500 million, ratio of total loans to total assets above 33%, and ratio of total deposits to total assets above 50%.
[13] We use rolling regressions of a bank’s daily stock returns on market returns, as a return generating process. We estimate risk measures for each bank using a moving window of 252 daily observations.

betas are used as a proxy of banks' systematic risk. From the residual term, we compute a measure of specific risk which we only use to check the robustness of our overall results. Bank specific risk is estimated as the standard deviation of the residuals generated from the single index rolling regressions of a bank's daily stock returns on the market index.

Furthermore, we use the market z-score, a metric for insolvency risk and default which is calculated as follows: MZ-Score $= \left(\overline{R_{i,t}} + 1\right)/\sigma_{R_{i,t}}$, where $\overline{R_{i,t}}$ is the mean and $\sigma_{R_{i,t}}$ the standard deviation of the monthly returns for a given year. A higher value of MZ-Score indicates a lower probability of failure (Lepetit et al., 2008).

2.3. Systemic risk measures

Besides the above standalone risk measures, we also consider three systemic risk measures. First, we follow Acharya et al. (2012) and Brownlees and Engle (2012) and use the Marginal Expected Shortfall (MES) which corresponds to the marginal participation of bank i to the Expected Shortfall (ES) of the financial system[14]. Formally, it corresponds to the expected stock return for bank i, conditional on the market return when the latter performs poorly. Acharya et al. (2012) define the MES as the expectation of the bank's equity return per dollar in year t conditional on a market crash in that given period.

$$MES_{i,t}^{q} \equiv E\left(R_{i,t} | R_{M,t} \leq VaR_{R_{M,t}}^{q}\right), \tag{2}$$

where $R_{i,t}$ is the daily stock return for bank i, $R_{M,t}$ is the daily market return[15], q-percent is a pre-specified extreme quantile enabling us to look at systemic events. $VaR_{R_{M,t}}^{q}$ stands for Value-at-

[14] Economically, the term "marginal" refers to the bank's capital shortfall stemming from each unit variation in the equity value $MES_{i,t}^{q}$. The MES measures the increase in systemic risk induced by a marginal increase in the exposure of bank i to the system.

[15] To estimate risk measures, we either employ the financial sector index for the most developed financial market or the broad market index.

Risk, which is a critical threshold value that measures the worst expected market loss over a specific time period at a given confidence level. Herewith, we follow the common practice and set q at 5-percent, the term $R_{M,t} \leq \mathrm{VaR}^{\mathrm{q}}_{\mathrm{R_{M,t}}}$ reflects the set of days when the market return is at or below the 5-percent tail outcomes in that given year. Thus, under the nonparametric assumption, the MES is the average of bank stock returns during market crash times, that correspond to the 5-percent worst days of the stock market index. It is expressed as:

$$MES^{q=5\%}_{i,t} = \frac{\sum R_{i,t} \times I\left(R_{M,t} < VaR^{q}_{R_{M,t}}\right)}{\sum I\left(R_{M,t} < VaR^{q}_{R_{M,t}}\right)} = \frac{1}{N} \sum_{R_{M,t} < VaR^{q}_{R_{M,t}}} R_{i,t}. \quad (3)$$

In equation (1), I (.) is the indicator function defining the set of days where the market experienced 5-percent worst days (crash period) and N is the number of days where the aggregate equity return of the entire market (proxied by a market index) experienced its 5-percent worst outcomes (Weiß et al., 2014). The higher a bank's MES is (in absolute value), the higher is its contribution to aggregate systemic risk and so its probability to be undercapitalized in bad economic conditions.

Second, we use CoVaR introduced by Adrian and Brunnermeier (2011) as a similar concept as VaR. It corresponds to the VaR of the entire financial system (i.e. the market index with a return of R_M) conditional on an extreme event leading to the fall of a bank i's stock return R_i beyond its critical threshold level ($\mathrm{VaR}^{\mathrm{q}}_{\mathrm{R_i}}$). $CoVaR^{q}_{R_{M|i,t}}$is the q-percent quantile of this conditional probability distribution and can be written as [16]:

$$Prob_{t-1}\left(R_{M,t} \leq CoVaR^{q}_{R_{M|i,t}} \mid R_{i,t} = VaR^{q}_{R_{i,t}}\right) = q \quad (4)$$

[16] As MES, CoVaR is a conditional VaR computed at time t given information available at time t-1 based on the financial system Expected Shortfall.

Explicitly, Adrian and Brunnermeier (2011) define bank ΔCoVaR as the difference between the VaR of the financial system conditional on the firm being in distress and the VaR of the system conditional on the bank being in its median state. It catches the externality a bank causes to the entire financial system. Therefore, bank ΔCoVaR is the difference between the $\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q=distress\ state}}$ of the financial system when bank i is in financial distress, i.e. the bank stock return is at its bottom q probability level, and the $\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q=median}}$ of the financial system when this bank i is on its median return level, i.e. the inflection point at which bank performance starts becoming at risk. Hence, $\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q}}$ measures the systemic risk contribution of bank i when its return is in its q-percent quantile (distress state). Here, we set q at 1-percent. Whereas, $\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q=50\%}}$ measures the systemic risk contribution of bank i when bank i's is in a normal state. The $\Delta\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q}}$ of individual ban is defined as:

$$\Delta CoVaR_{R_{M|i,t}}^{q} = CoVaR_{R_{M|i,t}}^{q} - CoVaR_{R_{M|i,t}}^{median} \quad (5)$$

Therefore, the systemic risk contribution of an individual bank i at q=1% can be written as:

$$\Delta CoVaR_{R_M|R_i=VaR_{R_{i,t}}^{1\%},t}^{q=1\%} = \hat{\lambda}_{R_{M|i,t}}^{1\%}\left(VaR_{R_{i,t}}^{1\%} - VaR_{R_{i,t}}^{50\%}\right) \quad (6)$$

$\Delta\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q}}$ is estimated given the bank i's unconditional VaRs, defined in equation (7), and the conditional VaRs { $\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q}} = \mathrm{VaR}_{\mathrm{R}_{\mathrm{M,t}}}^{\mathrm{q}} | \mathrm{VaR}_{\mathrm{R}_{\mathrm{i,t}}}^{\mathrm{q}}$ }, defined in equation (8). For bank's unconditional VaRs we run separately 1-percent and 50-percent quantile regressions, using daily stock prices over the whole period (Adrian and Brunnermeier, 2011). Specifically, we run the following quantile regressions over the sample period to obtain:

$$VaR_{R_i}^{q} = \hat{R}_{i,t} = \hat{\alpha}_i + \widehat{\gamma_i^{q}} R_{M,t-1} + \hat{\varepsilon}_{i,t} \quad (7)$$

$$CoVaR_{R_{M|i,t}}^{q=1\%} = \hat{R}_{M,t} = \hat{\alpha}_{R_{M|i}} + \hat{\lambda}_{R_{M|i,t}}^{1\%} VaR_{R_{i,t}}^{1\%} + \hat{\varepsilon}_{M|i,t} \tag{8}$$

Following regression model in equation (7), we estimate $VaR_{R_{i,t}}^{1\%}$ and $VaR_{R_{i,t}}^{50\%}$. Then, within the q-percent quantile regressions, we predict the systemic risk conditional on bank i in distress ($\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q=1\%}}$) and in median state ($\mathrm{CoVaR}_{\mathrm{R}_{\mathrm{M|i,t}}}^{\mathrm{q=50\%}}$), and estimate $\hat{\lambda}_{R_{M|i,t}}^{1\%}$, the slope coefficient of the 1-percent quantile regression (equation (8)) (Mayordomo et al., 2014; Adrian and Brunnermeier, 2011).

The third measure of systemic risk is Tail-beta (quantile-beta), based on De Jonghe (2010) and Engle and Manganelli (2004). It is obtained using a quantile regression model at the q pre-specified quantile and captures bank's sensitivity to extreme movements. We use the model presented in equation (8) and run a 1-percent quantile regression and tail betas of each bank i are estimated by regressing daily bank stock return $R_{i,t}$ on daily market return $R_{M,t}$. We predict tail-betas ($\beta_{i,\mathrm{M}}$) as the market index coefficients in the 1-percent quantile regression. Thus, the spillover coefficient ($\beta_{i,\mathrm{M}}$) measures the risk sensitivity of bank i at the 1% quantile. The larger is the spillover effect, the more vulnerable is bank i to a financial downturn.

2.4. Long-term performance: Bank charter value

Bank charter (franchise) value is our main explanatory variable and based on existing literature, we use Tobin's q as the proxy. Charter value is a forward-looking measure equal to the net present value of the expected stream of rents, which characterizes a bank's profit-generating potential beyond its merchantable assets (Marcus, 1984; Acharya, 1996; Demsetz et al., 1996). This value reveals more information than bank size and offers loss absorbing capacities. It sums up intangible assets as goodwill, growth possibilities, economic rents, degree of market power, financial strength, etc. (Furlong and Kwan, 2006; Jones et al., 2011). It is often used for comparability among varying size banks and/or banks with different pricing power (in loan, deposit or other marketable securities) (Keeley, 1990). Furthermore, it has a cyclical feature and is also dependant on banks' earnings expectations (Saunders and Wilson, 2001). Hence, the advocates of the so-called CVH argue that when charter is built up, banks (i.e. shareholders) seek to preserve it from adverse shocks, otherwise it cannot be fully liquidated at the event of closure. Bankruptcy is costly when charter value is high, with regards also to the additional cost of failure (Jones et al., 2011; Hellmann et al., 2000; Demsetz et al., 1996).

For publicly traded banks, the extent of charter value is reflected in Tobin's q, which is calculated as the bank's future economic profits reflected in the market value of assets (i.e. debt and market value of equity) divided by the book value of total assets. We follow Soedarmono et al. (2015), Haq and Heaney (2012), Gropp and Vesala (2004) and Keeley (1990) and define it as:

$$q_{i,t} = \frac{MVE_{i,t} + BVL_{i,t}}{BVA_{i,t}}. \qquad (9)$$

where $\mathrm{MVE}_{\mathrm{i,t}}$, $\mathrm{BVL}_{\mathrm{i,t}}$ and $\mathrm{BVA}_{\mathrm{i,t}}$ represent respectively: market value of equity, book value of liabilities and book value of assets of bank i at time t. Market value of equity is the annual average of daily bank market capitalization at year t and the two accounting measures denote values at the end of year t. The numerator of Tobin's q is the market value of assets, i.e. $\mathrm{MVA}_{\mathrm{i,t}} \equiv \mathrm{MVE}_{\mathrm{i,t}} + \mathrm{BVL}_{\mathrm{i,t}}$. It refers partly to higher run-up in stocks price with regards to other investments. Whereas, the denominator reflects the accounting value of assets and is equal to: $\mathrm{BVA}_{\mathrm{i,t}} + \mathrm{BVE}_{\mathrm{i,t}}$ (book value of equity).

Moreover, the literature highlights various factors that affect bank charter value. Furlong and Kwan (2006) and Demsetz et al. (1996) emphasize two main determinants: market regulation which leads to higher market power through M&A operations, and bank-related aspects other than market power as the expansion of off-balance sheet activities and noninterest income[17]. In a similar vein, González (2005), Allen and Gale (2004) and Hellmann et al. (2000) argue that bank charter value stems from financial liberalization, regulatory restrictions, deposit insurance and competition[18]. Again, Haq et al. (2016) argue that market discipline, bank capital, contingent

[17] According to the CVH, regulation promotes bank franchise value through more entry restrictions and more market concentration enhancing profit opportunities. By contrast, deregulatory efforts that increase financial service competition may erode charter value and thereby increase risk taking incentives (Anginer et al., Zhu 2014; Allen and Gale, 2004; Hellmann et al., 2000).

[18] Anginer et al. (2014) and Allen and Gale (2004) argue that in highly competitive markets, banks earn lower rents, which also reduces their incentives for monitoring.

liabilities, and non-interest income are factors that enhance bank charter value. In fact, bank charter value may have multiple roles. According to the CVH, it gives banks self-disciplining incentives and restrains excessive risk-taking appetite. Nevertheless, Gropp and Vesala (2004) found the CVH to be only effective for small banks, with lower charter values and that such a result could reflect lower moral hazard with the introduction of explicit deposit insurance in Europe. However, for large banks which are presumably "TBTF", charter value does not explain their risk-taking. Moreover, although many papers report a negative relationship between bank risk taking and bank charter value, consistent with the CVH (Park and Peristiani, 2007; Agusman et al., 2006; Konishi and Yasuda, 2004; Anderson and Fraser, 2000; Hellmann et al., 2000; Demsetz et al., 1996; Keeley, 1990), others find a positive or a non-linear relationship, i.e. a “U” shape relationship (Niu, 2012; Haq and Heaney, 2012; Jones et al., 2011; Martinez-Miera and Repullo, 2010; Saunders and Wilson, 2001; De Nicolo, 2001).

2.5. Control variables

We consider various control variables in our regressions. Specifically, two main types of controls are considered: bank-specific controls and country-level determinants. For bank-specific controls, we follow the literature and account for bank size, the capital ratio, profitability, the bank’s involvement in market-based activities, operational efficiency, and the bank's business model. Bank size is measured by the natural logarithm of total bank assets in U.S. dollars, the capital ratio is defined as total assets over equity and the return on assets as the ratio of net income to total assets). Ratio of net loans to total assets proxies asset mix and the cost-to-income ratio, which is measured by the importance of non-interest expense relatively to total operating revenue, proxies bank efficiency. As a proxy of bank complexity and diversification we use the ratio of non-interest income to total income (Ghosh, 2009; De Jonghe and Vennet, 2008).

Regarding country-level factors that capture cross-country variations, we control for the gross domestic product growth rate and the annual inflation rate. We also introduce the overall capital stringency index to control for the extent to which regulatory requirements are strict and effective (Barth, et al., 2013). We also consider macro-financial controls. We use interbank market rates to control for differences in interest rates and access to overnight cash markets across OECD countries (Haq et al., 2016; Furlong and Kwan, 2006). We introduce the LIBOR-OIS spread (difference between London Interbank Offered Rate and Overnight Indexed Swap) as a proxy of the liquidity risk premium. Besides, we control for M&As by introducing a dummy variable that takes the value of 1 if total assets grow by more than 15% in one year and 0 otherwise (De Jonghe and Öztekin, 2015). Finally, we introduce year dummies to capture year-specific effects.

2.6. Summary statistics

Descriptive statistics of our variables are presented in Table 1.3. The average (median) charter value is 1.06 (1.02), indicating that, on average, the market value of bank assets exceeds their book value by 5.60%. Dispersion in Charter value is relatively low with a standard deviation of 0.17. The remaining controls are comparable to what is observed in previous studies (De Jonghe et al., 2015; Laeven et al., 2015; Black et al., 2016; Niu, 2012; González, 2005). With regard to risk measures, all the measures exhibit substantial variations over the 13 years covered by our study[19]. MES ranges between -1.13% and 9.63% with an average (standard deviation) of 1.55% (1.72). ΔCoVaR varies around a mean (standard deviation) of 1.42% (1.67). Regarding standalone risk measures the average (standard deviation) values are 2.07% (1.09), 0.53(0.52), 2.23% (1.09), and 54.96 (22.53) for specific risk, systematic risk, total risk and MZ-score, respectively. All indicators of standalone and systemic risk exhibit substantial volatility as their standard deviations are high, indicating high bank risk-taking and high exposure to default risk.

We report the pair-wise correlation coefficients among the explanatory variables in Table 1.4. We perform the variance inflation factor (VIF) test which confirms the absence of major multicollinearity problems[20].

[19] The differences in the number of observations is due to missing accounting and market data for some banks.

[20] We compute the variance inflation factor (VIF) for each model estimates. The VIF statistics are always higher than 10, suggesting the absence of major multicolinearity issues.

Table 1.3. Descriptive statistics and variables definition

Table reports summary statistics for all variables: bank risks and explanatory variables, used in the regressions. Bank-level data consists of publicly traded OECD banks from 28 countries during the 2000-2013 period. The imbalanced sample explains why the number of observations are different. We report four basic summary statistics: number of observations, mean, standard deviation and median, for variables measured at time t. We document also data sources and definitions of variables. Detailed information on the construction of bank risk proxies are provided in section 3.

Variable	N	Mean	Standard deviation	P25	Median	P75	Source	Definition
MES (%)	9491	1.550	1.720	0.243	1.202	2.449	Bloomberg	The Marginal Expected Shortfall (Equation 2).
ΔCoVaR (%)	9491	1.422	1.671	0.343	1.231	2.368	Bloomberg	Delta conditional VaR (Equation 4).
Tail-beta	9491	0.643	0.834	0.083	0.673	1.197	Bloomberg	Quantile beta (subsection 2.3).
Specific Risk (%)	9491	2.072	1.086	1.380	1.784	2.424	Bloomberg	Market model (Equation 1).
Systematic Risk	9491	0.530	0.516	0.075	0.386	0.959	Bloomberg	Market model (Equation 1).
Total Risk (%)	9491	2.230	1.090	1.505	1.953	2.635	Bloomberg	Market model (Equation 1).
MZ-score	9491	54.96	22.53	38.78	52.06	67.44	Bloomberg	Market-based Z-score.
Charter	9491	1.057	0.170	0.984	1.019	1.068	Bloomberg, and Thomsen-Reuters Advanced Analytic (TRAA)	Charter value proxied by Tobin's q (Equation 9).
Size	9491	8.236	2.171	6.510	7.795	9.730	TRAA	Natural logarithm of bank total assets (in $billion).
CAPR	9487	0.096	0.062	0.062	0.086	0.111	Bloomberg, and TRAA	Capital ratio, total equity over total assets.
Diversification	9169	0.209	0.122	0.124	0.188	0.271	TRAA	Income diversification, noninterest income over total income.
Loans	8590	0.693	0.160	0.611	0.700	0.788	TRAA	Loans to total assets, net loans over total assets.
Efficiency	8516	0.464	0.150	0.359	0.446	0.558	TRAA	Cost income ratio, non-interest expense over total income.
ROA	9291	0.007	0.011	0.003	0.007	0.011	TRAA	Return on assets, ratio of net income to total assets.
d.(merger)	9491	0.361	0.480	0	0	1	SNL, and Bloomberg	Mergers and acquisitions dummy, takes value of 1, if bank had an M&A experience, the annul total assets variation exceeds 15%; 0, otherwise.
LiborOis	9491	27.11	26.26	14.22	19.14	29.25	Bloomberg	Liquidity premium, defined as the spread between 3-month London Inter-Bank Offered Rate (LIBOR) and Overnight Indexed Swaps rate (OIS). It reflects soundness of the banking system.
Growth strategy	5293	0.646	0.534	0.449	0.722	0.881	TRAA	Change in total assets between 2000 and 2006 divided by the average total assets over the pre-GFC period.
Activity-mix	5122	0.203	0.423	0.106	0.352	0.498	TRAA	Change in diversification ratio between 2000 and 2006 divided by the average diversification ratio over the pre-GFC period
InterbankRate	9361	2.527	2.121	0.430	2.106	4.060	Bloomberg	Short-term interbank lending interest rates, in each country.
GDP	9491	1.837	2.060	0.950	1.880	2.790	OECD stats Metadata, and IMF WEO	Gross domestic product growth, defined as annual real GDP growth rate.
Inflation	9491	2.279	2.357	1.500	2.300	3.200	OECD stats Metadata, and IMF WEO	Inflation, defined as annual inflation rate.
Cap_Stringency	9491	8.519	1.463	8	9	9	Barth et al. (2013)	Capital Stringency index.
Market share	9491	0.017	0.054	0.0001	0.0003	0.003	Bankscope, and TRAA	Share of individual bank's total assets in domestic total assets of the country's banking system.
Tangibility	9212	0.011	0.005	0.010	0.010	0.010	TRAA	Tangible assets ratio, book value of tangible assets to total assets.

Table 1.4 .Correlation matrix

Table presents the pairwise correlation matrix for bank-level characteristics and macroeconomics variables. * p < 0.05, ** p < 0.01, *** p < 0.001 denote statistical significance at the 10%, 5% and 1%, respectively. Definitions of all variables are listed in Table 1.3.

	Charter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Size (1)	-0.134***	1											
CAPR (2)	0.357***	-0.357***	1										
Diversification (3)	0.030**	0.397***	-0.017	1									
Loans (4)	0.253***	-0.160***	0.079***	-0.204***	1								
Efficiency (5)	0.043***	-0.017	-0.026*	0.401***	-0.081***	1							
ROA (6)	0.258***	-0.076***	0.417***	0.115***	-0.054***	-0.331***	1						
d.(merger) (7)	-0.101***	0.022*	0.022*	0.041***	-0.066***	-0.105***	0.159***	1					
LiborOis (8)	-0.065***	0.040***	0.005	-0.085***	0.045***	-0.052***	-0.163***	-0.0721***	1				
InterbankRate (9)	-0.053***	-0.081***	0.041***	-0.179***	-0.012	-0.516***	0.166***	0.175***	0.0798***	1			
GDP (10)	0.094***	-0.062***	0.036***	-0.018	-0.041***	-0.133***	0.241***	0.228***	-0.474***	0.221***	1		
Inflation (11)	0.100***	-0.110***	0.128***	-0.142***	0.011	-0.302***	0.163***	0.088***	0.089***	0.627***	0.304***	1	
Cap_Stringency (12)	0.071***	-0.201***	0.081***	-0.187***	0.039***	-0.001	0.075***	-0.054***	-0.077***	-0.057***	0.195***	0.127***	1
MES (13)	0.049***	0.448***	-0.0126	0.171***	-0.0956***	0.039***	-0.098***	-0.073***	0.259***	-0.068***	-0.206***	0.145***	-0.0322**
ΔCoVaR (14)	0.097***	0.323***	0.0461***	0.118***	-0.025*	0.066***	-0.030**	-0.083***	0.337***	-0.149***	-0.235***	0.084***	-0.044***
Systematic Risk (15)	0.111***	0.528***	-0.0330**	0.211***	-0.153***	-0.000	0.013	-0.063***	0.054***	-0.0182	0.0150	0.109***	0.007
Total Risk (16)	-0.021*	-0.094***	0.0346***	-0.032**	0.002	0.156***	-0.303***	-0.054***	0.265***	-0.140***	-0.302***	0.053***	-0.026*
MZ-score (17)	-0.0092	0.051***	-0.050***	0.0160	0.029**	-0.162***	0.192***	0.020*	-0.249***	0.137***	0.231***	-0.055***	0.044***
Tail-beta (18)	0.063***	0.300***	-0.0059	0.128***	-0.112***	-0.002	0.0186	-0.029**	-0.007	-0.014	0.0354***	0.060***	-0.004
Specific Risk (19)	-0.051***	-0.260***	0.0163	-0.102***	0.040***	0.144***	-0.313***	-0.026*	0.201***	-0.095***	-0.258***	-0.005	-0.042***

	MES (13)	(14)	(15)	(16)	(17)	(18)	(19)
ΔCoVaR (14)	0.633***	1					
Systematic Risk (15)	0.795***	0.511***	1				
Total Risk (16)	0.406***	0.237***	0.173***	1			
MZ-score (17)	-0.431***	-0.297***	-0.269***	-0.840***	1		
Tail-beta (18)	0.490***	0.293***	0.600***	0.128***	-0.191***	1	
Specific Risk (19)	0.100***	0.017	-0.123***	0.909***	-0.730***	-0.039***	1

3. Empirical specification

We consider a simultaneous equations model with unbalanced panel data. The specification of the second stage is represented by the following reduced form model:

$$Risk_{i,t} = \beta_1 \widehat{Charter}_{i,t} + \beta_2 X_{i,t-1} + \beta_3 C_{i,t} + \lambda_t + \mu_i + \varepsilon_{2i,t} \qquad (10)$$

where, $\mathrm{Risk}_{\mathrm{i,t}}$ is a set of risk measures, subscripts i denotes individual banks and t denotes each fiscal year. $\widehat{Charter}_{\mathrm{i,t}}$ represents the predicted value of bank charter value of the first stage regression. $X_{\mathrm{i,t-1}}$ and $C_{\mathrm{i,t}}$ are respectively vectors of time-varying bank-level explanatory variables for each bank i lagged by one year, to mitigate potential endogeneity concerns, and time-varying country-specific variables to control for macroeconomic variations. The coefficient β_1 captures the effect of charter value on bank risk and the rest of the coefficients are those of the control variables. λ_t is a set of year dummies ($\sum_{t=2001}^{2013} year_t$) included to further account for time trend varying effects through the business cycle and for possible structural changes in the banking industry. μ_i captures bank-specific effects, and standard errors are clustered at the individual bank level.

Our empirical setup may suffer from reverse causality. High-chartered banks might be systemically important and/or involved in high risk activities, or vise-versa. Moreover, bank charter value and risk taking may be simultaneously targeted in theory (Martinez-Miera and Repullo, 2010; Ghosh, 2009; Boyd and De Nicoló, 2005; Gropp and Vesala, 2004; Keeley, 1990)[21]. Some papers also argue that higher charter value may derive from high risky strategies (Laeven and Levine, 2007; Konishi and Yasuda, 2004; Saunders and Wilson, 2001; Park, 1997). We hence adopt an instrumental variable approach.

[21] Banks with higher default risk could have a higher market-to-book asset ratio if deposit insurance were underpriced and its value were capitalized on the market (but not on the book). Riskier banks could be over valuated, because risk shifting increases the option value of equity (Keeley 1990).

To tackle possible endogeneity issues regarding the effects of bank charter value on risk, we use the two-stage least squares (IV-TSLS) instrumental variables method with fixed effects. In the first stage, we instrument and estimate charter value $\widehat{Charter}_{\mathrm{i,t}}$. Previous literature has identified different determinants of charter value (Furlong and Kwan, 2006; Jones et al., 2011). Hereafter, we use three continuous and exogenous variables to instrument charter value. First, we use the one-year lagged value of charter value, assumed to be exogenous. Second, we follow González (2005) and include assets tangibility measured as the ratio of tangible assets to total assets to account for possible differences due to the extent of tangible assets, differences in efficiency, branching policy, or country size. Third, we follow Laeven and Levine, (2009) and Keeley (1990) and use market share defined as total assets of bank i over the aggregate assets of the banking system in a given country (all banks included, listed and non-listed) as a proxy of market power[22]. Subsequently in the second stage, risk regressions incorporate the predicted values of charter value from the first stage with the rest of the explanatory variables[23].

The relevance of the instrument set is assessed through the Kleibergen–Paap (KP) rank-LM (from the first stage) test for under-identification and the KP Wald rank F-statistic (Partial F-stat from the first stage) to test for weak identification (Kleibergen and Paap, 2006; Cragg and Donald, 1993)[24]. Besides, to ensure the reliability of the subsequent empirical results at the second stage, we statistically test the joint validity and strength of the chosen instruments. Under heteroscedasticity and robust-clustering, we perform the Hansen j overidentifying restriction test (from each second stage estimation) to check the exogeneity of the instruments in the estimated models (Hansen, 1982). Statistics from these respective tests are reported in the results' tables. Overall, the Hansen's j test confirms the validity of instruments.

[22] Although core deposits are regarded as important to explain charter value (Jones et al., 2011), we do not introduce them in the regressions because of insufficient observations for banks in countries other than the U.S.. Similarly, we do not use the entry denied index as an instrument of charter value, such as in (Laeven and Levine, 2009), because the index is not available for almost all the countries, including the U.S., during the 2008-2012 period. Instead, we use a proxy of market power.

[23] We follow Keeley (1990), Gropp and Vesala (2004) and González (2005) who use the same model specification.

[24] To confirm the validity of the IV, we report the KP rank F-statistics. Underidentification test is also assessed by the KP Cragg-Donald Wald F-statistics of the first stage (the null hypothesis of weak instruments is rejected if F-statistic is greater than the Stock-Yogo's critical value (Stock and Yogo, 2005; Cragg and Donald, 1993)).

4. Results

4.1. Impact of charter value on bank risk taking and systemic stability

Before closely looking at the relationship between charter value and bank risk prior, during and after the Global Financial Crisis, we provide the results for the full sample period.

Table 1.5. reports the coefficient estimates for the baseline IV-TSLS regressions[25] for systemic risk (columns 1 and 2), standalone risk (columns 3 and 4) and default risk (column 5) and the set of bank and country level control variables over the entire period of investigation (2000–2013). We also consider alternative measures of systemic risk (Tail-beta) and standalone risk (specific risk) in columns 6 and 7. Across these regressions, we do not find clear-cut results as the relationship between charter value and bank standalone and systemic risk measures is negative and statistically significant at the 5-percent level for only two risk variables: individual banks' systemic risk exposure (MES) and systematic risk (beta). These results are in line with the literature (e.g. Ghosh, 2009; Konishi and Yasuda, 2004; Hellmann et al., 2000; Demsetz et al., 1996; Keeley, 1990) and indicate that an increase in charter value encourages banks to take on less risk and become less exposed to systemic shocks that affect the whole financial system. The economic relevance of the coefficient estimates indicates that a one standard deviation increase in charter value (i.e., a 0.17 unit increase in the bank's charter value) would decrease the individual bank’s systemic risk exposure and systematic risk by 7% and 5%, respectively[26].

Regarding the control variables, most of them enter significantly and the coefficients carry the signs obtained in previous studies. Bank size has a positive and statistically significant effect on systemic risk and systematic risk and a negative and statistically significant effect on the rest of standalone risk variables. The coefficient of the capital ratio variable is positive and statistically

[25] Overall, the KP rank LM rejects the null hypothesis at the 1-percent level, indicating that the models are well identified. The Partial F-statistic, of the KP rank Wald F-test, from the first stage rejects this null hypothesis that the instruments are weak at the 1-percennt level. Hansen’s j tests (p-values) for overidentification of instruments show that the instruments are valid.

[26] [0.17*(-0.65)]/1.55=-7% and [0.17*(-0.17)]/0.53=-5%. This is also associated with 11% and 3% standard deviation reduction in the individual bank’s systemic risk exposure (the MES) and volatility risk (systematic risk), respectively.

significant for systemic and systematic risk but significantly negative for the other standalone risk proxies. The coefficient of the return on assets is significant for half of our specifications indicating that a higher ROA is associated with lower risk. The coefficient of the M&A dummy is significantly positive only for contagion risk (ΔCoVaR), but significantly negative for the MES, systematic risk, total risk and specific risk. The coefficient of the crisis dummy is positive and significant in all the estimations, meaning that systemic risk, risk-taking and default risk move up during crisis time. With respect to macroeconomic factors, the coefficients of economic growth are negative and significant for all risk measures (except for Tail-beta in column 6). This suggests that although higher economic growth is good for individual bank stability, it could have an adverse effect on the threat that banks might pose to the entire financial system. The inflation rate has a significantly positive impact on systemic risk exposure (MES), systematic risk and tail-beta, but a negative and statistically significant effect on specific and total risk. Thus, in presence of bad economic conditions such as inflationary pressures or high interbank rates, banks become riskier and more vulnerable to systemic shocks.

Table 1.5. Baseline regression. Standalone and systemic risks: effect of bank charter value on financial stability

Regression results for various bank risk measures on bank charter value over the whole period (2000–2013). In all regressions, columns report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering at the bank-level. Results of model $\text{Risk}_{i,t} = \beta_1 \widehat{Charter}_{i,t} + \beta_2 X_{i,t-1} + \beta_3 C_{i,t} + \lambda_t + \mu_{i,t} + \varepsilon_{2i,t}$, where dependent variables are two systemic risk measures: MES and ΔCoVaR (models in the columns: 1 and 2), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3 and 4) and default risk: MZ-score (model in the column 5). We also use other alternative risk measures: Tail-beta and specific risk (models in the columns 6 and 7). Bank charter value (Charter, proxied by Tobin's q) is modelled endogenously in all regressions. We instrument Charter by its one-year lagged value, Tangibility=tangible assets ratio, Market share = bank total assets over domestic total assets of the country banking system and their interactions. Regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Year dummies are not reported. Definitions of control variables are: Size=natural log of total assets, Loans=Loans to total assets, Diversification=non-interest income over total income, Efficiency=cost income over total income, CAPR=capital ratio, equity to total assets, ROA= Return on assets, d(merger)= dummy takes one if the bank experienced a merger-acquisition event (annul total assets variation exceeds 15%), and zero otherwise, and zero otherwise, d.(crisis)= dummy takes one during crisis time [2007-2009], and zero otherwise, GDP=gross domestic product growth, Inflation=annual inflation rate and Cap_Stringency=capital stringency. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * p < 0.1, ** p < 0.05, *** p < 0.01 denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	Systemic risk		Standalone risk		Default risk	Alternative dependent variables	
Dependent variables	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	Tail-beta	Specific Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Charter	-0.646**	-0.0815	-0.168**	0.0517	0.662	-0.186	0.0370
	(-2.18)	(-0.25)	(-2.04)	(0.27)	(0.16)	(-1.00)	(0.20)
Size	0.557***	0.178**	0.210***	-0.235***	2.638**	0.262***	-0.438***
	(6.40)	(2.05)	(8.20)	(-4.15)	(2.28)	(6.19)	(-7.59)
CAPR	5.117***	4.733***	1.510***	-0.973*	18.58*	1.743***	-3.489***
	(6.26)	(6.05)	(5.96)	(-1.65)	(1.66)	(3.64)	(-5.50)
Diversification	-0.0363	0.150	0.212**	0.451*	-2.324	-0.0420	0.295
	(-0.10)	(0.41)	(2.18)	(1.71)	(-0.49)	(-0.21)	(1.12)
Loans	0.703***	0.344	-0.0947	0.117	-1.868	0.125	-0.0165
	(2.76)	(1.48)	(-1.34)	(0.69)	(-0.54)	(0.97)	(-0.10)
Efficiency	-0.155	-0.262	-0.133	0.0823	-5.813	-0.0559	0.0832
	(-0.50)	(-0.88)	(-1.64)	(0.35)	(-1.45)	(-0.32)	(0.37)
ROA	-10.55***	3.234	-0.299	-35.62***	295.1***	2.244	-35.68***
	(-3.22)	(1.04)	(-0.45)	(-12.64)	(9.96)	(1.41)	(-12.03)
d.(merger)	-0.0647*	0.156***	-0.0285***	-0.0516**	0.355	-0.0225	-0.0586***
	(-1.74)	(3.93)	(-2.89)	(-2.54)	(0.75)	(-0.96)	(-2.97)
d.(crisis)	0.757***	0.805***	0.0360*	0.898***	-19.46***	-0.00510	0.694***
	(9.87)	(8.24)	(1.87)	(15.82)	(-17.72)	(-0.09)	(12.58)
LiborOis	0.0280***	0.00581	0.00113	0.0459***	-0.979***	-0.00137	0.0335***
	(4.52)	(0.82)	(0.75)	(10.48)	(-10.91)	(-0.34)	(8.16)
InterbankRate	-0.157***	-0.160***	-0.0214***	-0.118***	2.862***	-0.0452***	-0.0967***
	(-8.03)	(-8.19)	(-3.69)	(-9.65)	(9.63)	(-4.04)	(-8.60)
GDP	-0.122***	-0.0586***	-0.00976**	-0.0818***	1.246***	-0.00227	-0.0414***
	(-7.16)	(-3.73)	(-2.56)	(-8.93)	(6.85)	(-0.30)	(-4.56)
Inflation	0.142***	-0.0153	0.0579***	-0.0659***	-0.700	0.0324*	-0.0955***
	(3.61)	(-0.42)	(7.54)	(-2.91)	(-1.53)	(1.85)	(-4.28)
CapStringency	0.0280	0.0104	0.000489	0.00117	0.785**	0.00952	-0.000666
	(1.47)	(0.53)	(0.09)	(0.10)	(2.53)	(0.88)	(-0.06)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	No	No	No	No	No	No	No
Observations	6875	6875	6875	6875	6875	6875	6875
Banks	677	677	677	677	677	677	677
Hansen test (p-value)	0.001	0.398	0.000	0.001	0.001	0.005	0.014
LM χ^2	154.8***	154.8***	154.8***	154.8***	154.8***	154.8***	154.8***
Partial F-Stat	22.51***	22.51***	22.51***	22.51***	22.51***	22.51***	22.51**

4.2. Bank charter value and financial stability before, during and after the Global Financial Crisis

In this subsection, we investigate whether the impact of charter value on bank risk taking and bank systemic stability may depend on the considered period: the risk accumulating pre-crisis period (2000–2006), the acute crisis period (2007–2009) and the post-crisis period (2010–2013). In this perspective, we estimate the following cross-sectional regression:

$$Risk_{i,t} = (\beta_1 + \beta_2 D_{2007-2009} + \beta_3 D_{2010-2013}) \times \widehat{Charter}_{i,t} + \beta_6 X_{i,t-1} + \beta_7 C_{i,t} + \lambda_t + \mu_i + \varepsilon_{2i,t}. \quad (9)$$

Where $Risk_{i,t}$ stands alternatively for measures of standalone and systemic risk of bank i over the year t. $D_{2007-2009}$ and $D_{2010-2013}$ are two dummies[27] which respectively take a value of one if the year covers 2007–2009 and 2010–2013, and zero otherwise. We include two interaction terms to test whether there is a difference in the charter value effects on risk during the three considered periods. More precisely, the coefficients β_1, $\beta_1 + \beta_2$ and $\beta_1 + \beta_3$ capture the effect of the bank charter value on bank standalone and systemic risk measures during the pre-global financial crisis years (2000–2006), the acute global financial crisis years (2008–2009) and the post global financial crisis years (2010–2013), respectively. The remaining variables are the same as in the Eq. (10).

Table 1.6. displays TSLS estimations regarding systemic risk (columns 1 and 2), standalone risk (columns 3 and 4) and default risk (column 5) over the pre-crisis period (2000–2006), 2007–2009 and later (2010–2013). We match individual and systemic risk measures to investigate whether the impact of charter value may differ depending on the type of risk and economic conditions (pre-crisis period versus crisis and post-crisis periods). The coefficients estimates for bank charter value are positive and statistically significant in the pre-crisis period (columns 1, 3, 4,

[27] Studies using similar definitions include Saheruddin (2014), Berger and Bouwman (2015) and Temesvary (2014), among others.

6 and 7), indicating that an increase in charter value is associated with an increase in bank individual risk and systemic risk over the pre-GFC period. Similarly, the negative and significant relationship at the 1% level between charter value and the market-based z-score indicator (column 5) shows that higher charter value increases bank default. Taken together, the results indicate that an increase in bank charter value, i.e. availability of growth opportunities and presence of high earnings potential, is associated with higher risk-taking, which undermines stability and poses greater systemic risk.

When we look into the acute crisis (2007–2009) and the post crisis (2010–2013) periods (Table 1.6.), we find that the disciplining effect of charter value is only effective after the crisis and that charter value does not play any role during the crisis. Specifically, the Wald tests show that the effects of charter value on both systemic and standalone risk measures are significantly different from zero only during the post-GFC ($\alpha_1 + \alpha_3$), except for ΔCoVaR (column 2). However, during the acute crisis period, the effect of charter value on risk disappears; though for default risk (column 5), the Wald test ($\alpha_1 + \alpha_2$) is negative and significant at the 5-percent level, indicating that the effect of charter value is not reversed (but lessened) during the acute crisis period.

The impact of charter value on risk is also economically meaningful. For instance, before the crisis a one standard deviation increase in the charter value (0.17) leads to an increase in the MES of 16.7% ([1.67*0.10]/1.00) (column 1 of Table 1.6.) and a decrease in the MES in the subsequent period of 3.36% ([-0.25*0.27]/2.00) (column 1 of Table 1.6., period) [28].

Besides, in Columns (6 and 7) of Table .6., we consider alternative measures of systemic risk (Tail-beta) and standalone risk (specific risk) and obtain quantitatively similar results. We find that the effect of charter value on both tail-beta and specific risk flips from positive and significant during the pre-crisis period (α_1), to negative and significant during the post-crisis period (the Wald tests: $\alpha_1 + \alpha_3$).

On the whole, Table 1.6. shows that bank charter value and risk move together during the profitable, pre-crisis period (2000-2006), i.e. bank earnings potential (Tobin's q) accelerates bank

[28] Based on the standard deviations of the charter value and the mean values of the MES over the pre- and post-crisis periods, respectively.

risk-taking and the sensitivity to extreme systemic shocks. Therefore, the self-disciplining role induced by charter value is not effective during the years that preceded the GFC. However, the relationship disappears during the acute crisis period (2007–2009) and after the crisis (2010–2013), the coefficients of charter value take the opposite sign consistent with the CVH whereby bank charter value reduces both individual and systemic risks[29].

Table 1.6. Charter value and risk: the relationship between bank charter value, standalone and systemic risk in the pre-crisis, acute-crisis and the post-crisis periods

Table shows regression results for various bank risk measures on bank charter value over the whole period [2000-2013]. In all regressions, columns report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering on the bank-level. In all regression, $D_{2007-2009}$= dummy takes one during crisis time [2007-2009], and zero otherwise; $D_{2010-2013}$= dummy takes one if the year is 2010 to 2013, and zero otherwise. Dependent variables are four systemic risk measures: MES and ΔCoVaR (models in the columns: 1 and 2), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3 and 4) and default risk: MZ-score (model in the column 5). We also use other alternative risk measures: Tail-beta and specific risk (models in the columns 6 and 7). Bank charter value (Charter) is modelled endogenously in all regressions. We instrument Charter by one-year lagged Charter, tangible assets ratio, market share and their interactions. Besides, regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

Dependent variables	Systemic risk		Standalone risk		Default risk	Alternative dependent variables	
	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	Tail-beta	Specific Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Charter (α1)	1.671**	0.0188	1.651***	2.108***	-35.71***	1.569***	2.514***
	(2.01)	(0.03)	(7.50)	(3.13)	(-3.37)	(4.05)	(3.93)
Charter*$D_{2007-2009}$ (α2)	-1.920**	0.904	-1.482***	-1.910***	20.44**	-1.804***	-2.285***
	(-2.34)	(1.10)	(-6.95)	(-2.87)	(2.06)	(-4.41)	(-3.42)
Charter*$D_{2010-2013}$ (α3)	-1.925**	0.209	-1.699***	-2.321***	39.29***	-1.711***	-2.738***
	(-2.40)	(0.30)	(-7.86)	(-3.57)	(3.81)	(-4.46)	(-4.43)
$D_{2007-2009}$	2.952***	-1.138	1.498***	3.229***	-45.89***	1.560***	3.493***
	(3.42)	(-1.29)	(6.65)	(4.90)	(-4.52)	(3.63)	(5.24)
$D_{2010-2013}$	2.151**	-0.503	1.749***	2.863***	-53.76***	1.545***	3.182***
	(2.55)	(-0.69)	(7.77)	(4.31)	(-4.96)	(3.87)	(5.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6875	6875	6875	6875	6875	6875	6875
Hansen test (p-value)	0.001	0.312	0.000	0.001	0.002	0.001	0.020
LM χ^2	80.55***	80.55***	80.55***	80.55***	80.55***	80.55***	80.55***
Partial F-Stat	45.16***	45.16***	45.16***	45.16***	45.16***	45.16***	45.16***
Wald tests: $\alpha_1 + \alpha_2$	-0.249	0.923*	0.169	0.198	-15.27**	-0.235	0.229
$\alpha_1 + \alpha_3$	-0.254**	1.113	-0.048*	-0.213***	3.580***	-0.142**	-0.224***

[29] Considering sub-samples over the three sub-periods instead of the model in Eq. (11) with interaction terms yields similar conclusions (see Table A1.1. in Appendix 1).

In what follows, we go deeper in the investigation of the positive relationship between charter value and bank risk during the pre-crisis period. Specifically, we test whether differences in risk-taking culture across countries, bank size, and growth and diversification strategies are possible drivers of such an unexpected impact of charter value on risk.

4.3. Charter value-bank risk relationship before the crisis: the impact of cross-country heterogeneity, bank size, and growth and diversification strategies

We consider four potential determinants that could explain the positive relationship of charter value on risk uncovered for the pre-GFC period: differences in risk taking cultures, bank size, growth strategy and business model. We hence slightly modify Eq. (11) as follows:

$$Risk_{i,t} = (\beta_1 + \beta_2 Factor) \times \widehat{Charter}_{i,t} + \beta_3 X_{i,t-1} + \beta_5 C_{i,t} + \lambda_t + \mu_i + \varepsilon_{2i,t} \qquad (10)$$

Where $Risk_{i,t}$ represents measures of standalone or systemic risk of bank i over the year t. $Factor$ stands alternately for bank location to take into account differences in risk taking cultures (*d(EU)* and *d(NonUS-EU)*, which respectively take a value of one if banks are from Europe, the rest of OECD countries; and zero otherwise); bank size (*d(Large)* and *d(Small)*, which respectively take a value of one if \$1billion$<$ total assets$\leq$\$10 billion, \$500 million $<$ total assets$\leq$\$1 billion; and zero otherwise); growth strategy (*d(High growth)*, *d(Low growth)*, which respectively take a value of one if a bank is in the top quartile of total asset growth over the pre-GFC, in the bottom quartile of total asset growth over the pre-GFC; and zero otherwise) and business model (*d(Diversified)*, *d(Specialized)*, which respectively take a value of one if a bank is in the top quartile of the diversification ratio (asset mix)[30] change over the pre-GFC, in the bottom quartile of the

[30] The diversification ratio is defined as noninterest income over total income.

diversification ratio (asset mix) change over the pre-GFC; and zero otherwise[31]. We also include the same set of control variables as in Eq. (10).

The relationship between charter value and bank risk may depend on differences in risk taking cultures. For instance, Japanese banks are well known to be more conservative than their U.S. counterparts (Haq et al., 2016). We therefore take advantage of the heterogeneity of our OECD bank sample that comprises different countries and financial systems (market-based vs. bank-based financial systems). We define three geographical sub-groups: U.S., European countries and the rest of OECD countries (which is dominated by Japan). Panel A of Table 1.7. displays the results. They show that the positive relationship between charter value and bank risk during the pre-crisis period only holds for banks in the U.S. (coefficient α1, Panel A) and Europe (Wald tests α1+ α2) because, for the rest of OECD countries, the relationship is comparatively weaker or non-existent for more than half of our specifications (Wald tests α1+α3, Panel A). In the next step, we only keep U.S. and European banks, i.e. we eliminate from our sample banks from the rest of OECD countries for which the robust positive relationship between charter value and bank risk is not found, and test whether the charter value-bank risk relationship may be influenced by bank size. Panel B of Table 1.7. reports the results. We find that a high charter value increases both standalone and systemic risks for very large and large banks; whereas for small banks, such a relationship is either non-existent or strongly lessened (Wald tests α1+ α3).

[31] Growth strategy (business model) variation is computed as the change over the pre-GFC period (between 2000 and 2006) in total assets (diversification ratio) over the average total assets (diversification ratio) (see descriptive statistics, Table 1.3.).

Tables 1.7. Bank charter value and financial stability in the pre-crisis period [2000-2006]: effect of geographical distribution and size

Table shows the two-stage least squares (TSLS) IV estimation results on the relation between charter value and risk and the effect of bank size (Panel A) and geographical localization (Panels B and c) for all banks over the pre-crisis period [2000-2006]. In all regressions report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering on the bank-level. Dependent variables are four systemic risk measures: MES and ΔCoVaR (models in the columns: 1 and 2), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3 and 4) and default risk: MZ-score (model in the column 5). We also use other alternative risk measures: Tail-beta and specific risk (models in the columns 6 and 7). Bank charter value (Charter) is modelled endogenously in all regressions. We instrument Charter by one-year lagged Charter, tangible assets ratio, market share and their interactions. In Panels A and B, d(EU)= dummy takes a value of one if banks are from Europe banks, and zero otherwise; d(NonUS-EU)= dummy takes a value of one if banks are neither from U.S. nor Europe (from the rest of remaining OECD countries: Australia, Canada, Japan, South Korea and Turkey), and zero otherwise; d(Large)= dummy takes one if banks are large, those with total assets ranging between $1 and $20 billion), and zero otherwise; d(Small)= dummy takes one if banks are small, those with total assets between $500 million and $1 billion, and zero otherwise. Panel A presents the effect of the geographical areas (that differentiates risk-taking culture) on bank risk-taking and systemic risk for the broad sample of banks. Panel B presents the effect of bank size on risks for the U.S. and European sample of banks. Besides, regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

Dependent variables	Systemic risk		Standalone risk		Default risk	Alternative dependent variables	
	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	Tail-beta	Specific Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Geographical areas (risk-taking culture) effects on the relation between bank charter value and risk, broad sample.							
Charter (α1)	16.79***	13.64***	6.367***	4.215***	-92.51***	3.838**	0.934
	(6.24)	(5.01)	(7.26)	(2.59)	(-3.01)	(2.56)	(0.60)
Charter*d(EU) (α2)	-14.98***	-13.26***	-5.739***	-1.729	35.62	-2.549*	1.411
	(-5.14)	(-3.78)	(-6.61)	(-1.08)	(0.97)	(-1.65)	(0.93)
Charter*d(NonUS-EU) (α3)	-11.88***	-13.51***	-5.643***	-1.701	8.937	-3.063	1.675
	(-3.31)	(-4.39)	(-4.92)	(-0.91)	(0.18)	(-1.52)	(0.99)
Observations	3145	3145	3145	3145	3145	3145	3145
Hansen test (p-value)	0.004	0.324	0.001	0.003	0.001	0.612	0.047
LM χ^2	43.43***	43.43***	43.43***	43.43***	43.43***	43.43***	43.43***
Partial F-Stat	10.76***	10.76***	10.76***	10.76***	10.76***	10.76***	10.76***
Wald tests: $\alpha_1 + \alpha_2$	1.810**	0.380	0.628***	2.486***	-56.890***	1.289***	2.345***
$\alpha_1 + \alpha_3$	4.910*	0.130	0.724	2.514**	-83.573*	0.775	2.609**
Panel B. Size effects on the relation between bank charter value and risk, U.S. and European countries							
Charter (α1)	13.15***	7.779***	1.687	4.445***	-155.5***	3.692**	2.956**
	(6.23)	(3.53)	(1.64)	(4.05)	(-4.63)	(1.98)	(2.47)
Charter*d(Large) (α2)	-8.247***	-4.975**	0.403	-2.822**	107.4***	-1.708	-2.297*
	(-3.87)	(-2.25)	(0.39)	(-2.40)	(3.12)	(-0.90)	(-1.82)
Charter*d(Small) (α3)	-10.50***	-8.503***	-1.213	-2.971**	96.52**	-0.432	-1.772
	(-3.94)	(-3.14)	(-1.16)	(-2.15)	(2.36)	(-0.19)	(-1.23)
Observations	2639	2639	2639	2639	2639	2639	2639
Hansen test (p-value)	0.001	0.003	0.000	0.164	0.160	0.070	0.540
LM χ^2	35.82***	35.82***	35.82***	35.82***	35.82***	35.82***	35.82***
Partial F-Stat	42.78***	42.78***	42.78***	42.78***	42.78***	42.78***	42.78***
Wald tests: $\alpha_1 + \alpha_2$	4.903***	2.804***	2.090***	1.615***	-48.100***	1.984***	0.659
$\alpha_1 + \alpha_3$	2.650	-0.724	0.474*	1.474*	-58.980**	3.26*	1.184

Lastly, we consider the sample of very large and large banks for which the positive relationship between charter value and risk is confirmed (i.e. we eliminate from our sample small banks and banks from the rest of OECD countries), and then explore if differences in growth strategies and business models alter such a relationship. We define banks with high growth strategies as those in the top 75th percentile of bank total assets variation[32] during the pre GFC period, while banks with low growth strategies are those in the bottom 25th percentile. We use similar cutoffs for the business model (activity-mix) and consider the variation of the non-traditional income ratio as an indicator of bank diversification[33]. Table 1.8. (Panels A and B) displays the results[34]. It indicates that the positive impact of charter value on both standalone and systemic risks is confirmed only for large and very large banks following a high growth strategy (Panel A of Table 1.8.). In fact, charter value has no impact on both standalone and systemic risks when banks pursue a low growth strategy, except for total risk when banks are very large (Table 1.8., column (9)). As regards to bank business models, the positive impact of charter value on bank risk is confirmed only for the sample of large banks with a focus strategy, while it is non-existent for highly diversified banks (Table 1.8., Panels B).

[32] Table 1.3. contains the definitions of growth strategy and business model (activity-mix).
[33] We use the ratio of non-interest income to total income as the diversification ratio. Alternately, we consider the ratio of non-interest income to operating income and obtain similar results.
[34] To save space, Table 1.8. does not report the results obtained for alternative risk measures─ *Tail beta* and *Specific risk*.

Tables 1.8. The effects of growth strategies and business models in the relationship between charter value and financial stability over the pre-crisis period [2000-2006] for U.S. and European large and "TBTF" banks, with total assets above $1 billion

Table shows the two-stage least squares (TSLS) IV estimation results on the relation between charter value and risk and the effect of bank growth strategies (Panel A) and business models (Panel B) for U.S. and European banks over the pre-crisis period [2000-2006]. In all regressions report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering on the bank-level. Dependent variables are four systemic risk measures: MES and ΔCoVaR (models in the columns: 1,2,6 and 7), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3,4,8 and 9) and default risk: MZ-score (models in the columns 5 and 10). Bank charter value (Charter) is modelled endogenously in all regressions. We instrument Charter by one-year lagged Charter, tangible assets ratio, market share and their interactions. Panel A reports estimation results for banks group with high growth strategies (d(High growth)= dummy takes one if banks are in top quartile, Q75, of bank total assets variation during the pre-crisis period, and zero otherwise) and those with low growth strategies (d(Low growth)= dummy takes one if banks are in bottom quartile, Q25, of bank total assets variation during the pre-crisis period, and zero otherwise). Panel B reports estimation results for banks group with strong diversification strategies (d(Diversified)=dummy takes one if banks are in top quartile, Q75, of diversification ratio variation during the pre-crisis period, and zero otherwise) and those with focus strategies (d(Specialized)=dummy takes one if banks are in bottom quartile, Q25, of diversification ratio variation during the pre-crisis period, and zero otherwise). In these both analyses, we differentiate between large banks (with total assets ranging between $1 and $20 billion) and very large banks (with total assets above $20 billion). Besides, regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	Subsample of large banks					Subsample of very large banks				
Dependent variables	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Growth strategies and the effect of bank charter value on risk.										
Charter (α1)	5.094***	2.951***	2.819***	2.683***	-35.52**	21.12**	11.97	2.695*	9.069**	-246.5*
	(4.60)	(2.83)	(6.12)	(2.76)	(-1.98)	(2.07)	(1.55)	(1.72)	(2.02)	(-1.95)
Charter*d(High growth) (α2)	-0.0133	-0.117***	-0.0554***	-0.0417	-0.104	-4.058	-3.153	-0.304	-1.788	61.60*
	(-0.41)	(-3.77)	(-3.16)	(-1.45)	(-0.22)	(-1.57)	(-1.63)	(-0.65)	(-1.51)	(1.79)
Charter*d(Low growth) (α3)	-5.496	2.946	0.673	-1.247	148.5	-50.18*	-24.74	-4.930	-25.45**	618.6*
	(-0.39)	(0.30)	(0.11)	(-0.18)	(0.61)	(-1.82)	(-1.17)	(-1.15)	(-2.09)	(1.80)
Observations	1331	1331	1331	1331	1331	473	473	473	473	473
Hansen test (p-value)	0.260	0.457	0.607	0.623	0.440	0.359	0.077	0.362	0.756	0.393
LM χ^2	21.90***	21.90***	21.90***	21.90***	21.90***	10.25*	10.25*	10.25*	10.25*	10.25*
Partial F-Stat	33.35***	33.35***	33.35***	33.35***	33.35***	4.57***	4.57***	4.57***	4.57***	4.57***
Wald tests: $\alpha_1+\alpha_2$	5.081***	2.834***	2.764***	2.641***	-35.42**	17.162**	8.817*	2.391**	7.281**	-176.9**
$\alpha_1+\alpha_3$	-0.402	0.005	3.492	1.436	112.48	-28.96	-12.77	-2.235	-16.381**	399.5*
Panel B. Business models and the effect of bank charter value on risk.										
Charter (α1)	7.774***	6.350***	4.354***	5.789***	-80.81**	9.420**	3.078	2.060**	3.229*	-24.31
	(4.34)	(4.00)	(4.84)	(3.96)	(-2.24)	(2.06)	(0.85)	(2.44)	(1.93)	(-0.53)
Charter*d(Diversified) (α2)	-4.543	-8.782**	-2.962*	-6.171***	94.80*	-2.756	4.938	-2.580	2.186	-150.6
	(-1.60)	(-2.51)	(-1.90)	(-2.85)	(1.75)	(-0.28)	(0.39)	(-1.24)	(0.50)	(-1.19)
Charter*d(Specialized) (α3)	4.655*	5.298***	2.962**	5.662***	-83.15**	11.74	3.708	0.244	0.369	259.4
	(1.83)	(2.66)	(2.55)	(2.67)	(-2.02)	(0.66)	(0.27)	(0.06)	(0.05)	(1.21)
Observations	1331	1331	1331	1331	1331	473	473	473	473	473
Hansen test (p-value)	0.248	0.376	0.498	0.813	0.394	0.021	0.038	0.308	0.192	0.090
LM χ^2	11.15*	11.15*	11.15*	11.15*	11.15*	12.38*	12.38*	12.38*	12.38*	12.38*
Partial F-Stat	23.37***	23.37***	23.37***	23.37***	23.37***	5.70***	5.70***	5.70***	5.70***	5.70***
Wald tests: α1+ α2	3.231	-2.432	1.392	-0.382	3.99	6.664	8.016	-0.52	5.415*	-174.91*
α1+ α3	12.429***	11.648***	7.316***	11.451***	163.96**	21.16	6.786	2.304	3.598	235.09

5. Robustness checks

To check the robustness of the results, we proceed as follows. Firstly, the definition of TBTF banks we consider (banks with total assets above $20 billion) is presumably more accurate for banks operating in the most developed banking systems but less appropriate for the less developed OECD countries. Therefore, we keep the absolute size criterion of total assets above $20 billion for banks operating in the world's top 10 economies, and for the rest of the OECD countries in our sample, we use bank size relative to GDP. Very large banks with respect to the home country's GDP are defined as those with a ratio above 10 percent (De Jonghe et al., 2014). We re-estimate the regressions in Table 1.8. and find similar conclusions. Considering growth and diversification strategies during the pre-crisis period, the results of Table A1.2. (see Appendix 1) support our earlier findings although for very large banks, the relationship becomes positive and significant when banks have a strong diversification strategy. Secondly, we consider an alternative proxy of charter value. We use the standardized market value added (MVA)[35] and market-to-book ratio, as alternative measures of Tobin's q, and obtain similar conclusions (Table A1.3. in Appendix 1). In unreported results but available upon request, we use the median as a new cutoff to define high and low bank growth and diversification strategies during the pre-crisis period, instead of the top 75th and bottom 25th quartiles of total assets and non-traditional income ratio variations. Finally, we run all our regressions using subsamples instead of interaction terms and get similar conclusions. Our results are therefore robust to alternative definitions of TBTF banks, charter value and the choice of cutoffs.

[35] We calculate the standardized market value added MVA as (current market capitalization –total equity) divided by total equity.

6. Conclusion

Previous studies on the relationship between charter value and bank risk-taking have mainly focused on standalone risk measures and report mixed results. Although higher charter value is generally considered as beneficial in terms of bank stability, by reducing a bank's risk-taking incentives, some studies find this relationship not to be linear. This paper considers both standalone and systemic risk measures and shows that the relationship between charter value and risk is different during normal times and distress periods dependent on the state of the economy and the business cycle. Specifically, based on our investigation of 853 publicly-traded banks in 28 OECD countries over the 2000–2013 period, we find that before the global financial crisis charter value positively impacted both individual and systemic risks. Such a behavior is mostly effective for large and "too-big-to-fail" banks with fast growth policies or other large banks with focus strategies. Our findings highlight that instead of mitigating risk, charter value may have provided incentives to accumulate risk which in turn might have contributed to higher systemic risk. By contrast, the results show that during, and more specifically after, the global financial crisis, banks tend to protect their charter value and lessen their risk exposure thereby reducing their contribution to systemic risk.

Our findings have important policy implications. The one size fits all capital conservation buffers introduced by Basel III may not be enough to guarantee bank stability and should not only be based on the business cycle but also on the state of the financial system. Although banks are required to accumulate buffers during economic upturns, banks with a stronger position with higher charter value might be building up more aggressive expansion strategies during bullish financial markets. Regulators and supervisors should hence closely look into the behavior of very large "too-big-to fail banks" and large banks with high growth or strong focus strategies. For such banks the impact of charter value on bank stability can be a double-edged sword.

Chapter 2

Does Banks' Systemic Importance affect their Capital Structure and Balance Sheet Adjustment Processes?*

Abstract. Frictions prevent banks to immediately adjust their capital ratio towards their desired and/or imposed level. This paper analyzes (i) whether or not these frictions are larger for regulatory capital ratios vis-à-vis a plain leverage ratio; (ii) which adjustment channels banks use to adjust their capital ratio; and (iii) how the speed of adjustment and adjustment channels differ between large, systemic and complex banks versus small banks. Our results, obtained using a sample of listed banks across OECD countries for the 2001-2012 period, bear critical policy implications for the implementation of new (systemic risk-based) capital requirements and their impact on banks' balance sheets, specifically lending, and hence the real economy.

* This chapter draws from the working paper (Bakkar, De Jonghe and Tarazi "Does Banks' Systemic Importance affect their Capital Structure and Balance Sheet Adjustment Processes?") co-written with Olivier De Jonghe, from European Banking Center, Tilburg University and National Bank of Belgium, and Amine Tarazi, from Université de Limoges–LAPE. I am indebted to my supervisor Amine Tarazi, and my coauthor Olivier De Jonghe for guidance and advice. This paper has been presented at IFABS, August 31–September 2, 2017, Ningbo, China. I have also received very helpful comments from Sebastian De Ramon, Bob DeYoung, Iftekhar Hasan, Kose John, Ruth Tacneng; conference participants at IFABS 2017; as well as LAPE PhD seminar 2017 participants and LAPE summer meetings 2017 participants. This paper was written as a part of Europlace Institute of Finance research project. I would like to thank Europlace Institute of Finance, Louis Bachelier, for financial support.

1. Introduction

In the aftermath of the 2007-2008 global financial crisis, regulators have introduced stringent changes to the prudential regulation of banks, especially by redesigning existing frameworks for regulatory capital requirements and by tightening the supervision of the so called systemically important financial institutions (SIFIs), BIS (2010a, 2013). There is a rapidly growing literature analyzing the specific elements in the design of the Basel III capital requirements[36] (Cecchetti (2015), Dermine (2015), Repullo and Suarez (2013)) as well as their potential consequences for bank performance (Giordana and Schumacher (2012), Berger and Bouwman (2013), Admati et al. (2010)), bank risk-taking (Kiema and Jokivuolle (2014), Hamadi (2016)), economic and financial stability (Angelini et al. (2014), Rubio and Carrasco-Gallego (2016), Farhi and Tirole (2012), Acharya and Thakor (2016), Hanson et al. (2011), Brunnermeier and Pederson (2009)), and credit supply (e.g. Cosimano and Hakura (2011), Jimenez et al. (2017), De Jonghe et al. (2016), Kok and Schepens (2013), Francis and Osborne (2012), Ivashina and Scharfstein (2010)).

While this first stream of papers is interested in the equilibrium implications of capital requirements, there is another stream that investigates the dynamics of bank capital towards the new equilibrium. This other stream of research has analyzed how quickly banks can adjust their capital ratios and which mechanisms they can resort to (see e.g. Berger et al. (2008), Memmel and Raupach (2010), Öztekin and Flannery (2012), Lepetit, et al. (2015), De Jonghe and Öztekin (2015), Cohen and Scatigna (2016)).

We link these two strands of literature and aim to fill two specific gaps in the existing literature. First of all, we address the following questions: Are there differences in adjustment mechanisms and adjustment speed for leverage vis-à-vis regulatory capital requirements? Might they conflict? Second, while this first step results in unconditional, homogenous results describing average bank behavior, we subsequently differentiate between SIFI banks and non-SIFI banks given the new

[36] Regarding capital requirements, the most important innovations in Basel III are the introduction of a leverage requirement (next to risk-weighted capital requirements), a capital surcharge for systemically important banks and the introduction of a countercyclical capital buffer. The imposed changes aspire to achieve financial stability by increasing the resilience of banks to shocks and by forcing them to internalize systemic externalities.

regulatory and supervisory focus on the two groups. We analyze, both for leverage and risk-weighted capital ratios, whether systemically important financial institutions behave differently in terms of adjustment mechanisms and adjustment speed.

It is important to emphasize that, for both questions, we analyze the dynamics in banks' capital adjustment (mechanisms and speed) towards a bank-specific and time-varying optimal capital ratio. Such bank-specific and time-varying optimal capital ratios are determined by the regulatory minimum and banks' desire to hold a buffer over the minimum capital requirements. Both the requirement and the buffer are time-varying and bank-specific, and, unfortunately, cannot be disentangled as information on the former is not publicly available[37].

In the first part of the analysis, we focus on differences in adjustments of a leverage ratio (the equity-to-total asset ratio[38]) and two regulatory capital ratios (Tier 1 capital over risk-weighted assets and total capital over risk-weighted assets) for OECD banks. We follow the literature and estimate a partial adjustment model of bank capital towards a bank-specific and time-varying optimal capital ratio (see e.g. Berger et al., (2008), Memmel and Raupach (2010), Öztekin and Flannery (2012), Lepetit et al. (2015), De Jonghe and Öztekin (2015)). The partial adjustment model assumes that banks do have a target (or optimal) capital ratio, but that there might be frictions (such as adjustment costs) that prevent them from instantaneously adjusting towards the target. Hence, at each point in time, the actual capital ratio is a weighted average of the lagged capital ratio and the target capital ratio, where the weight is an indication of the magnitude of the frictions. It is ex-ante unclear whether the speed of adjustment should be higher for the regulatory capital ratios versus the leverage ratio. On the one hand, one could expect a faster adjustment for the Tier 1 and Total Capital ratio than for the leverage ratio given the regulatory focus on these measures at least during the sample period. On the other hand, the opposite could also be found because the set of adjustment mechanisms is smaller for the regulatory capital ratios vis-à-vis the leverage ratio,

[37] Regulators can use Pillar 2 to impose bank-specific and time-varying capital requirements. However, these requirements are typically communicated privately to the bank and they are confidential. Evidence on the magnitude and variation in these requirements is available from Aiyar et al. (2014), who report a standard deviation of 2.2% in bank-specific capital requirements for the UK for the 1998-2007 period, or De Jonghe et al. (2016) who report a similar value for the standard deviation of bank capital requirements, due to time-varying and bank-specific pillar 2 requirements, for Belgian banks over the 2011-2014 period.

[38] We use the terms "leverage" and "equity-to-asset" interchangeably to refer to the unweighted equity-to-asset capital ratio.

as not all types of equity count and because assets vary in risk weight[39]. Our findings show that banks are more flexible and faster in adjusting the common equity capital ratio than regulatory capital ratios. More specifically, in our sample of listed OECD banks over the 2001-2012 period, the speed of adjustment for the non-weighted equity-to-asset capital ratio structure is 0.48, which is larger than the one for the Tier 1 capital ratio, 0.31, and the total capital ratio, 0.35. In economic terms, these speeds of adjustment correspond with half-lives[40] (the time required for banks to halve the gap between their actual capital ratio and their target) of 1.05, 1.88 and 1.59 years, respectively. To understand better why the speeds of adjustment differ, we subsequently investigate how banks achieve their adjustments towards their targets. The estimation procedure allows us to back out the estimated target capital ratio and hence also the gap between the target and the actual capital ratio. We then investigate growth rates in various assets classes, liability categories and types of equity, according to the sign of the gap for both the leverage and regulatory capital ratios. Facing an opportunity cost, overcapitalized (underleveraged) banks have no incentives to remain above their targeted capital ratio, i.e. hold a capital surplus over their target. Therefore, bank managers make proactive efforts to converge to their target by reducing their capital levels. For all capital specifications, we find that banks lever up by expanding assets, through an unrestrictive lending policy and risk-taking preferences, increasing liabilities both with long-term and short-term borrowings (except for the leverage ratio) and lessening equity growth, both internally (smaller amount of retained earnings) and externally (equity repurchasing and/or less equity issues). In contrast, when banks have a capital shortfall with comparison to their target, we find that undercapitalized banks de-lever by an aggressive growth reduction in all its subcomponents; i.e. loans and risk-weighted assets.

In the second part of the analysis, we investigate whether or not systemically important financial institutions behave differently in terms of capital structure adjustments. Although SIFIs and large banking groups are subject to prudential regulations and considerable research has pointed out their characteristics and performance (see e.g. Bertay et al. (2013), Barth and Schnabel (2013), Laeven et al. (2015)), how they manage their capital structure and rebalance to converge

[39] For example, government bonds (of OECD countries) are securities that are easily adjustable, but have a zero risk-weight. They could help to adjust the leverage ratio, but not the regulatory capital ratios.
[40] The half-life is computed as log(0.5)/log(1- speed of adjustment).

to their optimal capital levels remains an open question with important policy implications. Indeed, SIFIs could behave very differently. On the one hand, because they enjoy favorable treatment from financial markets (higher debt ratings, lower interest rates) due to their favored access to government safety nets and subsidies, SIFIs might adjust their capital structure more quickly and more frequently. On the other hand, SIFIs might not weigh the need to adjust quickly if they expect public support and bailout or because their complexity and opacity make it costlier for them to raise external capital. Combining the insights from Bertay et al. (2013) and Barth and Schnabel (2013), we focus on four distinguishing aspects of SIFIs, which are their absolute size (natural log of total assets), their relative size (total assets over GDP), their systemic risk contributions (delta Conditional Value-at-Risk (ΔCoVaR)) and systemic risk exposures (Marginal Expected Shortfall (MES)). SIFIs are more likely to care about their sensitivity to a sudden market shortfall than to how much their operations might jeopardize the financial system in times of crisis. Nevertheless, regulatory scrutiny could also be effective in pushing SIFIs to internalize the threat that they pose on the system. We also construct a systemic risk index based on the quintiles of such indicators. We find that systemically important banks adjust slower than other banks to their target leverage ratios but quicker to their regulatory target ratios. Moreover, our results suggest that systemic banks might be more reluctant to change their capital base by either issuing or repurchasing equity and prefer sharper downsizing or faster expansion. Any unexpected need for banks to raise capital ratios might therefore be more harmful for firms and households who are clients of such large institutions. To the extent that systemic banks account for a large portion of a banking industry (market share) the negative impact on the economy as a whole could also be more important.

The rest of the paper proceeds as follows. Section 2 presents information on the sample construction and variables of interest, in particular the various concepts of capital and the measures of (systemic) size and systemic risk. In Section 3, we examine and contrast the adjustment speed and adjustment mechanisms for various concepts of bank capital. Analyzing how and how quick SIFIs adjust their balance sheet in response to deviations between the actual capital ratio and the optimal capital ratio is performed in Section 4. Section 5 concludes.

2. Data: sample and variables

2.1. Sample selection

For reasons of data availability and cross-country consistency, we limit the sample to listed banks headquartered in any of the OECD countries and analyze the 2001-2012 period. To better identify how banks have historically managed their leverage ratios and regulatory capital ratios, we end the sample in 2012, which is prior to the new rules introduced by Basel III in 2013 and the identification of globally systemically important banks (G-SIFIs) as well as stress tests performed by regulators[41]. Furthermore, we exclusively consider banks that have publicly traded equity, because of the focus on systemically important institutions. We combine accounting and market data from various sources. We retrieve bank stock price information and other market data from Bloomberg. We obtain bank-level accounting data from Thomsen-Reuters Advanced Analytics and Bloomberg. We collect macroeconomic data from the OECD Metadata stats. Starting from the matched accounting and market data, we further drop banks with illiquid stocks, that is banks with infrequently traded stocks and low variability in stock prices[42]. Subsequently, all bank-specific variables are ratios, scaled by total assets, total income or total liabilities except bank size which is a variable defined in levels (logarithmic transformation of total assets). All variables are winsorized at the top and bottom 1 percent level to eliminate the adverse effects of outliers and misreported data. Information on the sample composition by country and by year can be found in panel A and B of Table 2.1.

[41] We end the sample period in 2012 in order to avoid interference with the implementation of the Basel III regulations (starting from 2013) that among other things introduced a leverage ratio as well as capital surcharges for systemically important banks. Doing so, we can study how banks treat regulatory capital ratios differently from plain leverage ratios in the absence of regulation on the latter. Moreover, we are able to study differential behavior by SIFIs and other banks in a period where the proposed methodologies for identifying G-SIFIs were not yet published for public consultation. These were published in January 2014.

[42] More specifically, we disregard a stock if daily returns are zero over five rolling consecutive days. We also only regard bank stocks if more than 70% of the daily returns over the period are non-zero returns.

Table 2.1. Sample composition

Panel A shows the sample country composition used for estimating the speed of adjustments towards target capital structures. It presents the distribution of 567 listed banks from 28 OECD countries, Australia, Austria, Belgium, Britain, Canada, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Mexico, Netherlands, Norway, Poland, Portugal, Slovakia, South Korea, Spain, Sweden, Switzerland, Turkey, and United-States, totaling 5164 bank-year observations.

Country	Number of banks	Number of Bank-Year observations	Country	Number of banks	Number of Bank-Year observations
Australia	5	60	Luxembourg	1	6
Austria	7	55	Mexico	2	6
Belgium	2	24	Netherlands	1	7
Canada	8	86	Norway	11	103
Czech	1	6	Poland	5	20
Denmark	16	124	Portugal	3	36
Finland	1	12	Slovakia	1	1
France	6	59	South Korea	2	11
Germany	5	45	Spain	6	60
Greece	8	44	Sweden	4	46
Hungary	1	5	Switzerland	7	44
Ireland	2	22	Turkey	11	45
Italy	15	123	United-Kingdom	5	55
Japan	22	149	United-States	409	3910
			Total	567	5164

Panel B shows the distribution of the number of observations (banks) by year, both in absolute numbers as well as frequencies

Year	Freq.	Percent
2001	369	7.15
2002	382	7.40
2003	391	7.57
2004	403	7.80
2005	423	8.19
2006	472	9.14
2007	488	9.45
2008	498	9.64
2009	453	8.77
2010	442	8.56
2011	425	8.23
2012	418	8.09
Total	5164	100

We end up with an unbalanced panel dataset of 567 banks[43], from the 28 major advanced OECD countries. It consists of 409 U.S. banks and 158 non-U.S. banks, among which 96 are European (from 22 countries) and 22 are Japanese. Although we only consider publicly-traded OECD banks, our sample conveniently represents the U.S., euro area and Japanese banking sectors. The listed

[43] We use data on commercial banks, bank holding companies and cooperative and savings banks (S&L U.S. Thrifts included) which represent 65%, 23% and 11% of the sample, respectively.

banks included in our sample account for approximately 73%, 52% and 31% of the total assets of all U.S., euro zone and Japanese banks recorded in BSI/Bloomberg statistics, respectively.

2.2. Bank capital, size and systemic risk

We focus on two types of capital measures. On the one hand, we focus on capital ratios from a regulatory perspective (Basel II/III), by using the Tier1 regulatory capital ratio, defined as Tier 1 equity over total risk-weighted assets (RWA) and the total capital ratio, defined as the sum of Tier 1 and Tier 2 equity to total RWA. On the other hand, we consider the average non-weighted common equity ratio (leverage ratio), defined as common equity over total non-weighted assets. Blum (2008) argues that capitalization measures based on cruder risk-exposure proxies may be more relevant for stock market participants or debt holders, because risk weights may be viewed as highly opaque and uninformative.

In our analysis, we devote special attention to Systemically Important Financial Institutions (SIFIs). A first approach to capture whether banks are systemically important is assessing their size. Bertay et al. (2013) suggest the use of two proxies of systemic size, namely a bank's absolute size, defined as the logarithm of a bank's total assets, as well as a bank's relative size, defined as a bank's total assets over gross domestic product (GDP). Barth and Schnabel (2013) argue and document that bank size (be it absolute or relative) is not a sufficient measure of systemic risk because it neglects aspects such as interconnectedness, correlation, and the economic context. They suggest the use of market-based measures of systemic importance, such as the delta Conditional Value-at-Risk (ΔCoVaR, by Adrian and Brunnermeier (2016)), which captures the contribution to system wide risk of an individual bank, or a measure of an individual bank's systemic risk vulnerability/exposure to system wide distress such as the Marginal Expected Shortfall (MES, see Acharya et al. 2016 and Brownlees and Engle, 2012). The difference between the two concepts is the directionality. The former assesses the extent to which distress at a bank contributes to system-wide stress, whereas the latter identifies the extent to which a bank's stock will lose value when there is a systemic event. We follow common practice and use the opposite of returns in the computation, such that losses are expressed with a positive sign. The MES and ΔCovaR will typically be positive and higher values correspond to larger systemic risk exposures and contributions. More information on the construction of these measures is in appendix A2.1. (see Appendix 2) and the papers referenced therein.

We also construct a SIFI-index by allocating bank-year observations in quintiles according to the four aforementioned characteristics (size, relative size, MES and ΔCovaR). The construction of a composite SIFI-index covers in a meaningful way four equally-weighted dimensions of systemic importance: a proxy of absolute size, systemic size, systemic exposure and contagion risk. More specifically, for each of the four metrics, we divide the sample in quintiles and give a score of one to banks in the lowest quintile, two in the second quintile and so on, with five for the highest. Subsequently, we take the sum of the scores associated to each of these quintiles of the four size or risk metrics to obtain an index that ranges from four to twenty, with the highest value representing the highest level of systemic importance that an individual bank can exhibit. This equally-weighted index of four characteristics provides a summary statistic of systemic importance because it combines several measures of systemic risk and size in one metric.

Panel A of Table 2.2. reports definitions, sources and summary statistics on the bank-level capital ratios, systemic risk measures and the control variables we use in our estimations. The average equity-to-asset, Tier1RWA and Total capital ratios are 9.4%, 11.7% and 14.2%, respectively. Thus, on average, throughout the sample period banks' ratios remained above the regulatory minimum. Panel B of Table 2.2. presents the summary statistics of systemic risk and size measures at the individual bank level for the full sample period. The mean of the natural logarithm of total book assets is 8.17 and the median is 7.44 (which correspond to about $3 billion and $2 billion respectively). Although, we only consider publicly traded OECD banks, our sample still exhibits considerable size heterogeneity across banks as is clear from the standard deviation (2.313) and the range between the 5th percentile and the 95th percentile [5.585 to 13.085]. The relative bank size measure confirms the heterogeneity across banks and the presence of large banks relative to a country's economic importance. For example, relative size varies between 0.00% (fifth percentile) and 51.8% (95th percentile) out of the domestic GDP, with a standard deviation of 19.6%. The summary statistics also reveal that banks vary in terms of systemic importance. The average values of MES and ΔCoVaR are 1.69% and 1.55% but the systemic risk measures are disperse with standard deviations of 1.91% and 1.74%, respectively.

In Table 2.2., Panel C, we also provide descriptive statistics for the rest of the bank-level variables we use to examine the determinants of bank capital and capital adjustment. Overall, across the sample period and countries, we observe that the average bank has low credit risk (average loan loss provisions to total loans of 0.7%), is strongly reliant on retail market funding (89.6%), is reasonably liquid as indicated by the ratio of net loans to total deposits (108.5%), has a low amount of fixed assets (1.6%), is moderately diversified in terms of assets (average loans to assets is 69%) and revenue (average non-interest income share of 19.6%).

Table 2.3. presents pairwise correlations among all variables at the bank level.

Table 2.2. Descriptive statistics

This table provides the definition and summary statistics for all the regression variables of a sample of 567 publicly listed OECD banks from 2001 to 2012. We report summary statistics for variables measured at time t. For all variables (in panels A, B and C), we provide number of observations, mean, standard deviation, as well as some percentiles (p5, p25, median, p75 and p95) for each variable, across all banks and countries.

Variable	Definition	Source	N	Mean	SD	p5	p25	p50	p75	p95
Panel A: Determinants of the target capital structure										
Leverage	Common equity ratio defined as total equity over total unweighted assets.	Bloomberg, Thomsen-Reuters Advanced Analytic (TRAA)	5164	0.094	0.044	0.038	0.069	0.089	0.109	0.167
Tier1RWA	Ratio of capital tier1 over to total risk weighted assets.	Bloomberg, Bankscope.	5164	0.117	0.036	0.070	0.093	0.111	0.135	0.183
Total capital	Ratio of total capital tier1 over to total risk weighted assets.	Bloomberg	5164	0.142	0.040	0.101	0.116	0.132	0.156	0.212
Log(Total Assets)	Natural logarithm of bank total assets (in USD billion).	TRAA	5164	8.167	2.313	5.585	6.407	7.435	9.437	13.085
Credit Risk	Loan Loss Provisions over net loans.	TRAA	5164	0.007	0.009	0.000	0.002	0.004	0.008	0.024
Retail Funding	Total customer deposit divided by total funding (st borrow+Tot.Cust.Dep).	Bloomberg, TRAA	5164	0.896	0.119	0.649	0.862	0.936	0.978	1.000
Liquidity	Net loans over total deposit.	TRAA	5164	1.085	0.314	0.581	0.904	1.080	1.253	1.597
Fixed Assets	Net fixed assets over total assets.	Bloomberg, TRAA	5164	0.016	0.011	0.003	0.009	0.014	0.021	0.036
Diversification	Non-interest income over total income.	TRAA	5164	0.196	0.110	0.053	0.118	0.175	0.252	0.415
Loan-to-asset	Net loans over total assets.	TRAA	5164	0.691	0.148	0.440	0.610	0.694	0.776	1.000
Efficiency	Cost income ratio, non-interest expense over total income.	TRAA	5164	0.449	0.131	0.246	0.365	0.439	0.526	0.683
RoA	Return on assets, defined as the ratio of net income to total assets.	TRAA	5164	0.007	0.010	-0.009	0.004	0.008	0.011	0.017
Panel B: Determinants of the adjustment speed										
MES (%)	Marginal Expected Shortfall	Appendix 2 Equation A1	5058	1.691	1.919	-0.422	0.250	1.237	2.607	5.576
ΔCoVaR (%)	ΔConditional Value-at-Risk	Appendix 2 Equation A2	5038	1.550	1.742	-1.006	0.392	1.320	2.602	4.717
TAGdp	Natural logarithm of bank total assets over GDP.	TRAA, OECD stats Metadata, IMF WEO	5164	0.064	0.196	0.000	0.000	0.000	0.005	0.518
logTA	Natural logarithm of bank total assets (in USD billion).	TRAA	5164	8.167	2.313	5.585	6.407	7.435	9.437	13.085
SIFI-index	aggregated systemic importance index	Subsection 4.1.2	4947	11.98	4.76	5	8	12	16	19
Panel C: Growth in adjustment mechanisms										
Total Equity	Average growth in total equity scaled by average total equity	Bloomberg, TRAA	5164	0.082	0.182	-0.160	0.007	0.065	0.146	0.383
Tier1 capital	Average growth in Tier1 capital scaled by average total equity	Bloomberg, Bankscope.	5014	0.081	0.172	-0.147	0.008	0.061	0.136	0.377
Retained Earnings	Average growth in retained earnings by average total equity	Bloomberg, Bankscope.	5164	0.023	0.136	-0.191	-0.012	0.040	0.086	0.186
Total Assets	Average growth in total assets scaled by average total assets	Bloomberg, TRAA.	5164	0.081	0.195	-0.272	0.002	0.068	0.160	0.424
Net Loans	Average growth in net loans scaled by average total assets	Bloomberg, TRAA.	5164	0.054	0.093	-0.082	-0.003	0.043	0.098	0.227
Risk-Weighted Assets	Average growth in risk-weighted assets by average total assets	Bloomberg, TRAA.	5014	0.056	0.124	-0.107	-0.006	0.044	0.104	0.254
Total Liabilities	Average growth in total liabilities by average total liabilities	Bloomberg, TRAA.	5164	0.083	0.125	-0.091	0.006	0.064	0.144	0.313
LT borrowing	Average growth in long-term borrowing by average total liabilities	Bloomberg, TRAA.	5160	0.010	0.048	-0.056	-0.010	0.000	0.024	0.095
ST borrowing	Average growth in short-term borrowing scaled by average total liabilities	Bloomberg, TRAA.	5164	0.004	0.048	-0.073	-0.016	0.000	0.023	0.084
ΔLeverage	Change in common equity ratio (percentage)	Bloomberg, TRAA.	5164	-0.031	2.497	-3.987	-0.646	-0.018	0.563	3.905
ΔTier1RWA	Change in Tier1 capital ratio (percentage)	Bloomberg, Bankscope.	5164	0.126	1.727	-2.600	-0.670	0.080	0.820	3.000
ΔTotal capital	Change in total capital ratio (percentage)	Bloomberg, Bankscope.	5164	0.061	1.847	-2.860	-0.795	0.020	0.900	3.050
groLeverage	Average growth rates of common equity ratio.	Bloomberg, TRAA.	5164	0.023	0.239	-0.327	-0.076	-0.002	0.073	0.470
groTier1RWA	Average growth rates of Tier1 capital ratio.	Bloomberg, Bankscope.	5164	0.023	0.155	-0.195	-0.057	0.007	0.078	0.310
groTotal capital	Average growth rates of total capital ratio.	Bloomberg, Bankscope.	5164	0.014	0.131	-0.180	-0.058	0.001	0.069	0.254

Table 2.3. Pairwise Correlation matrix

This table reports the correlation matrix of the main regression variables for the sample of publicly listed OECD banks from 2001 to 2012. *, ** and *** indicate significance of pair-wise correlations at the 10%, 5%, and 1% level, respectively.

	Capital Ratio	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Tier1RWA (1)	0.591***	1													
Total capital (2)	0.646***	0.788***	1												
Log(Total Assets (3)	-0.366***	-0.291***	-0.223***	1											
Credit Risk (4)	-0.0349*	-0.0352*	-0.0633***	0.0560***	1										
Retail Funding (5)	0.303***	0.214***	0.138***	-0.553***	0.0373**	1									
Liquidity (6)	0.174***	0.320***	0.243***	-0.311***	-0.0312*	0.470***	1								
Fixed Assets (7)	0.253***	0.132***	0.0438**	-0.360***	0.106***	0.269***	0.177***	1							
Diversification (8)	-0.150***	-0.0725***	-0.108***	0.515***	0.0563***	-0.265***	-0.0176	0.0328*	1						
Loan-to-asset (9)	0.216***	-0.144***	-0.196***	-0.247***	0.0889***	0.246***	-0.438***	0.197***	-0.228***	1					
Efficiency (10)	0.0892***	0.111***	0.0343*	-0.160***	0.195***	0.274***	0.347***	0.370***	0.400***	-0.00376	1				
RoA (11)	0.275***	0.223***	0.154***	-0.0218	-0.626***	0.0219	0.0575***	-0.0361**	0.0781***	-0.0165	-0.299***	1			
MES (12)	-0.0593***	-0.0373**	-0.0495***	0.528***	0.303***	-0.221***	-0.143***	-0.143***	0.249***	-0.0728***	-0.0181	-0.143***	1		
ΔCoVaR (13)	0.0475***	0.0111	-0.00522	0.392***	0.245***	-0.130***	-0.0895***	-0.0951***	0.185***	0.0249	0.0133	-0.0850***	0.642***	1	
TAGdp (14)	-0.338***	-0.165***	-0.124***	0.651***	-0.00680	-0.518***	-0.314***	-0.269***	0.299***	-0.213***	-0.147***	-0.0779***	0.301***	0.195***	1
SIFI-index (15)	-0.201***	-0.184***	-0.170***	0.831***	0.167***	-0.405***	-0.264***	-0.285***	0.421***	-0.0946***	-0.109***	-0.0496***	0.777***	0.696***	0.423***
N	5164														

3. Leverage versus regulatory capital requirements: dynamic adjustment mechanisms

3.1. Inferring adjustment speeds and implied targets: a partial adjustment model

In a frictionless world, banks would always maintain their target capital ratio. However, if adjustment costs are significant, the bank's decision to adjust its capital structure depends on the trade-off between the adjustment costs and the costs of operating with suboptimal leverage (Flannery and Rangan (2006), Flannery and Hankins (2013)). To allow for sluggish adjustment, it has become common practice in the empirical (corporate and bank) capital structure literature to model leverage using a partial adjustment framework (see e.g., Flannery and Rangan (2006), Lemmon et al. (2008), Gropp and Heider (2010), De Jonghe and Öztekin (2015) and Lepetit et al. (2015)). In a partial adjustment model, a bank's current capital ratio, $K_{ij,t}$, is a weighted average (with weight $\lambda \in [0,1]$) of its target capital ratio, $K^{*}_{ij,t}$, and the previous period's capital ratio, $K_{ij,t-1}$, as well as a random shock, $\varepsilon_{ij,t}$:

$$K_{ij,t} = \lambda K^{*}_{ij,t} + (1-\lambda)K_{ij,t-1} + \varepsilon_{ij,t}. \quad (1)$$

Each year, the typical bank closes a proportion λ of the gap between its actual and target capital levels. The smaller the lambda, the more rigid bank capital is, and the longer it takes for a bank to return to its target after a shock to bank capital. Thus, we can interpret λ as the speed of adjustment and its complement $(1-\lambda)$ as the portion of capital that is inertial.

Banks' target capital ratio is unobserved and is not necessarily constant over time. We model each bank's target level of bank capital as a function of observed (lagged) bank and country characteristics, $X_{ij,t-1}$. We follow the recent literature on the selection of the variables that determine leverage targets[44]. Brewer et al. (2008) and Gropp and Heider (2010) provide surveys and investigate motivations on the factors that explain banks' target capital ratio.

$$K^{*}_{ij,t} = \beta X_{ij,t-1} \tag{2}$$

We also account for two sources of unobserved heterogeneity: bank fixed effects (which subsume country fixed effects) and year fixed effects. Flannery and Rangan (2006), Lemmon et al. (2008), Huang and Ritter (2009), and Gropp and Heider (2010) advocate the importance of including firm (bank) dummies for an unbiased estimation of targets.

Substituting the equation of target leverage, equation (2), in equation (1) yields the following specification:

$$K_{ij,t} = \lambda\beta X_{ij,t-1} + (1-\lambda)K_{ij,t-1} + \varepsilon_{ij,t} \tag{3}$$

In the presence of a lagged dependent variable and a short panel, using ordinary least squares (OLS) or a standard fixed effects model would yield biased estimates of the adjustment speed. Therefore, following Flannery and Hankins (2013), we estimate equation (3) using Blundell and Bond's (1998) generalized method of moments (GMM) estimator[45].

We estimate the partial adjustment model of equation (3) separately for each of the three alternative capital ratios: Leverage, Tier1RWA and Total capital. The results are reported in Table 2.4.

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[44] We include proxies for bank absolute size (natural logarithm of total assets), bank profitability (return on assets), bank credit risk (loan loss provisions to net loans), retail funding (customer deposits to total funding), liquidity ratio (net loans to total assets). We also include the ratio of fixed assets to total assets, a diversification proxy (non-interest income to total income) and a bank efficiency proxy (non-interest expense to total income).

[45] Using Stata's XTABOND2 procedure.

Table 2.4. Estimating the target capital ratio

This table presents results for two-step System Generalized Method of Moments (GMM) estimation (Blundell and Bond's (1998)) of a partial adjustment model of bank capital: $k_{i,j,t} = (1-\lambda)k_{i,j,t-1} + \lambda(\beta X_{i,j,t-1} + \delta' Country + \tau' Year + \mu_{i,j}) + \varepsilon_{i,j,t}$. Bank capital, $k_{i,j,t}$, is measure of capital for bank i in country j in period t. We use a sample of 567 listed banks from 28 OECD countries, over the 2000–2012 period. We estimate the partial adjustment model separately using three alternative capital ratio measures: Leverage ratio defined as total equity over total assets, Tier1RWA defined as regulatory capital Tier 1 capital over risk-weighted assets and Total capital defined as the sum of Tier 1 and Tier 2 capital to risk-weighted assets. $X_{i,j,t-1}$ is a vector of bank-characteristics that define banks' target capital ratio. To check the validity of the estimators, we conduct two tests, over-identifying test and test for autocorrelation. Hansen test is a test of exogeneity of all instruments as a group. Arellano-Bond test is a test of the absence of second order residual autocorrelation. In below, we report the summary statistics (mean, standard deviation, p5, p25, p50, p75 and p95) of the estimated target capital ratio. p-values based on robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A. Estimating bank capital targets

	(1)	(2)	(3)
Dependents	Leverage	Tier1RWA	Total capital
Lagged dependent variable	0.518***	0.690***	0.648***
	(0.0512)	(0.0403)	(0.0563)
Log(Total Assets)	-0.00244***	-0.00109***	-0.00110**
	(0.000681)	(0.000404)	(0.000549)
Credit Risk	0.199*	0.208***	0.234***
	(0.108)	(0.0749)	(0.0788)
Retail Funding	0.0576***	-0.000169	0.00265
	(0.00657)	(0.00442)	(0.00491)
Liquidity	-0.0458***	0.000503	-0.00358
	(0.00661)	(0.00308)	(0.00389)
Fixed Assets	-0.121	0.00789	-0.0309
	(0.139)	(0.0611)	(0.0783)
Diversification	-0.0120	-0.00919*	-0.0144**
	(0.00819)	(0.00541)	(0.00641)
Loan-to-asset	-0.137***	-0.0270***	-0.0351***
	(0.0133)	(0.00653)	(0.00898)
Efficiency	0.00296	-0.00527	-0.00821
	(0.00758)	(0.00530)	(0.00559)
RoA	0.197	0.0582	0.0761
	(0.134)	(0.0901)	(0.101)
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5,164	5,164	5,164
Bank	567	567	567
Country	28	28	28
Hansen test (p-value)	0.242	0.298	0.960
AR2 test (p-value)	0.315	0.669	0.570

Panel B. Deriving capital deviations

	N	Mean	SD	p5	p25	p50	p75	p95
Dev_CAPR	5164	-0.000	0.049	-0.081	-0.014	0.001	0.016	0.089
Dev_Tier1RWA	5164	0.004	0.031	-0.046	-0.011	0.006	0.022	0.048
Dev_TotalCap	5164	0.002	0.031	-0.047	-0.012	0.004	0.019	0.042

We focus the description of the results on the variable of interest, which is the coefficient on the lagged dependent variable.[46,47] The estimated adjustment speeds (λ, Eq. (3)) are significant and quite different for the three capital ratio models. The speed of adjustment for the non-weighted equity-to-asset capital ratio structure is 0.482 (=1–0.518, where 0.518 is the coefficient of the lagged equity-to-asset reported in the first column)[48]. The adjustment speed for the regulatory capital ratios is lower, namely 0.31 (1-0.69, column 2) for the Tier 1 RWA ratio and 0.352 (1-0.648, column 3) for the total capital ratio. This implies that adjustment is partial for each of the capital ratios, but faster when banks are closing the equity-to-asset ratio deviation during the next period t, than when they are closing the two regulatory capital deviations (columns 2 and 3). Another informative metric, which provides economic meaning to the estimated parameters, is the half-life. The half-life provides an indication of the time required for banks to halve the gap between their actual capital ratio and their target. The estimated adjustment speeds for the leverage, Tier1 RWA and total capital ratios deviations correspond with half-lives of 1.05, 1.88 and 1.59 years, respectively. The results highlight that banks are slightly more concerned about readjusting quickly towards optimal leverage ratios compared to the speed to adjust towards optimal regulatory capital. This finding can be rationalized by at least two arguments. On the one hand, it could indicate that deviations from optimal leverage ratios are more costly for bank shareholders (as the target capital should be chosen such to maximize bank value) than deviations from regulatory capital. On the other hand, it could also be created by differences in adjustment costs and the range of adjustment mechanism that can be used. All else equal, banks have more (and less costly) options in asset adjustments that affect non-risk weighted assets than risk weighted assets. For example, government bonds (of OECD countries) are securities that are easily adjustable, but have a zero risk-weight. They could help to adjust the leverage ratio, but not the regulatory capital ratios.

[46] For each model, we also report the coefficient estimates and the significance levels of bank-specific drivers of the target capital ratios. Smaller, riskier, and banks with more asset diversification (less loans) hold higher capital ratios. Besides, less liquid banks and banks with more retail funding have a higher equity-to-target ratio, but not higher regulatory capital ratios.

[47] At the bottom of panel A of Table 2.4., we report test statistics documenting the validity of the instruments. In particular, two crucial tests are required. Using the Hansen J test (test of exogeneity of the instruments), we cannot reject the null of joint validity of all GMM instruments (lagged values); we hence confirm the validity of the instruments. We also use the Arellano and Bond AR(2) test, and confirm the absence of second order serial autocorrelation in the residuals.

[48] These speeds of adjustment are similar to those of European banks (0.34, Lepetit, et al., 2015), a sample of banks in the U.S. and 15 European countries (0.47, Gropp and Heider, 2010), and large U.S. banks (0.40, Berger et al., 2008).

3.2. Balance sheet adjustment mechanisms

In this section, we investigate how banks adjust their capital structure to close their deviation (gap) from the target. To do that, we use the following procedure. Based on the estimated vector of coefficients $\hat{\beta}$ from equation (3) we can compute fitted time-varying target capital ratios[49] for each individual bank, $\widehat{K^*_{i,j,t}}$. Subsequently, we compute the time-varying capital deviation for bank i at time t-1, hereinafter called "the gap", and defined as $GAP_{ij,j,t-1}= \widehat{K}^*_{ij,t} - K_{ij,t-1}$. If banks make adjustments when there is a gap, then these adjustments should be reflected in their observed balance sheet transactions. We follow the approach of De Jonghe and Öztekin (2015) and evaluate the percentage growth rates in various balance sheet components for three quintiles of the gap (first, middle and fifth). To do this, we first allocate banks to quintiles based on their gap at the end of year. Subsequently, we compute the yearly change in the relevant variable in the following year. We then average these growth rates across all bank-year observations in that quintile.

In a first step, we analyze the balance sheet adjustments for each capital ratio separately. These results are reported in Table 2.5. In a second step, we examine balance sheet adjustments in situations where the gap of the leverage ratio and Tier 1 RWA ratio have similar or opposite signs (yielding four cases; (i) both signal overcapitalization, (ii) both signal undercapitalization, (3) overcapitalized leverage, but undercapitalized regulatory, and (4) undercapitalized leverage, but overcapitalized regulatory).

[49] We perform additional specification checks. We subject the baseline capital adjustment model (Eq. 3) to three alternative specifications, so as to re-estimate the target capital ratio, re-compute the deviation and ascertain that our results are not driven by the first stage regression specification. First, we follow Flannery and Rangan (2006) and use a pooled ordinary least squares OLS regression. Second, we follow Berrospide and Edge (2010) and Lemmon et al. (2008) and use country fixed effect regression to control for unobserved country heterogeneity while also controlling for year fixed effects. Third, we use a time varying country fixed effect to capture time varying country-specific regulation or business cycle effects on capital and heterogeneity at the country-year level. Non-reported results and analyses indicate that the statistical significance, the economic magnitudes as well as these alternative regression specifications are robust.

Table 2.5. Impacts of capital deviations quintiles on capital adjustment mechanisms

The table provides evidence of whether the average annual growth rates of the main banks' adjustment mechanisms vary in various quintiles of the capital ratio deviation (gap) for three definitions of capital deviations (leverage ratio, Tier1RWA and Total capital, respectively). For each of the three definitions of capital ratios, we report three columns corresponding with three of five quintiles (bottom, middle, and top quintile) of the gap between the estimated target and lagged actual capital ratio. Quintile 1 (Q1) corresponds with the most overcapitalized banks (underleveraged banks, i.e. largest negative gap), Quintile 3 (Q3) banks are closest to their capital ratio target, whereas banks in quintile 5 (Q5) are the most undercapitalized (overleveraged banks, i.e. largest positive gap). Thus, we compare the change rates of the capital ratios (ΔCapital ratio) and the scaled annual growth rates of the financial characteristics: the three definitions of capital ratios (groCapital ratio), total assets (Assets), total common equity (Equity), total liabilities (Liabilities), net loans (Loans), risk-weighted-assets (RWA), long-term (LT) and short-term (ST) borrowing, internal capital (Retained Earnings) and external capital (Tier1 capital). All variables are expressed in percentages (see Table 2.2. for more details). For each variable, we report the average growth rate, the number of observations per group (below the mean value) and the results of pairwise t-tests of equality of means of the extreme quintiles compared with the middle quintile, respectively. We report the difference in mean as well as the significance level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, for a bilateral test. Differences in the observations are due to differences in data availability.

	Leverage Gap			Test for equality of mean		Tier1RWA Gap			Test for equality of mean		Total capital Gap			Test for equality of mean	
Adjustment mechanisms	Q1	Q3	Q5	Quintile 1 vs 3	Quintile 3 vs 5	Q1	Q3	Q5	Quintile 1 vs 3	Quintile 3 vs 5	Q1	Q3	Q5	Quintile 1 vs 3	Quintile 3 vs 5
(Means/Observations)	Overcap.		Undercap.	p-value	p-value	Overcap.		Undercap.	p-value	p-value	Overcap.		Undercap.	p-value	p-value
ΔCapital ratio	-2.30%	0.07%	2.06%	**-2.37*** **	**-1.99*** **	-1.14%	0.09%	1.37%	**-1.23*** **	**-1.28*** **	-1.37%	0.04%	1.41%	**-1.41*** **	**-1.37*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
groCapital ratio	-15.31%	1.48%	23.54%	**-16.79*** **	**-22.06*** **	-7.63%	1.19%	14.15%	**-8.82*** **	**-12.96*** **	-7.62%	0.52%	11.74%	**-8.14*** **	**-11.22*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
Total Assets	22.34%	8.41%	-7.31%	**13.93*** **	**15.72*** **	13.34%	9.56%	1.32%	**3.78*** **	**8.24*** **	13.22%	8.08%	2.41%	**5.14*** **	**5.67*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
Total Liabilities	11.44%	8.73%	4.61%	**2.71*** **	**4.12*** **	12.49%	8.40%	3.96%	**4.09*** **	**4.44*** **	11.94%	8.10%	4.26%	**3.84*** **	**3.84*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
Common Equity	4.14%	9.37%	10.22%	**-5.23*** **	-0.85	6.17%	7.92%	10.45%	**-1.75** **	**-2.53*** **	5.62%	7.50%	10.73%	**-1.88*** **	**-3.23*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
Net Loans	6.81%	6.01%	2.80%	0.80*	**3.21*** **	8.64%	5.66%	1.60%	**2.98*** **	**4.06*** **	8.15%	5.33%	1.79%	**2.82*** **	**3.54*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1033		
Risk-Weighted Assets	7.73%	6.33%	2.64%	**1.4** **	**3.69*** **	11.04%	6.06%	-0.31%	**4.98*** **	**6.37*** **	9.87%	5.30%	0.87%	**4.57*** **	**4.43*** **
	997	1000	1008			995	1003	1003			1000	1003	1006		
LT borrowing	2.01%	1.06%	-0.51%	**0.95*** **	**1.57*** **	1.68%	1.09%	0.10%	**0.59*** **	**0.99*** **	1.75%	0.85%	0.15%	**0.90*** **	**0.70*** **
	1031	1033	1032			1033	1033	1030			1033	1033	1030		
ST borrowing	0.72%	0.31%	0.29%	0.41*	0.02	1.07%	0.51%	-0.67%	**0.56*** **	**1.18*** **	1.08%	0.48%	-0.55%	**0.60*** **	**1.03*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1033		
Retained Earnings (internal capital)	0.88%	3.22%	2.39%	**-2.34*** **	0.083	1.67%	2.75%	0.85%	**-1.08*** **	**1.90*** **	1.63%	3.09%	0.99%	**-1.46*** **	**2.10*** **
	1033	1033	1032			1033	1033	1032			1033	1033	1032		
Tier1 (external capital)	5.64%	9.67%	8.29%	**-4.03*** **	1.38*	5.30%	8.00%	10.78%	**-2.7*** **	**-2.78*** **	4.53%	7.34%	11.25%	**-2.81*** **	**-3.91*** **
	997	1000	1008			995	1003	1003			1000	1003	1006		

Looking at the three capital specifications, Table 2.5. presents the average growth rates of the main balance sheet items for banks allocated to the first quintile (i.e. most overcapitalized/underleveraged banks), the third quintile (i.e. banks with a negligible gap) and the fifth quintile (i.e. most undercapitalized/overleveraged banks) based on their gap at the end of year. For each capital set, we report the p-values of difference in means tests using the third quintile as benchmark.

First, with respect to the leverage ratio, overcapitalized (underleveraged) banks have a negative and significant change in leverage ratio (-2.30% vs. 0.07%) compared with the change rate of the third quintile, implying that banks reduce their capital ratio to reach their target capital level. In fact, facing an opportunity cost, banks have no incentives to remain above their targeted leverage ratio. Therefore, bank managers make proactive efforts to lever up so to converge to their target and reduce the ongoing costs of capital surplus accordingly. To achieve a negative capital growth, our results show for a global sample of banks that they significantly expand their asset growth (22.34% vs. 8.41%), debt growth (11.44% vs. 8.73%), while equity growth is significantly slowed down (4.14% vs. 9.37%) always compared to the growth rates in the third quintile (i.e. when the gap between actual and target capital is negligible). Analyzing the mechanisms through which those banks lever up, the results indicate that underleveraged banks progress by increasing loans (6.81%), riskier assets (7.73%), and to a smaller (economic) extent also long-term debt (2.01%). We note that the average loan growth is not economically significantly different with respect to the growth rate of the third quintile (6.01%). In the same line, banks having a capital surplus shrink their internal funding, the growth in bank retained earnings is roughly zero (0.88%), and the external funding (Tier1) growth is substantially lowered (5.64% vis-à-vis 9.67%). Such results indicate that banks tend to lever up by engaging more in risky activities, being financed more with long-term debt, but without engaging any significant change in their loan policy or reduction in the capital level.

In contrast, for undercapitalized (overleveraged) banks, results show that the change in leverage ratio is significantly larger (2.06% vs. 0.07%) than the third quintile, implying that bank managers also actively rebalance their capital ratios to revert to their targeted leverage when they are undercapitalized. To that extent, facing regulatory and market constraints, banks with a capital shortfall are more prone to deleverage in order to close the gap and get to their optimal target. More specifically, results for those undercapitalized banks show that the average asset expansion is significantly negative (-7.31% vs. 8.41%) and the average debt growth is significantly lower (4.61% vs. 8.73%), while the average equity growth is not significantly higher than the growth rate of the benchmark. Not surprisingly, this translates into a rationalized capital adjustment for banks to reach their leverage capital target, only by reducing assets rather than injecting external equity which is costly because of frictions and governance problems.

On the whole, what would actually pose a problem to the real economy is if lending falls when banks are undercapitalized but does not actually increase when they are overcapitalized. Hence, we analyze the key mechanisms through which overleveraged bank de-lever and rebalance their capital structure. We notice that all the subcomponents of the asset and the liabilities sides of balance sheet shrink. Thus, the average growth of loans (2.80% vs. 6.01%), riskier assets (2.64% vs. 6.33%), and long-term borrowings (-0.51% vs. 1.06%) are significantly lower than the benchmark. Indeed, deleveraging is achieved by downsizing (selling assets), restricting loan policy (reducing lending vis-à-vis a lower amount of debt), lowering risk-weighted assets (substituting riskier assets for safer ones) and shrinking long-term debt.

Second, with respect to regulatory capital ratio (Tier1RWA[50]), overcapitalized banks have a negative growth in the Tier1 capital ratio which is significantly different from the change rate in the third quintile of the gap (-1.14% vs. 0.09%). Hence, we inspect growth rates of adjustment mechanisms that lead these banks to reduce their capital surplus to converge to their optimal regulatory level. Findings show that banks allocated in this quantile lever up by a large and significant increase of their asset growth (13.34% vs. 9.56%), debt growth (12.49% vs. 9.56%), while their equity growth is significantly lower (6.17% vs. 7.92%) compared to the growth rates of the benchmark. Thus, overcapitalized banks proceed by significantly altering all the subcomponents of the balance sheet with regards to the benchmark. This translates into an expansion in loan (8.64%), risky assets (11.04%), long-term debt (1.68%) and short-term debts (1.07%); and a slow-down in internal capital (1.67%) and external capital (5.30%) growth. Therefore, a Tier1 capital surplus leads banks to lever up by combinations of an asset expansion

[50] Results and capital management patterns are similar for both regulatory measures of capital. Here, we only present results of Tier1 regulatory capital ratio.

strategy, risk-taking activities, an aggressive loan policy, long and short-term debt financing policies and a slower equity growth but without engaging any reduction in the capital level.

Concerning the undercapitalized banks, results show that the Tier 1 regulatory capital change is significantly higher (1.37% vs. 0.09% for equity-to-assets specification) than the change rate of the third quintile, where the gap is close to zero. Accordingly, banks are expected to increase their regulatory capital, so to reach their internal regulatory capital target and to comply with capital requirements. They proceed by significantly shrinking asset growth (1.32% vs. 9.56%), debt growth (3.96% vs. 8.40%) and significantly expanding equity (10.45% vs. 7.92%) compared with growth rates of the benchmark. Based on these results, we then analyze the key mechanisms through which these banks de-lever and rebalance their capital structure. Similarly, we find that these banks react actively by significantly altering all the subcomponents of the balance sheet, with regards to the benchmark. Results show that the loan growth (1.60%), risky asset growth (-0.31%), long-term debt (0.10%) and short-term debts (-0.67%) are significantly lower than the growth rates of the benchmark, while the external capital growth (10.78%) is significantly larger than the benchmark. Thus, facing a regulatory capital shortfall, deleveraging takes place by injecting external capital (equity issues), but not by using internal capital (earnings retention). Deleveraging is also achieved by downsizing, tightening loan policy (reducing lending vis-à-vis a lower amount of debt), selling risky assets and reducing long and short-term financing (selling debts). In the rightmost panel, we also show the adjustment mechanisms for the total capital ratio. They are by and large similar to the ones of the Tier 1 risk-weighted capital ratio and are for the sake of space not discussed here.

We now turn to an analysis of balance sheet adjustments when examining the joint stance of the leverage gap and the regulatory capital (Tier 1 capital over risk-weighted assets) gap. The results are reported in Table 2.6. The four blocks of columns correspond with the situations where (i) both signal overcapitalization, (ii) both signal undercapitalization, (iii) overcapitalized leverage ratio, but undercapitalized regulatory ratio, and (iv) undercapitalized leverage ratio, but overcapitalized regulatory ratio.

Table 2.6. Capital and adjustment mechanisms: joint stance of the leverage gap and Tier1RWA gap

This table presents average annual growth rates of the main banks' adjustment mechanisms in four blocks of columns, when examining the joint stance of the leverage gap and the regulatory capital. We report information for four groups of banks based on the situations of joint stance of the leverage gap and Tier1RWA gap: the situations where both signal overcapitalization (Group 1), both signal undercapitalization (Group 2), overcapitalized leverage, but undercapitalized regulatory (Group 3), and undercapitalized leverage, but overcapitalized regulatory (Group 4). Thus, we compare the change rates of the capital ratios (ΔLeverage and ΔTier1RWA) and the scaled annual growth rates of the financial characteristics: capital ratios (groLeverage and groTier1RWA), total assets (Assets), total common equity (Equity), total liabilities (Liabilities), net loans (Loans), risk-weighted-assets (RWA), long-term (LT) and short-term (ST) borrowing, internal capital (Retained Earnings) and external capital (Tier1 capital). All variables are expressed in percentages (see Table 2.2. for more details). For each variable, we report the number of observations per group, the average growth rate and the test results of pairwise t-tests of equality of means of a specific growth rate in a given group of banks with the corresponding growth rate for another group. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, for a bilateral test. Differences in the observations are due to differences in data availability.

Adjustment mechanisms (Observations, Means, p-values-**%**)	Group 1: **Above** target for leverage: k*<k **Above** target for Tier1RWA: k*<k		Group 2: **Below** target for leverage: k*>k **Below** target for Tier1RWA: k*>k		Test for equality of mean Group 1 vs. 2	Group 3: **Above** target for leverage: k*<k **Below** target for Tier1RWA: k*>k		Group 4: **Below** target for leverage: k*>k **Above** target for Tier1RWA: k*<k		Test for equality of mean Group 3 vs. 4	Test for equality of mean: Group 1 vs. 3	Group 1 vs. 4	Group 2 vs. 3	Group 2 vs. 4
					p-value					p-value	p-value	p-value	p-value	p-value
	(1)		(2)		(3)	(4)		(5)		(6)	(7)	(8)	(9)	(10)
ΔLeverage	1302	-1.24%	1903	1.14%	**-2.38*****	1167	-0.87%	792	0.37%	**-1.42*****	**-0.37*****	**-1.61*****	**2.01*****	**0.77*****
ΔTier1RWA	1302	-0.78%	1903	0.81%	**-1.59*****	1167	0.47%	792	-0.54%	**1.01*****	**-1.25*****	**-0.24*****	**0.34*****	**1.35*****
groLeverage	1302	-8.20%	1903	13.83%	**-22.03*****	1167	-5.79%	792	4.00%	**9.79*****	**-2.41*****	**-12.20*****	**19.62*****	**9.83*****
groTier1RWA	1302	-5.22%	1903	8.24%	**-13.46*****	1167	5.31%	792	-3.99%	**9.30*****	**-10.53*****	**-1.23****	**2.93*****	**12.23*****
Total Assets	1302	15.40%	1903	0.08%	**15.32*****	1167	13.55%	792	7.10%	**6.45*****	**1.85*****	**8.30*****	**-13.47*****	**-7.02*****
Total Liabilities	1302	12.42%	1903	5.55%	**6.87*****	1167	7.57%	792	9.16%	**-1.59*****	**4.85*****	**3.26*****	**-2.02*****	**-3.61*****
Common Equity	1302	5.58%	1903	10.58%	**-5.00*****	1167	6.20%	792	9.63%	**-3.43*****	-0.62	**-4.05*****	**4.38*****	0.95
Net Loans	1302	8.17%	1903	3.43%	**4.74*****	1167	4.17%	792	7.34%	**-3.17*****	**4.00*****	0.83*	**-0.74****	**-3.91*****
Risk-Weighted Assets	1258	9.85%	1858	2.88%	**6.97*****	1132	3.34%	766	8.77%	**-5.43*****	**6.51*****	1.08*	-0.46	**-5.89*****
LT borrowing	1300	2.15%	1903	0.09%	**2.06*****	1165	1.23%	792	0.71%	**0.52****	**0.92*****	**1.44*****	**-1.14*****	**-0.62*****
ST borrowing	1302	0.89%	1903	-0.03%	**0.92*****	1167	0.06%	792	1.02%	**-0.96*****	**0.83*****	-0.13	-0.09	**-1.05*****
Retained Earnings (internal capital)	1302	1.68%	1903	3.10%	**-1.42*****	1167	0.87%	792	3.52%	**-2.65*****	0.81	**-1.84*****	**2.23*****	-0.42
Tier1 capital (external capital)	1258	6.04%	1858	9.98%	**3.94*****	1132	8.00%	766	6.84%	1.16	**-1.96*****	-0.80	**1.98*****	**3.14*****

Table 2.6. shows that when both capital ratios show overcapitalization (Group 1), banks' equity growth is significantly lower, while asset growth and debt growth are significantly larger than when both capital ratios show undercapitalization (Group 2). In line with previous results, overcapitalized banks mainly lever up by expanding all assets and liabilities items, loans (8.1%), risky asset (9.85%), long-term debt (2.15%) and short-term debt (0.89%), which are statistically larger than the growth rates of the group of undercapitalized banks. In contrast, deleveraging for undercapitalized banks (Group 2) is more likely realized by external capital (9.98%) and earning retention (3.10%), which are statistically larger than the growth rates of the group of overcapitalized banks.

Now, we investigate the main disparities between these two groups of banks with two other groups that are regulatory overcapitalized but undercapitalized with regards to the leverage ratio, or vice-versa (Groups 3 and 4). Test results for equality of means test are reported in the rightmost panel. First, we explore differences with regards to Group 1. Underleveraged but regulatory undercapitalized banks (Group 3) have a significantly smaller asset growth compared to Group 1, and this is true for all their subcomponents (loan and risky assets) and liabilities growth (only short-term debt) compared to the growth rates of the overcapitalized banks (Group 1). However, in economic terms, we notice especially differences in the adjustments via loan growth and risk-weighted assets. Banks in Group 3 increase leverage mainly by expanding assets with low risk-weights. Regarding equity growth, their external capital growth is significantly larger compared to the growth rate of banks in Group 1. The non-significant growth of equity of banks in Group 3 (with regards to Group 1) is mainly due to the significantly lower growth of earnings retention (0.87% vs. 1.68%). Thus, to increase their regulatory capital, besides raising more external capital and decreasing risky assets, banks in Group 3 restrict their lending and long- and short-term financing policies. However, capital management of the banks in Group 4 (overleveraged but regulatory overcapitalized) differ from those in Groups 1 and 3. They are overleveraged, but regulatory overcapitalized (w.r.t. their target). Compared to underleveraged banks, their assets grow much less quickly and relatively speaking they rely more on earnings retention than external capital growth. Most strikingly is that the growth in net loans and risk-weighted assets is of similar magnitude in group 1 and 4, even though total asset growth in group 4 is much smaller compared to growth in group 1.

In sum, this analysis provides interesting insights in the mechanisms and the relative dominance of leverage vis-à-vis risk-weighted capital ratios. The sign of the leverage and risk-weighted capital ratio gap determines whether equity is adjusted via earnings retention (leverage dominates regulatory capital) or externally raised equity (regulatory stance matters). Moreover, it also determines whether asset side adjustments are done via loans and risky assets (regulatory gap matters), versus safer assets with a lower risk weight (such as securities).

4. Bank capital adjustments: are SIFIs different?

Adjustment speed depends on the trade-off between the costs (or the benefits) of being off the capital target and the costs of adjusting back to the optimal (target) capital structure. Both the cost of being off-target and the cost of adjustment need not be homogenous for all banks.

Theory and empirical studies document that institutional features affect banks' speed of adjustment by restricting the access to equity and debt markets, limiting the flexibility to easily alter capital structure and imposing more stringent capital requirements and supervisory monitoring (e.g. financial constraints, differences in regulatory and supervisory environments and financial system characteristics [51]). Not only a country's institutional setting but also bank-level characteristics could reduce (increase) costs or increase (reduce) benefits of being close to the target and thus lead to higher (lower) adjustment speeds (see Laeven et al. (2015), among others). We hence hypothesize that as costs and benefits of rebalancing the capital structure might be affected with bank-individual systemic risk and size characteristics, so does the speed with which banks adjust leverage and regulatory capital to reach their targets.

This section involves two steps. We first describe the approach we take to estimate the effects of systemic risk and size on the speed of adjustment of leverage and regulatory capital ratios toward their targets. We then examine their impact on banks' capital structure and balance sheet adjustments. Addressing this issue is paramount to draw effective regulatory and policy implications regarding SIFIs.

[51] See e.g. De Jonghe and Öztekin 2015; John et al., 2012; Faulkender et al., 2012a; Öztekin and Flannery 2011; Berger et al. 2008; Flannery and Hankins, 2013, among others.

4.1. Do SIFIs adjust their capital ratios quicker?

To analyze whether or not (relative) size and systemic risk (exposure/contribution) affects the speed of adjustment, we extend the partial adjustment model (as in equation (3)) to allow for time-varying and bank-specific adjustment speeds. We follow the approach of Berger et al. (2008), Oztekin and Flannery (2012) and De Jonghe and Öztekin (2015). More specifically, we adjust the model such that the adjustment speed, λ, can vary over time, banks, and countries:

$$\lambda_{ij,t} = \lambda_0 + \Lambda Z_{ij,t-1}, \qquad (4)$$

where Λ is a vector of coefficients for the adjustment speed function and $\mathrm{Z_{i,j,t-1}}$ is a set of covariates that could affect the adjustment speed. Substituting equation (4) in equation (3) yields the equation for a partial adjustment model with heterogeneity in the speed of adjustment:

$$\Delta K_{ij.t} = (\lambda_0 + \Lambda Z_{ij,t-1})\big(\beta X_{ij,t-1} - K_{ij,t-1}\big) + \varepsilon_{i,t}. \qquad (5)$$

As Berger et al. (2008), Öztekin and Flannery (2012) and De Jonghe and Öztekin (2015), we estimate equation (5) in two steps. In the first step, we estimate equation (3) using system GMM and obtain an estimate of the target capital ratio, $\widehat{K}^*_{ij,t} = \hat{\beta} X_{ij,t}$, which we use to compute each bank's deviation from its (estimated) target capital ratio, $GAP_{ij,j,t-1}$= $\widehat{K}^*_{ij,t} - K_{ij,t-1}$. Substituting the gap in equation (5) we get:

$$\Delta K_{ij.t} = (\lambda_0 + \Lambda Z_{ij,t-1}) GAP_{ij,t-1} + \varepsilon_{i,t}. \qquad (6)$$

Which is the second step that only involves a pooled OLS regression of the dependent variable (the change in a capital ratio) on a set of variables defined as the product of $GAP_{ij,t-1}$ and the covariates (proxies for systemic risk and (relative and absolute) size, introduced one-by-one) affecting the adjustment speed. The vector of estimated coefficients allows us to test various hypotheses on the determinants of the adjustment speed. To ease economic interpretation, we standardize the independent variables, $Z_{ij,t-1}$, before interacting them with $GAP_{ij,t-1}$. Hence, the coefficient λ_0 can be interpreted as the average speed of adjustment in the sample. Such a setup also allows investigating asymmetric effects of systemic risk and size for overcapitalized banks (above the target) and undercapitalized banks (below the target), by further interacting the variables in the vector $Z_{ij,t-1}$ with indicator variables that are one when the bank's capital ratio is above (below) target.

Table 2.7. reports the empirical results from a model where we allow for heterogeneity in the adjustment speed towards the optimal capital structure. The sources of heterogeneity we consider are fivefold. We include a measure of bank size (ln(total assets), relative bank size, systemic risk exposure and systemic risk contribution. In addition, we also use the SIFI-index which allocates bank-year observations in quintiles according to these four characteristics.

Table 2.7. Determinants of adjustment speed to target capital structure: effects of systemic risk and size on speed of adjustment.

This table reports the coefficient estimates for the ordinary least square (OLS) regressions (Eq. (6): $k_{i,j,t} - k_{i,j,t-1} = (\lambda_0 + \Lambda Z_{ij,t-1}) \times \text{Gap}_{i,j,t-1} + \varepsilon_{i,j,t}$) for a sample of listed OECD banks over 2001-2012 period, to sscess the determinants of a bank's adjustment speed. Capital deviation is computed using three definitions of capital ratio (Leverage, Tier1RWA and Total capital), corresponding with the three different panels in the Table. The determinants of the adjustment speed ($Z_{ij,t-1}$) are as follows: the MES is the marginal expected shortfall, ΔCoVaR is the delta Conditional Value-at-Risk, RelativeSize is the relative bank size to GDP, Size is the natural logarithm of bank total assets as well as an aggregate SIFI-Index. The latter is an indicator of systemic importance constructed based on the quintiles of the MES, ΔCoVaR, relative size and absolute size. All continuous variables are standardized before being interacted with the capital deviation to facilitate the economic magnitude interpretation. We show the results when we add interaction terms separately. P-values based on robust standard errors, clustered by bank are shown in parentheses. Coefficients significantly different from zero at the 1%, 5% and 10% level are marked with ***/**/*. The Wald test statistic refers to the null hypothesis that all coefficients on the determinants of capital deviation are jointly equal to zero.

Panel A:			ΔLeverage			
Gap(i,t-1)	0.403***	0.406***	0.397***	0.392***	0.392***	0.406***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)
Gap(i,t-1) * MES(i,t-1)		-0.022**				
		(0.010)				
Gap(i,t-1) * ΔCoVaR(i,t-1)			0.014*			
			(0.007)			
Gap(i,t-1) * RelativeSize(i,t-1)				-0.093***		
				(0.011)		
Gap(i,t-1) * Size(i,t-1)					-0.059***	
					(0.017)	
Gap(i,t-1) * SIFI-index(i,t-1)						-0.027**
						(0.011)
Observations	4339	4339	4339	4339	4339	4339
Adjusted R-squared	0.612	0.614	0.613	0.635	0.624	0.615
Panel B:			ΔTier1RWA			
Gap(i,t-1)	0.318***	0.320***	0.317***	0.318***	0.324***	0.323***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
Gap(i,t-1) * MES(i,t-1)		0.039***				
		(0.009)				
Gap(i,t-1) * ΔCoVaR(i,t-1)			0.009			
			(0.012)			
Gap(i,t-1) * RelativeSize(i,t-1)				0.020***		
				(0.005)		
Gap(i,t-1) * Size(i,t-1)					0.033***	
					(0.008)	
Gap(i,t-1) * SIFI-index(i,t-1)						0.034***
						(0.009)
Observations	4339	4339	4339	4339	4339	4339
Adjusted R-squared	0.281	0.285	0.281	0.282	0.284	0.284
Panel C:			ΔTotal capital			
Gap(i,t-1)	0.362***	0.367***	0.363***	0.362***	0.368***	0.370***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Gap(i,t-1) * MES(i,t-1)		0.038***				
		(0.011)				
Gap(i,t-1) * ΔCoVaR(i,t-1)			0.015			
			(0.011)			
Gap(i,t-1) * RelativeSize(i,t-1)				0.013*		
				(0.007)		
Gap(i,t-1) * Size(i,t-1)					0.031***	
					(0.009)	
Gap(i,t-1) * SIFI-index(i,t-1)						0.034***
						(0.010)
Observations	4339	4339	4339	4339	4339	4339
Adjusted R-squared	0.306	0.309	0.306	0.306	0.308	0.308

In the upper panel, we provide the results for the leverage ratio. In column 1, we report the homogenous speed of adjustment. In line with previous results, average leverage speed is 0.40. Thus, on average, banks adjust at 40 percent per year, if they are further away from the target leverage. In the next four columns, we introduce one-by-one the effects of systemic risk and size on leverage speed of adjustment. We find a negative and statistically strong (at the 1 percent level) relationship between the MES (systemic risk exposure), the relative bank size, the absolute bank size and the adjustment speed, while ΔCoVaR (systemic risk contribution) carries a positive effect, but statistically significant at the 10 percent level only, consistent with the fact that banks would care less about the threat they impose on the financial system than the opposite. On the whole, this implies that banks adjust their leverage more slowly toward the target (yielding a higher half-life) when the MES and both bank's size measures are higher; whereas, they adjust faster (yielding a lower half-life) if ΔCoVaR is higher. This suggests that omission of systemic risk and size effects in estimating the adjustment of banks' capital structure leads to biased results.

These results shed light on two aspects regarding SIFIs and TBTF. As highlighted above, ΔCoVaR apprehends the aggregate financial system performance conditional on a given bank's returns drop below a certain threshold. Such a measure is hence expected to capture contagion risks. Accordingly, banks are more sensitive to adjust their leverage faster when they choose to take more correlated risks and this appears to overweigh the MES effect. Although they have access to inexpensive external capital and cheap debt funding, sizeable banks can, presumably because of their TBTF status, afford to adjust their leverage ratio slowly. Such a ratio is indeed not a regulatory risk-based capital measure that they need to comply with. Such a finding is consistent with moral hazard behavior that leads banks to take on excessive risk-taking and engage in multiple activities (e.g., combining lending and trading), when they expect to be bailed out in case of distress. Alternatively, larger banks could be regarded as more complex and opaque making it relatively more difficult and costlier for them to raise capital. Finally, in column 6, using the index of systemic importance and risk, we find that SIFIs adjust slower towards their target ratio.

In the middle and lower panel, we report results for similar regressions except that we focus now on regulatory risk weighted capital ratios (Tier 1RWA ratio in middle panel and Total capital ratio in lower panel). The first column examines the average adjustment speed deviation from the targeted regulatory Tier1 ratio. In subsequent columns, conversely to what we find in the leverage ratio specifications, the coefficients on the interaction terms related to the MES, the relative bank size and the absolute bank size are now significantly positive. Hence, larger banks and/or banks with higher MES adjust faster to the target Tier 1 regulatory ratio. In the last column, using the systemic index, we thus find that SIFIs adjust their regulatory capital ratio faster whenever they deviate from their target regulatory ratio. The results are also economically important and similar in magnitude for each of the interaction effects. A one standard deviation increase in the index of systemic importance and risk increases the average Tier1 regulatory speed (0.32) by 0.034, leading to a slightly lower half-life. Such results confirm the hypothesis that SIFIs and TBTF institutions may find it easier to change their regulatory capital structure by altering the composition of new equity (Tier1) issuances and adjusting their risky asset compositions, and thus adjust faster. This is possibly because of higher financial flexibility through relative cost advantages on the one hand and adjustments in external growth funding on the other hand. The exposure to common shocks that affect the whole financial system (namely the MES[52]) dominates the effects of contagion risk and size effects, possibly because banks had to face internally increased market monitoring and macroprudential regulatory supervision on one hand and high expected capital shortfall on the second hand, which translate into higher regulatory adjustment speed. In addition, it confirms the hypothesis that systemic banks may find it easier to change their capital structure by raising inexpensive external capital, cheap debt funding and by altering the asset compositions of their balance sheets.

In the lower panel, we repeat the same regressions for the total regulatory capital. All results are similar to those we obtain for the Tier 1 regulatory ratio in the middle panel. In sum, our results show two important things. First of all, systemic risk and size affect the extent to which banks adjust their capital ratios. Second, these factors play an opposite role (on the speed of adjustment) for a leverage ratio vis-à-vis regulatory capital ratios.

[52] The MES captures bank performance conditional on a distress event in the financial system returns, so it is more closely capturing exposure to common shocks that affect the whole financial system.

4.2. Do SIFIs use different adjustment mechanisms?

The analyses thus far indicate that: (i) the mechanisms that banks use to adjust their capital ratios to return to target depend on whether they are over- or undercapitalized, (ii) the magnitude of the adjustments vary with the type of capital ratio, (iii) the speed of adjustment depends on the systemic importance of the bank. These combined insights lead to the last research question, which is analyzing whether SIFIs use different adjustment mechanisms and whether the heterogeneity in the adjustment is asymmetric with respect to the capital gap sign.

To address this question, we regress the average growth rates in key balance sheet components on the deviation from the target. This approach is similar to the one used by previous researchers to examine adjustment mechanisms (Berrospide and Edge, 2010; Francis and Osborne,2009, 2012; Lepetit et al. 2015; De-Ramon et al., 2016[53]). Banks can adjust to their target by either issuing or buying back equity capital (Tier1 capital), increasing or decreasing retained earnings or by reducing or increasing their size as well as by reshuffling their assets (change in total assets, net loans and risk-weighted assets) or liabilities (change in total liabilities, long-term borrowings and short-term borrowings). Furthermore, we allow not only for asymmetric adjustments depending on the sign of the gap but also for heterogeneous adjustments depending on how systemically important banks are. In particular, we estimate the following threshold regression model:

$$\Delta \mathrm{BS}_{\mathrm{i,t}} = \mathrm{c} + \beta_1 \mathrm{SIFI}_{\mathrm{i,t-1}} + \begin{cases} \left(\delta_0^+ + \delta_1^+ \mathrm{SIFI}_{\mathrm{i,t-1}}\right) \times \mathrm{Gap}_{\mathrm{i,t}}, & \text{if } \mathrm{Gap}_{\mathrm{i,t}} > 0 \\ \left(\delta_0^- + \delta_1^- \mathrm{SIFI}_{\mathrm{i,t-1}}\right) \times \mathrm{Gap}_{\mathrm{i,t}}, & \text{if } \mathrm{Gap}_{\mathrm{i,t}} < 0 \end{cases} + u_i + \varepsilon_{i,t} \qquad (7)$$

where $\Delta \mathrm{BS}_{\mathrm{i,t}}$ is the average growth rate for one of the balance sheet variables (Equity, Tier1 capital, Retained Earnings, Assets, RWA, Loans and Liabilities) which could be affected by the deviation

[53] De-Ramon et al. (2016) use a similar two-stage approach of estimating targets and subsequently analyzing balance sheet adjustments. They focus on a single country, the UK, whereas we take an international perspective. Furthermore, they analyze non-linearities in the adjustment in normal and crisis times, whereas we focus on asymmetric effects and the potential differences for small and average banks versus SIFIs.

from the optimal target and SIFI is the systemic risk index that we constructed based on the quintiles of MES, ΔCoVaR, size and relative size. The index has been standardized such that it has zero mean and unit standard deviation. Equation 7 allows us to look at the impact of capital deviations on the numerator and denominator of the target (and their components), when banks' actual capital ratio is either below or above the target. Furthermore, we assess whether the adjustment mechanisms depend on banks' systemic size and importance measured by the SIFI index.

Table 2.8. Effects of systemic risk and size on mechanisms of capital adjustments.

This table reports the coefficient estimates for the ordinary least square (OLS) regressions (Eq. (7)):

$$\Delta BS_{i,t} = c + \beta_1 SIFI_{i,t-1} + \begin{cases} (\delta_0^+ + \delta_1^+ SIFI_{i,t-1}) \times Gap_{i,t}, & \text{if } Gap_{i,t} > 0 \\ (\delta_0^- + \delta_1^- SIFI_{i,t-1}) \times Gap_{i,t}, & \text{if } Gap_{i,t} < 0 \end{cases} + u_i + \varepsilon_{i,t}$$

for a sample of OECD banks over the 2001-2012 period, to assess the relation between the annual growth rates of diverse balance sheet items and capital deviations, for banks with a Capital shortfall (positive gap, undercapitalized) or a Capital surplus (negative gap, overcapitalized) vis-à-vis its target capital ratio. $\Delta BS_{i,t}$ is the average growth rate for one of the balance sheet variables. Across columns, the specification is identical except for the dependent variable, which is respectively the average annual growth rates of total common equity (Equity), Tier1 capital, retained earnings, total assets (Assets), risk-weighted assets (RWA), net loans (Loans) and total liabilities (Liabilities). Growth rates variables are scaled by average total equity, total assets and total liabilities. The gap is computed using three definitions of capital ratio (Leverage, Tier1RWA and Total capital) corresponding with the three different panels. $SIFI_{i,t-1}$ is an aggregate systemic risk index (SIFI-Index) constructed based on the quintiles of the MES, ΔCoVaR, relative size and size. All regressions include a constant term. P-values based on robust standard errors, clustered by bank are shown in parentheses. *, ** and*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

Panel A: Leverage ratio

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	0.274**	-0.047	0.275***	-3.605***	-0.436***	-0.336***	-0.558***
	(0.130)	(0.127)	(0.093)	(0.097)	(0.083)	(0.050)	(0.069)
Capital shortfall(i,t-1) * SIFI-index(i,t-1)	-0.478***	-0.236*	-0.172*	0.654***	0.175**	0.139***	0.051
	(0.129)	(0.123)	(0.093)	(0.109)	(0.087)	(0.051)	(0.071)
Capital surplus(i,t-1)	0.164***	0.199***	-0.226***	-2.491***	-0.102	-0.027	-0.008
	(0.063)	(0.059)	(0.042)	(0.110)	(0.076)	(0.033)	(0.049)
Capital surplus(i,t-1) * SIFI-index(i,t-1)	0.187***	0.135**	0.036	-0.058	-0.078	-0.106***	-0.042
	(0.060)	(0.057)	(0.041)	(0.100)	(0.073)	(0.032)	(0.049)
SIFI-Index(i,t-1)	-0.043***	-0.047***	-0.055***	-0.070***	-0.067***	-0.062***	-0.064***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)
Constant	0.080***	0.086***	0.013***	0.095***	0.058***	0.057***	0.089***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.025	0.027	0.038	0.602	0.082	0.125	0.093

Panel B: Tier 1 over risk-weighted assets ratio

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	1.753***	1.958***	0.086	-2.255***	-1.418***	-0.753***	-0.806***
	(0.267)	(0.254)	(0.218)	(0.282)	(0.168)	(0.117)	(0.156)
Capital shortfall(i,t-1) * SIFI-index(i,t-1)	0.571*	0.403	0.103	0.335	0.120	0.146	-0.061
	(0.293)	(0.259)	(0.216)	(0.248)	(0.161)	(0.116)	(0.159)
Capital surplus(i,t-1)	-0.308	0.363	-0.667***	-1.670***	-1.340***	-0.503***	-0.683***
	(0.296)	(0.288)	(0.255)	(0.443)	(0.251)	(0.158)	(0.238)
Capital surplus(i,t-1) * SIFI-index(i,t-1)	-0.017	0.293	0.006	-0.960**	-0.145	-0.076	0.112
	(0.306)	(0.294)	(0.287)	(0.382)	(0.234)	(0.155)	(0.223)
SIFI-Index(i,t-1)	-0.077***	-0.084***	-0.050***	-0.063***	-0.046***	-0.054***	-0.055***
	(0.008)	(0.008)	(0.006)	(0.009)	(0.006)	(0.004)	(0.006)
Constant	0.053***	0.055***	0.014***	0.098***	0.063***	0.059***	0.086***
	(0.005)	(0.005)	(0.004)	(0.006)	(0.003)	(0.002)	(0.003)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.039	0.058	0.036	0.078	0.136	0.140	0.099

Panel C: Total capital ratio

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	1.653***	1.904***	-0.136	-1.775***	-1.255***	-0.748***	-0.793***
	(0.270)	(0.262)	(0.230)	(0.299)	(0.182)	(0.127)	(0.176)
Capital shortfall(i,t-1) * SIFI- index(i,t-1)	0.334	0.103	0.128	0.435	0.137	0.186	-0.130
	(0.293)	(0.269)	(0.218)	(0.265)	(0.187)	(0.130)	(0.180)
Capital surplus(i,t-1)	-0.144	0.378	-0.517**	-1.876***	-0.945***	-0.543***	-0.757***
	(0.253)	(0.237)	(0.215)	(0.366)	(0.211)	(0.145)	(0.227)
Capital surplus(i,t-1) * SIFI- index(i,t-1)	0.011	0.150	-0.105	-1.034***	-0.190	-0.208	-0.096
	(0.270)	(0.244)	(0.207)	(0.323)	(0.224)	(0.159)	(0.239)
SIFI- Index(i,t-1)	-0.069***	-0.075***	-0.050***	-0.072***	-0.054***	-0.057***	-0.057***
	(0.008)	(0.008)	(0.006)	(0.008)	(0.006)	(0.004)	(0.006)
Constant	0.059***	0.061***	0.018***	0.085***	0.061***	0.057***	0.084***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.034	0.052	0.036	0.069	0.111	0.138	0.098

In Table 2.8., we report the results of our estimates of the model presented in equation (7). The columns correspond with the growth rates in balance sheet elements of interest used to view behavior of banks' capital adjustment. In the three different panels, we use deviations between target and actual capital for the leverage ratio (panel A) the Tier 1 over risk-weighted asset ratio (panel B) and the total capital ratio (panel C), respectively. The results are also presented graphically in Figures 2.1., 2.2. and 2.3. Figure 2.1. (panel A of Table 2.8.) shows the results for the leverage ratio and Figures 2.2. and 2.3. (panels B and C of Table 2.8.) for the two risk-weighted regulatory ratios, Tier1RWA and Total capital respectively. Each subplot in the graph corresponds with the fitted values of equation (7) over the relevant range of the gap between the actual and target capital ratio. Three fitted value lines are plotted corresponding with $\Delta BS_{i,j,t}$ over the range of $Gap_{i,j,t}$ for SIFIs (standardized SIFI index gets value 1, i.e. one standard deviation above the mean, short dashed line), average banks (SIFI score is average and hence 0 for the standardized index, full line) and small banks (standardized SIFI index gets value of minus one, i.e. banks for which SIFI index is one standard deviation below the mean, long-dashed line).

Figure 2.1. Leverage ratio deviation and bank capital structure adjustments for SIFIs, average banks and non-SIFIs

We present graphical evidence on the behavior of bank-specific balance sheet characteristics (fitted values of Eq. (7) corresponding with $\Delta BS_{i,j,t}$) over the estimated gap of the targeted leverage ratio. The graphs plot average growth rates of total common equity, Tier1 capital, retained earnings, total assets, risk-weighted-asset, total net loans and total liabilities, for SIFIs (short-dashed line), average banks (full line) and non-SIFI (long-dashed Line), over the relevant range of the gap between the actual and target leverage ratio. A positive gap indicates a situation where banks have capital shortfalls and a negative gap indicates a situation where banks have capital surpluses. We define as SIFIs (non-SIFIs) those banks with a one standard deviation above (below) the mean standardized SIFI index, while average banks have a zero mean of the standardized SIFI index.

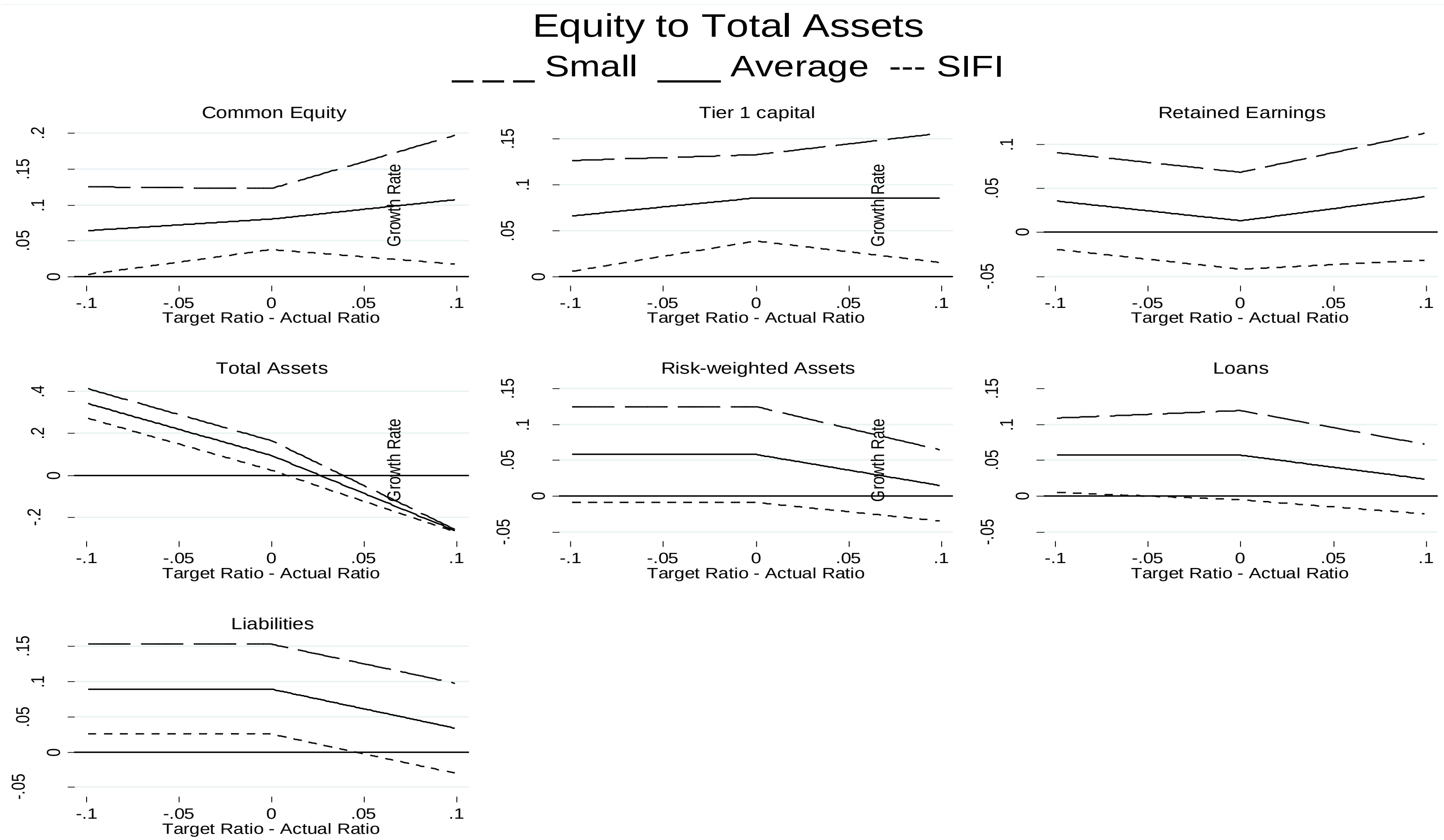


Figure 2.2. Tier1 capital ratio deviation and bank capital structure adjustments for SIFIs, average banks and non-SIFIs

We present graphical evidence on the behavior of bank-specific balance sheet characteristics (fitted values of Eq. (7) corresponding with $\Delta BS_{i,j,t}$) over the estimated gap of the targeted regulatory Tier1 over risk-weighted-assets ratio. The graphs plot average growth rates of total common equity, Tier1 capital, retained earnings, total assets, risk-weighted-asset, total net loans and total liabilities, for SIFIs (short-dashed line), average banks (full line) and non-SIFIs (long-dashed Line), over the relevant range of the gap between the actual and target Tier1RWA ratio. A positive gap indicates a situation where banks have capital shortfalls and a negative gap indicates a situation where banks have capital surpluses. We define as SIFIs (non-SIFIs) those banks with a one standard deviation above (below) the mean standardized SIFI index, while average banks have a zero mean of the standardized SIFI index.

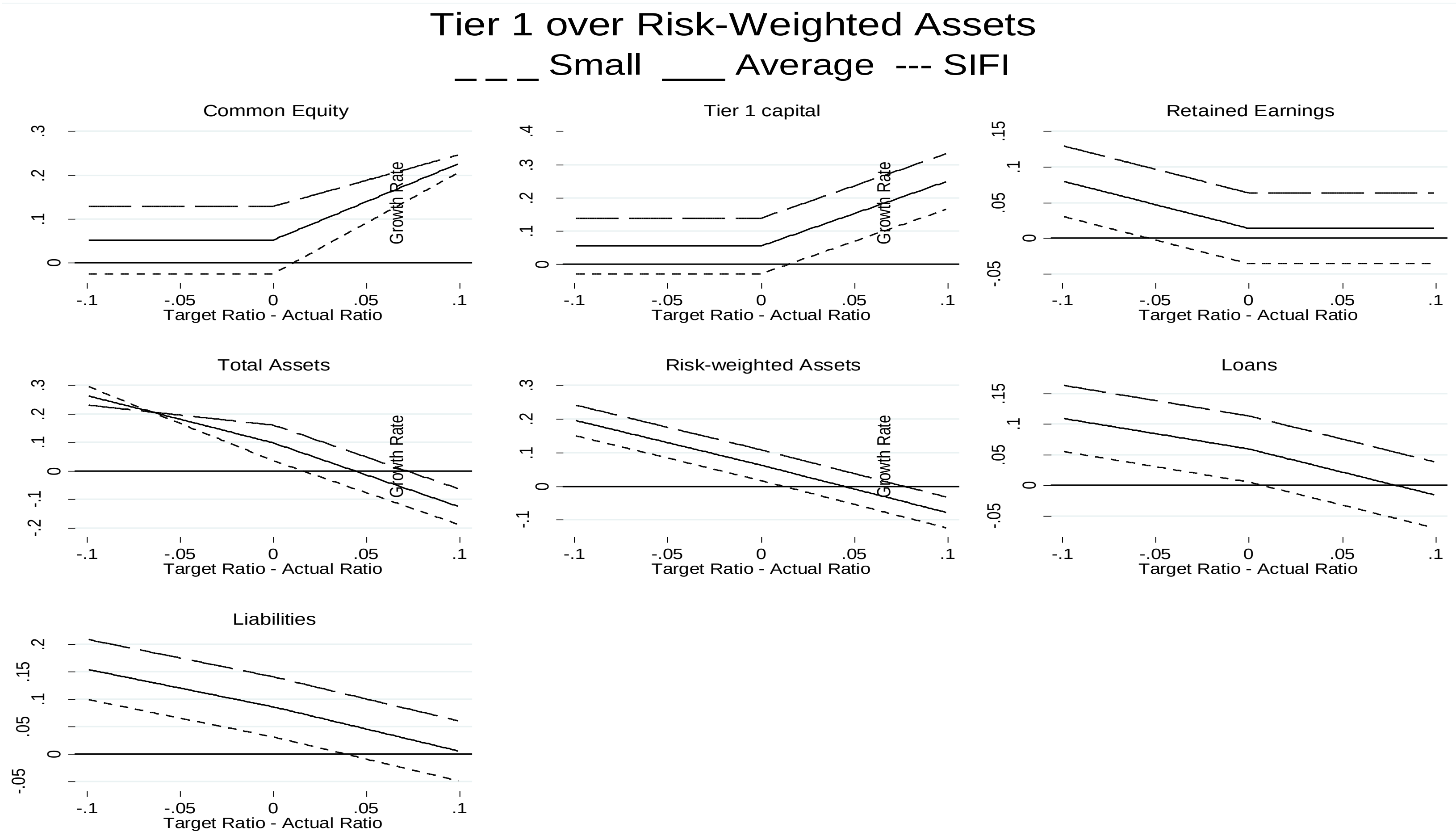
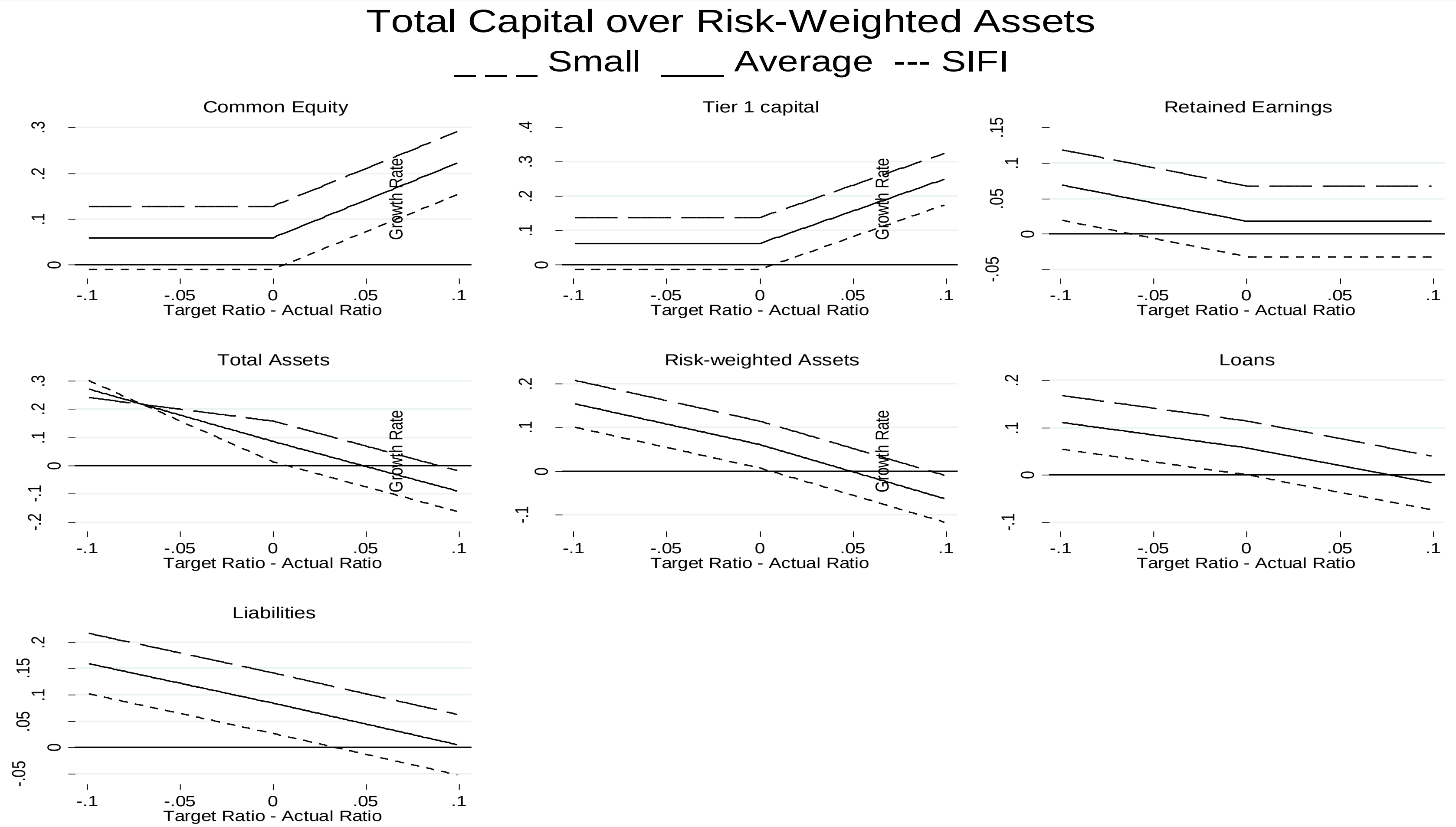


Figure 2.3. Total capital ratio deviation and bank capital structure adjustments for SIFIs, average banks and non-SIFIs

We present graphical evidence on the behavior of bank-specific balance sheet characteristics (fitted values of Eq. (7) corresponding with $\Delta BS_{i,j,t}$) over the estimated gap of the targeted regulatory total capital ratio. The graphs plot average growth rates of total common equity, Tier1 capital, retained earnings, total assets, total net loans, risk-weighted-asset and total liabilities, for SIFIs (short-dashed line), average banks (full line) and non-SIFIs (long-dashed Line), over the relevant range of the gap between the actual and target total capital ratio. A positive gap indicates a situation where banks have capital shortfalls and a negative gap indicates a situation where banks have capital surpluses. We define as SIFIs (non-SIFIs) those banks with a one standard deviation above (below) the mean standardized SIFI index, while average banks have a zero mean of the standardized SIFI index.



First of all, the coefficients associated with the systemic index variable (SIFI-index) are always significantly negative indicating that compared to "less" systemic banks, "more" systemic banks have ceteris paribus a lower growth rate in total assets but also in the different balance sheet components. Graphically, this implies a downward (upward) shift for SIFI (small) banks.

Second, to be consistent with a return to target capital, we expect, when banks are below the target, a (piecewise) flat or upward sloping line for the equity components, whereas for assets and liability categories, we expect a downward sloping line. That is, the more positive the gap is (undercapitalized banks), the larger the growth in equity needs to be (relative to the growth in assets) to close the gap. If a bank is above target (negative gap) we expect banks close to the gap by either reducing equity growth or accelerating asset growth (compared to growth rates of equity and assets when banks are on or close to target).

We begin by looking at the impact of deviations from the optimal leverage ratio on the capital structure adjustments in Panel A. An increase in the leverage ratio shortfall will lead to a significantly larger growth rate of total common equity (Equity), particularly by increasing capital internally (Retained Earnings) rather than issuing equity (Tier1 capital). Furthermore, an increase in the gap (when undercapitalized) results in significantly decreasing growth of total assets (Assets) and adjusting their compositions (both loans and RWA). The relative magnitudes of these estimated coefficients provide interesting insights in how the mix of equity and asset adjustments change the leverage speed of adjustment. In absolute magnitude, the coefficients on the capital shortfall variable is larger for total assets growth (as well as RWA growth and loan growth) than the corresponding coefficient in the total common equity growth (or retained earnings growth) regression. This finding indicates that as the gap becomes larger (as banks become more undercapitalized), banks might become constrained in raising equity and need to resort more to adjustments via the assets side (relative downsizing).

The interaction terms with the SIFI index enter negative and statistically significant for the three mechanisms of capital adjustments (Equity, Tier1 capital and Retained Earnings) and positive and statistically significant for the three elements of asset adjustments (Assets, RWA and Loans). In all instances, these findings imply that SIFIs' balance sheet adjustments are less responsive to the extent of undercapitalization. This suggests that undercapitalized SIFIs tend to adjust the capital structure at a lower speed than less systemic ones, which is confirmed by the slower adjustment speed for SIFIs obtained in the last column of panel A of Table 2.7.

Turning to the situation in which banks are underleveraged (overcapitalized, negative gap), we find that, as the gap becomes more negative, equity growth becomes much smaller. Moreover, while overall asset growth rates are strongly and significantly related to the extent of being underleveraged, growth of risk-weighted assets and lending policies are unaffected by the extent of capital surplus hence indicating that the size expansion is mainly achieved by venturing into low-risk weight, non-lending activities such as cash and sovereign debt. As assets grow faster than equity, banks seem to take advantage of such a situation to reduce equity dilution and also adjust their size (volume of assets), rather conservatively by tilting the composition to lower-risk weight assets. In addition, we find that SIFIs behave differently when it comes to equity adjustments (whenever overcapitalized) but not assets, suggesting that the response of capital adjustment is more pronounced (strong negative effect, sharp decrease), in response to a capital surplus, with regards to the less systemic banks. Also, such larger and more systemic banks lever up by increasing significantly their lending growth compared to the less systemic banks, which indicates less prudent expansions compared to non-SIFIs which mainly expand via cash and securities.

We now turn to Panels B and C where we investigate the balance sheet adjustments in response to gaps in the regulatory capital ratios, also allowing for heterogeneity depending on the SIFI index and the sign of the gap. First of all, results are very similar in panel B and C, and we discuss them together. When banks are below their regulatory capital targets, an increase in undercapitalization leads to significantly higher growth rates in common equity and Tier 1 capital and significantly lower (risk-weighted) asset growth. The coefficient in the Tier 1 capital column is larger than in the risk-weighted assets column indicating that as banks become more undercapitalized they have to resort more to raising capital externally in order to swiftly close the gap. In general, we do not find that small banks or SIFIs behave differently in this respect. None (but one, weakly) of the interaction effects between the shortfall and the SIFI index is significant.

When banks are overcapitalized in terms of regulatory ratios (negative values for the gap), we find that equity growth rates are unaffected by the size of the gap, whereas assets and liabilities growth strategies depend on the magnitude of the capital surplus. These findings are consistent with the idea that banks with excess capital have more capacity to grow, lend and/or get into debt compared with other banks. The only significant interaction effect with the SIFI index is obtained when analyzing the effect on the growth rate of total assets. The (negative) slope becomes steeper for SIFIs, but only for total assets and not for risk-weighted assets or loans. This indicates that for increasingly larger gaps, compared to smaller banks, SIFIs allow their asset base to expand more. As there is no differential behavior between SIFIs and small banks with respect to loans or risk-weighted assets, this implies that SIFIs also use this situation to additionally scale up their safe assets even though that does not contribute to closing their regulatory gap. Surprisingly, when banks are above their regulatory capital targets, an increase in the gap leads to higher growth in their retained earnings. This can be observed for both definitions of regulatory risk-weighted capital ratios (Panels B and C). As for the findings in Panel A, banks seem to be more reluctant to distribute earnings in these situations for two reasons. They may hoard it as a buffer as they expect new investment opportunities might arise or they might become more cautious that extremely good times might be followed by bad times where they would face a shortfall.

To summarize, our results show that when banks are below target for any of the three capital definitions (Leverage, Tier1RWA and Total capital) they always accelerate equity and more generally capital growth except when they are systemically very important and adjusting to the leverage ratio. With respect to earnings retention, we observe a discrepancy between leverage and regulatory capital ratios. Banks tend to increase earnings retention (hence limiting dividend distribution) to move upwards towards the target leverage ratio but earnings distribution policy is not affected when banks are shocked below their weighted regulatory ratios. Somewhat surprisingly, the more overcapitalized banks are with respect to their regulatory targets, the larger the earnings retention is; but still relatively smaller than growth in (risk-weighted) assets such that they do get back to target. In all cases banks always decelerate assets growth, loan growth and risk-weighted assets. However, when it comes to leverage adjustments, banks show more flexibility in their balance sheets adjustments when they experience a negative capital shock (and hence have a positive gap); but when they are above their target leverage, banks of a given size or systemic importance expand their loans and risk-weighted assets at the same speed.

4.3. Robustness checks and further issues

In this section, we present evidence of the robustness of our results to alternative specifications. In addition, we also perform some additional tests to examine the role of non-linearities over the sample period and the scope for adjustments via liquid, marketable assets.

First, we consider a battery of alternative target estimation techniques for the baseline adjustment model (Eq. 3) to ensure that our results (estimated target capital ratios and computed deviation) are robust to different regression specifications. We build on the insights of Flannery and Rangan (2006) and use ordinary least squares (OLS) estimations. Then, we follow Berrospide and Edge (2010) and Lemmon et al. (2008) and use country fixed effect regressions to control for unobserved country heterogeneity and year fixed effects. Finally, we use a regression that includes time varying country fixed effect to capture time varying country-specific regulation or business cycle effects on capital and heterogeneity at the country-year level. Our results for the capital adjustment model are not driven by the first stage regression specification.

Second, we consider an alternative measure of the regulatory capital ratio, defined as the Total capital ratio (including Tier 1 and Tier 2 capital). Throughout the analyses, the results are always very similar to those we obtain with the Tier 1 regulatory ratio (Tables 2.5. to 2.8.).

Third, we discuss different specifications based on baseline regressions performed on the full sample (Eq. 7). As the number of observations varies widely across countries, larger countries with more banks may be overrepresented in our sample. For example, the majority of banks within the sample operate in the U.S. and Japan. This could either lead to U.S. or Japan-biased results, or lead to invalid results. Therefore, we also use weighted least squares (WLS) to estimate the baseline regression model to give an equal weight to each country in the pooled approach. In particular, we take the inverse of the number of country observations for each country as the weight for each individual bank. Table A2.2. in Appendix 2 displays the results from the WLS estimations. The results are by and large in line with our main findings.

Fourth, De-Ramon et al. (2016) have shown that the balance sheet adjustments that UK banks make to get back to target have changed since the global financial crisis. We investigate a similar issue, but rather than looking at each and every adjustment mechanisms, we look at the impact on the speed of adjustment, which summarizes the underlying adjustment mechanism. In particular, we not only check whether the speed of adjustment has changed since 2007, but also whether systemic importance have different effects on the adjustment speed during the pre-global financial crisis period and during the (post-)crisis period. Indeed, capital management and balance sheet behavior may be influenced by banks' ability to tap capital markets. For that purpose, we analyze the impact of systemic importance on adjustment speed estimations allowing for non-linearity in the relationship by a dummy capturing the normal pre-crisis times (2001-2006) and crisis and post GFC sample years (2007-2012). In panel A of Table A2.3. in Appendix 2, we report the regression results. In the lower panel B, we present the adjustment speeds implied by the estimated coefficients (by capital ratio definition) for the pre-crisis and post-2007 period, for small banks, average banks and SIFIs. Small banks (SIFIs) are defined as those for which the normalized SIFI index is -1 (+1), i.e. one standard deviation below (above) the mean. First of all, we find that adjustment speeds went up since 2007, both for small and average banks as well as SIFIs and for all capital ratio definitions. Second, we find prior to 2007 that SIFIs adjust slower than small banks, with larger differences between the two groups for leverage ratios compared to regulatory capital ratios. Third, in the post 2007 period, SIFIs still adjust their leverage ratio slower than small banks, but the difference in adjustment speeds between the two groups has narrowed compared to the pre-2007 period. Fourth, an opposite pattern is found for regulatory capital ratios. Since the global financial crisis, the adjustment speed of regulatory capital ratios has been higher for SIFI banks vis-à-vis small banks. The observation that SIFIs adjust slower to their leverage capital ratio, and faster to their regulatory capitals ratios, indicates that SIFIs have become more concerned about their regulatory capital levels than their leverage) since the global financial crisis.

Fifth and last, loans are assumed to be illiquid assets which cannot easily be sold before maturity; only the maturing part of a loan portfolio can be reinvested. As opposed to loans, liquid assets and marketable securities are liquid and can be sold at market price, offering a counterbalancing capacity against funding risk (i.e. fluctuations in available funds). Hence, commercial banks (with a large investment) banking arm, which are active on liquid markets, are therefore more likely to extend and shrink their business volume to adjust their capital ratio than other banks, which mainly hold illiquid loans. In Table A2.4. in Appendix 2, we treat this liquidity option, through liquid assets and (short-term) cash and marketable securities, and capital adjustment. Three interesting findings emerge. First, we only find an effect of the regulatory capital gap, and not of leverage gaps, on the growth rates of cash and marketable securities as well as liquid assets. Second, the effect of regulatory capital gaps on the growth rates of these liquid instruments is asymmetric and only present when banks have a capital shortfall. These effects are opposite to the effects on loans and risk-weighted assets, indicating that banks reshuffle their asset holdings to meet regulatory capital requirements. Third, this asymmetric effect is weaker for SIFIs than for smaller banks. As the gap between actual and target regulatory capital becomes larger, SIFIs are prone to rely less than other banks, on sales of marketable securities and liquidation of assets to adjust regulatory capital ratios more quickly.

5. Conclusion

The Basel III Accord has, among other things, introduced more stringent capital requirements faced by banks, a new leverage ratio and also capital surcharges for systemically important banks. In this paper, we investigate how banks adjust their capital ratios to reach their desired levels by focusing on two dimensions. We look at whether the adjustment speeds and mechanisms are different for ratios set by regulators (risk-weighted capital ratios) and those internally targeted by bank managers (leverage) and pay special attention to systemically important banks. We consider a pre-Basel III period ranging from 2001 and 2012 to examine how banks have managed their capital ratios by using a sample of listed banks across OECD countries. We augment standard partial adjustment models of bank capital towards bank-specific and time-varying optimal capital ratios with various SIFI indicators as well as a systemic risk index based on the quintiles of such indicators.

On the whole, our findings reveal that the speed at which banks adjust and the way they adjust show large differences. In general, banks are more flexible and faster in adjusting to their leverage capital ratio than to regulatory capital ratios. However, SIFIs are slower than other banks in adjusting to their target leverage ratio but quicker in reaching their target regulatory ratios.

Hence for systemically important banks the adjustment speed is roughly similar for all capital ratios, whereas the wedge between leverage adjustment speed and regulatory capital adjustment speed is larger for small banks. Our results also suggest that systemically important banks might be more reluctant to change their capital base by either issuing or repurchasing equity and prefer sharper downsizing or faster expansion.

Our findings contribute to the bank capital structure adjustment literature and carry various policy implications. In case of any sudden need to augment capital ratios at systemically important, banks regulators and supervisors should be aware that such institutions would, according to our results, downsize to a larger extent than smaller banks. If in a given country the market share of systemic banks is relatively large, the real effect on the economy will consequently be more important. Symmetrically, a relief in capital constraints or a positive capital shock is also expected to push SIFIs to expand faster than other banks. On the whole, this procyclical behavior is more pronounced for systemic institutions which are however also found to more extensively rely on equity issues when needed than other banks. Such findings are also expected to be particularly useful for supervisors when they gauge and adjust the specific capital requirement they can impose on each bank in the industry differently and separately, which they are allowed to do through Pillar 2 of the Basel III Accord.

Chapter 3

Internationalization, Foreign Complexity and Systemic Risk: European Banks Perspective*

Abstract. We evaluate the impact of the international organization structure and the geographic expansion of 105 European listed banks that have foreign affiliates around the world on bank level measures of systemic risk during the 2005–2013 period. We investigate how the peak of the global financial crisis of 2008–2009 and the height of the European sovereign debt crisis of 2010–2011 might have affected such measures. We find that internationalization and foreign complexity are important drivers of bank systemic risk, particularly during the 2008–2013 financial stress years. Our findings contribute to the ongoing debate on the merits of imposing systemic risk-based and organizational complexity capital surcharges (as in Basel III requirements), and carry various policy implications for too-complex and systemically important banks.

* This chapter draws from the working paper (Bakkar and Pamen-Nyola "Internationalization and systemic risk: Evidence from a sample of European listed banks") co-authored with Annick Pamen-Nyola, from Université de Limoges–LAPE. I am grateful to my supervisors, Amine Tarazi and Clovis Rugemintwari, and Alain Sauviat, from Université de Limoges–LAPE, for encouragement, advise, help and comments.

1. Introduction

Deregulation and financial innovation have prompted a particularly important degree of globalization among large financial institutions (e.g. Frame and White (2015), Claessens and van Horen (2012)). These profound and rapid changes have transformed the scale and the scope of global banking institutions and increased their size and their complexity over the past two decades. The broader networks of banking institutions' affiliates, geographically scatter global banks, and interconnected banking legal entities. From both home and host countries' banking authorities' perspectives, the issues of too-big- and too-complex-to-fail entities and Global Systemically Important Banks (G-SIBs) have received renewed attention in recent years (Goetz et al. (2016), Gropp et al. (2010)). Consequently, how global financial institutions manage their complexity and the potential influence on different financial systems has surged to the top position on policy agenda and academic debate. And, the global financial crisis followed by the European sovereign debt crisis have even more increased the concern about the interconnectedness of complex institutions and the contagion of risk to different sectors of the economy as well as to different economies. Our paper investigates the impact of bank internationalization (through foreign subsidiaries) on the systemic risk of European listed banks and whether such impact in normal times changes in times of financial turmoil[54].

The issue of systemically important financial institutions and the effect on financial fragility have caught more attention of researchers and policy makers. The Financial Stability Board (FSB (2011)) has published an integrated set of policy measures to address the systemic and moral hazard risks associated with systemically important financial institutions (SIFIs). The FSB uses the notion of "*complexity*" as one important factor affecting systemic risk and the identification of G-SIBs. Besides, the G-SIBs designation methodology is also based on four distinguishing aspects:

[54] Before the crisis, cross-border banking surged as many of the world's largest banks expanded internationally, lending more to one another and investing in other foreign assets. After the creation of the euro, for example, eurozone banks expanded significantly. Foreign claims held by eurozone banks (and their subsidiaries) soared from $6.6 trillion in 2000 to $23.4 trillion in 2007. Most important, a majority of that growth was within the eurozone itself, where an integrated European banking market was emerging, leading some to believe that a common currency and shared rules meant country risk had almost disappeared (according to research from the McKinsey Global Institute "*new dynamics of financial globalization*", see: https://www.mckinsey.com/industries/financial-services/our-insights/the-new-dynamics-of-financial-globalization).

interconnectedness, substitutability within the financial institution infrastructure and cross-jurisdictional activity in addition to size. Thus, the Basel Committee for Banking Supervision (BCBS (2011)) has proposed capital surcharges and liquidity requirements on large and systemically important banks to contain systemic risk, and also measures to reduce their involvement in market-based activities and their organizational complexity. Also, the Dodd–Frank Act in the U.S. (the Volcker Rule, Vickers (2011)) and Liikanen (2012) proposals in Europe have supported restrictions on risky bank activities. Other authors have advocated outright limits on the individual size of banks including capping of size, breakup and separation of the institution along business lines and organizational restructuring to limit the cross-border dimension of complexity. However, the literature has not yet offered any evidence on the effect of complexity, through the affiliates' types and the worldwide geographic dispersion of counterparts, on bank systemic risk.

In the context of these initiatives, there is a growing consensus that banking complexity and geographic expansion are relevant factors that lower banks' risk if it involves adding assets whose returns are imperfectly correlated with existing assets (e.g. Goetz et al. (2016), Gropp et al. (2010)). Dell'Ariccia and Marquez (2010) analyze the choice between branches and subsidiaries in banking in a theoretical framework. Carmassi and Herring (2016) investigate how different aspects of complexity may enhance systemic risk. They also refer to a number of possible reasons for becoming too-complex such as economies of scale and scope, regulation and tax rules (see also Gropp, et al. (2010)). An extensive literature reviews bank holding companies and their complex organization and geographic expansion around the world as well as their potential implication for standalone risk (e.g. Goetz et al. (2016), Deng and Elyasiani (2008), Akhigbe and Whyte (2003)), diversification and financial fragility (e.g. Carmassi and Herring (2016), Barth and Wihlborg (2016), Calomiris (2000)), risk monitoring and adverse effects on asset quality (e.g. Berger et al. (2005) and Brickley et al. (2003)), loan quality and bank fragility (e.g. Denis et al. (1997), Servaes (1996), Berger and Ofek (1995)), and capital and loans (e.g. Acharya et al. (2006), Demsetz and Strahan (1997)).

Nevertheless, the existing literature focusses on analyzing bank complexity implications on only individual aspects of bank risk (e.g. Goetz et al. (2016)), not the exposure of banks to systemic risk, the contagion risk or the magnitude of systemic shocks. Apart from Carmassi and Herring (2016) who show that the organizational complexity of 29 G-SIBs (8 from U.S.) has increased in pre-crisis times, and slightly decreased in the aftermath of the crisis, and the large mergers and acquisitions being the main drivers of this effect, there is still no academic consensus on whether internationalization and foreign complexity has led to greater bank systemic risk.

In this paper we seek to link these two strands of literatures and address the following questions: Are internationalization, affiliates structures, and geographic expansion of activities adding to the instability of the financial system? And to what extent these aspects of organizational and geographic complexity might affect banks' systemic risk during sound and stress periods (of accumulations of systemic risk)? Hence, the acute time of the global financial crisis in 2008–2009, followed by the 2010–2011 European sovereign debt crisis provides a natural environment that allows us to investigate the effect of bank complexity on systemic risk during financial distress. Accordingly, we turn our attention to European financial institutions that conduct operations by establishing foreign subsidiaries within the Euro Zone and around the world and to European financial institutions that do not.

The objective of this paper is to investigate the relation between bank organizational forms in foreign markets and geographic complexity and bank systemic risk. This paper takes a narrower approach to explain the potential systemic risk repercussions of internationalization and foreign complexity. It seeks to explain how the organizational choice, i.e. separately incorporated subsidiaries, and geographic complexity, i.e. geographical diversity in terms of affiliate locations, might contribute to systemic disruption. It also asks whether the choice to expand counterparts abroad and geographical complexity –that might potentially maximize the benefits and reduce default cost and the possibility of a state bailout– make banks systemically riskier than in the absence of such foreign complexity. Therefore, we follow the insights from Anginer et al. (2013), Bertay et al. (2013) and Barth and Schnabel (2013), and we distinguish five measures of systemic banks, to metric systemic risk exposures (Marginal Expected Shortfall (MES) and SRisk its expected capital shortfall), systemic risk contributions (delta Conditional Value-at-Risk (ΔCoVaR), systemic default risk (Merton's probability-of-default measure (PD)) and sensitivity to extreme systemic shock (Tail-beta)).

To the best of our knowledge, this is the first paper on European listed banks that seeks to examine the relationships between bank internationalization and foreign complexity and bank systemic risk and that investigates possible changes over the 2005–2013 period covering the peak of the global financial crisis (2008–2009), the height of European sovereign debt crisis (2010–

2011), and the aftermath stages of these financial crises (2012–2013). Our findings reveal that internationalization and foreign complexity appear to be an important driver of bank systemic risk, specifically over both crisis and post-crisis periods. However, the effect is either reversed or non-important during sound period (2005–2007). Moreover, our results suggest that complex banks might be less reluctant to build capital shortfall buffers during sound period –risk accumulating period– that can be drawn down in the event of a systemic shock. Our findings contribute to the bank complexity literature and carry various policy implications, especially for too-complex and systemically important financial institutions.

In the remainder of the paper, Section 2 presents the sample and the empirical methodology. Section 3 describes the data and variables and reports some univariate analysis. Section 4 presents the results and discusses additional analyses, and Section 5 provides robustness tests. Section 6 concludes our study.

2. Sample and model specification

In this section, before presenting the empirical methodology we describe the procedures we follow to construct our sample.

2.1. Sample

To address the effect of foreign presence and complexity on systemic risk, which requires market-based data, we focus exclusively on banks that have publicly traded equity. We consider listed banks that specialized in commercial, cooperative and savings activities and are established in Europe. Our study spans the 2005–2013[55] period. From Bloomberg we retrieve bank stock price information and other market data which we combine with accounting and structural data from

[55] We end the sample period in 2013 in order to avoid interference with the implementation of the Basel III regulations in Europe (starting from 2013) that among other things introduced measures for large banks to reduce their involvement in market-based activities and their organizational complexity. Doing so, we can study how complex banks potentially affect systemic risk. Then, we are able to investigate the change in this relationship before the global financial crisis (GFC), during the acute financial crisis and at the later stage of financial crisis years.

various sources. We extract unconsolidated bank-level annual accounting data from the Bureau Van Djik (BvD) BankScope and Thomsen-Reuters Advanced Analytics (TRAA) databases. Bloomberg is a well-known proprietary database collecting market data across publicly listed companies, while TRAA and BankScope are databases collecting balance sheet statements across a large sample of countries. All the banks in our sample report annual financial statements following an accounting period running from January 1 to December 31. To obtain a homogenized sample, we apply several selection criteria and make some restrictions. First, we drop banks with infrequently traded stocks and low variability in stock prices. Then, we restrict the subsample to banks with continuously traded stocks. More specifically, we disregard a stock if daily returns are zero over five rolling consecutive days. Third, we consider bank stocks with more than 70% of the daily returns over the period that are non-zero returns. Finally, for each year we eliminate outliers and extreme values of all variables. Moreover, to map the level of internationalization of banks around the world, we collect the number and locations of their foreign subsidiaries from BankScope. For each bank and its affiliates, we go through bank annual reports and web sites to match the collected data and, in cases of discrepancies, we extract and add complementary data. Finally, considering the full availability of accounting, market, and international data each year, we end up with a sample of 105 banks from 15 European countries[56] publicly traded on financial markets: Austria, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Poland, Portugal, Slovakia, Spain, and Sweden. From all the filtering procedures, we build a panel of 945 bank-year observations.

Table 3.1. presents a breakdown of the sample of the 105 listed banks by country. Our dataset indicates that while most of the banks publicly traded on financial markets are from Denmark (21.90%), France (17.14%), and Italy (16.19%), Czech Republic (0.95%), Hungary (0.95%), and Ireland (0.95%) have the fewest representatives in the whole sample.

[56] We focus of European countries for reasons of data availability and cross-countries consistency

Table 3.1. Distribution of listed banks

The table shows the breakdown of the 105 listed banks by country, and the indicator of geographic complexity for foreign subsidiaries (*GeoComplex**S***), (the detailed method of calculation can be found in Section 2) for the three sets of extraction in BankScope [(2005–2007), (2008–2010) and (2011–2013)] of international observations. Delta measures in percentage the variation between (2010–2008) and (2007–2005) and between (2013–2011) and (2010–2008) for the variable in the column at the left side. We extract most of the information on banks, and number and locations of foreign from BankScope and we complete them with data from annual reports and bank web site. "/" indicates unavailable or unknown data.

	Listed banks	Banks with a foreign activity	Number of foreign subsidiaries	Delta %	Number of host countries	Delta %	Number of world regions	GeoComplexS [Mean]
				2013–2011				
Austria	6	6	15	-75	6	-64.71	2	0.05
Czech Republic	1	1	1	0	1	0	1	/
Denmark	23	4	38	-35.59	20	-13.04	7	0.35
Finland	2	/	/	/	/	/	/	/
France	18	6	140	-67.74	47	-17.54	8	0.48
Germany	7	4	43	-87.68	24	-48.94	6	0.43
Greece	6	4	23	-43.90	7	-22.22	2	0.06
Hungary	1	1	6	-57.14	5	-58.33	2	0.51
Ireland	1	/	/	/	/	/	/	/
Italy	17	10	62	-61.96	20	-25.93	7	0.20
Poland	10	2	2	-33.33	2	100	1	0
Portugal	2	2	14	-56.25	8	-27.27	5	0.82
Slovakia	2	/	/	/	/	/	/	/
Spain	6	6	72	-36.84	28	7.69	6	0.45
Sweden	3	3	68	-55.56	26	0	8	0.82
Observations	**105**	**49**	**484**	**-66.13**				**0.34**
				2010–2008				
Austria	6	5	60	275	17	70	3	0.05
Czech Republic	1	1	1	0	1	0	1	0
Denmark	23	4	59	-30.59	23	-4.17	6	0.26
Finland	2	1	5	0	4	0	2	0.54
France	18	6	434	-25.94	57	-9.52	8	0.47
Germany	7	4	349	-19.03	47	-17.54	8	0.53
Greece	6	5	41	-16.33	9	0	3	0.08
Hungary	1	1	14	0	12	0	2	0.28
Ireland	1	1	1	-80	1	-75	1	0
Italy	17	10	163	-53.43	27	-50	8	0.20
Poland	10	3	3	50	1	0	1	0
Portugal	2	2	32	-3.03	11	0	6	0.71
Slovakia	2	/	0	/	/	/	/	/
Spain	6	4	114	-9.52	26	-18.75	6	0.65
Sweden	3	3	153	13.33	26	4	7	0.60
Observations	**105**	**50**	**1429**	**-22.25**				**0.31**
				2007–2005				
Austria	6	4	16		10		1	0
Czech Republic	1	1	1		1		1	0
Denmark	23	3	85		24		6	0.31
Finland	2	1	5		4		2	0.36
France	18	6	586		63		8	0.56
Germany	7	4	431		57		8	0.47
Greece	6	5	49		9		3	0.15
Hungary	1	1	14		12		2	0.28
Ireland	1	1	5		4		2	0.36
Italy	17	12	350		54		8	0.25
Poland	10	2	2		1		1	0
Portugal	2	2	33		11		6	0.69
Slovakia	2	/	0		/		/	/
Spain	6	5	126		32		7	0.66
Sweden	3	3	135		25		6	0.45
Observations	**105**	**50**	**1838**					**0.33**

2.2. Model specification and empirical methodology

This paper investigates the effect of the internationalization and complexity of 105 listed banks that are headquartered in Europe and operate foreign subsidiaries around the world on the individual bank risk of systemic disruptions. More precisely we study how this effect differs according to the state and soundness of the banking industry. Indeed, our period of study that spans on 2005–2013 covers two main events, namely the global financial crisis and the European sovereign debt crisis, which might have affected both the bank presence abroad and bank systemic risk differently. To capture the state and soundness of all countries banking systems, we define a large timeline to include both the global financial and the sovereign debt crises. The dummy variable *Crisis08_11* takes the value of one if the year is 2008, 2009, 2010, and 2011[57], and zero otherwise. In another analysis we decompose *Crisis08_11* into two other dummies *Fin08_09* and S*ov10_11* to capture more precisely the individual effect of the acute years of the global financial crisis and the sovereign debt crisis, respectively. As the dummy *Crisis08_11* encompasses both crises, we decompose the years left into a relatively calm period prior to the crises (2005–2007) and an aftermath period (2012–2013). *Post12_13* is a dummy equal to one for the years 2012 and 2013, and zero otherwise. With regards to these three states of financial systems stability, to determine the impact of internationalization and foreign complexity on bank individual systemic risk over the 2005–2013 period, we estimate the following model:

$$Risk_{i,j,t} = \alpha_0 + (\alpha_1 + \beta_1 Crisis08\_11 + \beta_2 Post12\_13) * International_{i,t} + \varphi X_{i,t-1} + \omega_j + \varepsilon_{ij} \quad (1)$$

Where $Risk_{i,j,t}$ is the vector of the different measures of systemic risk of the publicly traded bank *i* in country *j* over the year *t*. In one specification of our study we examine three measures of bank individual systemic risk over the period 2005 to 2013: MES, SRISK, and ΔCoVaR and in another we analyze other measures of risk: PD (probability of default) and Tail-beta. $International_{i,t}$

[57] Crossing different timelines given by the BIS (2010) and the Banque de France (2010, 2012), the financial crisis started in July 2007 in the USA, intensified after the collapse of Lehman Brothers in September 2008, and turned into a global economic crisis in early 2009. The aftermath of this period led to the European sovereign debt crisis which started in the late 2009 in some countries (e.g. Greece, Ireland, Portugal and Spain) and had profoundly affected all European economies in 2011. In 2012, the agreement of the EU to bailout Greece on February 21st and the adoption of an EU fiscal compact treaty on March 2nd mark the beginning of strong interventionist measures in order to stop the contagion of the crisis and provide stability for all countries. Hence, we define the crises over the 2008–2011 period.

comprises different measures of bank internationalization: presence abroad (with subsidiaries), number of host countries, number of subsidiaries, and geographic dispersion and complexity of the foreign affiliates. The parameters α_1, (α_1+β_1), and (α_1+β_2) capture the effect of the bank foreign presence and foreign complexity on bank individual systemic risk during the pre-financial crisis period (2005–2007), the acute years of both financial (2008–2009) and sovereign debt crises (2010–2011), and during the post-crisis time (2012–2013), respectively. $X_{i,t-1}$ is a vector of bank characteristics computed at time $t-1$ which are presented in section 2.3.4, ω_j is a country fixed effect, and $\varepsilon_{ij,t}$ is the error term. In all regressions, we include country fixed effects ω_j and the standard errors are clustered at the country level.

We use Ordinary Least Squares (OLS) to estimate the model with all dependent variables resulting from previous estimation methodologies. In the presence of a lagged control variables, we build on the insights of Laeven et al, (2015) and use ordinary least squares (OLS) estimation.

In what follow we turn to the definitions of our variables of interest (foreign presence and complexity), our dependent variables measuring bank systemic risk and the different control variables include in the regressions.

3. Data and variables

In this section, we define the internationalization criteria and present the foreign complexity indicators and the measures of systemic risk at the bank-level. We also present all the bank financial characteristics we use in the empirical framework.

3.1. Building of foreign presence and complexity variables

Our paper aims to investigate whether the internationalization and foreign complexity of publicly traded banks affect systemic risk and whether the effect in normal times differs from times of financial distress. We evaluate the internationalization of a bank in terms of its presence abroad or not and the widespread of such presence in multiple countries. And, to determine the foreign complexity, we consider the penetration of foreign markets with subsidiaries; an entity with 50% or more of its shares owned by another company that competes directly and deeply on the local market, abides the laws of that country, owns its full accounting statements, and is a total independent entity from the parent bank.

From BankScope we identify banks that have at least one foreign subsidiary and collect data as of the end of 2007, 2010, and 2013. Taking into account the legal procedures and costs related to the closing of foreign affiliates, we assume that the speed of change of the presence abroad should not be faster over few years. Henceforth, the measures of the internationalization constructed for the year 2007, 2010, and 2013 are assumed to be the same for 2006 and 2005, 2009 and 2008, and 2011 and 2012, respectively. Using these data, we create the dummy variable $Foreign_i$ that takes the value one when the listed bank *i* from home country *j* owns at least one subsidiary abroad, and zero otherwise (either the bank is not present abroad or operates another type of foreign affiliate or does not conduct foreign operations through subsidiary). Another variable included in the regressions is the continuous variable $NbHost_i$ that measures the wide presence of each bank around the world through the number of host countries where there is a foreign affiliate. Given the (economic, political, social, cultural) differences between all host countries, the two previous variables do not represent all the potential channels of transmission of multinational banks' impact on systemic risk. Hence, we deepen the analysis with a focus on the complexity of the foreign structure and locations of multinational banks. Following prior studies (Carmassi and Herring (2013, 2016), Barth and Wihlborg (2016), Laeven et al. (2015)) we introduce the (natural logarithm of the) number of subsidiaries $NbSubsidiaries_i$ as an indicator of foreign complexity.

Additionally, regarding the locations of the international banks, we consider another measure of the concept of foreign complexity: the geographic dispersion of the different regions where banks operate their foreign subsidiaries. On the basis of the World Bank regional division of countries around the world, we defined the following eight regions[58]: East Asia & Pacific (EAP),

[58] The World Bank (WB) regional division of countries consists of seven groups with Europe and Central Asia (ECA) representing a unique group. Considering the countries and their economic, sociologic, cultural, and political specificities we divide ECA into Europe (EUR) for countries in ECA and on the Europe continent and Central Asia

Europe (EUR), Central Asia (CA), Latin America & Caribbean (LAC), Middle East & North Africa (MENA), North America (NA), South Asia (SA), and Sub-Saharan Africa (SSA). For each listed bank *i* we include the continuous variable $NbRegions\_Sub_i$ that accounts for the number of regions where the foreign subsidiaries are located. And following Cetorelli and Goldberg (2014) we construct a normalized Herfindhal index that captures the complexity of foreign banks located in different world regions *r* and ranges from 0 (lowest complexity) to 1 (highest complexity). By construction of *GeoComplex**S***, the lowest complexity also indicates a presence in a unique region and the highest complexity describes a presence in all regions with the same number of subsidiaries. We use the previously defined regions *r*[59] to build an index for each one of the banks that have established subsidiaries abroad:

$$GeoComplexS_i = \frac{R}{R-1}\left(1 - \sum_{r=1}^{R}\left(\frac{NbSubsidiaries_{i,r}}{NbSubsidiaries_i}\right)^2\right) \qquad (2)$$

Where R is the total number of regions r around the world (i.e. 8); $NbSubsidiaries_{i,r}$ is the number of subsidiaries of bank i in region r; and $NbSubsidiaries_i$ is the total number of subsidiaries of bank i.

Finally, for each aforementioned indicator we introduce interacted terms that capture the specific effect of bank internationalization and foreign complexity during times of financial instability in Eq. (1).

Table 3.1. reports the distribution of the 105 listed banks by European countries and global foreign activities over the three periods of 2005–2007, 2008–2010, and 2011–2013. We observe that on average 50 banks in the sample owned foreign subsidiaries around the world. Through the whole period, French and German banks globally have the wider international presence in terms of host countries [and number of regions] with subsidiaries located in 63 [8] (2005–2007) then 57 [8] (2008–2010), and 47 [8] (2011–2013) host countries [world regions] for French banks and 57 [8] (2005–2007) then 47 [8] (2008–2010), and 24 [6] (2011–2013) host countries [world regions]

(CA) for the rest. As well, while examining countries in MENA region as defined by the WB, we remove Malta and Gibraltar from the list and move them in the newly created Europe region.

[59] Figure in Appendix A3.1. displays the map of World with the regions by the World Bank.

for German banks. Moreover, comparing the number of subsidiaries we find that while during 2005–2007 (and 2008–2010) French, German, and Italian banks operate most of the foreign subsidiaries with respectively 586, 431, and 350 (434, 349, and 163) affiliates, the representativeness is different in 2011–2013 as Spanish (72) and Swedish (68) banks now hold the second and third position[60]. Considering the index of geographic complexity of foreign subsidiaries, the overall complexity decreases from 0.33 in 2005–2007 to 0.31 in 2008–2010, before increasing back to 0.34 in 2011–2013. Among all banks that operate foreign subsidiaries, banks from Portugal (0.69, 0.71, and 0.82) are always the ones with the most regionally diversified affiliates in the sample.

Table 3.2. shows the dispersion of foreign bank subsidiaries owned by listed European banks in different world regions. Regardless of the region, the total number of subsidiaries has significantly decreased throughout the period of study; from 1838 to 1429 (-22.25%) and then to 484 (-66.13%). Going through the downfall of the financial and sovereign debt crises, banks have faced numerous losses which might have forced them to close some of their counterparts abroad. As we could have imagined, most of the foreign subsidiaries are located in Europe (1001, 753 and then 202) and North America (372, 297 and 78).

[60] The drop of the number of foreign subsidiaries (French and German banks more specifically) observed between the extraction at end of 2010 and the one at end of 2013 might have different causes. First, according to Chapter 2 of the Global Financial Stability Report (GFSR) by the IMF (April 2015), the pre-crisis level of cross-border operations reflected a temporary unsustainable boom. Hence, one implication of the recent global financial crisis on banks' organizational network was a shift away from international activities to more local lending through domestic branches and subsidiaries. Consequently, between 2008 and 2013, international banks have significantly reduced their number of foreign affiliates in order to refocus on core markets, rebalance their business models away from capital-intensive activities to more fee-based businesses, refocus their geographical presence on fast-growing markets (Claessens and van Horen 2014), and limit their risk exposures and contagion among entities. The GFSR explains this decline of cross-border lending by a combination of regulatory and supervisory changes, weaknesses in banks' balance sheets, and some macroeconomic factors. Second, in case the drop might come from databases' issues, we conduct additional checks of our sample. Going through all filtering procedures, controlling and comparing them with other extractions, we were not able to find any discrepancies. However, since Bankscope do not give exhaustive information and/or do not report details about what might explain the changes, were there any problems with the information initially collected and/or reported in the database, we are not able to expose them.

Table 3.2. Distribution of foreign subsidiaries over regions

The table shows the distribution of the foreign subsidiaries in eight world regions: East Asia & Pacific (EAP); Central Asia (CA); Europe (EUR); Latin America & Caribbean (LAC); Middle East & North Africa (MENA); North America (NA); South Asia (SA); Sub-Saharan Africa (SSA).

2011–2013	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	15	0	14	1	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	38	9	20	2	1	0	1	2	3
Finland	/	/	/	/	/	/	/	/	/
France	140	23	58	7	10	11	15	1	15
Germany	43	9	16	3	5	0	9	0	1
Greece	23	0	22	0	0	1	0	0	0
Hungary	6	0	4	2	0	0	0	0	0
Ireland	/	/	/	/	/	/	/	/	/
Italy	62	5	21	1	0	2	27	3	3
Poland	2	0	2	0	0	0	0	0	0
Portugal	14	1	4	0	4	1	0	0	4
Slovakia	/	/	/	/	/	/	/	/	/
Spain	72	2	16	0	39	2	12	0	1
Sweden	68	13	25	4	5	1	14	2	4
Observations	484	62	202	20	64	18	78	8	31

2010–2008	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	60	1	55	4	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	59	4	45	2	2	0	2	0	4
Finland	5	0	2	3	0	0	0	0	0
France	434	55	224	11	23	20	57	25	19
Germany	349	29	103	5	12	4	176	11	9
Greece	41	0	39	0	0	1	1	0	0
Hungary	14	0	12	2	0	0	0	0	0
Ireland	1	0	1	0	0	0	0	0	0
Italy	163	15	106	5	1	4	27	4	1
Poland	3	0	3	0	0	0	0	0	0
Portugal	32	1	17	0	3	1	3	0	7
Slovakia	/	/	/	/	/	/	/	/	/
Spain	114	5	43	0	44	3	17	0	2
Sweden	153	12	102	14	3	0	14	7	1
Observations	1429	122	753	46	88	33	297	47	43

2007–2005	Total	EAP	EUR	CA	LAC	MENA	NA	SA	SSA
Austria	16	0	16	0	0	0	0	0	0
Czech Republic	1	0	1	0	0	0	0	0	0
Denmark	85	3	76	3	1	0	1	0	1
Finland	5	0	4	1	0	0	0	0	0
France	586	59	299	20	19	36	119	8	26
Germany	431	45	160	7	14	6	184	12	3
Greece	49	0	43	0	0	4	1	0	1
Hungary	14	0	12	2	0	0	0	0	0
Ireland	5	0	4	0	0	0	1	0	0
Italy	350	77	209	9	8	5	39	1	2
Poland	2	0	2	0	0	0	0	0	0
Portugal	33	1	20	0	4	2	3	0	3
Slovakia	/	/	/	/	/	/	/	/	/
Spain	126	4	48	2	52	1	17	0	2
Sweden	135	6	107	11	3	0	7	1	0
Observations	1838	195	1001	55	101	54	372	22	38

3.3. Bank-level systemic risk measures

We compute in this section the main dependent variables reflecting individual bank systemic risk in order to investigate the systemic dimension of bank risk and capture the bank' sensitivity to system-wide distress. This differs from the individual dimension of bank risk as it also encompasses different aspects such as interconnectedness in the banking industry, correlation in returns between the bank and the financial system, and the economic context. We define and measure market-based measures of systemic importance, approach base on market data. We devote attention to, the systemic risk exposures and vulnerability to system wide distress (the Marginal Expected Shortfall (*MES*)), the expected capital shortfall during a period of system distress (*SRisk*), the contribution to system wide risk of an individual bank (the delta Conditional Value-at-Risk (Δ*CoVaR*)), systemic default risk (the Merton's probability-of-default measure (*PD*)) and sensitivity to extreme systemic shock (quantile Tail-beta (*Tail-beta*)).

We follow common practice and use the opposite of returns in the computation, such that losses are expressed with a positive sign. Systemic risk measures will typically be positive and higher values correspond to larger systemic risk exposures, contributions, default and sensitivity. All measures are constructed by estimating the return model using daily data over the period January 2000 to December 2013. Then we compute annual systemic risk values using the average of the predicted values over each year.

Hypothesizing that some publicly traded banks with critical market power or large amount of total assets might generate a risk that, due to the importance of the bank in the system, will turn out systemic and shaken the whole banking system, and others on the contrary rather suffer from systemic risk, we separate the five risk measures into two categories: systemic risk–maker (*MES*, *SRisk*, and Δ*CoVaR*) and systemic risk–taker (*PD* and *Tail-beta*).

3.3.1. MES, SRisk, and ΔCoVaR

The Marginal expected shortfall (MES) is introduced as a risk measure in Acharya et al. (2010). We follow Brownlees and Engle (2017) (e.g. Brownlees and Engle (2015), Zhou and Tarashev (2013) and Engle (2002), among other) and define MES as the expected return (tail expectation) of a bank's stock return conditional on a market return (i.e. the market index) being in its lower tail[61]. The market-based systemic risk measure MES thus assesses the extent to which distress at a bank contributes to system-wide stress. Here, the MES is defined as:

$$MES_{i,t}^{q=5\%} \equiv E\left(R_{i,t} | R_{M,t} \leq VaR_{R_{M,t}}^{q}\right) \qquad (3)$$

Where $R_{i,t}$ is the daily stock return for bank i, $R_{M,t}$ is the daily market return[62], q-percent is a pre-specified extreme quantile enabling us to look at systemic events. $VaR_{R_{M,t}}^{q}$ stands for Value-at-Risk, which is a critical threshold value that measures the worst expected market loss over a specific time period at a given confidence level. Herewith, we follow the common practice and set q at 5-percent, the term $R_{M,t} \leq \mathrm{VaR}_{\mathrm{R_{M,t}}}^{\mathrm{q}}$ reflects the set of days when the market return is at or below the 5-percent tail outcomes in that given year.

An extension of the MES, called SRisk, was proposed by Acharya et al. (2012). It is determined by bank's total asset, and bank's equity. It metrics the expected capital shortfall of an individual bank i when the financial system is undercapitalized. Therefore, an individual bank is considered systemically risky if it is faced to a capital shortfall when the system is under distress. Formally, Acharya et al. (2012) and Laeven et al. (2015) measure SRisk's as following[63]:

$$SRisk_{i,t} = E_{t-1} \times (Capital\ Shortfall_i | Crisis) = \left(k * D_{i,t}\right) - \left(VE_{i,t} \times (1-k) \times \left(1-LRMES_{i,t}\right)\right. \qquad (4)$$

[61] Economically, the term "marginal" means that each unit increase or decrease in the equity value MES implies the variation in the bank's capital shortfall.
[62] To estimate risk measures, we either use the financial sector index or the broad market index.
[63] Unlike Acharya et al. (2012) methodology, we do not limit SRisk from below to zero. Acharya et al. (2012) are interested in estimating capital shortages, which theoretically cannot take on negative values. Here, we allow SRisk to take on negative values, with a view that highly capitalized banks with large buffers can easily absorb systemic shocks and subtract systemic risk from the financial system.

where k is the prudential capital ratio equal to 8 percent, VE_i is market value of equity, D_i is book value of debts (total liabilities) and $LRMES_{i,t}$ (Long Run MES, $LRMES_{i,t} = (1 - k)exp^{(-18\,MES_i)}$) is tail expectation of the bank's return conditional on a market decline[64].

Adrian and Brunnermeier (2011) introduce another concept of systemic risk, computed at the bank-level, called ΔCoVaR, similar to the value-at-risk (VaR). The market-based systemic risk measure CoVaR corresponds to the VaR of the entire financial market (i.e. of the market index, R_M), conditional on a certain bank i being in distress (at its lower tail). Specifically, the distress of bank i is captured by that bank being at its own individual ($\mathrm{VaR}^{q}_{R_{i,t}}$), that is when bank i's stock return ($R_{i,t}$) is beyond a critical threshold q probability level. Here, we set q at 1-percent. As in Adrian and Brunnermeier (2009), we compute a time series CoVaR measure for each of the banks in our sample using quantile regressions. $CoVaR^{q}_{R_{M|i,t}}$ is the q-percent quantile of this conditional probability distribution and can be written as[65]:

$$Prob_{t-1}\left(R_{M,t} \leq CoVaR^{q}_{R_{M|i,t}} \mid R_{i,t} = VaR^{q}_{R_{i,t}}\right) = q \quad (5)$$

Thus, explicitly, Adrian and Brunnermeier (2011) define bank $\Delta CoVaR_i$ as the VaR of the financial market when bank i is in distress (i.e. when bank stock return is at its bottom 1-percent level), minus the VaR of the market when bank i is at its median value (i.e. when this bank i is on its median return). Additionally, this relation is allowed to depend on additional estimated covariates (see Hautsch et al. 2014; Mayordomo et al. 2014; Adrian and Brunnermeier, 2014). It catches the externality a bank causes to the entire financial system. ΔCoVaR of individual bank i is expressed as[66]:

$$\Delta CoVaR^{q=1\%}_{R_{M|i,t}} = CoVaR^{q=1\%}_{R_{M|i,t}} - CoVaR^{median}_{R_{M|i,t}} Prob_{t-1}\left(R_{M,t} \leq CoVaR^{q}_{R_{M|i,t}} \mid R_{i,t} = VaR^{q}_{R_{i,t}}\right) = q \quad (6)$$

[64] An approximation of equity values falls in the crisis scenarios when the market goes down below a given threshold, 40 percent over 180 days (e.g. Laeven et al. (2015), Acharya et al. (2012), among other).

[65] Quantile regressions estimate the functional relationship among variables at different quantiles (Koenker and Hallock (2001)) and allow the risk co-dependence during stress periods by taking into account nonlinear relationships when there is a large negative shock.

[66] As MES, ΔCoVaR computed at time t given information available at time t–1 based on the financial system Expected Shortfall.

3.3.2. PD and Tail-beta

We compute the two additional measures of bank risk that capture another dimension of systemic risk to identify banks more likely to be strongly affected by a sharp system dowturn.

Following Campbell et al. (2008) and Hillegeist et al. (2004) methodology, we model and compute the Merton's distance-to default (DD) measure for each of the banks in our sample. Formally, DD at the end of year t is expressed as:

$$DD_{it} = \frac{log\left(\frac{VA_{i,t}}{D_{i,t}}\right) + \left(r_f - 0.5 * (\sigma_{i,t}^A)^2\right) * T}{\sigma_{i,t}^A \sqrt{T}} \qquad (7)$$

Where $VA_{i,t}$ is the market value of the bank's assets at the end of the fiscal year t; $D_{i,t}$ is the book value of total liabilities maturing at time T (as a proxy for the face value of debt); r_f is the risk-free rate (10-year government bond obtained for each country from the Bloomberg), and $\sigma_{A,i,t}$ is the volatility of the bank's assets at t (based on equity returns in a given year).

However, the distance to default cannot be measured directly. $DD_{i,t}$ requires estimates of $VA_{i,t}$ and $\sigma_{A,i,t}$ neither of which are directly observable. Following the option pricing model of Black and Scholes (1973), equity can be modelled as a call option on the underlying bank's assets. Therefore, the market value of equity and volatility are estimated from observed stock prices ($VE_{i,t}$) and their volatility ($\sigma_{i,t}^E$), by solving simultaneously the following system of nonlinear equations:

$$VE_{i,t} = VA_{i,t} N(d_1) - X_t e^{-r_f T} N(d_2) \qquad \sigma_{i,t}^E = \left(\frac{VA_{i,t}}{VE_{i,t}}\right) * N(d_1) * \sigma_{i,t}^A \qquad (8)$$

Where $VA_{i,t} = VE_{i,t} + D_{i,t}$ and N is the cumulative normal distribution function and d_1 and d_2 are given by:

$$d_1 = \frac{log\left(\frac{VA_{i,t}}{D_{i,t}}\right) + \left(r_f + 0.5 \times (\sigma_{i,t}^A)^2\right) \times T}{\sigma_{A,it}\sqrt{T}} \qquad d_2 = d_1 - \sigma_{A,it}\sqrt{T} \qquad (9)$$

Since the bank's total liabilities is on an annual basis (an accounting data), we quadratically interpolate the values of debt for all dates over the period, using beginning and end of year values for total liabilities. The interpolation method has the advantage of producing a smooth implied liabilities value process and avoids jumps in the implied default probabilities at year end (Anginer et al. 2015).

In this paper, we focus specifically on the default probability defined as the normal transformation of the Merton's distance-to-default measure, computed as: $PD_{i,t} = F(-DD_{i,t})$, where F is the cumulative distribution function of a standard normal distribution. The $DD_{i,t}$ model is suitable indicators of bank distress during the crisis time and bank fragility. Thus, according to this model, default happens when the market value of assets $VA_{i,t}$ falls below the book value of the debt $D_{i,t}$. Hence, the larger the $DD_{i,t}$, the greater is the distance of a bank from the default point, and the lower is the probability of default.

Following De Jonghe (2010) and Engle and Manganelli (2004), we compute Tail-beta (quantile-Tail-beta) for each of the banks in our sample using a quantile regression model at the q-specified quantile. Tail-beta captures bank's sensitivity to extreme movements. We conduct a 1-percent quantile regression. We estimate Tail betas of each bank *i* by regressing daily bank stock return $R_{i,t}$ on daily market return $R_{M,t}$ (as in Eq. (7)). Thus, Tail-beta (spillover coefficient) measures the risk sensitivity of bank at the 1% quantile. The larger is the spillover effect, the more vulnerable is bank to a financial downturn.

3.4. Control variables

In examining the relationship between bank internationalization and systemic risk, we include in our estimations a vector of control variables which are expected to affect our bank individual systemic risk measures. We follow previous studies in the literature (Laeven et al. (2015), Anginer et al. (2014), Weiß et al. (2014), Beck et al. (2013); among others) and calculate for each bank, each year, all a set of controls. We use Size, which is defined as the natural logarithm of a bank's total assets to control for bank absolute size and -Leverage, measured as the ratio of equity to total assets to account for bank capitalization. We also consider Diversification for the reliance on non-interest income activities (noninterest income over total income), Deposits to capture a bank's involvement in market-based activities (deposits to total assets) and Loans funding (net loans over total assets), Efficiency (cost income ratio, non-interest expense over total income) and ROA return on assets ratio (net income to total assets).

4. Empirical results

In this section, we first present univariate mean analyses of the main bank financial characteristics we use in the empirical framework, and examine presence abroad across three periods: 2005–2007, 2008–2011, and 2012–2013. Then, we estimate regressions to examine the effect and the changes of internationalization and organization complexity on bank systemic risk depending on the state and soundness of the banking industry using the same periods: before the GFC, during the acute financial crises years and at the later stage of the financial crises.[67]

4.1. Descriptive statistics and univariate analysis

We report in Table 3.3.[68] the descriptive statistics of the variables used in this study and compares bank financial characteristics throughout the 2005–2007, 2008–2011, and 2012–2013 periods. We observe that on average our two main measures of systemic risk (i.e. the MES and SRisk) were at the lowest levels (resp. 1.17 and 4.83) during the years 2005–2007 prior to both crises. And, the already extremely high levels (resp. 3.30 and 12.43) consequently during economic distress from 2008–2011 are even higher (resp. 3.32 and 13.32) in the 2012–2013 post crisis period. Looking at the standard deviation and maximum values, the previous pattern stands. Moreover, while the evolution of the ΔCoVaR, probability of default, and Tail-beta globally follow the same track, we point out that maximum levels of ΔCoVaR (6.84) and probability of default (0.57) were

[67] Our study provides an analysis of the effect of foreign bank affiliates and international complexity on the European banking industry systemic risk. Although we picture great changes in cross-border operations through the data collected, we do not analyze the drivers of those changes. In a further research, we aim to go beyond the scope of what we did and question the different factors likely to explain the transformation of multinational banks' organizational networks.

[68] In Table A3.2. (see Appendix 3) contents the definitions of all variables, the sources, and the summary statistics over the global 2005–2013 period.

reached during the crisis period. Considering the control variables, while the values of some variables have increased (decreased) during the distress period and the tendency had continued in the aftermath, other variables have seen the levels almost coming back in 2012–2013 to the state of 2005–2007. For instance, the downfall of average and maximum bank capitalization (total equity to total assets ratio) observed in 2008–2013 (from 9.09% to 8.68% and from 44.82% to 35.68%) have continued in 2012–2013 (from 8.68% to 8.01% and from 35.68% to 30.35%). Throughout the three periods, the average and maximum returns on assets of listed banks were also lower (from 1.17% to 0.35% and from 5.85% to 3.61%) during the 2008–2011 crisis and even lowest the years after (from 0.35% to 0.06% and from 3.61% to 3.24%). However, Deposits and cost-to-income (Efficiency) which were on average higher in 2012-2013 (49.58% and 45.20%) than in 2008-2011 (49.36% and 42.33%) and 2005–2007 (48.52% and 40.08%). In contrary, Diversification (and Loans) that measure the bank degree of reliance on nontraditional activities (and traditional activities), have declined (increased) during the crisis but, have almost regain the pre-crisis levels. In contrary, Diversification has declined, and Loans has increased during the crisis (from 29.82% to 26.10% and from 69.19% to 72.61%, respectively) but, have almost regained the pre-crisis levels in the post-crisis period (from 26.10% to 28.80% and from 72.61% to 69.23%, respectively).

Table 3.3. Bank descriptive statistics, across the 2005–2007, 2008–2011 and 2012–2013 periods

MES= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; SRisk= Systemic risk, expected capital shortfall; ΔCoVaR= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level; PD= Probability of default; Tail-beta= quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries; *NbSubsidiaries*= continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplexS*= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions. *Size (log TA)*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets ; *Deposits(%)*= ratio of customer deposits to total assets; *Diversification (%)* = ratio of noninterest income to total income; *Loans(%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets.

	Pre-Crisis 2005–2007					**Crisis 2008–2011**					**Post Crisis 2012–2013**				
	Obs.	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max	Obs.	Mean	Std. Dev.	Min	Max
MES	315	1.17	1.30	-1.21	5.74	420	3.30	2.26	-1.64	9.63	210	3.32	2.32	-1.56	9.17
SRisk	315	4.83	17.57	-6.12	165.21	420	12.43	34.03	-6.21	223.80	210	13.32	35.84	-5.02	202.98
ΔCoVaR	315	1.12	1.11	-2.80	4.08	420	2.61	1.46	-2.01	6.85	210	2.02	1.50	-1.57	6.16
PD	312	0	0.01	0	0.21	416	0.03	0.07	0	0.57	208	0.06	0.10	0	0.53
Tail-beta	315	0.69	0.81	-1.46	3.05	420	1.01	0.77	-1.57	3.07	210	1.02	0.92	-1.41	3.17
Foreign	315	0.47	0.50	0	1	420	0.48	0.50	0	1	210	0.49	0.50	0	1
NbHost	149	13.21	16.38	1	63	201	10.75	13.36	1	57	102	9.55	13.05	1	54
NbSubsidiaries	149	37.21	70.39	1	378	201	23.78	49.30	0	289	102	9.47	13.49	0	60
NbRegions_Sub	149	3.06	2.36	1	8	197	2.84	2.27	1	8	94	2.79	2.23	1	8
GeoComplex**S**	149	0.34	0.31	0	0.87	197	0.31	0.34	0	0.95	94	0.34	0.37	0	0.95
Size (log TA)	315	-3.69	2.14	-8.18	0.16	420	-3.40	2.12	-7.99	0.16	210	-3.32	2.12	-7.97	0.16
Leverage (%)	315	9.09	5.80	0.78	44.82	420	8.68	5.05	0.78	35.68	210	8.01	4.79	0.78	30.35
Deposits (%)	309	48.52	19.66	5.69	88.91	412	49.36	18.91	5.69	88.68	206	49.58	20.78	5.69	91.43
Diversification (%)	309	29.82	10.95	1.06	66.54	412	26.10	12.16	1.06	66.54	206	28.80	12.37	1.06	66.54
Loans (%)	294	69.19	16.66	13.02	96.28	392	72.61	15.30	23.37	100	196	69.23	17.12	13.02	100
Efficiency (%)	294	40.08	12.73	14.87	79.52	392	42.33	13.77	14.87	89.93	196	45.20	13.44	14.87	84.41
ROA (%)	315	1.17	0.92	-2.09	5.85	420	0.35	1.06	-4.58	3.61	210	0.06	1.32	-4.58	3.24

In a univariate analysis that tests the significance of the descriptive statistics, we compare the financial characteristics and risk measures of banks that operate foreign subsidiaries and those who do not over the full period of study and then across 2005–2007, 2008–2011, and 2012–2013. Table 3.4. indicates that irrespective of the period, the exposure to systemic risk for banks with foreign subsidiaries is always significantly higher than other banks. From the values of the t-statistics, the difference is greater during the crises' years, than during the years after, and even before. The cost-to-income ratio (Efficiency) for listed banks with and without international affiliates is not different. Overall regardless of the period, the data show that multinational banks are larger (higher TA), less capitalized (lower equity to total asset ratio), rely less on deposits and loans, and are less profitable (lower return on assets).

Table 3.4. Bank characteristics by foreign presence across the 2005–2007, 2008–2011 and 2012–2013 periods

This table compares the characteristics of banks that operate at least one subsidiary abroad and banks that do not across the 2005–2007, 2008–2011, and 2012–2013 periods. T-statistics test the null hypothesis: "bank characteristics are not different between international and non-international banks during the 2005–2007, the 2008–2011, and the 2012–2013 periods." * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate the significance of p-value for a bilateral test. *MES*= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRisk*= Systemic risk, expected capital shortfall; Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level; *PD*= Probability of default ; *Tail-beta* = quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *TA*= the bank total assets ; *Size (log TA)*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets ; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= ratio of noninterest income to total income ; *Loans(%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets.

	All 2005–2013			**Pre-Crisis 2005–2007**			**Crisis 2008–2011**			**Post-Crisis 2012–2013**		
	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics	Foreign = 0	Foreign = 1	t-statistics
MES	1.75	3.51	-13.05***	0.77	1.62	-6.15***	2.27	4.41	-11.01***	2.22	4.48	-8.09***
SRisk	0.59	20.46	-10.67***	0.43	9.73	-4.86***	0.75	25.15	-7.85***	0.51	26.88	-5.72***
ΔCoVaR	1.5	2.51	-10.78***	0.85	1.42	-4.7***	2.11	3.16	-7.86***	1.28	2.8	-8.54***
PD	0.02	0.04	-2.79***	0	0	1.20	0.03	0.04	-2.79***	0.05	0.07	-1.49*
Tail-beta	0.61	1.22	-12.08***	0.45	0.95	-5.70***	0.71	1.33	-9.09***	0.66	1.4	-6.32***
TA	1.70E+08	2.90E+08	-1.19	2.01E+04	1.40E+08	-2.13**	2.25E+04	4E+05	-8.34***	7.70E+08	1.10E+09	-0.70
Size (log TA)	-4.82	-2.01	-26.95***	-5.02	-2.2	-15.49***	-4.81	-1.85	-19.89***	-4.54	-2.04	-10.56***
Leverage (%)	11.06	6.06	16.54***	11.83	6.04	10.20***	10.91	6.24	10.64***	10.17	5.72	7.57***
Deposits (%)	54.59	43.38	9.08***	54.1	42.29	5.52***	54.46	44.3	5.65***	55.61	43.18	4.49***
Diversification (%)	27.4	28.53	-1.44*	29.19	30.51	-1.06	26.56	25.6	0.80	26.35	31.41	-2.99***
Loans (%)	74.21	67.25	6.51***	73.52	64.8	4.64***	75.91	69.35	4.34***	71.81	66.71	2.11**
Efficiency (%)	42.62	41.81	0.89	40.79	39.36	0.96	42.81	41.85	0.69	45.06	45.33	-0.14
ROA (%)	0.73	0.37	4.73***	1.44	0.86	5.80***	0.5	0.19	3***	0.11	0.02	0.50

We display in Table 3.5. the correlation matrix for all variables on the whole 2005–2013 period. However, because the variables of internationalization are observable only for bank with a presence abroad, the correlation test indicates a strong collinearity between *NbHost*, *NbSubsidiaries*, *NbRegions_Sub*, and *GeoComplex**S*** and the dummy variable *Foreign*. We hence omit Foreign. The correlation matrix suggests that there is a structural reason why some banks become large, with lower capital, more non-interest activities, and more systemic risk at the same time. Yet, from the test statistics and variance inflation factor (VIF), we find no additional collinearity issues that would prevent us from using all the variables simultaneously in the regressions.

Table 3.5. Correlation Matrix

Table presents the pairwise correlation matrix for foreign presence and complexity variables and systemic risk measures. Definitions of all variables are listed in section 3.

	NbHost	NbSubsidiaries	NbRegions_Sub	GeoComplexS	MES	SRisk	ΔCoVaR	PD	Tail-beta
NbHost	1								
NbSubsidiaries	0.82	1							
NbRegions_Sub	0.86	0.69	1						
GeoComplexS	0.64	0.43	0.87	1					
MES	0.16	0.04	0.19	0.22	1				
SRisk	0.71	0.58	0.65	0.50	0.35	1			
ΔCoVaR	0.05	-0.01	0.05	0.06	0.65	0.17	1		
PD	0.04	-0.01	-0.01	-0.02	0.48	0.16	0.36	1	
Tail-beta	0.26	0.10	0.26	0.28	0.67	0.25	0.43	0.39	1
Crisis08_11	-0.04	-0.03	-0.02	-0.03	0.36	0.10	0.45	0.12	0.14
Size (log TA)	0.59	0.40	0.61	0.57	0.40	0.47	0.30	0.23	0.38
Leverage (%)	-0.30	-0.24	-0.29	-0.23	-0.04	-0.24	0.05	-0.20	-0.08
Deposits (%)	-0.37	-0.28	-0.40	-0.33	-0.01	-0.30	0.10	-0.08	-0.05
Diversification (%)	0.30	0.23	0.30	0.24	0.03	0.27	-0.15	0.01	0.06
Loans (%)	-0.50	-0.45	-0.47	-0.39	-0.02	-0.42	0.09	-0.01	-0.11
Efficiency (%)	0.06	0.01	0.04	0.01	0.13	0.22	-0.08	-0.04	0.04
ROA (%)	0.02	0.03	0.05	0.06	-0.31	-0.11	-0.11	-0.35	-0.18

	Crisis08_11	Size (log TA)	Leverage (%)	Deposits (%)	Diversification (%)	Loans (%)	Efficiency (%)
Crisis08_11	1						
Size (log TA)	0.08	1					
Leverage (%)	0.06	-0.30	1.00				
Deposits (%)	0.06	-0.30	0.46	1			
Diversification (%)	0.04	-0.21	0.10	-0.18	1		
Loans (%)	-0.21	-0.01	0.33	0.52	-0.28	1	
Efficiency (%)	0.12	-0.18	0.10	0.03	0.55	-0.20	1
ROA (%)	0.01	-0.31	0.52	0.19	0.23	-0.01	-0.15

4.2. Regression results

We first examine the effect of five international and foreign complexity indicators on the estimated measures of systemic risk of listed European banks depending on the state and soundness of the banking industry after controlling for bank-level characteristics. Specifically, we determine whether the relationship between bank international activities and systemic risk is different during the financial and sovereign debt crises and at the later stage of the financial crises. We also investigate the effect of other measures of foreign organizational strategies on listed banks systemic risk over the 2011–2013 period.

4.2.1. Effect of bank internationalization and complexity on systemic risk

In Table 3.6., we examine for a sample of listed European banks over 2005–2013 period the effects of five foreign complexity measures: presence abroad with subsidiaries (Foreign), number of host countries around the world (NbHost), number of subsidiaries (NbSubsidiaries), number of regions where the foreign subsidiaries are located (NbRegions_Sub), and geographical complexity index (GeoComplex**S**) on the bank risk measures that generate systemic effect: MES (columns (1a)–(5a)), SRisk (columns (1b)–(5b)), and ΔCoVaR (columns (1c)–(5c)).

Before the crisis (2005–2007), banks with a foreign presence have a significantly lower systemic risk (MES (1a), SRisk (1b), and ΔCoVaR (1c)). These results are consistent with the arguments that geographic expansion lowers risk by reducing exposure to idiosyncratic local risks (Goetz et al. (2016), Carmassi and Herring (2016), Gropp, et al. (2010)). Moreover, while banks operating a network of foreign subsidiaries in many host countries around the world appear slightly less vulnerable to systemic event (MES (2a)), they display a higher and significant exposure to common shocks that affect the whole financial system (SRisk (2b)). Yet, given the absence of significance on ΔCoVaR (2c), the value of the stocks of such banks is not affected probably because the banks are not under distress. Then, looking at the affiliates dispersion, our results indicate that the growth of the number of subsidiaries and the widespread in different world regions are positively and slightly significantly (at a 10% level) associated with SRisk only (columns (3b) and (4b)) and bear zero impact on the other measures. The coefficients accounting for the influence of the Herfindhal index of geographic complexity and diversity of the bank's subsidiaries around the different world regions indicate no significance on all three risk measures. Globally, these findings imply that during the normal times before the crisis, the internationalization of banks either decrease the contribution of a bank to the system-wide stress or increase a bank capital expected shortfall when domestic and foreign markets are financially stable. We also investigate the previous relationships in times of financial distress and in the aftermath. Our results reveal that relatively to the pre-crisis (2005–2007) period, the effect of bank internationalization and foreign complexity on listed banks systemic risk are either reversed or amplified during the global financial crisis and sovereign debt crisis years (2008–2011). When significant, the Wald test indicates that while the effect of internationalization and complexity on MES and ΔCoVaR are reversed during the 2008–2011 crisis (α_1+β_1 carries the same positive sign as β_1 and opposite to α_1), the effect on SRisk is aggravated (α_1+β_1 carries the same positive sign as α_1 and β_1). Looking at the post-crisis period (2012–2013), the effects observed during the crises continue to stand and are globally greater in intensity and significance. For the three risk measures, all Wald tests (α_1+β_2) are positive and significant (from a 10% level to a 1% level) and display a similar pattern of signs as (α_1+β_1).

Comparing both sets of Wald tests on a statistical axis, the extent of the effect is more sizable in the post-crisis years (2012–2013). The "normal" and expected increase of the bank systemic risk due to financial distress is long-lived. Probably, during the post-crisis years, banks, central banks, and banking regulators are in the process of changing their behavior, are recovering from the losses of the previous years, and are subject to various macroeconomic policies (fiscal, monetary, and Basel, among others). Hence, the continued increase of the systemic risk and downfall of the financial system.

Regardless of the periods, the economic relevance of the result of listed banks internationalization and complexity is considerable. A bank growing its structure from not operating foreign subsidiaries (*Foreign = 0*) to having a presence abroad with subsidiaries (*Foreign = 1*) decreases the MES by 49% of its mean. Before the financial turmoil, a one standard deviation increases in the number of host countries around the world (i.e. a 1.40 unit increase in *NbHost*) would increase the SRisk by 95% of its mean.

On the whole, internationalization and foreign complexity appear to be an important driver of bank systemic risk, specifically over the crisis times and the post-crisis period. However, our results show that across the calm period, bank foreign complexity contributed to increase the capital shortfall capacity against a systemic risk event, without increasing the bank systemic risk exposure.

Regarding the control variables, most of them carry the signs obtained in previous studies. Not surprisingly, the coefficients of both the acute crises dummy and the post-crises dummy show an increase in the MES. Bank size has a positive and statistically significant effect on the MES. It is a factor that drives systemic risk exposure and not the capital shortfall. With respect to share of loans in total assets, coefficient shows that the MES is negatively associated with loans/assets ratio, while the coefficient related to the share of noninterest income in total income shows a significant increase in the MES. Return on assets has a negative and significant effect on both systemic risks, indicating that higher bank profitability is associated with less systemic risk.

Table 3.6. Effect of the internationalization of bank on systemic risk

This table displays the results of the estimation of Eq. (1) regarding the effects of bank internationalization on listed banks systemic risk over the 2005-2013 period. *MES*= Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRisk*= Systemic risk, expected capital shortfall; Δ*CoVaR*= ΔConditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries; *NbSubsidiaries*= natural logarithm of the continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad ; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplex**S***= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions ; Crisis08_10 is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise; Post12_13 is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; *Size (log TA)*= natural logarithm of the total assets ; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= ratio of noninterest income to total income; *Loans(%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets. We use the Ordinary Least Square (OLS) model and the robust adjusted standard error are reported in parentheses. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels.

	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR	MES	SRisk	ΔCoVaR
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)	(5a)	(5b)	(5c)
Foreign (α_1)	-0.969***	-10.06*	-0.462***												
	(-3.82)	(-1.79)	(-3.06)												
Foreign*Crisis08_11 (β_1)	1.476***	15***	0.386*												
	(6.78)	(3.48)	(1.84)												
Foreign*Post12_13 (β_2)	1.592***	17.16***	0.834**												
	(5.80)	(3.60)	(2.69)												
NbHost (α_1)				-0.017*	0.678***	0.004									
				(-2.02)	(3.27)	(0.31)									
NbHost*Crisis08_11 (β_1)				0.034**	1.543***	0.005									
				(2.81)	(8.15)	(0.63)									
NbHost*Post12_13 (β_2)				0.056***	1.415**	0.019									
				(5.93)	(2.82)	(1.34)									
NbSubsidiaries (α_1)							-0.038	8.050*	0.165						
							(-0.37)	(2.05)	(1.44)						
NbSubsidiaries*Crisis08_11 (β_1)							0.379***	10.50***	0.069						
							(3.91)	(3.70)	(0.90)						
NbSubsidiaries*Post12_13 (β_2)							0.497**	15.11***	0.334***						
							(2.38)	(4.26)	(3.18)						
NbRegions_Sub (α_1)										-0.035	4.190*	0.066			
										(-0.48)	(2.11)	(0.94)			
NbRegions_Sub*Crisis08_11 (β_1)										0.192*	7.879***	0.010			
										(2.13)	(3.93)	(0.17)			
NbRegions_Sub*Post12_13 (β_2)										0.343***	8.086***	0.098			
										(3.91)	(3.09)	(1.35)			
GeoComplexS (α_1)													0.118	0.326	0.466
													(0.20)	(0.05)	(1.13)
GeoComplexS*Crisis08_11 (β_1)													0.911	36.56**	0.049
													(1.20)	(2.72)	(0.12)
GeoComplexS*Post12_13 (β_2)													1.780**	39.17***	0.120
													(2.19)	(3.31)	(0.28)
Crisis08_11	1.152***	-1.563	1.131***	1.980***	-2.580	1.367***	1.708***	-3.768	1.411***	1.850***	-9.515*	1.439***	2.114***	-0.189	1.442***
	(5.62)	(-0.99)	(4.87)	(5.96)	(-0.84)	(7.87)	(4.55)	(-0.82)	(7.14)	(3.85)	(-1.98)	(6.84)	(4.55)	(-0.05)	(6.72)
Post12_13	1.034***	-5.369***	0.484**	1.695***	1.855	1.035***	1.680**	-1.838	0.875**	1.414**	-8.111*	0.937**	1.784**	-2.090	1.153***
	(4.51)	(-3.31)	(2.47)	(3.72)	(0.46)	(4.42)	(2.69)	(-0.38)	(2.99)	(2.69)	(-1.87)	(2.94)	(2.99)	(-0.49)	(3.73)
Size	0.422***	9.985***	0.237***	0.526***	4.570	0.223***	0.401***	2.059	0.073	0.468***	5.605**	0.195***	0.487***	11.23***	0.228***
	(3.87)	(3.81)	(6.12)	(4.87)	(1.64)	(5.36)	(3.51)	(1.15)	(1.22)	(5.09)	(2.32)	(5.74)	(7.44)	(3.06)	(9.86)
Leverage	-1.918	42.44	-1.496	-0.427	22.88	-6.558	0.547	91.93	-6.311	-0.265	32.48	-6.556*	-0.754	45.26	-6.196
	(-0.92)	(1.29)	(-1.49)	(-0.10)	(0.28)	(-1.66)	(0.14)	(0.84)	(-1.67)	(-0.06)	(0.29)	(-1.79)	(-0.20)	(0.35)	(-1.58)
Deposit	0.148	14.19	0.259	-0.597	-7.826	-0.254	-0.295	-5.457	0.120	-0.250	-4.335	0.028	-0.352	-8.557	03
	(0.25)	(1.02)	(0.76)	(-0.54)	(-0.48)	(-0.34)	(-0.28)	(-0.36)	(0.16)	(-0.23)	(-0.27)	(0.04)	(-0.31)	(-0.35)	(0)
Diversification	2.464**	20.36	0.432	0.675	-17.48	-0.617	0.172	-16.76	-0.575	0.121	-23.15	-0.651	-0.085	-15.92	-0.709
	(2.64)	(0.84)	(0.61)	(0.49)	(-0.54)	(-0.55)	(0.13)	(-0.59)	(-0.51)	(0.09)	(-0.81)	(-0.54)	(-0.06)	(-0.49)	(-0.60)
Loans	-0.798**	-32.49***	-0.507	-0.123	-0.550	0.464	0.217	02	0.770	0.176	-3.163	0.588	0.297	-15.24	0.490
	(-2.20)	(-4.28)	(-1.37)	(-0.24)	(-0.02)	(0.64)	(0.45)	(0)	(1.45)	(0.37)	(-0.10)	(0.89)	(0.60)	(-0.38)	(0.69)

Effeciency	-0.268	36.45	-0.843	0.751	34.88	-0.380	1.379	49.63	-0.316	1.338	46.60	-0.027	1.688	68.39	0.154
	(-0.22)	(1.63)	(-0.97)	(0.46)	(1.09)	(-0.29)	(0.86)	(1.39)	(-0.23)	(0.97)	(1.62)	(-0.02)	(1.26)	(1.68)	(0.12)
ROA	-11.40	-135.6	21.63*	-28.37**	-13.64	18.80	-29.61*	-190.6	8.680	-31.59*	-102.2	10.16	-28.32*	-16.29	11.67
	(-1.54)	(-1.71)	(1.94)	(-2.55)	(-0.06)	(0.85)	(-1.79)	(-1.03)	(0.50)	(-2.14)	(-0.50)	(0.58)	(-2.08)	(-0.08)	(0.65)
Constant	-3.780**	-100.0**	0742	-5.486***	-58.03	-0.320	-4.892***	-53.52	0.452	-5.315***	-68.93	-0.472	-5.701***	-118.3*	-0.750
	(-2.72)	(-2.55)	(0.01)	(-3.51)	(-1.55)	(-0.57)	(-3.15)	(-1.47)	(0.81)	(-3.97)	(-1.72)	(-0.81)	(-5.07)	(-1.93)	(-1.10)
Observations	784	784	784	394	394	394	382	382	382	382	382	382	382	382	382
R-squared	0.652	0.549	0.464	0.658	0.786	0.448	0.671	0.751	0.496	0.668	0.758	0.473	0.667	0.678	0.468
Adjusted R-squared	0.640	0.534	0.445	0.635	0.772	0.410	0.647	0.734	0.461	0.645	0.741	0.436	0.644	0.656	0.431
Wald tests: $\alpha_1 + \beta_1$	0.507*	4.94	-0.076	0.017**	2.221***	09	0.341**	18.550***	0.235**	0.157*	12.069***	0.075	1.029	36.886**	0.516**
$\alpha_1 + \beta_2$	0.623*	7.100*	0.372*	0.043***	2.093***	0.023*	0.459*	23.160***	0.499***	0.308**	12.276***	0.164***	1.898**	39.496***	0.586***

4.2.2. Exploration of alternative systemic risk measures

For deeper insights, we investigate the effect of bank internationalization and how the large period marked by both the global financial crisis and the sovereign debt crises might have affected the different relationships. For simplicity and a better readability of Table 3.7., we regroup and comment the results by our different variables of interest instead by the risk measures. While banks present abroad with subsidiaries face lower probability of default (PD) before the period of crisis (negative α_1), the relation is reversed during the crisis (positive β_1) and this effect is statistically worsened in the aftermath of the crisis (positive and higher β_2). In these years after the crises, the impact on the Tail-beta also becomes significant (positive β_2). For this set of regressions, the Wald tests ($\alpha_1+\beta_1$) only indicate an increase of the sensitivity to extreme movements (Tail-beta) whereas ($\alpha_1+\beta_2$) points to an increase of both PD and Tail-beta. Regarding the four other indicators of bank internationalization and foreign complexity (*NbHost*, *NbSubsidiairies*, *NbRegions_Sub*, and *GeoComplex**S***), we only observe lower risk (PD) before the crisis (2005–2007) for banks in many host countries and a slightly significant (at a 10% level) increase of the sensitivity of geographic complex banks to the extreme movements of the financial markets (Tail-beta). Also, for all variables, our findings globally signal higher financial instability during both crises (2008–2011) and post-crises (2012–2013) periods. All significant Wald tests ($\alpha_1+\beta_1$ and $\alpha_1+\beta_2$) point to higher bank risk and thus, greater banking fragility. Regarding the bank financial characteristics, we observe in all estimation highly profitable banks are the less risky ones. Albeit a lost in the significance of most coefficients, the rest of control variables globally portray the same impact as what can be seen in Table 3.6.

Table 3.7. Effect of the internationalization of banks on alternative systemic risk measures

This table displays the results of the estimation of Eq. (1) regarding the effects of bank internationalization on listed banks systemic risk over the 2005-2013 period. *PD*= Probability of default; *Tail-beta*= quantile-beta, a measure of the sensitivity to extreme movements of beta. *Foreign* = a dummy that takes the value one when the listed bank owns at least one subsidiary abroad ; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries ; *NbSubsidiaries*= natural logarithm of the continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad ; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located ; *GeoComplex**S***= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions; *Crisis08_10* is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise ; *Post12_13* is a dummy equal to one if the year is 2012 or 2013, and zero otherwise ; *Size (log TA)*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= ratio of noninterest income to total income; *Loans(%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income ; *ROA(%)*= return on assets is the ratio of net income to total assets. We use the Ordinary Least Square (OLS) model and the robust adjusted standard error are reported in parentheses. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels.

	PD (1d)	Tail-beta (1e)	PD (2d)	Tail-beta (2e)	PD (3d)	Tail-beta (3e)	PD (4d)	Tail-beta (4e)	PD (5d)	Tail-beta (5e)
Foreign (α_1)	-2.378**	0.108								
	(-2.83)	(0.88)								
Foreign*Crisis08_11 (β_1)	3.174***	0.167								
	(3.92)	(1.56)								
Foreign*Post12_13 (β_2)	4.312***	0.355**								
	(3.25)	(2.27)								
NbHost (α_1)			-0.041**	0.005						
			(-2.40)	(1.25)						
NbHost*Crisis08_11 (β_1)			0.122***	0.002						
			(3.99)	(0.51)						
NbHost*Post12_13 (β_2)			0.129***	0.013**						
			(4.51)	(2.47)						
NbSubsidiaries (α_1)					-0.149	0.046				
					(-0.57)	(1.67)				
NbSubsidiaries*Crisis08_11 (β_1)					1.188***	0.018				
					(5.86)	(0.36)				
NbSubsidiaries*Post12_13 (β_2)					1.169**	0.086**				
					(2.93)	(2.41)				
NbRegions_Sub (α_1)							-0.208	0.036		
							(-1.38)	(1.39)		
NbRegions_Sub*Crisis08_11 (β_1)							0.578***	07		
							(3.18)	(0.31)		
NbRegions_Sub*Post12_13 (β_2)							0.290	0.049		
							(0.65)	(1.12)		
GeoComplex**S** (α_1)									-0.802	0.377*
									(-0.58)	(1.78)
GeoComplex**S***Crisis08_11 (β_1)									2.865	0.086
									(1.66)	(0.48)
GeoComplex**S*** Post12_13 (β_2)									0.452	0.290
									(0.15)	(0.91)
Crisis08_11	-0.041	0.078	1.155	0.180**	0.400	0.168	0.914	0.166	1.667	0.160*
	(-0.09)	(0.88)	(1.44)	(2.11)	(0.55)	(1.28)	(0.83)	(1.59)	(1.54)	(1.68)
Post12_13	-0.049	-0.061	1.779	0.0625	1.680	0.086	2.539	0.042	3.237	0.076
	(-0.09)	(-0.52)	(1.11)	(0.50)	(1.03)	(0.70)	(1.01)	(0.27)	(1.43)	(0.57)
Size	0.051	0.124***	0.167	0.123***	-0.0954	0.119**	0.329	0.129***	0.406*	0.123***
	(0.25)	(4.06)	(0.69)	(2.75)	(-0.39)	(2.86)	(1.52)	(3.22)	(2)	(3.81)
Leverage	-2.640	0.629	-28.38	1.448	-33.15	1.890	-29.06	1.588	-26.81	1.349
	(-0.54)	(0.92)	(-1.35)	(0.97)	(-1.60)	(1.04)	(-1.43)	(1.12)	(-1.36)	(1)
Deposit	-2.225	-0.114	-1.788	-0.404	-1.571	-0.373	-1.735	-0.377	-1.905	-0.361
	(-1.20)	(-0.53)	(-0.58)	(-1.22)	(-0.52)	(-0.93)	(-0.54)	(-1.11)	(-0.60)	(-1.11)
Diversification	5.517	0.679**	4.402	0.546	3.535	0.519	3.255	0.474	31	0.416
	(1.61)	(2.38)	(0.66)	(1.63)	(0.55)	(1.28)	(0.51)	(1.34)	(0.46)	(1.19)
Loans	-1.509	-0.402**	-0.641	-0.155	0.224	-0.158	-0.620	-0.145	-0.696	-0.126
	(-0.97)	(-2.14)	(-0.55)	(-0.59)	(0.16)	(-0.55)	(-0.50)	(-0.58)	(-0.50)	(-0.55)
Efficiency	-6.154	-0.119	-7.717	0.0256	-6.281	0.164	-5.309	0.154	-4.707	0.164
	(-1.69)	(-0.39)	(-1.39)	(0.07)	(-1.19)	(0.39)	(-1.12)	(0.42)	(-0.95)	(0.47)
ROA	-229.6***	-5.772	-329.2***	-16.40**	-308.0***	-18.09***	-301.0***	-18.15**	-297.6***	-17.89**
	(-3.06)	(-1.54)	(-5.41)	(-2.32)	(-5.04)	(-3.61)	(-5.13)	(-2.66)	(-5.03)	(-2.63)
Constant	5.461**	-0.837**	5.475*	-0.799*	7.069***	-0.856	3.265	-0.898**	1.937	-0.805**
	(2.58)	(-2.45)	(2.11)	(-1.84)	(3.22)	(-1.64)	(1.75)	(-2.27)	(1.01)	(-2.24)
Observations	776	784	390	394	378	382	378	382	378	382
R-squared	0.431	0.463	0.499	0.475	0.483	0.463	0.469	0.466	0.466	0.478
Adjusted R-squared	0.411	0.445	0.464	0.439	0.446	0.425	0.431	0.428	0.428	0.442
Wald tests: $\alpha_1+\beta_1$	0.796	0.275***	1.182**	07	1.731***	0.064	0.370**	0.042	2.063	0.463***
$\alpha_1+\beta_2$	1.942**	0.463***	1.250**	0.018***	1.020**	0.132***	0.082	0.085**	-0.35	0.667***

4.2.3. Deeper investigation: impact of foreign organizational complexity on systemic risk

To conduct an additional analysis, we focus on the 2011-2013 window and, instead of using the number of subsidiaries as a measure of complexity, we build three dummies that more precisely map more precisely the different foreign affiliates' strategies banks have established abroad on that period of study. In fact, because of the limited availability of data on branches we were only able to hand-collect such data from the SNL database[69] as of end of 2013. Following the same logic, we did for foreign subsidiaries; we apply the information of the year 2013 to 2012 and 2011. Considering our global sample of listed banks, $Bank\_Sub_i$ is a dummy equal to one when the bank is structured through a network of foreign subsidiaries only (at least one subsidiary abroad and zero branch) and zero otherwise; $Bank\_Brh_i$ is equal to one when the bank operates a network of foreign branches only (at least one foreign branch and no foreign subsidiary) and zero otherwise, and $Bank\_Both_i$ takes the value one when the bank has a foreign network with both foreign subsidiary and branch, and zero if not. Note that a branch is an extension of the parent bank which undergoes the parent home country supervision and all its activities are accounted for by the parent bank.

In Table 3.8., we present this complementary aspect of complexity as we look more closely at the impact of the foreign organizational choice of affiliates on the listed bank systemic risk. We replace the three dummy variables in the vector of variables of interest $International_{i,t}$ in Eq. (1) and we estimate the new model:

$$Risk_{i,j,t} = \alpha_0 + International_{i,t} + \varphi X_{i,t-1} + \omega_j + \varepsilon_{ij,t} \qquad (10)$$

Where $Risk_{i,j,t}$ represents systemic risk measures MES and SRisk of the publicly traded bank i in country j over the year t. $international_{i,t}$ corresponds to the three dummies representing penetration strategies: $Bank\_Sub_i$, $Bank\_Brh_i$, and $Bank\_Both_i$. We include the same set of control variables as in Eq. (1).

The results show that while on the whole establishing a network of branches exclusively is significantly negatively associated with the marginal expected shortfall of multinational listed

[69] SNL only provides data on branches for the latest accounting exercise. Unfortunately, since we lost our access to the database in 2014 and were not able to find additional as detailed data elsewhere, the sample of branches is limited to the year 2013.

bank, there is no impact on SRisk. In contrast, owning foreign subsidiaries produce an opposite effect as it is ineffective on the bank MES and slightly negatively affects SRisk (at a 10% level of significance). However, we do not find any impact on the systemic risk of banks that set up the more complex foreign organizational model of both subsidiaries and branches.

Table 3.8. Effect of foreign organizational complexity (branches and subsidiaries) on listed banks systemic risk (2011–2013)

This table displays the results of the estimation of Eq. (11) regarding the effects of bank internationalization and organizational complexity on listed banks systemic risk over the 2011-2013 period. *MES* = Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes; *SRisk*= Systemic risk, expected capital shortfall. *Foreign*= a dummy that takes the value one when the listed bank owns at least one subsidiary abroad; *NbHost*= continuous variable that accounts the number of host countries of the foreign subsidiaries ; *NbSubsidiaries*= natural logarithm of the continuous variable that accounts the exact number of foreign subsidiaries a listed bank operate abroad; *NbRegions_Sub*= the number of regions where all foreign subsidiaries are located; *GeoComplex**S***= the geographic complexity indicator of the dispersion of all subsidiaries in different world regions ; *Crisis08_10* is a dummy equal to one if the year is 2008, 2009,2010, or 2011, and zero otherwise; *Post12_13* is a dummy equal to one if the year is 2012 or 2013, and zero otherwise; *Size(log TA)*= natural logarithm of the total assets; *Leverage(%)*= ratio of total equity to total assets ; *Deposits(%)*= ratio of customer deposits to total assets ; *Diversification(%)*= ratio of noninterest income to total income; *Loans (%)*= ratio of net loans to total assets ; *Efficiency(%)*= cost to income ratio defined as non-interest expense divided by total income; *ROA(%)*= return on assets is the ratio of net income to total assets. We use the Ordinary Least Square (OLS) model and the robust adjusted standard error are reported in parentheses. Variables were winsorized at 1% and 99% levels to limit the influence of extreme values. ***, **, and * indicate significance of the p-value respectively at the 1%, 5%, and 10% levels.

	MES			SRisk		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
Bank_Sub	0.192			-8.740*		
	(0.56)			(-1.95)		
Bank_Brh		-1.260**			0.753	
		(-2.72)			(0.18)	
Bank_Both			-0.233			11.84
			(-0.49)			(1.32)
Size (logTA)	0.580***	0.585***	0.615***	13.68***	13.63***	11.90***
	(4.48)	(4.54)	(3.90)	(4.23)	(4.32)	(5.04)
Leverage	0.679	0.361	0.412	97.44	109.7	109.6
	(0.19)	(0.11)	(0.12)	(1.55)	(1.72)	(1.71)
Deposits	1.139	1.297*	1.162	33.61	34.77*	32.29
	(1.61)	(1.84)	(1.64)	(1.60)	(1.78)	(1.71)
Diversification	3.228**	3.096**	3.153**	29	30.01	32.70
	(2.39)	(2.25)	(2.36)	(0.66)	(0.73)	(0.80)
Loans	-1.358*	-1.247*	-1.439**	-19.25	-22.44	-14.78
	(-2.03)	(-1.98)	(-2.32)	(-1.36)	(-1.66)	(-1.28)
Efficiency (CIR)	-0.716	-0.582	-0.692	68.26**	68.02**	67.05**
	(-0.58)	(-0.51)	(-0.56)	(2.41)	(2.23)	(2.45)
ROA	-27.33***	-26.13***	-26.48***	-346.8***	-384.0***	-385.6***
	(-3.75)	(-3.86)	(-3.87)	(-4.31)	(-4.47)	(-4.50)
Constant	-4.515**	-4.453**	-4.609**	-174.1***	-175.7***	-169.1***
	(-2.56)	(-2.66)	(-2.56)	(-3.33)	(-3.31)	(-3.40)
Observations	294	294	294	294	294	294
R-squared	0.720	0.724	0.720	0.620	0.613	0.620
Adjusted R-squared	0.698	0.701	0.697	0.589	0.581	0.589

5. Robustness checks

In this section, we perform additional regressions to check for the robustness and the validity of our main results obtained in Section 4.2.

First, we decompose the timeline dummy of crisis that covers the 2008 to 2011 large period of global economic instability into two other dummies Fin08_09 and Sov10_11 to capture more precisely the individual effect of the acute years of the global financial crisis and the sovereign debt crisis, respectively. We introduce both dummy variables in the regressions (by augmenting Eq.(1) by these two binary variables) and analyze the influence on the individual bank systemic risk. With the exception of the negative relationship between *Sov10_11* and *SRisk* in the regression where the variable of interest assesses the presence abroad with subsidiaries or not i.e. Foreign, the effects of *Fin08_09* and *Sov10_11* mirror *Crisis08_11* in sign and significance. Also, considering all interacted terms, the results of Wald tests align with the baseline. Globally, regardless of the definition or type or timeline of the crisis, shocks increase the systemic risk of publicly trade banks with international operations and geographic complex structure (see Table A3.3. in Appendix 3). The rest of results are consistent with the main findings.

Second, to make sure that using lagged variables did not affect our results, we consider each control variables at time *t* and the estimated coefficients from these regressions are consistent with the previous findings.

6. Conclusion

The objective of this study is to empirically investigate whether the internationalization and geographic complexity of listed banks affect the systemic risk and how both the global financial crisis and the European sovereign debt crisis might have modified the existing relationship. For this purpose, we construct a data set on banks' network of foreign affiliates and systemic risk measures of 105 publicly traded banks headquartered in 15 European countries from 2005 to 2013. Specifically, we question the impact of owning foreign subsidiaries, having a wide presence in many host countries and different world regions, and the geographic dispersion of all the subsidiaries around all the regions on bank stability in periods prior (2005–2007), during (2008–2013), and post (2012–2013) the aforementioned crises.

On the whole, our findings show that while operating a subsidiary abroad is associated with lower systemic risk in normal times, the impact is totally reversed when the banking system undergoes global shocks. Indeed, our results point to an increase in the fragility of international publicly traded banks during years of distress. A closer look at the period after both global financial and European sovereign debt crises indicates that just like during the crisis, the effect of the presence of a bank abroad was long lived with an even worse contribution to bank systemic risk. Moreover, we find that the relationship stands when we examine the impact of owning many subsidiaries, and spreading the foreign presence in different host countries and multiple world regions. These findings suggest that bank internationalization appears as a source of greater stability in calm periods but turns out to increase instability during the 2008–2011 crises. As listed banks are more affected by the changes on financial markets, expanding different affiliates in other markets increase the sensitivity of banks to multiple shocks relatively to banks that conduct domestic operations only.

GENERAL CONCLUSION

Amid global fears of financial instability, since the 2007–2009 global financial crisis, systemic risk has become a permanent threat to the worldwide financial system and poses several challenges for banks regulators and supervisors. Generally, systemic risk refers to a financial shock leading to severe economic contagion, i.e. risk of collapse of the entire system, as a result of the actions taken by individual entities or/and the possibility of a cascading series of failures in an interconnected system. In this process of cascading failures, perhaps the notable example from 2008 is the way that the failure of the U.S. investment bank Lehman Brothers affected the insurance company AIG and Merrill Lynch, while also leading to intense pressure on overall financial conditions. In the end, given this, managing systemic risk, as well as identifying too-big-to-fail and systemic financial institutions capable of imposing contagion when they fail were the main issues being addressed in financial regulation frameworks.

So far, the academic literature on risk management, as well as the regulatory standards, have mainly focused on the study of individual banks in isolation. Therefore, after the global crisis, systemic risk has dramatically shifted the economic research contours of global finance and drawn more attention of policy-makers, regulators and academics on how to strike the right balance between financial stability, negative effects – including increased systemic risk – of financial liberalization and preventing banks turmoil from causing severe economic damage in the banking industry. At the same time, several studies have examined the nature of externalities that financial institutions may create for others, and measured systemic risk that lies with each individual entity. Besides, many studies have looked at the potential bank features driving systemic risk and focused on the implications of systemic risk for banking regulation and financial stability. The aftershocks from the financial crisis have also led to a re-examination of risk assessment practices, policy implications and regulation of the financial system, with a renewed interest in systemic fragility and banking macro-prudential regulation. To that extent, international regulators had adopted a system-wide macroprudential approach and bank regulation reforms (e.g. Basel III Accord, among others) to prevent financial turmoil from causing severe economic damage and to increase the resilience of the financial system; and therefore, mitigating contagion and systemic risk effects.

This thesis relates to the recent literature on systemic risk in the banking system and stock market contagion using publicly available information (see e.g. Adrian and Brunnermeier (2011), Acharya, Pedersen, Philippon, and Richardson (2010), and Brownlees and Engle (2012), among others). It applied systemic risk measures from different measurement approaches, and also proposed estimation formulations based on idiosyncratic risk factors. Then, it drew the attention to the potential bank features driving systemic risk and assessed the systemic risk implications for banking regulation and financial stability. Precisely, the thesis is devoted to three major issues in the area of banking raised by the recent financial crises: bank market valuation, capital adjustment structure and bank complexity, with a renewed interest in systemic stability and macro-prudential regulation, and hence attempts to investigate empirically systemic risk from these three important issues. It also shed light on the ongoing debate over the too-big-to-fail banks, systemically important financial institutions (SIFIs) and complex entities and the merits of restricting their market value and their unstable funding and risky-activities, imposing capital surcharges (systemic risk-based) on large banks and limiting the cross-border dimension of international complexity. Results were relevant both for the systemically important largest banks and the less-systemically important entities.

The dissertation tackled these three aforementioned issues, by introducing empirical methodologies to investigate quantitatively a large collection of risk measures from different perspectives and measurement approaches proposed in the literature. The objectives of this thesis have been to address new research questions on the largest OECD listed banks. To achieve this, we conducted three empirical essays, guided by the existing research gaps, each of them is comprised in a dedicated chapter. In the *first chapter*, we assessed the dynamics of effects of bank charter value on bank risk-taking and systemic exposure in different economic conditions (in pre-, over and post-crisis period). We also investigate the bank charter value effect on risk before the crisis by considering several dimensions such as different risk-taking cultures, bank size, bank growth strategy and business mix. The *second chapter* investigated capital structure and adjustment mechanisms through which systemically important banks adjust to their implicit capital ratio target. The *third chapter* addressed the independent effects of internationalization and organizational complexity characteristics on bank systemic risks and investigated the effects of the global financial crisis and the European sovereign debt crisis on such relationships.

Motivated by the new perception of bank risk – based not only the idiosyncratic risk dimension, but also on the vulnerability of banks and their contribution to systemic risk –, the *first chapter* went beyond the literature addressing the nexus between bank charter value and risk and examine the impact of bank market valuation (charter value) on both systemic and idiosyncratic risk, in the light of the charter-value-hypothesis in banking industry. It investigated the extent to which the charter values among publicly traded OECD banks have been tied to the institution-specific characteristic reflecting individual and systemic risks, and the effectiveness of its risk-disciplining effect regarding the profound transformations of the banking industry (i.e. deregulation, technological changes and reforms modified both structure and operating conditions in the banking industry, thus causing a rise in down side risks) before, during and after the global financial crisis of 2007–2008. This chapter contributed to the empirical literature in several distinct ways. It was the first study to explore the interlinkage between charter value and bank risk-taking and systemic risk exposure during normal times and distress periods (i.e. different economic conditions), and reexamined the charter-value-hypothesis, over different bank sizes, regimes and regarding banks that work in different ways, is necessary for OECD listed banks. Among the key findings, bank charter value effect on both risk-taking and systemic risk exposure depended to the economic conditions and business expansion/contraction. The results suggested that instead of mitigating risk, charter value enhancing expansion increases both risk dimensions during economic upturns (2000–2006), by providing incentives to accumulate risk which in turn contribute to higher systemic risk, resulting in an inversion of the relationship expected under the charter-value-hypothesis. Specifically, bank charter value was positively associated with risk-taking and systemic risk for very large "too-big-too-fail" banks and large U.S. and European banks. Whereas, the results showed that during distress periods, specifically after the global financial crisis (2010–2013), banks tend to protect their charter value and lessen their risk exposure thereby reducing their contribution to systemic risk (inverted relationship). A deeper investigation highlighted the importance of the bank size, institutional risk-taking environment and growth and diversification strategies for effective risk incentive of bank charter value before the financial crisis 2000–2006. The analyses of such behavior before the crisis, i.e. charter value incentives to increase risk-taking and systemic exposure, was mostly relevant for very large banks and large banks with high growth strategies; banks' business models also influence this relationship. The findings highlighted that for banks following a focus strategy, higher charter value amplifies both standalone and systemic risk for large U.S. and European banks.

Next, one of the new elements in the Basel III guidelines is the requirement of a capital surcharge for global SIFIs, which creates a higher loss absorbency capacity. Hence, SIFIs will be (partly) internalizing the costs of the risk externality they impose on the other banks and the overall economy. While this regulatory adjustment may prove to be successful in the long-run, it currently poses at least two challenges. First, it requires the identification of SIFIs, as well as an estimate of their systemic risk contribution. Second, there is little knowledge on whether and how SIFIs make capital structure adjustments and the extent to which their adjustment process differs from or affects non-SIFIs. Therefore, the *second chapter* of this thesis mainly aimed to contribute to the second issue, while touching upon the first one. To achieve this, we studied the capital structure and empirical features of adjustment speed, which could help understanding how publicly traded OECD financial institutions can adjust to their capital ratio targets, whether through a combination of equity issues/repurchases and changes in dividend policies or by adjusting their assets, loans and other assets. Then, we developed methods for exploring if SIFI banks adjust their capital ratio, both when they are over- and undercapitalized with regards to the target, at the same speed as non-systemic banks. The empirical analyses of this chapter showed that, generally, banks were more concerned about readjusting quickly towards optimal leverage, than towards optimal risk-weighted regulatory capital; and therefore, deviations from optimal leverage ratios might be costlier for bank shareholder. Results also showed that banks have more (and less costly) options in asset adjustments that affect non-risk weighted assets than risk weighted assets. The deviations from optimal leverage and risk-weighted capital ratio determined whether equity is adjusted via earnings retention or externally raised equity, or by asset side adjustments via loans and risky assets. These can be understood as an adjustment cost story with costs/benefits (capital adjustment trade-off) to deviate from an optimal level. In addition, the findings revealed that the speed at which banks adjust and the way they adjust show large differences between large, systemic and complex banks versus small banks. They thereby showed that systemic risk and size measures affected the extent to which banks adjust their capital ratios, and played an opposite role (on the speed of adjustment) for leverage ratio vis-à-vis regulatory capital ratios. They indicated that SIFIs are slower than other small banks in adjusting to their target leverage ratio but quicker in reaching to their target regulatory ratios. Moreover, analysis demonstrated that SIFIs are reluctant to change their capital base by either issuing or repurchasing equity and prefer sharper downsizing and/or faster expansion.

Finally, the main objective in the third chapter is to bridge the gap between micro evidences of the impact of internationalization, affiliates structures and geographic expansion on financial stability. This last chapter provided a comprehensive picture of recent changes in foreign bank affiliates and international complexity in European banking industry and investigated the potential consequences for financial stability. To that extent, we empirically studied the potential effects of international organization structure of 105 European listed banks, that have foreign affiliates around the world, on banks' systemic risk exposure during the 2005–2013 period. For this, we constructed a data set on internationalization (number of foreign subsidiaries and number of host countries) and foreign complexity (number of foreign subsidiaries and number of host countries) of listed European banks based in 15 Western European countries, that have networks of affiliates around the world during the 2002–2013 period; and then investigated how the peak of the global financial crisis of 2008–2009 and the height of the European sovereign debt crisis of 2010–2011 might have affected such relationships. Among the key findings, we showed that internationalization and foreign complexity are important drivers of bank systemic risk, particularly during the 2008–2013 financial stress years, when the banking system (European banking industry) undergoes global shocks. Therefore, international complex banks increased the fragility of international publicly traded banks during years of distress. In contrast, results highlighted the existence of a reversed effect of internationalization and foreign complexity on financial stability before financial crisis period (2005–2007). Bank internationalization appeared as a source of greater stability in calm periods but turns out to increase instability during the crisis period. Due to the specific nature of complex banks, results were in line with the Basel III guidelines requiring additional capital for complex banks, especially during upturn periods, so as to increase their loss absorbency capacity during stress times.

Indeed, the global financial system today is about to get a comprehensive package of regulation focused on capital requirements and leverage, transparency, ratings, limits on the scope of financial firms and resolution mechanisms. The objective is that such reforms will reduce the likelihood and severity of the negative externalities that global financial institutions may impose for the overall health of global financial system. Therefore, our research contributed to this global effort of macroprudential re-regulation and prudential oversight of systemic risk, which is in sharp contrast with the microprudential features of the Basel accords. Thus, our findings on individual banks' systemic and standalone risk shed light particularly on the issue of SIFI and complex financial entity capital surcharge for banks in the most developed countries. The outcomes of our research gave support, especially, to the authorities to enact comprehensive micro- and macroprudential regulation schemes. They also helped to design the regulation needed to monitor banks (particularly SIFI banks). In this sense results aimed to develop new tools which will be useful for policy makers, regulatory authorities, private rating agencies and for the banking industry itself to improve the existing framework. Moreover, the research contributed for a better understanding of recent trends in the banking industry, like the dynamic effects of bank charter value on risk exposition, the specific aspects characterizing systemically important banks' capital structure and adjustment process, the fact that complex global banking institutions are generally thought to contribute more to the risk of systemic disruptions, and their implications for the stability of the financial system and the economy as a whole.

APPENDICES

Appendix 1

Table A1.1. Relationship between bank charter value and financial stability in the pre-crisis, acute-crisis and the post-crisis periods

Regression results for various bank risk measures on bank charter value over the pre-crisis period [2000-2006], the acute-crisis period [2007-2009] and the post-crisis period [2010-2013]. In all regressions, columns report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering at the bank-level. Results of model $\mathrm{Risk}_{i,t} = \beta_1 \widehat{Charter}_{i,t} + \beta_2 X_{i,t-1} + \beta_3 C_{i,t} + \lambda_t + \mu_{i,t} + \varepsilon_{2i,t}$, where dependent variables are two systemic risk measures: MES and ΔCoVaR (models in the columns: 1 and 2), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3 and 4) and default risk: MZ-score (model in the column 5). We also use other alternative risk measures: Tail-beta and specific risk (models in the columns 6 and 7). Bank charter value (Charter, proxied by Tobin's q) is modelled endogenously in all regressions. We instrument Charter by its one-year lagged value, Tangibility=tangible assets ratio and Market share = bank total assets over domestic total assets of the country banking system. Regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

Dependent variables	Systemic risk		Standalone risk		Default risk	Alternative dependent variables	
	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	Tail-beta	Specific Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: The effects of bank charter value on risk in the pre-crisis period [2000-2006]							
Charter	7.673***	5.422***	2.819***	3.255***	-75.18***	2.283***	1.918**
	(6.05)	(4.89)	(6.31)	(4.88)	(-5.58)	(3.24)	(2.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3145	3145	3145	3145	3145	3145	3145
Hansen test (p-value)	0.001	0.051	0.000	0.032	0.000	0.562	0.173
LM χ^2	44.70***	44.70***	44.70***	44.70***	44.70***	44.70***	44.70***
Partial F-Stat	25.65***	25.65***	25.65***	25.65***	25.65***	25.65***	25.65***
Panel B: The effects of bank charter value on risk in acute-crisis period [2007-2009]							
Charter	-7.064	7.585	-1.193	-3.621*	30.50	-4.043	-3.085
	(-1.26)	(1.35)	(-0.90)	(-1.65)	(0.73)	(-1.56)	(-1.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1583	1583	1583	1583	1583	1583	1583
Hansen test (p-value)	0.019	0.926	0.000	0.213	0.108	0.447	0.558
LM χ^2	9.01*	9.01*	9.01*	9.01*	9.01*	9.01*	9.01*
Partial F-Stat	2.085*	2.085*	2.085*	2.085*	2.085*	2.085*	2.085*
Panel C: The effects of bank charter value on risk in post-Crisis period [2010-2013]							
Charter	-0.488**	-0.545*	-0.0825**	-0.552***	6.515***	-0.0558	-0.387***
	(-2.17)	(-1.82)	(-2.04)	(-3.71)	(3.45)	(-0.34)	(-2.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2017	2017	2017	2017	2017	2017	2017
Hansen test (p-value)	0.018	0.675	0.045	0.127	0.005	0.394	0.780
LM χ^2	96.98***	96.98***	96.98***	96.98***	96.98***	96.98***	96.98***
Partial F-Stat	30.94***	30.94***	30.94***	30.94***	30.94***	30.94***	30.94***

Table A1.2. Alternative definitions of TBTF. The effects of growth strategies and business models in the relationship between charter value and financial stability over the pre-crisis period [2000-2006] for U.S. and European large and "TBTF" banks, with total assets above $1 billion

We define TBTF as very large banks operating in the world's top 10 economies, and with a relative size, with respect to the home country's GDP, above 10 percent (non-TBTF, otherwise). Table shows the two-stage least squares (TSLS) IV estimation results on the relation between charter value and risk and the effect of bank growth strategies (Panel A) and business models (Panel B) for U.S. and European banks over the pre-crisis period [2000-2006]. In all regressions report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering on the bank-level. Dependent variables are four systemic risk measures: MES and ΔCoVaR (models in the columns: 1,2,6 and 7), matched with two standalone risk measures: systematic risk and total risk (models in the columns: 3,4,8 and 9) and default risk: MZ-score (models in the columns 5 and 10). Here, bank charter value (Charter) is Tobin's q, modelled endogenously in all regressions. Panel A reports estimation results for banks group with high growth strategies (d(High growth)= dummy takes one if banks are in top quartile, Q75, of bank total assets variation during the pre-crisis period, and zero otherwise) and those with low growth strategies (d(Low growth)= dummy takes one if banks are in bottom quartile, Q25, of bank total assets variation during the pre-crisis period, and zero otherwise). Panel B reports estimation results for banks group with strong diversification strategies (d(Diversified)=dummy takes one if banks are in top quartile, Q75, of diversification ratio variation during the pre-crisis period, and zero otherwise) and those with focus strategies (d(Specialized)=dummy takes one if banks are in bottom quartile, Q25, of diversification ratio variation during the pre-crisis period, and zero otherwise). Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	Subsample of non-TBTF					Subsample of TBTF				
Dependent variables	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score	MES	ΔCoVaR	Systematic Risk	Total Risk	MZ-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Growth strategies and the effect of bank charter value on risk.										
Charter (α1)	5.315***	3.481***	2.717***	2.633***	-36.18**	19.49**	11.70*	2.720*	8.498**	-221.0**
	(4.80)	(3.33)	(6.09)	(2.69)	(-2.03)	(2.42)	(1.87)	(1.95)	(2.31)	(-2.16)
Charter*d(High growth) (α2)	-0.0221	-0.135***	-0.0550***	-0.0418	-0.0537	-3.188	-2.471	-0.227	-1.499	50.24*
	(-0.64)	(-4.23)	(-3.11)	(-1.44)	(-0.11)	(-1.51)	(-1.55)	(-0.52)	(-1.53)	(1.78)
Charter*d(Low growth) (α3)	-5.857	2.332	0.506	-1.141	148.8	-43.37**	-23.08	-4.258	-23.58**	543.6**
	(-0.40)	(0.23)	(0.08)	(-0.16)	(0.61)	(-2.13)	(-1.44)	(-1.12)	(-2.52)	(2.10)
Observations	1315	1315	1315	1315	1315	489	489	489	489	489
Hansen test (p-value)	0.446	0.333	0.283	0.273	0.568	0.397	0.142	0.147	0.663	0.619
LM χ^2	16.81**	16.81**	16.81**	16.81**	16.81**	17.25**	17.25**	17.25**	17.25**	17.25**
Partial F-Stat	33.78***	33.78***	33.78***	33.78***	33.78***	5.29***	5.29***	5.29***	5.29***	5.29***
Wald tests: $\alpha_1 + \alpha_2$	5.293***	3.345***	2.662***	2.591***	-36.126**	16.302***	9.229*	2.493**	6.999**	-170.76**
$\alpha_1 + \alpha_3$	-0.242	1.148	3.223	1.492	112.62	-23.88*	-11.38	-1.538	-15.082**	322.6*
Panel B: Business models and the effect of bank charter value on risk.										
Charter (α1)	7.987***	7.995***	4.181***	5.600***	-79.95**	11.78***	5.405	2.474***	4.195**	-65.40
	(4.38)	(4.56)	(4.77)	(3.73)	(-2.23)	(2.59)	(1.54)	(3.15)	(2.39)	(-1.42)
Charter*d(Diversified) (α2)	-5.299	-15.05***	-3.545**	-6.726***	105.9*	-0.343	13.45***	-1.115	1.411	-87.60
	(-1.52)	(-3.30)	(-2.02)	(-2.61)	(1.65)	(-0.06)	(2.84)	(-0.96)	(0.53)	(-1.17)
Charter*d(Specialized) (α3)	4.847*	6.849***	2.785**	5.448**	-81.21*	17.64	8.705	0.673	3.724	131.8
	(1.90)	(3.11)	(2.45)	(2.46)	(-1.91)	(0.91)	(0.59)	(0.16)	(0.43)	(0.55)
Observations	1315	1315	1315	1315	1315	489	489	489	489	489
Hansen test (p-value)	0.452	0.330	0.338	0.428	0.513	0.265	0.288	0.163	0.398	0.134
LM χ^2	10.26***	10.26***	10.26***	10.26***	10.26***	15.76**	15.76**	15.76**	15.76**	15.76**
Partial F-Stat	18.68***	18.68***	18.68***	18.68***	18.68***	8.39***	8.39***	8.39***	8.39***	8.39***
Wald tests: α1+ α2	2.688	-7.055*	0.636	-1.126	25.95	11.437***	18.855***	1.324	5.606***	-153**
α1+ α3	12.834***	14.844***	6.966****	11.048***	-161.16**	29.42	14.11	3.147	7.919	66.4

Table A1.3. Alternative measures of bank charter value: standardized market value added and market-to-book ratio

Table displays the results on the baseline model for standardized market value added (Panel A) and market-to-book ratio (Panel B) as alternative definitions of bank charter value (Tobin's q). We consider only very large banks (as banks with total assets greater than USD20 billion) and large banks (total assets ranged between USD1 and USD20 billion) operating in U.S. and Europe. SMVA is computed as the difference between the market value and capital contribution over book value of equity normalized by total equity. Columns report second stage coefficients from a two-stage least squares (TSLS) IV estimator with bank-specific fixed effects, time dummies and a robust-clustering on the bank-level. Table shows regression results for various bank risk measures on SMVA value or /Market-to-Book ratio the whole span of investigations [2000-2013], the pre-GFC [2000-2006] and the post-GFC [2010-2013] periods. Dependent variables are four systemic risk measures: MES and ΔCoVaR, matched with two standalone risk measures: systematic risk and total risk. Standardized market value added (SMVA) and market-to-book ratio (Market-to-Book) are modelled endogenously in all regressions. We instrument SMVA by one-year lagged SMVA, tangible assets ratio and market share. Market-to-Book is instrumented by one-year lagged Market-to-Book, tangible assets ratio and market share. Besides, regressions control for one-year lagged bank-level characteristics to mitigate endogeneity concerns and possible omitted variables. We control also for macro-financial variables and country-level variables. Control variables and year dummies are not reported. Heteroscedasticity consistent and robust standard errors t statistics are in brackets below their coefficients estimates. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ denote statistically significant at 10%, 5% and 1% levels, respectively. Hansen j test (from the second stage) reports p-value of overidentification test. Kleibergen-Paap rank LM statistic (LM χ^2 from the first stage) tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor. Kleibergen-Paap rk Wald F-statistic (Partial F-Stat from the first stage) testing for weak identification. We do not face muticollinearity problems (VIF test is less than 10 basis points, not reported).

	Pre-crisis period [2000-2006]			
Dependent variables	MES	ΔCoVaR	Systematic Risk	Total Risk
	(1)	(2)	(3)	(4)
Panel A: results for the standardized market value added (SMVA)				
SMVA	1.093***	0.809***	0.367***	0.224***
	(6.93)	(5.60)	(6.02)	(3.05)
Observations	2086	2086	2086	2086
Hansen test (p-value)	0.055	0.420	0.142	0.040
LM χ^2	52.59***	52.59***	52.59***	52.59***
Partial F-Stat	85.60***	85.60***	85.60***	85.60***
Panel B: results for the market to book ratio				
Market-to-Book	11.82***	6.962***	4.318***	3.430***
	(6.16)	(4.48)	(6.86)	(4.74)
Observations	2096	2096	2096	2096
Hansen test (p-value)	0.139	0.782	0.367	0.0708
LM χ^2	38.09***	38.09***	38.09***	38.09***
Partial F-Stat	58.32***	58.32***	58.32***	58.32***

Appendix 2

Appendix A2.1. Construction of the two systemic risk measures

The Marginal Expected Shortfall (MES) corresponds to the marginal participation of bank i to the Expected Shortfall (ES) of the financial system (Acharya et al. 2016 and Brownlees and Engle, 2012). Formally, it corresponds to the mean expected stock return for bank i, conditional on the market return when the latter performs poorly. Acharya et al. (2016) define the MES as the expectation of the bank's equity return conditional on market crash.

$$MES_{i,t}^{q} \equiv E\left(R_{i,t} | R_{M,t} \leq VaR_{R_{M},t}^{q}\right) \tag{A1}$$

where R_i is one-day stock return for bank i, R_M is one-day market return[70], q is a pre-specified quantile and $VaR_{R_M,t}^{q}$ is the critical threshold equal to the p-percent quantile of the market return $R_{M,t}$ distribution. Herewith, we take q to be equal to 5-percent, the term $R_{M,t} \leq \mathrm{VaR}_{\mathrm{R_M,t}}^{\mathrm{q}}$ reflects the set of days when the market return is being at or below the worst 5-percent tail outcomes.

The CoVaR is introduced by Adrian and Brunnermeier (2016) (based on the VaR concept). $CoVaR_{R_{M|i}}^{q}$is the q-percent quantile of a conditional probability distribution which is written as [71]:

$$\mathrm{Prob}_{t-1}\left(\mathrm{R_M} \leq \mathrm{CoVaR}_{\mathrm{R_{M|i,t}}}^{\mathrm{q}} \mid \mathrm{R_{i,t}} = \mathrm{VaR}_{\mathrm{R_{i,t}}}^{\mathrm{q}}\right) = \mathrm{q} \tag{A2}$$

Explicitly, Adrian and Brunnermeier (2016) define bank's ΔCoVaR as the difference between the VaR of the financial system conditional on the firm being in distress and VaR of the system

[70] We refer to the broader stock market index, as market portfolio benchmark; so as to, catch bank's contribution to the economy stability.

[71] MES and ΔCoVaR are computed at time t given information available in t-1 on the financial system tail-risk. Our paper derives systemic risk based on two standard measures of tail risk: value-at-risk (VaR) and expected shortfall (ES). Losses are expressed in positive sign. The MES and ΔCovaR are positive and given in absolute risk value. I.e. an increase in these bank's systemic risk measures is thus given by a positive change

conditional on the bank being in its median state. It catches the externality a bank causes to the entire financial system. Therefore, bank ΔCoVaR is the difference between the $\mathrm{CoVaR}_{R_{M|i,t}}^{q=\text{distress state}}$ of the financial system when bank i is in financial distress (i.e. the bank stock return is at its bottom q probability level), and the $\mathrm{CoVaR}_{R_{M|i,t}}^{q=\text{median}}$ of the financial system when this bank i is on its median return level (i.e. the inflection point at which bank performance starts becoming at risk). The $\Delta\mathrm{CoVaR}_{R_{M|i,t}}^{q}$ of individual bank is defined as:

$$\Delta\mathrm{CoVaR}_{R_{M|i,t}}^{q} = \mathrm{CoVaR}_{R_{M|i,t}}^{q} - \mathrm{CoVaR}_{R_{M|i,t}}^{\text{median}} \qquad \textit{(A3)}$$

MES and ΔCoVaR are computed at time t given information available in t-1 on the financial system tail-risk. Our paper derives systemic risk based on two standard measures of tail risk: value-at-risk (VaR) and expected shortfall (ES). Losses are expressed in positive sign. MES and ΔCovaR are positive and given in absolute risk value. I.e. an increase in these bank's systemic risk measures is thus given by a positive change.

Table A2.2. Effect of systemic risk and size on mechanisms of capital adjustment (WLS)

Table reports the coefficient estimates for the weighted least squares (WLS) regressions (Eq. (7)) for a sample of 567 OECD banks over 2001-2012 period, to assess the relation between the annual growth rates of diverse balance sheet items and capital deviations, for banks with a capital shortfall (positive gap, undercapitalized) or a capital surplus (negative gap, overcapitalized) regarding its optimal capital. Here, the weight for each individual bank in the country is proportional to the inverse of the number of country observations for each country**.** The gap is computed using three definitions of capital ratio (equity-to-asset (Leverage), Tier1RWA and Total capital (TotalCap)). groTCE, groTier1, groRtErg, groTA, groLoan and groRwa are, respectively, the annual growth of total equity, Tier 1 capital, retained earnings, total assets, net loans and risk-weighted assets scaled by average assets. All regressions include bank fixed effects. P-values based on robust standard errors, clustered by bank are shown in parentheses. *, **and*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

Panel A: Leverage ratio

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	0.143	-0.047	0.848	-1.985***	-0.349**	-0.419***	-0.695***
	(0.424)	(0.394)	(1.027)	(0.273)	(0.141)	(0.154)	(0.189)
Capital shortfall(i,t-1) * SIFI-Index(i,t-1)	-1.441***	-0.916***	-1.246**	0.552*	0.023	-0.085	-0.196
	(0.363)	(0.268)	(0.528)	(0.318)	(0.149)	(0.138)	(0.206)
Capital surplus(i,t-1)	0.866**	0.589**	0.096	-2.291***	-0.115	0.027	-0.074
	(0.391)	(0.233)	(0.192)	(0.291)	(0.176)	(0.171)	(0.205)
Capital surplus(i,t-1) * SIFI-Index(i,t-1)	0.733***	0.501**	0.381	-0.123	-0.233	-0.048	-0.113
	(0.278)	(0.236)	(0.254)	(0.231)	(0.228)	(0.183)	(0.293)
SIFI-Index(i,t-1)	-0.034*	-0.041*	-0.071***	-0.087***	-0.079***	-0.075***	-0.099***
	(0.020)	(0.024)	(0.020)	(0.017)	(0.014)	(0.012)	(0.014)
Constant	0.182***	0.169***	0.128***	0.172***	0.121***	0.144***	0.201***
	(0.020)	(0.022)	(0.017)	(0.015)	(0.013)	(0.011)	(0.013)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.062	0.060	0.056	0.252	0.112	0.129	0.157

Panel B: Tier 1 over risk weighted assets

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	1.939*	1.247*	0.571	-0.923**	-1.382***	-0.562*	-0.588
	(1.104)	(0.639)	(0.946)	(0.418)	(0.373)	(0.310)	(0.367)
Capital shortfall(i,t-1) * SIFI-Index(i,t-1)	2.426***	1.845***	1.374*	0.583	0.395	0.541*	0.176
	(0.855)	(0.685)	(0.830)	(0.469)	(0.346)	(0.315)	(0.457)
Capital surplus(i,t-1)	-0.868	0.120	-1.636***	-1.693**	-1.373***	-0.939**	-1.023**
	(0.573)	(0.625)	(0.590)	(0.687)	(0.363)	(0.431)	(0.515)
Capital surplus(i,t-1) * SIFI-Index(i,t-1)	-1.224	-0.308	-1.112*	-1.451***	-0.283	-0.715**	-0.681*
	(0.770)	(0.750)	(0.654)	(0.543)	(0.372)	(0.284)	(0.388)
SIFI-Index(i,t-1)	-0.162***	-0.137***	-0.130***	-0.112***	-0.070***	-0.089***	-0.111***
	(0.027)	(0.028)	(0.027)	(0.016)	(0.014)	(0.012)	(0.015)
Constant	0.180***	0.177***	0.126***	0.198***	0.122***	0.144***	0.204***
	(0.025)	(0.024)	(0.019)	(0.016)	(0.013)	(0.011)	(0.014)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.109	0.106	0.069	0.102	0.139	0.123	0.128

Panel C: Total Capital Ratio

Dependent variable. Growth in:	Equity	Tier1 capital	Retained Earnings	Assets	RWA	Loans	Liabilities
Capital shortfall(i,t-1)	2.625*	1.433**	0.268	-0.032	-0.765**	-0.086	0.111
	(1.521)	(0.675)	(0.868)	(0.563)	(0.325)	(0.389)	(0.484)
Capital shortfall(i,t-1) * SIFI- Index(i,t-1)	0.581	0.522	1.332*	-0.347	-0.103	0.039	-0.658
	(1.175)	(0.792)	(0.718)	(0.453)	(0.314)	(0.348)	(0.415)
Capital surplus(i,t-1)	-1.396**	-0.573	-0.895	-1.713***	-1.335***	-1.068**	-1.323**
	(0.603)	(0.649)	(0.656)	(0.630)	(0.399)	(0.429)	(0.537)
Capital surplus(i,t-1) * SIFI- Index(i,t-1)	-0.499	0.278	-1.312**	-0.604	-0.097	-0.540*	-0.186
	(0.606)	(0.578)	(0.532)	(0.427)	(0.344)	(0.287)	(0.388)
SIFI- Index(i,t-1)	-0.112***	-0.097***	-0.121***	-0.094***	-0.062***	-0.077***	-0.094***
	(0.027)	(0.029)	(0.024)	(0.016)	(0.013)	(0.012)	(0.014)
Constant	0.162***	0.165***	0.128***	0.181***	0.110***	0.132***	0.188***
	(0.027)	(0.028)	(0.019)	(0.018)	(0.013)	(0.013)	(0.016)
Observations	4339	4231	4339	4339	4231	4339	4339
Adjusted R-squared	0.069	0.059	0.066	0.102	0.143	0.127	0.138

Table A2.3. Effects of systemic risk and size on SOA and nonlinearity in the relationship across the pre-crisis (2001–2006) and the acute crisis (2007–2012) periods.

This Table shows the estimation results on the effects of systemic risk and size on bank's adjustment speed (Eq. (6)) for a sample of listed OECD banks over 2001–2012 period taking into account that the effects may have changed since the onset of the global financial crisis starting in 2007. In panel A, we report the obtained regression coefficients. Capital gap is computed using three definitions of capital ratio (Leverage, Tier1RWA and Total capital), corresponding with the columns 1, 2 and 3, respectively. In all regression, $D_{2007-2012}$ is a dummy takes one during crisis time (2007–2012), and zero otherwise, and SIFI-index$_{i,t-1}$ is an aggregate systemic risk index (SIFI-Index) constructed based on the quintiles of the MES, ΔCoVaR, relative size and size. P-values based on robust standard errors, clustered by bank are shown in parentheses. *, ** and*** indicate statistical significance at the 10%, 5% and 1% levels respectively. In panel B, we report the implied adjustment speeds in the pre and post crisis periods for small banks, average banks and SIFIs, corresponding respectively with cases where the standardized SIFI index takes on the value of -1, 0 and 1.

Panel A: regression results			
	ΔLeverage	ΔTier1RWA	ΔTotal Capital
Gap(i,t-1)	0.226***	0.241***	0.305***
	(10.86)	(14.37)	(12.22)
Gap(i,t-1) * D(2007–2012)	0.195***	0.111***	0.0903***
	(9.44)	(5.40)	(3.21)
Gap(i,t-1) * SIFI-index(i,t-1)	-0.0858***	-0.0337**	-0.0119
	(-4.12)	(-1.98)	(-0.52)
Gap(i,t-1) * SIFI-index(i,t-1) * D(2007–2012)	0.0573***	0.0838***	0.0509**
	(2.99)	(4.13)	(2.02)
Observations	4339	4339	4339
Adjusted R-squared	0.625	0.292	0.312

Panel B: implied adjustment speeds			
	ΔLeverage		
	SIFI = -1	SIFI = 0	SIFI = 1
2001-2006	0.3118	0.226	0.1402
2007-2012	0.4495	0.421	0.3925
	ΔTier1RWA		
	SIFI = -1	SIFI = 0	SIFI = 1
2001-2006	0.2747	0.241	0.2073
2007-2012	0.3019	0.352	0.4021
	ΔTotal Capital		
	SIFI = -1	SIFI = 0	SIFI = 1
2001-2006	0.3169	0.305	0.2931
2007-2012	0.3563	0.3953	0.4343

Table A2.4. Effects of systemic risk and size on cash and marketable securities and Liquid assets

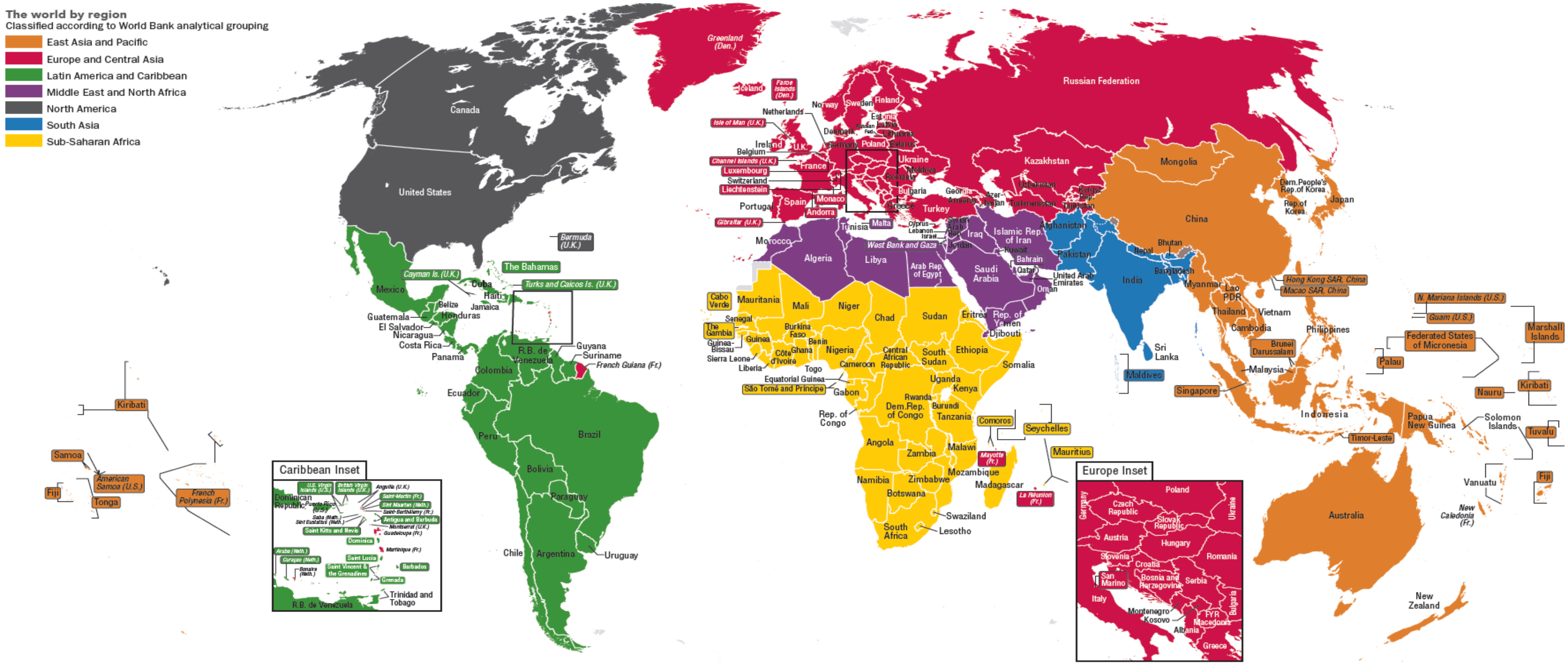
This table reports the coefficient estimates for the ordinary least square (OLS) regressions (Eq. (7)) for a sample of OECD banks over the 2001-2012 period, to assess the relation between the annual growth rates of diverse balance sheet items and capital deviations, for banks with a Capital shortfall (positive gap, undercapitalized) or a Capital surplus (negative gap, overcapitalized) vis-à-vis its target capital ratio. Across columns, the specification is identical except for the dependent variable, which is respectively the average annual growth rates of cash and marketable securities (CashMktSec) and Liquid assets (LiquidAs). Growth rates variables are scaled by average total assets. The gap is computed using three definitions of capital ratio (Leverage, Tier1RWA and Total capital) corresponding with the three different panels. $SIFI_{i,t-1}$ is an aggregate systemic risk index (SIFI-Index) constructed based on the quintiles of the MES, ΔCoVaR, relative size and size. All regressions include a constant term. P-values based on robust standard errors, clustered by bank are shown in parentheses. *, ** and*** indicate statistical significance at the 10%, 5% and 1% levels respectively.

Dependent variable: Growth in…	**Cash and Marketable Securities**			**Liquid Assets**		
	Leverage	Tier1RWA	Total Capital	Leverage	Tier1RWA	Total Capital
Capital shortfall(i,t-1)	0.025	1.191***	1.420***	-0.071	1.310**	1.307**
	(0.268)	(0.436)	(0.487)	(0.308)	(0.529)	(0.58)
Capital shortfall(i,t-1) * SIFI-index(i,t-1)	-0.055	-0.871**	-1.081**	-0.215	-1.061**	-1.261**
	(0.25)	(0.423)	(0.458)	(0.278)	(0.514)	(0.563)
Capital surplus (i,t-1)	-0.142	0.034	-0.098	-0.002	-0.068	0.159
	(0.2)	(0.517)	(0.459)	(0.215)	(0.607)	(0.521)
Capital surplus (i,t-1) * SIFI-index(i,t-1)	0.095	0.406	0.18	0.066	0.443	0.406
	(0.201)	(0.513)	(0.412)	(0.22)	(0.633)	(0.463)
SIFI-index(i,t-1)	0.023***	0.033***	0.032***	0.022***	0.033***	0.033***
	(0.007)	(0.01)	(0.009)	(0.008)	(0.012)	(0.011)
Constant	0.071***	0.058***	0.058***	0.074***	0.056***	0.060***
	(0.006)	(0.009)	(0.009)	(0.008)	(0.011)	(0.01)
Observations	4,230	4,230	4,230	3,081	3,081	3,081
Adjusted R-squared	0.001	0.004	0.004	0.001	0.003	0.003
Country Effects	NO	NO	NO	NO	NO	NO
Year Fixed Effects	NO	NO	NO	NO	NO	NO
Clustered SE	Bank	Bank	Bank	Bank	Bank	Bank

Appendix 3

Appendix A3.1. Map of all world countries into seven world regions.

Source: World Bank – World Development Indicator (2017) – http://databank.worldbank.org/data/download/site-content/wdi/maps/2017/world-by-region-wdi-2017.pdf



Note: These regions include economies at all income levels, and may differ from common geographic usage or from regions defined by other organizations. For more information see https://datahelpdesk.worldbank.org /knowledgebasearticles/906519-world-bank-country-and-lending-groups.

Table A3.2. Definition of variables, Sources and summary statistics over 2005–2013

This table reports the descriptive of variables used in the paper for our sample of publicly traded banks over the whole period 2005-2013.

Variable Name	Definitions	Sources	Obs.	Mean	Std. Dev.	Min	Max
MES	Marginal Expected Shortfall, marginal participation of a bank to the Expected Shortfall (ES) of the financial system, a measure of bank equity sensitivity to market crashes (Equation 3).	Bloomberg	945	2.59	2.24	-1.64	9.63
SRisk	Systemic risk, expected capital shortfall (Equation 4).		945	10.09	30.25	-6.21	223.8
ΔCoVaR	Conditional Value-at-Risk of a bank to an entire financial system or benchmark/reference market conditional on an extreme event leading to the fall of a bank stock return beyond its critical threshold level (Equation 6).		945	1.98	1.51	-2.80	6.85
PD	Merton's probability of default (Equation 7)		936	0.03	0.07	0	0.57
Tail-beta	Measure of the sensitivity to extreme movements of beta, quantile-beta.		945	0.90	0.83	-1.57	3.17
Foreign	Dummy equal to one when the bank owns at least one foreign subsidiary, and zero if not	BankScope	945	0.48	0.50	0	1
NbHost	Number of foreign countries where a bank has a foreign presence with subsidiary		452	11.29	14.40	1	63
NbSubsidiaries	Number of foreign subsidiaries per bank		452	24.98	53.38	0	378
NbRegions_Sub	Number of world regions where a bank has established its foreign subsidiaries, among eight world regions	World Bank	440	2.90	2.29	1	8
GeoComplex**S**	Indicator of the geographic dispersion of a bank foreign subsidiary(ies) in different world regions.	BankScope – World Bank	440	0.33	0.33	0	0.95
Size (log TA)	Natural logarithm of total assets (USD billion).	TRAA	945	-3.48	2.13	-8.18	0.16
Leverage (%)	Ratio of total equity to total assets, measure of leverage/bank capitalization	Bloomberg	945	8.67	5.27	0.78	44.82
Deposits (%)	Ratio of customer deposits to total assets	BankScope – TRAA	927	49.23	19.58	5.69	91.43
Diversification (%)	Ratio of noninterest income to total income		927	27.94	11.93	1.06	66.54
Loans (%)	Ratio of net loans to total assets (%)		882	70.72	16.25	13.02	100
Efficiency (%)	Cost to income ratio = non-interest expense divided by total income		882	42.22	13.48	14.87	89.93
ROA (%)	Return on assets = ratio of net income to total assets		945	0.56	1.17	-4.58	5.85

Table A3.3. Effect of bank internationalization on listed banks systemic risk – Global Financial Crisis Fin08_09 and European Sovereign Debt Crisis Sov10_11

	MES (1a)	SRisk (1b)	MES (2a)	SRisk (2b)	MES (3a)	SRisk (3b)	MES (4a)	SRisk (4b)	MES (5a)	SRisk (5b)
Foreign (α_1)	-0.965***	-9.994*								
	(-3.80)	(-1.77)								
Foreign×Fin08_09 (β_1)	1.432***	16.22***								
	(4.10)	(3.02)								
Foreign×Sov10_11 (β_2)	1.543***	14***								
	(5.42)	(4.01)								
Foreign×Post12_13 (β_3)	1.578***	17.01***								
	(5.48)	(3.67)								
NbHost (α1)			-0.020**	0.676**						
			(-2.37)	(3.33)						
NbHost×Fin08_09 (β_1)			0.044**	1.734**						
			(2.59)	(13.09)						
NbHost×Sov10_11 (β_2)			0.018	1.329**						
			(1.25)	(4.10)						
NbHost×Post12_13 (β_3)			0.054***	1.404**						
			(5.27)	(2.71)						
ln(NbSubsidiaries) (α_1)					-0.076	8.107*				
					(-0.82)	(2.09)				
ln(NbSubsidiaries)×Fin08_09 (β_1)					0.454***	10.92**				
					(4.43)	(3.38)				
ln(NbSubsidiaries)×Sov10_11 (β_2)					0.223	10.08**				
					(1.52)	(3.76)				
ln(NbSubsidiaries)×Post12_13 (β_3)					0.461**	15.15**				
					(2.28)	(4.20)				
NbRegion_Sub (α1)							-0.053	4.097*		
							(-0.76)	(2.12)		
NbRegion_Sub×Fin08_09 (β_1)							0.283***	8.568**		
							(3.06)	(4.28)		
NbRegion_Sub×Sov10_11 (β_2)							0.073	7.023**		
							(0.63)	(3.35)		
NbRegion_Sub×Post12_13 (β_3)							0.330***	8.010**		
							(3.77)	(3.03)		
GeoComplexS (α_1)									0.100	-0.310
									(0.17)	(-0.05)
GeoComplexS×Fin08_09 (β_1)									1.675**	38.28**
									(2.17)	(2.51)
GeoComplexS×Sov10_11 (β_2)									0.135	34.09**
									(0.15)	(2.81)
GeoComplexS×Post12_13 (β_3)									1.688*	38.40**
									(2.07)	(3.24)
Fin08_09	1.511***	1.047	2.207***	-3.939	1.809***	-4.945	1.915***	-9.786	2.209***	3.188
	(6.33)	(0.46)	(7.51)	(-1.30)	(5.22)	(-0.86)	(4.40)	(-1.72)	(5.28)	(0.68)
Sov10_11	0.762**	-4.404***	1.772***	-1.130	1.644***	-2.603	1.827***	-8.938*	1.997***	-3.841
	(2.31)	(-3.56)	(3.94)	(-0.35)	(3.43)	(-0.66)	(3.13)	(-2.11)	(3.60)	(-1.02)
Post12_13	0.976***	-5.894***	1.593***	1.773	1.583**	-1.710	1.333**	-8.479*	1.706**	-3.246
	(3.57)	(-3.47)	(3.12)	(0.46)	(2.37)	(-0.35)	(2.31)	(-1.91)	(2.69)	(-0.67)
Size (logTA)	0.438***	10.13***	0.568***	4.659	0.466***	1.986	0.511***	5.830**	0.515***	11.58**
	(4.16)	(3.81)	(5.24)	(1.61)	(4.59)	(1.15)	(5.39)	(2.24)	(7.68)	(2.99)
Leverage	-1.185	49.76	2.782	26.61	3.562	87.85	3.101	49.30	3.331	90.50
	(-0.65)	(1.57)	(0.56)	(0.29)	(0.82)	(0.77)	(0.66)	(0.39)	(0.82)	(0.60)
Deposits	0.182	14.38	-0.565	-8.056	-0.292	-5.402	-0.246	-4.335	-0.350	-8.388
	(0.28)	(1.06)	(-0.53)	(-0.49)	(-0.28)	(-0.35)	(-0.24)	(-0.27)	(-0.33)	(-0.35)
Diversification	2.841**	24.23	1.213	-16.38	0.579	-17.32	0.699	-19.96	0.433	-10.10
	(2.87)	(0.96)	(0.89)	(-0.50)	(0.48)	(-0.61)	(0.54)	(-0.68)	(0.32)	(-0.32)

Loans	-0.573	-30.18***	-0.135	0.495	0.135	0.234	0.154	-3.134	0.230	-15.92
	(-1.66)	(-3.93)	(-0.26)	(0.02)	(0.29)	(0.01)	(0.32)	(-0.10)	(0.44)	(-0.39)
Efficiency (CIR)	0.101	40.23	1.290	37.05	1.880	49.27	1.854	49.39	2.096	73.45
	(0.08)	(1.66)	(0.76)	(1.09)	(1.15)	(1.34)	(1.27)	(1.59)	(1.51)	(1.70)
ROA	-16.49**	-182.6*	-37.65**	-19.88	-38.36*	-180.7	-40.92**	-147.9	-38.53**	-143.5
	(-2.52)	(-2.02)	(-2.79)	(-0.08)	(-1.99)	(-0.93)	(-2.26)	(-0.60)	(-2.24)	(-0.62)
Constant	-4.355***	-105.7**	-6.340***	-60.89	-5.811***	-52.67	-6.175***	-73.61	-6.380***	-126.4*
	(-3.26)	(-2.50)	(-4.07)	(-1.52)	(-4.21)	(-1.44)	(-4.66)	(-1.69)	(-5.91)	(-1.92)
Observations	784	784	394	394	382	382	382	382	382	382
R-squared	0.663	0.554	0.671	0.789	0.681	0.751	0.683	0.759	0.683	0.682
Adjusted R-squared	0.651	0.538	0.647	0.773	0.656	0.732	0.658	0.741	0.659	0.658
Wald tests: $\alpha_1 + \beta_1$	0,467	6,226	0.024*	2.410**	0.378***	19.027*	0.230**	12.665*	1.775**	37.970
$\alpha_1 + \beta_2$	0.578*	4,006	-0,001	25***	0,147	18.187*	0,02	11.12**	0,235	33.78**
$\alpha_1 + \beta_3$	0.613*	7.016*	0.034***	2.080**	0.385*	23.257*	0.277**	12.107*	1.788**	38.090*

BIBLIOGRAPHY

Acharya, Viral V., 2009. "A Theory of Systemic Risk and Design of Prudential Bank Regulation", Journal of Financial Stability 5(3): 224–55.

Acharya, Viral V., Hasan, I., Saunders, A., 2006. "Should banks be diversified? Evidence from individual bank loan portfolios", Journal of Business 79: 1355–1411.

Acharya, Viral V., L. H. Pedersen, T. Philippon, and M. P. Richardson, 2016. "Measuring Systemic Risk", Review of Financial Studies 30(1): 2–47.

Acharya, Viral V., Robert Engle, and Matthew Richardson, 2012. "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks", The American Economic Review 102(3): 59–64.

Acharya, Viral V, Thakor A., 2016. "The dark side of liquidity creation: leverage-induced systemic risk and implications for the lender of last resort", Journal of Financial Intermediation, 28: 4–21.

Acharya, Sankarshan, 1996. "Charter Value, Minimum Capital Requirement and Deposit Insurance Pricing in Equilibrium", Journal of Financial Stability 20: 351–75.

Admati, A., P. DeMarzo, M. Hellwig, and P. Pfleiderer, 2010. "Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is not Expensive", Stanford GSB Research Paper No. 2063.

Adrian, T. and M. K. Brunnermeier, 2016. "CoVaR", American Economic Review 106(7): 1705–1741.

Adrian, Tobias, and Markus K. Brunnermeier, 2011. "CoVaR.". National Bureau of Economic Research. Federal Reserve Bank of New York Staff Report No. 348.

Adrian, T. and H. S. Shin, 2010. "Liquidity and leverage", Journal of Financial Intermediation 19(3): 418–437.

Aiyar, S., Calomiris, C., Wieladek, T., 2014. "Does Macro-Prudential regulation leak? Evidence from a UK policy experiment", Journal of Money, Credit and Banking 46(S1): 1538–4616.

Akhigbe, A., Whyte, A. M., 2003. "Changes in market assessment of bank risk following the Riegle-Neal Act of 1994", Journal of Banking and Finance 27: 87–102.

Allen, Franklin, and Douglas Gale, 2004. "Competition and Financial Stability", Journal of Money, Credit and Banking 36(3): 453–80.

Anderson, Ronald C, and Donald R Fraser, 2000. "Corporate Control, Bank Risk Taking, and the Health of the Banking Industry", Journal of Banking and Finance 24(8): 1383–98.

Angelini, P., L. Clerc, V. Cúrdia, L. Gambacorta, A. Gerali, A. Locarno, R. Motto, W. Roeger, S. Van den Heuvel, and J. Vlcek, 2011. "Basel III: long-term impact on economic performance and fluctuations", Banque de France working paper No. 323.

Anginer, Deniz, Asli Demirguc-Kunt, and Min Zhu, 2014. "How Does Competition Affect Bank Systemic Risk?", Journal of Financial Intermediation 23(1): 1–26.

Bakkar, Y., De Jonghe, O., Tarazi, A., 2017. "Does Banks' Systemic Importance affect their Capital Structure and Balance Sheet Adjustment Processes?", working paper.

Bakkar, Y., Pamen-Nyola, A., 2017. "Internationalization and systemic risk: Evidence from a sample of European listed banks", working paper.

Bakkar, Y., Rugemintwari, C., Tarazi, A., 2017. "Charter Value and Bank Stability Before and After the Global Financial Crisis of 2007–2008", working paper.

Banque de France, 2010. "De la crise financière à la crise économique." Documents et Débats N°3.

Banque de France, 2012. "La crise de la dette souveraine." Documents et Débats N°4.

Barth, James, Gerard Caprio Jr., & Ross Levine, 2013. "Bank Regulation and Supervision in 180 Countries from 1999 to 2011", Journal of Financial Economic Policy 5 (2): 111-219.

Barth, A. and Schnabel, I., 2013. "Why banks are not too big to fail - Evidence from the CDS market", Economic Policy 28(74): 335–369.

Barth, J.R., and Wihlborg, C., 2016. "Too Big to Fail and Too Big to Save: Dilemmas for Banking Reform", National Institute Economic 235(1): R27–R393

Barry, Thierno Amadou, Laetitia Lepetit, and Amine Tarazi, 2011. "Ownership Structure and Risk in Publicly Held and Privately Owned Banks", Journal of Banking and Finance 35(5): 1327–40.

Baum, C. F., A. Stephan, and O. Talavera, 2009. "The effects of uncertainty on the leverage of nonfinancial firms", Economic Inquiry 47(2): 216–225.

Berger, A., Bouwman, C., 2013. "How does capital affect bank performance during financial crises?", Journal of Financial Economics 109: 146–176.

Berger, A. N., El Ghoul, S., Guedhami, O., Roman, R., 2015. "Internationalization and bank risk", Federal Reserve Bank of Kansas City Research Working Paper 15–8.

Berger, A., Miller, N., Petersen, M., Rajan, R., Stein, J., 2005. "Does function follow organizational form? Evidence from the lending practices of large and small banks", Journal of Financial Economics 76: 237–269.

Bertay, A. C., Demirgüç-Kunt, A., and Huizinga, H., 2013. "Do we need big banks? Evidence on performance, strategy and market discipline", Journal of Financial Intermediation 22(4): 532–558.

BIS, Basel Committee on Banking Supervision, 2010a. "An assessment of the long term economic impact of stronger capital and liquidity requirements", LEI Report.

BIS, Basel Committee on Banking Supervision, 2013. "Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement", BCBS Paper No. 255.

Berger A, Bouwman C., 2013. "How does capital affect bank performance during financial crises?", Journal of Financial Economics 109(1):146–76.

Berger, A., DeYoung, R., Flannery, M., Lee, D., Öztekin, Ö., 2008. "How do large banking organizations manage their capital ratios?", Journal of Financial Services Research 34(2): 123–149.

Berrospide, J. and R. Edge, 2010. "The Effects of Bank Capital on Lending: What Do We Know, and What Does It Mean?", International Journal of Central Banking 6(4): 5–54.

Bhamra, H. S., L. A. Kuehn, and I. A. Strebulaev, 2010. "The aggregate dynamics of capital structure and macroeconomic risk", Review of Financial Studies 23(12): 4187–4241.

Black, Lamont, Ricardo Correa, Xin Huang, and Hao Zhou, 2016. "The Systemic Risk of European Banks During the Financial and Sovereign Debt Crisis", Journal of Banking and Finance 61(C): 107–125.

Blum, J.M., 2008. "Why basel II may need a leverage ratio restriction", Journal of Banking and Finance 32(8): 1699–1707.

Blundell, R. and S. Bond, 1998. “Initial conditions and moment restrictions in dynamic panel data models”, Journal of Econometrics 87(1): 115–143.

Bostandzic, Denefa, and Gregor N. F. Weiss, 2016. “Why Do U.S. Banks Contribute More to Global Systemic Risk?” Working Paper.

Boyd, John H., and Gianni De Nicoló, 2005. “The Theory of Bank Risk Taking and Competition Revisited”, The Journal of Finance 60(3): 1329–43.

Brewer, E., Kaufman, G., Wall, L., 2008. “Bank capital ratios across countries: Why do they vary?”, Journal of Financial Services Research 34(2): 177–201.

Brickley, J., Linck, J., Smith, C., Jr., 2003. “Boundaries of the firm: evidence from the banking industry”, Journal of Financial Economics 70: 351–383.

Brownlees, Christian T., Robert Engle, 2012. “Volatility, correlation and tails for systemic risk measurement”, Working Paper, NYU Stern School of Business.

Brunnermeier, Markus K., G. Nathan Dong, and Darius Palia, 2012. “Banks’ Non-Interest Income and Systemic Risk”, AFA 2012 Chicago Meetings Paper.

Brunnermeier, M.K., and L.H. Pedersen, 2009. “Market liquidity and funding liquidity”, Review of Financial Studies 22(6): 2201–2238.

Byoun, S., 2008. “How and when do firms adjust their capital structures toward targets?”, Journal of Finance 63(6): 3069–3096.

Calomiris, C., 2000. “U.S. Bank Deregulation in Historical Perspective”, Cambridge University Press, New York.

Campbell, J.Y., J. Hilscher, J. Szilagyi, 2008. “In search of distress risk”, Journal of Finance 63(6): 2899–2939.

Caglayan, M. and A. Rashid, 2014. “The response of firms’ leverage to uncertainty: Evidence from UK public versus non-public firms”, Economic Inquiry 52(1): 341–363.

Carmassi, J. and Herring, R., 2016. “Corporate Structures, Transparency and Resolvability of Global Systemically Important Bank’s", Journal of Financial Services Research 49(2): 175–201.

Carmassi, J. and Herring, R.J., 2013. “Living wills and cross-border resolution of systemically important banks”, Journal of Financial Economic Policy 5(4): 361–387.

Cetorelli, N. and Goldberg, L. S., 2014. "Measures of Complexity of Global Banks." Federal Reserve Bank of New York (FRBNY) Economic Policy Review 20(2).

Cetorelli, N. and Goldberg, L. S., 2016. "Organizational complexity and balance sheet management in global banks." FRBNY Staff Reports 772

Cecchetti, S. G., 2015. “The Road to Financial Stability: Capital Regulation, Liquidity Regulation, and Resolution”, International Journal of Central Banking 11(2): 127–139.

Chen, H., 2010. “Macroeconomic conditions and the puzzles of credit spreads and capital structure”, Journal of Finance 65(6): 2171–2212.

Claessens, S., Herring, R.J. and Schoenmaker, D., 2010. “A Safer World Financial System: Improving the Resolution of Systemic Institutions”, Geneva Reports on the World Economy 12, International Center for Monetary and Banking Studies.

Claessens, S. and van Horen, N., 2012. “Foreign Banks: Trends, Impact and Financial Stability”, IMF, International Monetary Fund.

Cohen, B. H., and Scatigna, M., 2016. “Banks and capital requirements: Channels of adjustment”, Journal of Banking and Finance 69(S1): S56–S69.

Cosimano, T.F. and Hakura, D., 2011. “Bank Behavior in Response to Basel III: A Cross-Country Analysis”, International Monetary Fund Working Paper 119: 1–34.

Cragg, J. G., and Donald, S. G., 1993. "Testing Identifiability and Specification in Instrumental Variable Models", Econometric Theory 9(2): 222–240.

De Jonghe, O., Dewachter, H., Mulier, K., Ongena, S. and Schepens, G., 2016. "Some borrowers are more equal than others: Bank funding shocks and credit reallocation", Working Paper, available at SSRN: https://ssrn.com/abstract=2774441.

De Jonghe, Olivier, Maaike Diepstraten, and Glenn Schepens, 2015. "Banks' Size, Scope and Systemic Risk: What Role for Conflicts of Interest?", Journal of Banking and Finance 61 (S1): 3-13.

De Jonghe, O., Öztekin, Ö., 2015. "Bank capital management: International evidence", Journal of Financial Intermediation 24(2): 154–177.

De Jonghe, Olivier, and Rudi Vander Vennet, 2008. "Competition versus Efficiency: What Drives Franchise Values in European Banking?", Journal of Banking and Finance 32 (9): 1820–35.

De Nicolo, Gianni, 2001. "Size, Charter Value and Risk in Banking: An International Perspective." International Finance Discussion Papers No. 689, Board of Governors of the Federal Reserve System: 1–41.

De-Ramon, S. J. and Francis, W. and Harris, Q., (2016) "Bank Capital Requirements and Balance Sheet Management Practices: "Has the Relationship Changed after the Crisis?", Bank of England Working Paper No. 635, available at SSRN: https://ssrn.com/abstract=2885244.

Demirgüç-Kunt, Asli, and Harry Huizinga, 2013. "Are Banks Too Big to Fail or Too Big to Save? International Evidence from Equity Prices and CDS Spreads", Journal of Banking and Finance 37 (3): 875–94.

Demsetz, Rebecca S., Marc R. Saidenberg, and Philip E. Strahan, 1996. "Banks with Something to Lose: The Disciplinary Role of Franchise Value", Federal Reserve Bank of New York Economic Policy Review 2(2): 1–14.

Distinguin, Isabelle, Caroline Roulet, and Amine Tarazi, 2013. "Bank Regulatory Capital and Liquidity: Evidence from US and European Publicly Traded Banks", Journal of Banking and Finance 37(9): 3295–3317.

Dermine, J., 2015. "Basel III leverage ratio requirement and the probability of bank runs", Journal of Banking and Finance 53(C): 266–277.

Dell'Ariccia G., and Marquez, A., 2010. "Risk and the Corporate Structure of Banks", Journal of Finance 65: 1075–1096.

Demsetz, R. S., Strahan, P. E., 1997. "Diversification, size, and risk at bank holding companies", Journal of Money, Credit, and Banking 29: 300–313.

Deng, S., Elyasiani, E., 2008. "Geographic diversification, bank holding company value, and risk", Journal of Money, Credit and Banking 40: 1217–1238.

Denis, D. J., Denis D. K., Sarin, A., 1997. "Agency problems, equity ownership, and corporate diversification", Journal of Finance 52: 135–160.

Drobetz, W. and G. Wanzenried, 2006. "What determines the speed of adjustment to the target capital structure?", Applied Financial Economics 16(13): 941–958.

Engle, R. F., and S. Manganelli, 2004. "CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles", Journal of Business and Economic Statistics 22(4): 367–381.

Faulkender, M., M. J. Flannery, and J. M. Hankins, K. W. and Smith, 2012a. "Cash flows and leverage adjustments", Journal of Financial Economics 103(3): 632–646.

Farhi E, Tirole J., 2012. "Collective moral hazard, maturity mismatch, and systemic bailouts", American Economic Review 102(1): 60–93.

Flannery, M. and K. W. Hankins, 2013. "Estimating Dynamic Panel Models in Corporate Finance", Journal of Corporate Finance 19: 1–19.

Flannery, M. and K. Rangan, 2006. "Partial adjustment toward target capital structures", Journal of Financial Economics 79(3): 469–506.

Flannery, Mark J. and Kasturi P. Rangan, 2006. "Partial adjustment toward target capital structures", Journal of Financial Economics 79(3): 469–506.

Flannery, M.J., and Rangan, K.P., 2008. "What caused the bank capital build-up of the 1990s?", Review of Finance 12(2): 391–429.

Frame, W.S. and White, L.J., 2015. "Technological Change, Financial Innovation, and Diffusion in Banking", in Berger, A.N., Molyneux, P. and Wilson, J.O.S., Oxford Handbook of Banking, 2nd Edition, Oxford University Press.

Francis, W. and M. Osborne, 2012. "Capital requirements and bank behavior in the UK: Are there lessons for international capital standards?", Journal of Banking and Finance 36(3): 803–816.

FSB, 2011. "Progress in the Implementation of the G20 Recommendations for Strengthening Financial Stability", available at: http://www.fsb.org/wp content/uploads/r_110415a.pdf?page_moved=1.

Furlong, Frederick, and Simon Kwan, 2006. "Sources of bank charter value", Federal Reserve Bank of San Francisco, working Paper.

Gan, Jie, 2004. "Banking Market Structure and Financial Stability: Evidence from the Texas Real Estate Crisis in the 1980s", Journal of Financial Economics 73(3): 567–601.

Ghosh, Saibal, 2009. "Bank Risk, Charter Value and Depositor Discipline: A Simultaneous Equations Approach", Applied Economics Letters 16(6): 639–44.

Giordana, Gaston A., and I. Schumacher, 2013. "Bank liquidity risk and monetary policy. Empirical evidence on the impact of Basel III liquidity standards", International Review of Applied Economics 27(5): 633–55.

Goetz, Martin, Luc Laeven, and Ross Levine, 2016. "Does the Geographic Expansion of Banks Reduce Risk?", Journal of Financial Economics 120(2): 34–62.

González, Francisco, 2005. "Bank Regulation and Risk-Taking Incentives: An International Comparison of Bank Risk", Journal of Banking and Finance 29(5): 1153–84.

Gropp, R., Hakenes, H., Schnabel, I., 2011. "Competition, risk-shifting, and public bail-out policies", Review of Financial Studies 24: 2084–2120.

Gropp, R. and F. Heider, 2010. "The Determinants of Bank Capital Structure", Review of Finance 14(4): 587–622.

Gropp, Reint, and Jukka Vesala, 2004. "Deposit Insurance, Moral Hazard and Market Monitoring." Review of Finance 8(4): 571–602.

Hackbarth, D. Miao, J. and Morellec, E., 2006. "Capital structure, credit risk, and macroeconomic conditions", Journal of Financial Economics 82(3): 519–550.

Hamadi, M., Heinen, A., Linder, S., and Porumb, V. A., 2016. "Does Basel II affect the market valuation of discretionary loan loss provisions?", Journal of Banking and Finance 70: 177–92.

Hansen, L., 1982. "Large sample properties of generalized method of moments estimators", Econometrica 50(3): 1029–54.

Hanson S, Kashyap A, Stein J., 2011. "A macroprudential approach to financial regulation", Journal of Economic Perspectives 25(1): 3–28.

Haq, Mamiza, and Richard Heaney, 2012. "Factors Determining European Bank Risk", Journal of International Financial Markets, Institutions and Money 22(4): 696–718.

Haq, Mamiza, Amine Tarazi, Necmi Avkiran, and Ana Rosa Fonceca, 2016. "Does market discipline impact bank charter value? The case for Australia and Canada", Accounting and Finance.

Hartmann, Phillip, 2009. "Systemic risk in banking." ECB Financial Stability Review: 134-142

Hellmann, Thomas F., Kevin C. Murdock, and Joseph E. Stiglitz, 2000. "Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough?", The American Economic Review 90(1): 147–65.

Hovakimian, Armen, Edward J. Kane, and Luc Laeven, 2015. "Tracking Variation in Systemic Risk at US Banks During 1974-2013." Institute for New Economic Thinking. Working Papers Series 16.

Huang, R., and Ritter, J.R., 2009. "Testing theories of capital structure and estimating the speed of adjustment", Journal of Financial and Quantitative Analysis 44(2): 237–271.

Ivashina, V. and D. Scharfstein, 2010. "Bank lending during the financial crisis of 2008", Journal of Financial Economics 97(3): 319–338.

IMF, 2015. "Global financial stability report: navigating monetary policy challenges and managing risks.Chapter2: International banking after the crisis: increasingly local and safer?". available at: https://www.imf.org/~/media/Websites/IMF/.../_c2pdf.ashx.

Jimenez G. Z., S. Ongena, J. L. Peydró, J. Saurina, 2017. "Macroprudential Policy, countercyclical bank capital buffers and credit supply: Evidence from the Spanish Dynamic Provisioning Experiments", Journal of Political Economy, forthcoming.

John K., Kim T., Palia D., 2012. "Heterogeneous Speed of Adjustment in Target Capital Structure," Working paper Stern School of Business NYU.

Jones, Jeffrey S., Scott A. Miller, and Timothy J. Yeager, 2011. "Charter Value, Tobin's Q and Bank Risk during the Subprime Financial Crisis", Journal of Economics and Business 63 (5): 372–91.

Keeley, Michael C., 1990. "Deposit Insurance, Risk, and Market Power in Banking", The American Economic Review 80(5): 1183–1200.

Kiema, I. and E. Jokivuolle, 2014. "Does a leverage ratio requirement increase bank stability?", Journal of Banking and Finance 39: 240–254.

Kleibergen, F., and Paap, R., 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition", Journal of Econometrics 133(1): 97–126.

Koenker, R., Hallock, K., 2001. "Quantile regression », Journal of Economic Perspectives 15: 143–156.

Köhler, Matthias, 2015. "Which Banks Are More Risky? The Impact of Business Models on Bank Stability", Journal of Financial Stability 16(2): 195–212.

Kok, C. and G. Schepens, 2013. "Bank reactions after capital shortfalls", ECB Working Paper No. 1611.

Konishi, Masaru, and Yukihiro Yasuda, 2004. "Factors Affecting Bank Risk Taking: Evidence from Japan", Journal of Banking and Finance 28(1): 215–32.

Laeven, Luc, and Ross Levine, 2007. "Is There a Diversification Discount in Financial Conglomerates?", Journal of Financial Economics 85 (2): 331–67.

Laeven, Luc, and Ross Levine, 2009. "Bank Governance, Regulation and Risk Taking", Journal of Financial Economics 93(2): 259–75.

Laeven, Luc, Lev Ratnovski, and Hui Tong, 2015. "Bank Size, Capital, and Systemic Risk: Some International Evidence", Journal of Banking and Finance 69(S1): S25–S34.

Leary, M.T., and Roberts, M.R., 2005. "Do firms rebalance their capital structures?", Journal of Finance 60(6): 2575–2619.

Lemmon, M., Roberts, M. and Zender, J., 2008. "Back to the beginning: Persistence and the cross-section of corporate capital structure", Journal of Finance 63(4): 1575–1608.

Lepetit, Laetitia, Emmanuelle Nys, Philippe Rous, and Amine Tarazi. 2008. "Bank Income Structure and Risk: An Empirical Analysis of European Banks", Journal of Banking and Finance 32(8): 1452–67.

Lepetit, L., Saghi-Zedek N. and Tarazi, A., 2015. "Excess Control Rights, Bank Capital Structure Adjustments, and Lending", Journal of Financial Economics 115(3): 574–591.

Liikanen, E. (Chair), 2012. The High-Level Expert Group on Reforming the Structure of the EU Banking Sector: Final Report.

Marcus, Alan J., 1984. "Deregulation and Bank Financial Policy", Journal of Banking & Finance 8: 557–565.

Martinez-Miera, David, and Rafael Repullo. 2010. "Does Competition Reduce the Risk of Bank Failure?", The Review of Financial Studies 23(10): 3638–64.

Martynova, Natalya, Ratnovski Lev and Vlahu Razvan, 2014. "Bank Profitability and Risk-Taking,", working paper.

Mayordomo, Sergio, Maria Rodriguez-Moreno, and Juan Ignacio Peña, 2014. "Derivatives Holdings and Systemic Risk in the U.S. Banking Sector", Journal of Banking and Finance, 45(8): 84–104.

Memmel, C., and Raupach, P., 2010 "How do banks adjust their capital ratios?", Journal of Financial Intermediation, 19(4): 509–528.

Merton, R.C., 1977. "On the pricing of contingent claims and the Modigliani-Miller theorem". Journal of Financial Economics 5: 241–249.

Niu, Jijun, 2012. "An Empirical Analysis of the Relation between Bank Charter Value and Risk Taking", The Quarterly Review of Economics and Finance 52(3): 298–304.

Öztekin, Ö., and Flannery, M.J., 2012. "Institutional determinants of capital structure adjustment speeds", Journal of Financial Economics 103(1): 88–112.

Park, Sangkyun, 1997. "Risk-Taking Behavior of Banks under Regulation", Journal of Banking and Finance 21 (4): 491–507.

Park, Sangkyun, and Stavros Peristiani, 2007. "Are Bank Shareholders Enemies of Regulators or a Potential Source of Market Discipline?", Journal of Banking and Finance 31(8): 2493–2515.

Repullo, R. and J. Suarez, 2013. "The Procyclical Effect of Bank Capital Regulation", Review of Financial Studies 26(2): 452–490.

Roodman, D., 2006. "How to do Xtabond2: an introduction to "Difference" and "System" GMM in Stata", Center for Global Development Working Paper 103.

Rubio, M. and Carrasco-Gallego, J.A., 2016. "Coordinating Macroprudential Policies in the Euro Area: The case of Spain", Economic Modelling: 59(C): 570–582.

Saheruddin, H., 2014. "Bank capital, reputation, and relationship lending: Evidence from bank loan announcements during normal times and financial crises", Working paper.

Saunders, Anthony, and Berry Wilson, 2001. "An Analysis of Bank Charter Value and Its Risk-Constraining Incentives", Journal of Financial Services Research 19(2-3): 185–95.

Servaes, H., 1996. "The value of diversification during the conglomerate merger wave", Journal of Finance 51: 1201–1225.

Soedarmono, Wahyoe, Romora Edward Sitorus, and Amine Tarazi, 2015. "Bank Charter Value, Systemic Risk and Credit Reporting Systems: Evidence from the Asia-Pacific Region." Working Paper.

Stiroh, Kevin J., 2004. "Diversification in Banking: Is Noninterest Income the Answer?", Journal of Money, Credit and Banking 36(5): 853–82.

Stock, James H. and Motohiro Yogo, 2005. "Testing for weak instruments in linear IV regression," in Identification and Inference for Econometric Models (eds. D. W. K. Andrews and J. H. Stock). New York: Cambridge University Press (Chap. 5): 80–108.

Vickers, J. (Chair), 2011. "Final Report of the Independent Commission on Banking".

Weiß, Gregor N. F., Denefa Bostandzic, and Sascha Neumann, 2014. "What Factors Drive Systemic Risk during International Financial Crises?", Journal of Banking and Finance 41(4): 78–96.

Weiß, Gregor N. F., Sascha Neumann, and Denefa Bostandzic, 2014. "Systemic Risk and Bank Consolidation: International Evidence", Journal of Banking and Finance 40(3): 165–81.

ABSTRACT

The aim of this thesis is to contribute on the current debate on the systemic risk and its policy implications for the implementation of new (systemic risk-based) capital requirements in the banking industry. We extend the existing literature in many aspects. In the *first chapter*, we investigate how bank charter value affects risk for a sample of OECD banks by using standalone and systemic risk measures before, during, and after the global financial crisis of 2007–2008. We revisit the self-discipline role of charter value on bank's risk-taking and systemic risk prior, during and after the crisis. We show that bank charter value is positively associated with risk-taking and systemic risk for very large "too-big-too-fail" banks and large U.S. and European banks prior to the crisis, but such a relationship is inverted during and after the crisis. Then, we deepen investigation on this relation between charter value and risk-taking and systemic risk prior to the crisis, regarding differences in risk taking cultures, bank size and bank strategies. The *second chapter* analyzes the dynamics of banks' capital structure towards their desired and/or imposed capital level. It analyzes several interesting features. (i) whether or not market frictions and capital adjustment costs are larger for regulatory capital ratios vis-à-vis a plain leverage ratio. (ii) which adjustment channels banks use to adjust their capital ratio. (iii) how the speed of adjustment and adjustment channels differ between large, systemic and complex banks versus small banks. Findings suggest that banks are more flexible and faster in adjusting to their leverage capital ratio than to regulatory capital ratios. Whereas, systemically important banks are slower than other banks in adjusting to their target leverage ratio but quicker in reaching their target regulatory ratios. Further explores show that SIFIs might be more reluctant to change their capital base by either issuing or repurchasing equity and prefer sharper downsizing or faster expansion. In the *third chapter***,** we analyze how the international organization structure and the geographic expansion, of 105 European listed banks that have foreign affiliates around the world, could affect bank level measures of systemic risk during the 2005–2013 period. We also investigate how the peak of the global financial crisis of 2008–2009 and the height of the European sovereign debt crisis of 2010–2011 might have affected such relationships. We find that internationalization and foreign complexity are important drivers of bank systemic risk, particularly during the 2008–2013 financial stress years.

Keywords: systemic risk; idiosyncratic risk; charter value; bank strategies; capital structure; speed of adjustment; bank regulation; internationalization; foreign complexity; global financial crisis; European sovereign debt crisis.

RESUME

Cette thèse a pour objectif de prendre part à la réflexion sur le risque systémique et ses conséquences négatives sur l'économie réelle, et au débat sur la mise en place d'une règlementation macro-prudentielle (effets systémiques) efficace pour l'industrie bancaire en visant la stabilité financière. Pour cela, ce travail contribue à la littérature existante à travers plusieurs aspects. Dans le *premier chapitre* de cette thèse, sur un échantillon de banques de l'OCDE, nous étudions la manière dont la valeur de la franchise affecte le risque bancaire avant, pendant et après la crise financière mondiale de 2007–2008, en utilisant des mesures de risque individuelles et systémiques. Nous réétudions l'hypothèse de la valeur de la franchise bancaire et son rôle disciplinant au regard de la prise de risque et de l'expansion au risque systémique avant, pendant et après la crise financière. Nous montrons qu'avant la crise, la valeur de la franchise bancaire impacte positivement la prise de risque et le risque systémique non seulement des très grandes banques dites "*too-big-too-fail*" mais aussi des grandes banques européennes et américaines. Cependant, nos résultats montrent que pendant et après la crise, cet effet s'inverse. En considérant la période d'avant crise, nous allons plus loin dans nos investigations sur la relation entre la valeur de la franchise d'une part et la prise de risque et l'exposition au risque systémique d'autre part, en prenant en compte les effets des différences entre les cultures de prise de risque, la taille des banques et les stratégies bancaires. Le *deuxième chapitre* analyse la dynamique de la structure du capital des banques en fonction de leur niveau de capital interne ciblé et/ou externe imposé. Plus précisément, il examine plusieurs caractéristiques. (i) si les frictions du marché et les coûts d'ajustement du capital sont plus considérables lorsqu'il s'agit d'ajuster les ratios de fonds propres réglementaires par rapport à un ratio de levier simple. (ii) les mécanismes d'ajustement utilisés par les banques pour ajuster leur ratio de capital. (iii) comment la vitesse d'ajustement et les mécanismes d'ajustement diffèrent entre les grandes banques systémiques et complexes d'une part, et les banques moins systémiques d'autre part. Les résultats suggèrent que les banques sont plus flexibles et plus rapides dans l'ajustement de leur ratio de levier que dans l'ajustement de leurs ratios de capital réglementaire. Tandis que les banques d'importance systémique (SIFI) sont moins réactives que les autres banques dans l'ajustement de leur ratio de levier cible, elles sont néanmoins plus rapides à atteindre leurs ratios réglementaires cibles. D'autres investigations montrent que les SIFIs pourraient être plus réticentes à modifier leur base de capital en émettant ou en rachetant des actions et préfèrent une réduction plus importante ou une expansion plus rapide de leur taille. Dans le *dernier chapitre*, nous analysons comment la structure organisationnelle internationale et l'expansion géographique de 105 banques européennes cotées qui ont des filiales à travers le monde, pourrait affecter leur importance systémique au cours de la période 2005–2013. Nous examinons également comment le pic de la crise financière mondiale de 2008–2009 et l'ampleur de la crise de la dette souveraine européenne de 2010–2011 pourraient avoir affecté ces relations. Nous montrons que l'internationalisation et la complexité organisationnelle sont des facteurs importants du risque systémique bancaire, en particulier pendant les années de stress financier 2008–2013.

Mots clés : risque systémique ; risque individuel ; valeur de la franchise ; stratégies bancaires ; structure de capital ; vitesse d'ajustement ; régulation bancaire ; internationalisation ; complexité ; crise financière globale ; crise de la dette souveraine Européenne.