The role of on- and off-balance-sheet leverage of banks in the late 2000s crisis

Nikolaos I. Papanikolaou[a*] **and Christian C.P. Wolff**[a,b]
[a]*Luxembourg School of Finance, University of Luxembourg, 4 rue Albert Borschette, L-1246 Luxembourg*
[b]*Centre for Economic Policy Research (CEPR), London, United Kingdom*

Abstract
Extensive regulatory changes and technological advances have transformed banking systems to a great extent. Banks have reacted to the challenges posed by the new operating environment by creating new products and expanding their activities to some uncharted business areas. In this paper, we study how modern banking that gave birth to the off-balance-sheet leverage activities affected the risk profile of U.S. banks as well as the level of systemic risk before and after the onset of the late 2000s financial crisis. Towards this, we separate on- from off-balance-sheet leverage and capture the latter with different, yet complementary, measures which do not exist in the current literature. Special attention is paid on the deleveraging process that occurred in the banking market after the crisis erupted, which is an additional innovative feature of our study. Our findings reveal that leverage, both explicit and hidden off-the-balance-sheet, increases the individual risk of banking firms making them vulnerable to financial shocks. Reverse leverage, on the other hand, is good for individual banks' health, but is found to be harmful for financial stability. We also demonstrate that the banks which concentrate on traditional lines of business typically carry less risk compared to those involved with modern financial instruments.

Keywords: bank leverage; deleveraging process; individual bank risk; systemic risk; financial crisis
JEL classification: C23; C26; D02; G21; G28

[*]Corresponding author: Tel.: +352 466644 6938; fax: +352 466644 6835; E-mail address: nikolaos.papanikolaou@uni.lu

1. Introduction

The late 2000s crisis, whose origins can be traced in the rising delinquencies in the U.S. sub-prime mortgage market in 2006 and the succeeding collapse in housing prices in August 2007, has revealed several inadequacies in the functioning of the financial system: loose monetary policies, performance-based remuneration practices, and inefficient regulatory and supervisory rules in the years preceding the crisis are amongst the perceived causes of making the entire system more vulnerable to shocks. A factor which is related to the aforementioned shortfalls and is identified in the current crisis literature as having a substantial role in the buildup of severe structural weaknesses and adverse market dynamics during the pre-crisis period is the high leverage of financial institutions worldwide.

In general terms, leverage is viewed as one of the main underlying features of banks' balance sheets. Traditionally, leverage arises directly through formal debt where the most popular types of debt are bonds and credit lines. Nevertheless, in the years before the crisis, banking firms seemed to have leveraged their positions to a much greater extent than they used to by taking advantage of financial engineering techniques, which allowed them to transfer a large part of their leverage off their balance sheets.[1] Therefore, a significant degree of leverage was assumed implicitly, in the sense that it was not recorded on the balance sheet of banks. However, shortly after the crisis erupted, financial organisations sought to deleverage their positions thus amplifying the already existing downward pressure on asset prices which, in turn, encouraged the deleveraging spiral even further. This procyclical process was exacerbated by the large size of the institutions that were engaged in off-balance-sheet activities as well as the systemic importance of these institutions. Overall, the malfunctions of the banking industry were transmitted to the rest of the financial system resulting in a massive contraction of liquidity and credit availability which, shortly later, exerted a serious adverse influence on the real economy.

Even though the impact of leverage on the health of the financial system has been discussed in several policy and academic studies (see, e.g., CRMP Report, 2008; Greenlaw et al., 2008), not enough empirical evidence has been gathered to provide definite answers to the relevance of leveraging and, mostly, of deleveraging in the propagation and prolongation of the late 2000s financial crisis. Along these lines, little attention has been paid to the overall leverage behaviour

[1] It is true that the corporate financial sector was also engaged in high-leverage business projects before the onset of the crisis. However, this issue is out of the scope of the current paper.

of banks in the sense that the extant literature mainly focuses on the traditional on-balance-sheet leverage, neglecting, to a great extent, the importance of the implicit leverage in the operation and the health of the banking system. In this paper, we make an attempt to fill part of this void by empirically assessing how modern banking, which has given birth to off-balance-sheet leverage, has affected the health and the soundness of the U.S. banking firms as well as the level of systemic risk in the U.S. banking system before and after the onset of the late 2000s crisis. To this aim, we separate on- from off-balance-sheet leverage activities and capture the latter set of activities with different, yet complementary, measures which do not exist in the relevant literature. Special attention is paid on the deleveraging process that took place in the banking market after the crisis erupted.

Our findings reveal, among other things, that on-balance-sheet leverage has a negative impact on the health of individual banks as well as on the fragility of the system. By the same token, we find that different types of off-balance-sheet leverage are negatively linked to the soundness of the banking system as a whole. This result is even stronger in case systemic risk is considered. Reverse leverage, on the other hand, might have beneficial effects on individual banks' health, but is very harmful for the stability of the entire system. We also show that banks which concentrate on the traditional activity of taking deposits from households and making loans to agents that require capital are reported to carry less risk to the system than those that are involved with new financial instruments. Overall, our results provide a better understanding of one of the root causes of the late 2000s crisis and contribute to the discussion on the restructuring and strengthening of the existing regulatory framework for banks.

The remainder of the paper proceeds in the following way. In Section 2 we examine in depth how on- and off-balance-sheet leverage as well as reverse leverage are linked to the soundness of banking firms and to the health of the financial system as a whole; both an empirical and a theoretical approach are taken to illustrate the aforementioned relationship. Section 3 provides a description of the data set and a justification of the variables used in our baseline empirical analysis together with the descriptive statistics. The regression model and the estimation methodology are also presented in Section 3. Section 4 then presents and discusses the empirical findings, where Section 5 is devoted to robustness checks. The policy implications of our results along with the concluding remarks are presented in Section 6.

2. The nexus between leverage, reverse leverage and risk in the banking system

2.1. An empirical perspective

Generally speaking, bank leverage refers to the use of debt in financing new assets. Regarding the on-balance-sheet (traditional) leverage of banks, this is related to the use of deposited funds or any other balance sheet items like, for instance, bonds to supplement bank's equity capital in financing fresh loans and investments. By doing so, banks expect that the granted loans will produce a higher rate of return compared to the interest rate that they have agreed to pay to its depositors (or, investors in the case of bonds). If the loan/investment return rates turn out to be lower than anticipated, bank's net worth will inevitably shrink simply because the bank will be forced to cover the difference between deposit and lending rates by resorting to its equity capital. In the case that a loan fails, the bank will not be in a position to recover it and, as a consequence, the loan will be charged off, implying that the institution will lose an amount of assets equal to the loan loss. Charge-offs also have an impact on the liabilities side of the bank's balance sheet as they reduce equity capital (net worth) by the amount of the loss. However, equity is viewed as a buffer against the losses a bank suffers in case loans -or other bank investments- go sour. Apparently, if, several, let alone many, borrowers default on their obligations, then the bank's equity will be in peril. Should nonperforming and defaulted loans accumulate, which is a common phenomenon in bad economic times, equity capital would disappear. In sum, on-balance-sheet leverage maps the riskiness of a bank's asset position into the riskiness of its equity stake.

Nevertheless, leverage can also be traced off the balance sheet of banking organisations. More specifically, in the years running up to the crisis, banks have been transferring a part of their leverage and the accompanying risk off their balance sheets mainly through their engagement in securitisation activities and Over-The-Counter (OTC) derivatives trading. Both these undertakings are strongly linked to the so-called 'regulatory arbitrage'. This sort of arbitrage refers to the response of banks to regulatory restrictions -especially those on capital requirements- that were imposed by Basel I and II. In more details, regulatory arbitrage is the game that takes place between banking firms and regulatory authorities, whereby the former innovate and develop new financial instruments in order to elude the scrutiny of supervisors and increase their returns, and the latter tighten the rules to avoid excessive risk-taking with the utmost purpose to safeguard the stability of the financial system.[2]

Securitisation was mainly achieved through the setup of Asset Backed Commercial Paper (ABCP) conduits and Structured Investment Vehicles (SIVs) where banks could transfer large portions of their assets. More specifically, a considerable amount of bank assets was transferred to the above-mentioned investment pools, whereas, at the same time, the sponsoring banking institutions were providing these pools with liquidity and credit enhancements in order to ensure funding liquidity for them. These enhancements (backstops) could attract a low charge under Basel Agreements and were funded mostly by short-term securitised debt and only by very little equity capital -or any other long-term investments- which has been always costly for banks. In so doing, the sponsoring institutions were able to free up capital and, hence, originate more assets -generally of lower quality (e.g., subprime mortgage loans)- that were typically hidden in the so-called shadow banking system.[3] Therefore, banks deliberately avoided issuing new equity capital in order to originate new assets and to finance their activities in general.[4] As a consequence, conduits and SIVs contained a significant degree of bank leverage and risk in an implicit form that was achieved through the structuring of the financial instruments *per se*. Nonetheless, under the aforementioned business scheme of funding which had come to be known as the ‘originate-to-distribute model’, investors in conduits and SIVs would return the assets back to the originating bank once they suffered a loss; and banks were, indeed, legally obliged to take bad assets back on their books. This is to say, asset risk was still burdened the sponsoring institutions.

Derivative products, on the other hand, grew up as part of an effort to better manage the investment risks amongst the international market participants. In specific, derivatives trading facilitated capital flows worldwide by unbundling and then more efficiently reallocating the various sources of risk which were associated with traditional banking products such as bank loans, bonds, and securities. Hence, the financial innovation of introducing derivatives to capital

---

[2] For a thorough discussion of regulatory capital arbitrage via derivative instruments, see Breuer (2002).

[3] Shadow banking consisted of non-bank financial institutions like hedge funds, insurance funds, investment funds, pension funds, SIVs, conduits, to name the most important ones. Some of these institutions, like SIVs and conduits, do not exist anymore.

[4] Banks were very keen on engaging in securitised activities not only because they could qualify for lower capital requirements, but also because securitisation had the additional advantage of generating fee income. Fees did not have to be returned in case securities suffer losses thus providing banks with an additional incentive to structure products and leverage their positions even further.

markets allowed the rather traditional arrangements of risk to be redesigned in order to better meet the desired risk profiles of the issuers and holders of these instruments. To put it differently, through the use of derivatives, a part of risk could be taken away from investors who were not willing to undertake it and moved towards those who were more risk-lovers and thus more willing and (probably) more able to bear it.

While the risk-shifting function of derivatives can play the useful role of hedging and thereby facilitating capital flows, derivatives can at the same time create new risks for the health of banking institutions and for the soundness of the system. The extensive use of derivative contracts is likely to lead to a lower degree of transparency between counterparties as well as between regulators and market investors, which can potentially harm the stability of the financial system. This holds true especially for the derivative products that are traded over-the-counter and are directly related to the off-balance-sheet leverage exposure of banking firms. Indeed, derivatives are traded in the following two main ways: either on exchanges, where trading is public and can be regulated by governments while observed and controlled by the market participants themselves, or in the OTC markets where trading is non-public and remains outside authorities' supervision and regulation. That is, unlike derivatives trading on stock exchanges, transactions in the OTC markets are neither registered nor systematically reported to the public and, as such, comprehensive information on them is limited.

Furthermore, derivatives can be utilised for non-productive purposes such as avoiding capital adequacy requirements (what has been mentioned above as 'regulatory arbitrage'), evading taxation, manipulating accounting rules, and misleading credit rating agencies. For instance, derivative products can be used to raise the level of market risk exposure relative to the bank capital in the pursuit of banks for higher-yielding investment strategies. In case of an unexpected or a sharp change in the exchange rate or other market prices, the larger the amount of market exposure -most likely created by open positions in derivatives contracts-, the greater will be the effect on the asset portfolio of individual banks and, hence, on the banking sector as a whole. In this regard, the use of derivatives to reduce the amount of capital that acts as a cushion to market turmoil raises the risk of bank failure and heightens doubts about the soundness of the entire sector.

It should be apparent thus far that leverage (either on- or off-the-balance-sheet of banks) can be potentially harmful for the stability of the financial system. Equally, if not more harmful than leverage itself is the so-called ‘reverse leverage’, or ‘deleveraging’, which refers to the phenomenon in which financial intermediaries all attempt to shrink their balance sheets together by selling part of their assets or by reducing their debt with the chief purpose to return to a safe level of capital. When a significant number of banks attempt to deleverage their balance sheets with the aim to strengthen their leverage ratios, various destabilising factors can be set in motion. If, for instance, several institutions attempt to sell part of their assets at the same time, the market prices of these assets will almost immediately fall, especially in the case that the selling assets are of the same class (e.g., mortgage loans, housing assets, etc.). Asset prices will then decline to the point where the sale proceeds will not retire enough debt to improve leverage ratios. In fact, ratios may actually deteriorate. Banks will, in turn, hold off selling as long as possible and the market will freeze up. As a consequence, a large volume of hard-to-value assets carried by highly leveraged institutions is looming over the markets. Overall, any serious fall in asset prices, or any large losses in loans or securities, or any cut in cash flows can exert reverse leverage effects on the system. Arguably, the deleveraging process puts additional downward pressure on financial markets, especially in a system that consists of highly leveraged institutions.

2.2. A theoretical perspective

In a theoretical analysis of the causes of the late 2000s crisis, Brunnermeier (2009) focuses on the U.S. banking industry to claim that the traditional relationship business model, in which banks issue loans and hold them until they are repaid, has been replaced by a new model. Under this new model, financial engineering techniques help banks to pool the loans, slice them into tranches and then sold them to both primary and secondary markets via securitisation. This transformation has, on the one hand, weakened the ability of banks to monitor the incentives of the agencies involved in this ‘originate-to-distribute-process’ while, on the other, it has increased the possibility for investors of holding a large amount of securities without fully understanding the associated risk.

Van Oordt (2013) makes an attempt to shed more light on the dark side of diversification. He constructs a theoretical model to show that tranching plays an important role for the economy from both microprudential and macroprudential perspectives. Regarding the former perspective, tranching is found to promote a fall in the likelihood of individual failures beyond the minimum level that could be achieved by linear diversification policies. This latter kind of policies is referred to the diversification of asset holdings by the construction of linear combinations of loan portfolios. In fact, Wagner (2010), again in a theoretical modelling context, illustrates how linear diversification can lead to an upsurge in the probability of joint failures amongst financial institutions and, hence, to an increase in the level of systemic risk. Turning to the macroprudential view, Van Oordt (2013) proves that tranching offers the opportunity to banks to adopt diversification strategies which are non-linear, and that these non-linearities can reduce the bankruptcy risk of individual institutions beyond the minimum level attainable by linear diversification. Importantly, these non-linear diversification policies do not increase systemic risk.

Kiff and Kisser (2013) investigate the economics of securitisation comparing the results of equity and mezzanine tranche retention in the context of systemic risk, moral hazard, accounting frictions and funding distortions. They show that loan screening activity is maximised via the maximization of due diligence when the bank which originates the loan retains the equity tranche. Moving further into the heart of securitisation puzzle, they evaluate the relevance of market frictions in their conclusions testing whether equity or mezzanine tranche retention maximises the profits of banks. They document that, in case capital structure irrelevance does not hold and the costs of debt and equity are very high, mezzanine tranche retention is more likely to help banks maximising their profits.

Regarding the derivatives trading activity of banks, Fabozzi and Choudhry (2004) argue that the use of credit derivatives allow banks to increase the use of scarce capital by means of risk mitigation where, at the same time, help them to improve their management of regulatory capital. Duffee and Zhou (2001) and Morrison (2005) develop two theoretical models which demonstrate how the credit derivatives markets can reduce economic welfare. They show that credit risk transfer can lead to a decline in welfare through contagious effects that can harm the stability of the entire system. More specifically, Morrison illustrates that credit derivatives can destroy the signaling value of debt and this may cause disintermediation and welfare reduction.

Turning to reverse leverage which typically takes place during economic downturns, Cornett et al. (2011) suggests that, from the onset of the crisis, the pressure for banking firms to deleverage was exacerbated by having to honour prior commitments to credit lines, which were mainly nominated in U.S. dollars. Their paper documents the sharp decrease in leverage via the new loans emanating especially from banks needing to deleverage. The impressive extent to which financial institutions deleveraged during the crisis is also discussed in Adrian and Shin (2010).

3. Empirical analysis

3.1. Description of the data set

Our empirical analysis is based on a data set that consists of 20 U.S. banks as reported in Table 1 that follows. These banks are of the very same institution type as they are all defined as 'Domestic U.S. Financial Holding Companies' from National Information Center of the Federal Financial Institutions Examination Council (NIC/FFIEC). Sample institutions have been selected primarily on the basis of their systemic importance (as we discuss in detail below) and the degree of their off-balance-sheet exposure as documented in the 'Bank Derivatives Reports' of the Office of the Comptroller of the Currency (OCC).

Table 1

Sample of banks. This table reports the 20 U.S. banks which are employed in our empirical analysis.

Bank name	
1. BANK OF AMERICA CORP.	11. JP MORGAN CHASE & CO
2. BANK OF NY MELLON CORP.	12. KEYCORP
3. BB&T CORP.	13. NORTHERN TRUST CORP.
4. CAPITAL ONE FINANCIAL CORP.	14. PNC FIN. SERVICES GROUP INC.
5. CITIGROUP INC.	15. REGIONS FINANCIAL CORP.
6. CITY NATIONAL CORP.	16. STATE STREET CORP.
7. COMERICA INC.	17. SUNTRUST BANKS INC.
8. FIFTH THIRD BANKCORP	18. US BANK CORP.
9. FIRST HORIZON NATIONAL CORP.	19. WELLS FARGO & CO
10. HUNTINGTON BANKSHARES INC.	20. ZIONSBANKCORP.

The number of institutions we incorporate in our analysis is larger compared to previous studies in the relevant literature (see, e.g., O'Hara and Shaw, 1990; Flannery & Sorescu, 1996; De Nicoló and Kwast, 2002), which are also focused on Systemically Important Financial Institutions (SIFIs).[5] The 20 banks of our sample possess more than 50% of the entire sector's

[5] A sample of the recent works that belong to the burgeoning crisis literature and focus exclusively on large, systemically important financial institutions are those of Huang et al. (2009) that constructs a framework for measuring and stress testing the systemic risk of 12 U.S. major commercial and investment banks, Adrian and Shin (2010) that examines the procyclicality in leverage of the 5 biggest U.S. investment banks before the crisis, and Patro et al. (2013) that uses the 22 largest commercial and investment banks in U.S. to analyse the relevance of stock return correlations in assessing the level of systemic risk.

total assets,[6] whereas their relative importance (*i.e.*, their relative size) is getting higher throughout the data period.[7] In fact, the U.S. federal authorities have been reluctant to let any of them to go bankrupt as this would have shattering effects on the entire financial system. To provide strong support to this argument, we mention that all sample banking firms are amongst the top 50 Holding Companies as reported in the relevant list of the NIC/FFIEC. Further, not a single entity among those failed or acquired by some other financial institution from the beginning of the crisis onwards is included in our data set. To the contrary, all sample banks have received huge financial assistance from the U.S. government through the Troubled Asset Relief Program (TARP) according to the U.S. Department of Treasury. It is also important to note that, in early 2009, the U.S. government performed a series of stress tests on the 19 largest banks and near-banks that were of systemic importance for the economy. Under that exercise, which was named as Supervisory Capital Assessment Program (SCAP), each bank would need to safeguard that it had sufficient capital in case the economy got even worse. All the 14 commercial pure banking organisations which took part in SCAP in 2009 are included in our sample.[8] [9]

To sum up, we have constructed a homogeneous set of banks which provide the bulk of financing to industry and households in U.S. and elsewhere, meaning that, if any of them were allowed to fail, this would inevitably cause, *inter alia*, serious systemic liquidity shortages in the economy.[10] As a consequence, our data set is very representative of the 'operating behaviour' of this very special category of banking firms (SIFIs) and also of the way the U.S. banking industry as a whole operates. We, therefore, expect to get meaningful and robust empirical results.

---

[6] This percentage is based on the average size of each bank as measured by the ratio of a bank's assets to the sector's total assets over the whole data period.

[7] Several prominent studies focus on the biggest U.S. Bank Holding Companies -on the basis of their relative size- that account for approximately half of the total U.S. bank population: Keeley (1990), Demsetz and Strahan (1997), Galloway et al. (1997), just to name a few.

[8] Five of the institutions that participated in SCAP were not part of the commercial banking industry. These were: American Express Company, GMAC Inc., Goldman Sachs Group, Inc., Metlife Inc., and Morgan Stanley. Hence, these institutions are not included in our analysis.

[9] SCAP was limited to Holding Companies with total assets not less than USD 100 billion. Based on U.S. Department of Treasury data, the 14 banks that were qualified to participate in SCAP and take part in our sample are the following: Bank of America Corp., Bank of NY Mellon Corp., BB&T Corp., Capital One Financial Corp., Citigroup Inc., Fifth Third Bankcorp., JP Morgan Chase & Co, Keycorp, PNC Financial Services Group Inc., Regions Financial Corp., State Street Corp., Suntrust Banks Inc., US Bank Corp., and Wells Fargo & Co.

[10] Clearly, institutions other than commercial banks like, for instance, insurance companies (e.g., AIG) or investment banks (e.g., Lehman Brothers) also had a systemic role and contributed to the emergence of the crisis.

On the basis of the discussion so far, it does not come by surprise that the banking organisations that comprise our data set have been engaged in non-traditional banking activities to a much greater extent than their smaller counterparts. Large banks have indeed been entangled with a very broad range of bank-related activities, others than the pure commercial banking activities like loan granting and deposit taking. These activities are explicitly defined by the Gramm-Leach-Bliley Act of 1999 and include -amongst others- securities dealing and underwriting, insurance underwriting, financial and investment advisory services, merchant banking, and issuing or selling securitised interests in bank-eligible assets. Indeed, literature (see, e.g., Rime and Stiroh, 2003) has showed that big banks are very prone to universal banking activities in contrast to small and mid-sized institutions, which are less diversified and resemble single-line businesses. Therefore, the distinction between on- and off-balance-sheet leverage is expected to be much clearer by relying on a sample that consists exclusively of very large financial entities.

The key reason why we restrict our attention on commercial banks (and not, for instance, on investment, or savings banks) is because the commercial banking sector is both heavily regulated and largely supervised. This is in sharp contrast to what holds for investment banks as well as near- and non-banks that do not rely on deposits and, hence, do not need to keep much money in the form of capital. To give an example, the larger U.S. investment Bank Holding Companies and their subsidiaries were regulated by the U.S. Securities and Exchange Commission and were not subjected to any leverage requirements. Indeed, light leverage restrictions were only imposed -at individual firm level- on the amount of customer receivables an investment bank could hold as a multiple of capital (the so-called ‘net capital rule’). In other words, the non-commercial banking institutions face no serious restrictions on the level of their leverage.

We believe it is also important to justify at this point why we focus our analysis on the U.S. banking sector and not on some other banking market. First and foremost, the crisis originated in the U.S. before spilled over to other economies around the globe. Hence, by looking at the U.S. banking industry, we are capable of better tracing some of the root causes of the current financial turmoil. Second, the differences in the accounting regimes can lead to large variations in the off-balance-sheet behaviour of banks, which lie at the centre of the present analysis. Evidently, Generally Accepted Accounting Principles (GAAP) allowed U.S. commercial banks to treat their SIVs and ABCP conduits as being entirely off their balance sheets. In contrast, the International

Financial Reporting Standards (IFRS) that European institutions followed were somewhat less tolerant toward off-balance-sheet business as they required from banks to keep record of this sort of items on their balance sheets. Along the same lines, the use of IFRS results in significantly higher amounts of total assets and hence lower leverage ratios for the same or similar exposures, than does the use of U.S. GAAP. The reason for this is the netting of OTC derivatives, which is allowed under the former reporting systems. More concretely, the netting conditions are stricter under IFRS in that the gross replacement value of derivatives is generally shown on the balance sheet even when positions are held under master netting agreements with the same counterparty.

To illustrate with an example, we examine Deutsche Bank's balance sheet which is reported under both accounting principles. In 2009, the systemically important German bank reported an amount of total assets of approximately 1.5 trillion euros under IFRS standards, where total assets were equal to almost 0.9 trillion euros if U.S. GAAP were taken into account. Given that the reported equity capital is (more or less) the same under both accounting principles, the on-balance-sheet leverage ratio for Deutsche Bank in 2009 was much higher in IFRS values. And, of course, this has been the case for every other accounting year.

Apparently GAAP provided U.S. banks with more incentives to undertake a higher degree of intangible leverage compared to their European counterparts. As a consequence, our emphasis on U.S. banking institutions allows us to develop more solid measures of their off-balance-sheet leverage activities, and then proceed to empirically gauge the effects of these activities on individual bank soundness and on system's health, which are the key issues examined in this study.

3.2. Sample period

The data we employ in our analysis are of quarterly frequency and cover the period 2002q1-2012q3. We do not examine the years before 2002 mainly for two reasons. First, the two international financial crises that erupted in East Asia and in Russia at the end of the 90s together with the Long Term Capital Management (LTCM) crisis of 1998 all had a destabilising impact on the U.S. banking system. Second, no considerable regulatory or other similar reforms occurred in the U.S. banking market from 2002 onwards, meaning that the operation of banks has remained largely unaffected by exogenous factors throughout the examined period. In fact, the latest legislative activity in the U.S. that largely influenced the operation of the entire banking sector was the already mentioned Gramm-Leach-Bliley Act of 1999, which opened up the local market allowing commercial and investment banks, securities firms and insurance companies to merge their activities. If any additional reforms had taken place in the banking regulatory environment after 2002, it would be highly likely to have exerted an impact on the leverage decisions of banks and hence to have biased our results.[11]

The whole data period is divided into two sub-periods: the earlier one (2002q1-2007q2) includes the years before the outbreak of the crisis, that is before August 2007 when the difference between the interest rates on interbank loans and short-term U.S. government bills (the so-called TED spread) widened to 150-200 basis points relative to a historically stable range of 10-50 basis points. The pre-crisis years were characterised by stable financial conditions and strong economic expansion. The second period extends from 2007q3 to 2012q3 and refers to the crisis period in which financial turbulence, uncertainty, and distress prevailed in the economy.[12]

We perform a simple Chow (1960) test for a structural break at the beginning of the crisis (2007q3). We find strong evidence of a structural change in 2007q3. In particular, the Chow test rejects the null hypothesis of no break (or constant parameter values), thereby providing evidence that the difference in the sub-period regressions is statistically significant. We further split the crisis period into two and run a Chow test for the following two periods: 2007q3-2008q3 and 2008q4-2012q3. The breakpoint in 2008q3 is based on the collapse of Lehmann Brothers on 15 September, 2008. We basically fail to reject H_0, thus providing little or no evidence of structural changes in the on- and off-balance-sheet leverage variables which we employ in our analysis and are described below.

3.3. Variables selection

In this Section, we describe the variables employed in our baseline econometric model. All variables are summarised in Appendix A.

To start with the left-hand-side variables, we measure individual bank soundness with total bank risk (*TOTRISK*), which is calculated as the quarterly standard deviation of each sample

[11] It is well established in the banking literature that regulation strongly affects industry structure and alters the behaviour of banks in terms of performance and risk-taking (see, e.g., Brissimis et al., 2008).
[12] Other recent studies -like that of Cornett et al. (2011)- also use 2007q3 as the starting point of the crisis.

bank's daily stock market returns.[13] This metric of risk captures the total volatility of equity prices for each individual bank. As such, it incorporates credit risk, market risk, and liquidity risk. To calculate *TOTRISK*, we first obtain the weekly (Friday-to-Friday) returns for each individual bank using its stock market prices:

$$R_{iw} = \ln \overline{P}_{iw} - \ln \overline{P}_{iw-1} \tag{1}$$

where R_{iw} denotes the weekly (*w=1, 2, …, W*) stock market returns of bank *I* (*i=1,2,…, N=20*), and $\ln \overline{P}_{iw}$ stands for the natural logarithm of the weekly average of bank *i*'s stock market daily price *P*, where daily returns are adjusted to account for dividend payouts and stock splits. In the cases where Friday was a holiday and no stocks were traded, we use the Thursday-to-Friday, or Friday-to-Thursday returns instead. Along the same lines, in cases where the return was not available for a given stock on a given Friday, that stock's weekly return was coded as missing. *TOTRISK* is then obtained by the following formula:

$$\sigma_{iq} = \sqrt{\frac{\sum_{w=1}^{W}(R_{iw} - \overline{R}\ )^2}{W-1}} \tag{2}$$

where σ_{iq} is the quarterly (*q=2002q1, 2002q2,…, 2012q3*) standard deviation of bank *i*'s daily returns and $\overline{R}$ is the quarterly average of bank *i*'s weekly returns. Sigma is strongly related to bankruptcy both statistically and conceptually: if a bank has more variable cash flows (and, hence, more volatile stock returns), then the bank is expected to have a higher probability of bankruptcy.

We measure systemic risk (*CoVaR*) relying on the approach of Adrian and Brunnermeier (2011). *CoVaR* is the Value at Risk (*VaR*) of a financial institution conditional on other institutions of the financial system being in distress. The analytical procedure we follow to calculate *CoVaR* is as follows:

[13] Similar risk measures have been used in the study of Galloway et al. (1997) and -more recently- in those of Gonzalez (2005) and Wu et al. (2011).

We start by defining $VaR_{p,q}^{i}$ as the p-quantile of the asset return R_q^i that bank i will lose with probability p over time q, where q = quarters:

$$Prob\left(R_q^i \leq VaR_{p,q}^i\right) = p \tag{3}$$

We then define $CoVaR_{p,q}^{system|i}$ as the VaR of the entire banking system (treated as a portfolio of banks) conditional upon bank i being in financial distress:

$$Prob\left(R_q^{system} \leq CoVaR_{p,q}^{system|i} \middle| R_q^i = VaR_{p,q}^i\right) = p \tag{4}$$

In a similar vein, we define $CoVar_{p,q}^{system|i,normal}$ as the VaR of the whole banking system conditional upon bank i operating under normal conditions (*i.e.*, when R_q^i is equal to its median level):

$$Prob\left(R_q^{system} \leq CoVaR_{p,q}^{system|i,normal} \middle| R_q^i = normal_{p,q}^i\right) = p \tag{5}$$

As a consequence, the contribution of bank i to the risk of the whole system (systemic risk) is given by:

$$\Delta CoVaR_{p,q}^{i} = CoVaR_{p,q}^{system|i} - CoVaR_{p,q}^{system|i,normal} \tag{6}$$

To estimate the contribution of bank i to systemic risk as given by $\Delta CoVaR_{p,q}^{i}$ in eq. (6), we need to first estimate the two right-hand side terms and then calculate their simple difference. To this purpose, we resort to quantile regression analysis. A quantile regression, first introduced by Koenker and Bassett (1978), estimates the conditional probability that a variable falls below a given threshold (quantile) when another random variable is also below the same quantile.[14] In the context of *CoVaR* measurement, quantile regression techniques are preferred compared to

[14] An overview of quantile regression analysis illustrated with a comprehensive empirical application can be found in Chernozhukov and Umantsev (2001).

their OLS counterparts. In Appendix B, we analytically explain the main reasons behind this decision.

We obtain $CoVaR_{p,q}^{system|i}$ by running the following two quantile regressions setting p equal to 0.01, which corresponds to the 1% distress level:

$$R_q^i = \alpha^i + \beta^i M_{q-1} + \varepsilon_q^i \tag{7}$$

$$R_q^{system|i} = \alpha^{system|i} + \beta^{system|i} M_{q-1} + \gamma^{system|i} R_q^i + \varepsilon_q^{system|i} \tag{8}$$

where R_q^i is the quarterly growth rate of bank i's total assets conditional on bank i being distressed, and $R_q^{system|i}$ is the quarterly growth rate of total assets of all N=20 banks that comprise our banking system conditional on bank i being distressed. Both bank i's total assets and system's total assets are expressed in market values.

Similarly, we calculate $CoVaR_{p,q}^{system|i,normal}$ by running the following quantile regressions at the 50% level this time, where 50% corresponds to the median level of asset returns under normal financial and economic conditions:

$$R_q^{i,normal} = \alpha^{i,normal} + \beta^{i,normal} M_{q-1} + \varepsilon_q^{i,normal} \tag{9}$$

$$R_q^{system|i,normal} = \alpha^{system|i,normal} + \beta^{system|i,normal} M_{q-1} + \gamma^{system|i,normal} R_q^{i,normal} + \varepsilon_q^{system|i,normal} \tag{10}$$

where $R_q^{i,normal}$ is the quarterly growth rate of bank i's total assets conditional on bank i's operation under normal conditions and $R_q^{system|i,normal}$ is the quarterly growth rate of total assets of all N=20 banks of our system conditional on bank i's normal operation. Like it was the case in eq. (7) and (8), total assets in eq. (9) and (10) are also expressed in market values.

In eq. (7), (8), (9) and (10), M_{q-1} is the one-quarter lag of the vector of the financial and macroeconomic state variables that influence bank soundness. These state variables are: i) the market return volatility measured with the Implied Volatility Index (VIX) found in the Chicago

Board Options Exchange Market, ii) the liquidity risk spread given by the quarterly difference between the 3-month LIBOR rate and the 3-month U.S. T-bill rate, iii) the change in the slope of the yield curve given by the change in the quarterly difference between the 10-year U.S. T-bill rate and the 3-month U.S. T-bill rate, iv) the interest rate risk defined as the quarterly standard deviation of the day-to-day 3-month U.S. T-bill rate,[15] and v) the credit risk, measured by the quarterly change in the credit spread between the 10-year BAA-rated bonds and the 10-year U.S. T-bill rate.

We resort to the Im-Pesaran-Shin (2003)'s unit root test for panel data to test for stationarity of the data series included in the return equations (eq. 7, 8, 9 and 10). This test relies upon the Augmented Dickey-Fuller (ADF) methodology and, contrary to the widely used Levin-Lin-Chu (2002) test, it allows for heterogeneity in both the constant and the slope terms of the ADF regression. We incorporate an individual specific constant term and run the test with and without a time deterministic trend that picks up the non-stochastic influence of common factors on asset returns across banks over time. The null hypothesis of the Im-Pesaran-Shin test is that the considered variables contain a unit root against the alternative hypothesis of stationarity. The test rejects the null at 1% and 5% significance levels for all series except liquidity risk spread, and credit risk. In other words, only these two data series exhibit some non-stationary behaviour as shown in Table 2 (Panel A).

Since the levels of liquidity risk spread and of credit risk are found to be integrated of order 1, we express the two variables in first differences with the purpose to remove the possible trends in their variances. The differences specification guarantees that all panels are stationary as we are able to reject the null hypothesis of Im-Pesaran-Shin's test at 1% significance level for both variables, which implies that the non-stationary process that the two variables follow is a random walk. Consequently, instead of level series we include the differenced data series of liquidity risk spread and credit risk in the return equations (eq. 7, 8, 9 and 10).

Table 2
Panel unit root test and cointegration test. Panel A reports the values of *W*-statistic from the panel unit root test of Im-Pesaran-Shin (2003) and the corresponding *p*-values. All data series included in the

[15] This measure describes the changes in interest rates and/or security prices that are expected to have an impact on bank income and on the market value of bank equity. To be more specific, interest rate risk arises predominantly from mismatches in the durations of assets and liabilities. It, therefore, reveals the interest rate cycle movements that influence the deposit-taking and lending activities of banks.

return equations (eq. 7, 8, 9 and 10) in the *CoVaR* measurement are tested for stationarity. The null hypothesis under study is that of a unit root against the alternative of stationarity. Panel B summarises the results of the Pedroni cointegration test, which examines the null hypothesis of no cointegration between the variables of interest. The Pedroni test relies on four statistics: the panel *v*-statistic, the panel PP *ρ*-statistic, the panel PP *t*-statistic, and the panel DF *t*-statistic. These statistics account for common time factors and heterogeneity across the sample banking institutions.

Panel A: Panel Unit root test		
Variables	Im-Pesaran-Shin *W*-statistic	*p*-value
Growth rate of total assets	-2.345**	(0.031)
Market return volatility	-3.519**	(0.028)
Liquidity risk spread	-1.810	(0.341)
Yield curve	-3.109***	(0.007)
Interest rate risk	-2.930***	(0.005)
Panel B: Cointegration test	Pedroni test statistics	*p*-value
v-statistic	0.184	(0.150)
ρ-statistic (PP)	-1.593*	(0.094)
t-statistic (PP)	-0.328	(0.139)
t-statistic (DF)	-0.540	(0.111)

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

In view of the non-stationarity characteristics of the data series of liquidity risk spread and of credit risk and, in order to avoid spurious regression problems, we move to a panel cointegration framework. The cointegration test proposed by Pedroni (1999) is utilised here to show whether there exists a long-run relationship between the variables under study. The cointegration technique of Pedroni has been a significant improvement over conventional cointegration techniques applied in a time series framework, as it allows the cointegrating vectors to vary across the members of the panel data set. Examining the null of no cointegration, the Pedroni test is basically a test of unit roots in the estimated residuals of the panel.

The within dimension approach of the Pedroni test relies on four statistics: the panel *v*-statistic, the panel Philips-Peron (1988) *ρ*-statistic, the panel Phillips-Peron (1988) *t*-statistic, and the panel Dickey-Fuller (1979) *t*-statistic. These statistics account for common time factors and heterogeneity across the sample banking institutions. The results, which are summarised in Table 2 (Panel B), cannot reject the null of no cointegration between the examined variables. Hence, no long-run cointegration relationship can be established.

We now continue with the description of the right-hand side variables of our empirical analysis. We use three measures to describe the on-balance-sheet leverage of banks. These measures refer to the so-called gross balance sheet leverage ratio, which is calculated as the ratio of bank's total assets to the book value of total equity capital (*LEV1*), the inverted Tier 1 leverage ratio (*LEV2*), and the ratio of total liabilities to book equity capital (*LEV3*). The latter two measures are utilised as instruments for *LEV1* in the instrumental variables regression model, which is analytically presented in the following subsection. In that subsection, we also discuss why all the on- and off-balance-sheet leverage measures which are presented in the current paragraphs are introduced in our model in first differences instead of levels.

Several different measures of banks' off-balance-sheet leverage which are complementary to each other are employed in our econometric analysis. More concretely, we capture derivatives leverage by using the on-balance-sheet asset equivalent component of the exposure implied by the off-balance-sheet derivatives contracts. This measure is calculated by the ratio of credit equivalent amount of OTC derivatives outstanding to book equity capital (*DERLEV1*) and maps the off-balance-sheet derivatives positions of the sample banks onto their on-balance-sheet equivalents. We instrument *DERLEV1* with the the credit exposure across all derivative contracts divided by the bank regulatory capital which is given by the sum of Tier 1 and Tier 2 capital requirements (*DERLEV2*), and with the ratio of trading revenue from derivatives activities to total revenue (*DERLEV3*).[16]

In addition to the derivatives activities of banks, we also measure loan securitisation through conduits and other special vehicles. As earlier discussed, numerous loans and other assets were securitised and/or sold to other institutions all the years preceding the crisis. The originating banks, however, retained the servicing rights to the bundle of securitised loans. We thus report the ratio of the outstanding principal amount of loans and other assets sold and securitised with servicing retained or with recourse or any other credit backstops provided to total assets (*SECLEV1*) to capture the magnitude of banks' off-balance-sheet leverage due to asset securitisation activity. *SECLEV1* is instrumented with the amount of credit exposure arising from recourse or other seller-provided credit enhancements to SIVs and other conduits divided by total assets (*SECLEV2*).

We further employ two versions of the OBS leverage ratio as proposed by the Bank for International Settlements (BCBS, 2009).[17] The first measure is given by the sum of commitments, direct credit substitutes, acceptances, and repurchase agreements divided by the

[16] A detailed explanation of the derivation and the properties of *DERLEV2* can be found in Breuer (2002).

[17] The BIS off-balance-sheet ratio is considerably similar to the one used by the Bank of Canada. The main difference between the two ratios is the value of transaction- and trade-related contingencies which is added in the numerator of the Canadian leverage ratio, but not in that of the BIS ratio.

book equity capital (*OBSLEV1*). The second measure (*OBSLEV2*) is employed as an instrument for *OBSLEV1* and is equal to the ratio of standby letters of credit and guarantees to the regulatory capital. Apparently securitised assets and derivatives contracts which are captured in the measures discussed above are neither considered in *OBSLEV1*, nor in *OBSLEV2*. This reveals the complementary nature of the off-balance-sheet leverage measures we employ in our analysis, which is confirmed by the relevant pairwise tests.

In Table 3 that follows, we perform Pearson pairwise correlation tests for the two risk variables as well as for the on- and off-balance-sheet leverage measures and their instruments. The tests are performed for both the pre-crisis and the crisis periods (see Panel A and Panel B in Table 3, respectively). We observe that the correlations between the same leverage types are significant at 1% and 5% levels. However, no (or low) statistically significant correlations are reported among different leverage types like, for example, between *LEV1* and *OBSLEV1*, or between *SECLEV2* and *OBSLEV2*. This verifies that the chosen off-balance-sheet leverage measures are indeed complementary to each other in the sense that do not overlap one another thus covering the broad spectrum of modern banking activities. We, moreover, observe that *CoVaR* is significantly correlated with *TOTRISK* only in the pre-crisis period.

Table 3
Correlation tests. This table contains the Pearson correlations between the two risk variables of the empirical analysis as well as between the leverage variables and their instruments. *P*-values are reported below the correlation coefficients. Panel A shows the correlations for the pre-crisis period that starts in 2002q1 and ends in 2007q2. Panel B presents the correlations for the crisis period that extends from 2007q3 to 2012q3.

Panel A	*TOTRISK*	*CoVaR*	*LEV1*	*LEV2*	*LEV3*	*DERLEV1*	*DERVEL2*	*DERLEV3*	*OBSLEV1*	*OBSLEV2*	*SECLEV1*	*SECLEV2*
TOTRISK	1.000											
CoVaR	0.234***	1.000										
	0.006											
LEV1	-0.089	-0.108	1.000									
	0.231	0.310										
LEV2	-0.408	-0.435	0.393**	1.000								
	0.187	0.261	0.040									
LEV3	-0.129	-0.182	0.198**	0.285*	1.000							
	0.341	0.411	0.034	0.056								
DERLEV1	-0.156	-0.090*	0.733	0.649	0.524	1.000						
	0.105	0.081	0.389	0.576	0.289							
DERLEV2	-0.341	-0.222	0.402	0.501	0.506	0.510**	1.000					
	0.129	0.183	0.219	0.253	0.210	0.043						
DERLEV3	-0.480	-0.504	0.537	0.529	0.589	0.672***	0.561**	1.000				
	0.206	0.278	0.333	0.275	0.302	0.005	0.034					
OBSLEV1	0.256	0.308	-0.521	-0.430	-0.481	0.071*	0.098	0.183	1.000			
	0.424	0.494	0.387	0.369	0.286	0.094	0.119	0.124				
OBSLEV2	0.306	0.279	-0.732	-0.556	-0.634	0.274	0.241	0.304*	0.386**	1.000		
	0.556	0.443	0.378	0.471	0.388	0.116	0.132	0.077	0.029			
SECLEV1	-0.023	0.073	-0.392	-0.431	-0.544	0.964	0.781	0.883	0.397*	0.402	1.000	

	0.101	0.135	0.251	0.229	0.340	0.199	0.143	0.194	0.096	0.131		
SECLEV2	-0.036	0.060	-0.430	-0.490	-0.413	0.504	0.463	0.560	0.733	0.670*	0.925***	1.000
	0.201	0.184	0.318	0.292	0.299	0.102	0.154	0.152	0.175	0.088	0.001	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

Panel B	*TOTRISK*	*CoVar*	*LEV1*	*LEV2*	*LEV3*	*DERLEV1*	*DERLEV2*	*DERLEV3*	*OBSLEV1*	*OBSLEV2*	*SECLEV1*	*SECLEV2*
TOTRISK	1.000											
CoVar	0.347	1.000										
	0.124											
LEV1	-0.134	-0.167	1.000									
	0.201	0.205										
LEV2	-0.304	-0.330	0.515***	1.000								
	0.140	0.217	0.001									
LEV3	-0.541	-0.503	0.411**	0.319**	1.000							
	0.321	0.420	0.032	0.046								
DERLEV1	-0.111	-0.143	0.677	0.556	0.430	1.000						
	0.121	0.129	0.280	0.310	0.297							
DERLEV2	-0.142	-0.397	0.212	0.277	0.186	0.544**	1.000					
	0.186	0.272	0.197	0.265	0.145	0.017						
DERLEV3	-0.189	-0.420	0.174	0.203	0.274	0.433**	0.187*	1.000				
	0.202	0.310	0.387	0.349	0.402	0.033	0.086					
OBSLEV1	0.340	0.429	-0.484	-0.429	-0.378	0.107*	0.128	0.167	1.000			
	0.388	0.441	0.303	0.341	0.211	0.089	0.101	0.143				
OBSLEV2	0.322	0.301	-0.681	-0.502	-0.432	0.341	0.404	0.387	0.862***	1.000		
	0.489	0.510	0.360	0.410	0.299	0.130	0.117	0.129	0.000			

SECLEV1	-0.039	0.106	-0.344	-0.398	-0.330	0.876	0.893	0.788	0.439	0.480	1.000	
	0.120	0.100	0.308	0.255	0.204	0.214	0.222	0.231	0.119	0.139		
SECLEV2	-0.044	0.102	-0.483	-0.561	-0.438	0.454	0.562	0.521	0.808	0.778*	0.897***	1.000
	0.120	0.231	0.345	0.321	0.221	0.110	0.150	0.187	0.199	0.089	0.000	

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

The combination of the recent financial stability literature (see, e.g., Berger et al., 2009; Uhde and Heimeshoff, 2009) and bank risk literature (see, e.g., Gonzalez, 2005) provides us with the basis for the selection of two measures for possible alterations in the traditional services of banks. The first is banks' asset composition (*ASSETCOMP*) that captures the changes in bank lending activity. This is proxied by the ratio of net loans and leases to total assets. The second is a measure for the composition of bank liabilities (*LIABCOMP*), which shows any changes in the traditional funding sources of banks and which is calculated as the ratio of demand deposits to total liabilities.

It is widely accepted that economic performance has a considerable effect on the demand and supply of banking services. More precisely, high levels of banking activity are generally related to favourable economic conditions like price stability and economic development. In this context, the macroeconomic environment is largely considered to have an impact on the risk-taking behaviour of banks. We thus employ the quarterly change in the U.S. Consumer Price Index (*INF*) to control for fluctuations in the level of prices, and the GDP output gap (*GDP*) to control for variations in economic growth.

Importantly, we trace the history of each banking firm in our sample to investigate whether a bank has experienced some merger and/or acquisition (M&A) over the entire data period. To achieve this, we resort to the relevant information provided by NIC/FFIEC. We find that the majority of our sample banks and, more specifically, 18 out of 20 banks have been involved in at least one M&A transaction over the data period. However, it is important to mention here that none of these banks has been targeted from some other financial institution; to the contrary, all 18 banks have only been acted as acquirers in these M&A deals. This strengthens even further our choice of sample banks on the basis of their systemic importance, which has been analytically discussed earlier in the paper. We control for the possible impact of M&As with the purpose any spurious bursts of systemic risk and individual bank risk due to M&A transactions to be excluded from our sample. We introduce a dummy variable in our model (*MA*), which is equal to unity in the quarter q that bank i has been involved in some M&A transaction. For example, if a transaction has occurred on, say, April 15 2008, then this transaction is recorded in the second quarter of 2008, meaning that the binary variable *MA* takes the value of one in 2008q2.

Table 4 reports the summary statistics for all the variables we employ in our analysis for each of the two periods under examination. What mainly comes out from these statistics and is important for our research is the reported upsurge in the off-balance-sheet leverage activities of banks during the pre-crisis period, which is followed by a downward trend in all such kind of activities in the later time period. This supports the argument that banking institutions accumulated a high degree of leverage off their balance sheets during the economic upturn, while they moved to reduce their off-balance-sheet holdings by large after the eruption of the crisis in mid-2007. Moreover, total bank risk is found to be on average higher in the years before the outbreak of the crisis compared to the post-2007q2 period. The converse holds true for systemic risk, which shows an upward trend in the crisis era.

Table 4

Descriptive statistics. The summary statistics of all the variables employed in our baseline empirical analysis are reported in this table. Panel A shows the statistics for the pre-crisis period which extends from 2002q1 to 2007q2, while Panel B refers to the crisis period that commences in 2007q3 and ends in 2012q3. Variables are distinguished into four categories: the left-hand side risk variables, the leverage variables, the bank-specific control variables, and those variables that capture the macroeconomic environment. The description of each variable together with the relevant data sources are provided in Appendix A.

Panel A: Pre-crisis period	Mean	Median	Maximum	Minimum	St. Dev.	Obs
Risk variables						
TOTRISK	2.287	1.212	5.259	0.214	2.221	432
CoVaR	3.112	2.860	7.194	0.713	1.890	429
Leverage variables						
LEV1	7.879	7.174	12.121	5.732	0.256	436
LEV2	0.121	0.118	0.197	0.069	0.021	435
LEV3	7.123	6.875	10.564	4.784	0.598	436
DERLEV1	10.989	9.112	17.804	3.731	3.098	419
DERLEV2	1.865	1.775	3.122	0.484	2.883	427
DERLEV3	3.167	3.001	5.713	0.965	1.119	426
SECLEV1	7.005	6.603	11.434	1.740	1.794	431
SECLEV2	11.995	10.953	21.805	3.842	1.980	432
OBSLEV1	14.719	13.992	26.141	3.095	2.395	420
OBSLEV2	9.813	9.175	19.530	1.408	3.592	421
Traditional banking variables						
ASSETCOMP	0.522	0.513	0.798	0.185	0.178	438
LIABCOMP	0.223	0.208	0.421	0.063	0.063	439
MA	0.154	0.143	1.000	0.000	0.211	440

	Mean	Median	Maximum	Minimum	St. Dev.	Obs
Macroeconomic environment						
INF	0.036	0.034	0.093	-0.035	0.086	439
GDP	0.026	0.023	0.067	-0.019	1.514	439

Panel B: Crisis period	Mean	Median	Maximum	Minimum	St. Dev.	Obs
Risk variables						
TOTRISK	1.989	1.897	4.342	0.089	1.341	401
CoVaR	6.959	6.794	10.853	2.805	1.852	392
Leverage variables						
LEV1	6.184	5.953	10.909	3.882	0.954	413
LEV2	0.110	0.107	0.174	0.041	0.017	413
LEV3	6.007	5.843	8.904	3.211	0.765	412
DERLEV1	5.999	5.755	12.004	0.653	4.783	400
DERLEV2	1.126	1.100	2.275	0.087	3.341	397
DERLEV3	1.605	1.509	3.009	0.252	3.006	404
SECLEV1	4.976	4.672	8.843	0.656	2.845	407
SECLEV2	8.784	8.432	14.734	1.956	2.165	408
OBSLEV1	9.643	9.462	19.943	1.134	2.742	389
OBSLEV2	7.683	7.459	15.629	0.747	4.131	392
Traditional banking variables						
ASSETCOMP	0.652	0.643	1.074	0.099	0.349	416
LIABCOMP	0.241	0.231	0.382	0.061	0.089	417
MA	0.127	0.119	1.000	0.000	0.087	420
Macroeconomic environment						
INF	-0.029	-0.032	0.121	-0.274	3.731	418
GDP	-0.034	-0.038	0.282	-0.341	4.174	418

Regarding the data sources, all bank accounting variables are obtained from the FR Y-9C forms filed by Bank Holding Companies with the Federal Reserve. We also collect data from OCC's Quarterly Reports on Bank Derivatives Activities to develop the off-balance-sheet leverage measures employed in our analysis. The market interest rates used in the construction of total bank risk (*TOTRISK*) and of systemic risk (*CoVaR*) variables are obtained from Thomson Reuters Datastream, GFDatabase, and Moody's. As concerns the short-term interest rates, which are also needed for the production of *CoVaR*, these are taken from the Federal Reserve Board website and the U.S. Department of the Treasury. To continue, data on M&As are collected from

NIC/FFIEC, as previously mentioned. Finally, inflation data are obtained from the Bureau of Labor Statistics of the U.S. Department of Labor, whereas GDP data are taken from the Bureau of Economic Analysis of the U.S. Department of Commerce.

3.4. The model

To evaluate the effects of leverage and reverse leverage on individual bank soundness and on systemic risk, we estimate the following model:

$$\begin{aligned} Y_{iq} = \alpha_{iq} &+ \beta_{1,iq} \Delta LEV_{iq} + \beta_{2,iq} \Delta DERLEV1_{iq} + \beta_{3,iq} \Delta SECLEV1_{iq} + \beta_{4,iq} \Delta OBSLEV1_{iq} \\ &+ \gamma_{1,iq} ASSETCOMP_{iq} + \gamma_{2,iq} LIABCOMP_{iq} + \gamma_{3,iq} MA_{iq} \\ &+ \delta_{1,q} INF_q + \delta_{2,q} GDP_q + \varepsilon_{iq} \end{aligned} \tag{11}$$

where: i=1, 2…, N=20

q=2002q1, 2002q2,…,Q=2012q3

In the above model, Y_{iq} stands for either *TOTRISK*, or *CoVaR*; $\Delta LEV1_{iq}, \Delta DERLEV1_{iq,} \Delta SECLEV1_{iq}, \Delta OBSLEV1_{iq}$ are the average quarterly changes in *LEV1*, *DERLEV1*, *SECLEV1*, and *OBSLEV1*, respectively; $ASSETCOMP_{iq}, LIABCOMP_{iq}, MA_{iq}$ are the three bank-specific control variables; INF_q, GDP_q are the two macroeconomic variables; ε_{iq} is the regression error term, whereas the vectors α, β, γ, and δ contain the parameters of interest to be estimated. The reason why the on- and off-balance-sheet leverage variables are introduced in the model in first differences rather than in levels is because we wish to capture the effects of increasing (positive) and declining (negative) trends of leverage on bank risk-taking and systemic risk.

It is likely that our model suffers from endogeneity bias as regressors may be endogenously determined along with the dependent variables. At a micro-level, *i.e.* when *TOTRISK* is considered to be the dependent variable of our model, the cause for this is, presumably, the endogenous character of leverage and risk-taking decisions, which are both taken from bank managers. Of course, we recognise that these decisions depend to some extent on the rules imposed on banking firms by regulatory and supervisory authorities. Nonetheless, even under these constraints that managers face in their banks' profit maximisation problem, it is their own decisions that eventually affect the level of leverage and the degree of risk-taking.

From a macroprudential perspective, systemic risk -captured by *CoVaR*- is viewed as being dependent on the collective leverage behaviour of banks and, as such, is very likely to be endogenous. To be more specific, the leverage decisions of banks have an impact on the quantities transacted (e.g., borrowed and lent), the prices of financial assets, and, subsequently, on the soundness of the economy and the stability of the entire financial system. This, in turn, has powerful feedback effects on the health of banking institutions, which affects their ability to extend credit by leveraging their resources.

Parameter estimates from simple Ordinary Least Squares (OLS) regression might be biased in the case of endogeneity and this can lead to erroneous inference. To tackle the problem of potential endogeneity, we estimate the model by means of two-stage least squares instrumental variables (2SLS IV) regression for each of the two examined periods. Therefore, *ΔLEV1* is instrumented with *ΔLEV2* and *ΔLEV3* in the first-stage OLS regressions. Similarly, *ΔDERLEV2 and ΔDERLEV3* are used as instruments for *ΔDERLEV1*, whereas *ΔSECLEV1* is instrumented with *ΔSECLEV2* and *ΔOBSLEV1* with *ΔOBSLEV2*. The second-stage regressions of the 2SLS IV approach are then estimated with the predicted values of *ΔLEV1*, *ΔDERLEV1*, *ΔSECLEV1*, and *ΔOBSLEV1*.

To estimate eq. 11 we rely on a set of variables that we observe over time and which have been already described in Section 3.3. Nevertheless, there might exist some unobserved variables which are likely to have an impact on the examined relationship and are not incorporated in our model. Omitted variables in general can be either constant over time, or time-dependent. Regardless of their time dimension, omitted variables are difficult, or sometimes impossible to be measured and be controlled for. If we search to find instrumental variables, or proxies, for the likely omitted variables, a series of rather strong assumptions which are hardly met in practice has to be made. Moreover, it is necessary to know how to correctly model each omitted variable's influence on the dependent variable of the regression equation as well as the relationship that holds between the instruments and the possible omitted variables. Most importantly, it is hard to identify the specific variables which are correlated with the main model variables thus producing flawed estimates and which have been omitted from the model.

We include individual (bank-level) fixed effects in our regression analysis to account for the influence of the time-invariant factors which are correlated with our main variables. Fixed effects can control for these factors as they focus on within-bank variation. Further, a statistical test that unobserved bank heterogeneity does not drive the empirical findings is provided by the use of fixed effects. From this perspective, the choice of the fixed-effects estimator is based on the view that our sample banks are not drawn randomly from the entire population of U.S. banks; rather, as previously discussed, our sample consists of all the major U.S. banking companies, which have a systemically important role in the U.S. economy.

The fixed-effects model is more appropriate when differences across banks deemed to be substantial, time-invariant, and correlated with the explanatory variables. The random-effects model, on the other hand, is appropriate when correlated omitted variables are not an issue to be considered. Given the potential for omitted variables bias and the importance of bank-specific effects in our model setup, we anticipate the fixed-effects approach to be the most appropriate one. Indeed, we can easily reject the use of random effects on the basis of the Hausman (1978) test. At standard levels of statistical significance (*i.e.*, 1% and 5%), we reject the null hypothesis that the differences in coefficients obtained from the two estimation methods are not significant. Accordingly the fixed-effects model is our preferred estimator.[18]

Before moving to discuss the produced outcome of the regression analysis, we use the Maddala and Wu (1999) panel unit root test to examine the stationarity of our data set. The Maddala and Wu test is a Fisher-type test, which combines the *p*-values of the test-statistic for a unit root in each sample bank. This test does not necessarily require a balanced panel data set like most of the relevant tests do. We reject the null hypothesis of non-stationarity at the 5% significance level for all the variables of our model.

[18] From a theoretical viewpoint, Hsiao (1986) argues that, when inferences are made about a population of effects from which those in the data are considered to be a random sample then the effects must be considered as random. As analytically explained in Section 3.1, our data set covers the 20 U.S. systemically important banking institutions and, as such, it cannot be considered as a small sample of a much larger population of systemically important institutions. That is, even from a conceptual viewpoint, the fixed-effects model is more appropriate than its random-effects counterpart.

4. Discussion of the empirical results

4.1. First-stage results

The results of the first-stage regressions of the 2SLS IV approach for both data periods are summarised in Tables 5a and 5b that follow. We resort to Sargan-Hansen test (or *J*-test for overidentifying restrictions) which relies on the studies of Sargan (1958) and Hansen (1982) to examine whether the chosen instrumental variables are correlated with the error term of the model. This is, in fact, the essential condition for an instrumental variable to be valid. The application of the Hansen *J*-test provides us with *p*-values which range from 0.264 to 0.464. We therefore fail to reject the null hypothesis that overidentifying restrictions are valid thus providing support to the validity of the selected instruments. We also examine the joint statistical significance of our instruments using a heteroskedasticity-robust *F*-statistic test. The results of the *F*-test confirm the validity of the instrumental variables used in our analysis.

It is important to mention at this point that, in practice, it is not easy to know whether an explanatory variable is endogenous or not. Apparently, if the OLS estimators are consistent, they should be preferred from those obtained with 2SLS IV regression. To deal with this in our baseline model (eq.11), we test the null hypothesis of no endogeneity against its alternative using the Hausman's (1978) test:

$$H_0: Cov\ (X_2, \varepsilon) = 0$$
$$H_1: Cov\ (X_2, \varepsilon) \neq 0$$

In essence, what the Hausman test does is to evaluate the significance of two estimators obtained with different econometric techniques: one with OLS, and the other with 2SLS IV. If a statistical difference is documented between the two estimators, then our concern of endogeneity is substantiated. The Hausman test we run examines the null hypothesis of no statistically significant difference between the OLS and 2SLS IV estimates. Table 5a and Table 5b show that the calculated Hausman *p*-values are all lower than the selected level of statistical significance (α = 0.05 or 5%). This is to say, our concern of endogeneity is substantiated and this provides support to the use of 2SLS IV instead of OLS.

Table 5a

First-stage regression results. This table presents the first-stage results obtained by the 2SLS IV fixed-effects regression model with total bank risk (*TOTRISK*) as the dependent variable of the second-stage. Panel A reports the results for the pre-crisis period (2002q1-2007q2) and Panel B the results for the crisis period (2007q3-2012q3). The average quarterly change in on-balance-sheet leverage (*ΔLEV1*) is instrumented with *ΔLEV2* and *ΔLEV3*, the average quarterly change in derivatives leverage (*ΔDERLEV1*) is instrumented with *ΔDERLEV2* and *ΔDERLEV3*, the average quarterly change in leverage from securitisation (*ΔSECLEV1*) is instrumented with *ΔSECLEV2*, while the average quarterly change in off-balance-sheet leverage ratio (*ΔOBSLEV1*) with *ΔOBSLEV2*. The exogenous control variables which are also included in the second-stage regressions are: asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), a dummy variable (*MA*) which accounts for M&A transactions, the rate of inflation (*INF*), and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term is included in the regression model, but is not reported in the table. The Hansen-*J* test of overidentifying restrictions tests the null hypothesis that the excluded instruments are uncorrelated with the error term of the model and are correctly excluded from the regression in the second stage. The *F*-test of instrumental variables reports the joint significance of identifying instruments. The Hausman test examines whether 2SLS and OLS coefficients are statistically different. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	Panel A: Pre-crisis period				**Panel B: Crisis period**			
	ΔLEV1	*ΔDERLEV1*	*ΔSECLEV1*	*ΔOBSLEV1*	*ΔLEV1*	*ΔDERLEV1*	*ΔSECLEV1*	*ΔOBSLEV1*
ΔLEV1		0.165*	0.061*	-0.154		0.293**	0.054	-0.184
		(1.71)	(1.68)	(1.19)		(1.88)	(1.39)	(0.97)
ΔLEV2	0.088***	0.196**	0.043	-0.131	0.123***	0.223*	0.047	-0.161
	(2.99)	(1.89)	(1.58)	(1.01)	(2.56)	(1.74)	(1.33)	(0.85)
ΔLEV3	0.096***	0.213*	0.069*	-0.188	0.134***	0.250*	0.082	-0.228
	(3.90)	(1.69)	(1.68)	(0.85)	(3.59)	(1.67)	(1.56)	(0.76)
ΔDERLEV1	0.218*		0.260	0.275*	0.187		0.295**	0.243**
	(1.67)		(1.45)	(1.68)	(1.59)		(1.75)	(1.90)
ΔDERLEV2	0.199	0.175**	0.231*	0.302**	0.232	0.222**	0.244**	0.329**
	(1.43)	(1.87)	(1.66)	(1.92)	(1.54)	(1.83)	(1.82)	(1.87)
ΔDERLEV3	0.256*	0.254**	0.288**	0.267**	0.203*	0.294**	0.304**	0.351*
	(1.69)	(1.91)	(1.89)	(1.86)	(1.66)	(1.78)	(1.87)	(1.64)
ΔSECLEV1	0.101	0.065**		0.069*	0.096	0.098*		0.102*
	(1.22)	(1.76)		(1.61)	(0.93)	(1.65)		(1.63)
ΔSECLEV2	0.089	0.053	0.088**	0.080*	0.089	0.112*	0.131**	0.110*
	(1.18)	(1.59)	(1.87)	(1.64)	(1.04)	(1.69)	(1.86)	(1.62)
ΔOBSLEV1	-0.148	0.158*	0.160		-0.172	0.131	0.141	
	(0.79)	(1.72)	(1.32)		(1.11)	(1.59)	(1.28)	

ΔOBSLEV2	-0.132	0.166*	0.201	0.276***	-0.164	0.112*	0.189	0.303***
	(0.80)	(1.70)	(1.44)	(2.98)	(1.02)	(1.64)	(1.52)	(3.64)
ASSETCOMP	0.261***	0.119	0.126**	0.093	0.209**	0.087	0.155*	0.099
	(2.65)	(0.88)	(1.79)	(0.94)	(1.91)	(1.41)	(1.64)	(1.24)
LIABCOMP	0.052	0.214	0.022	0.015	0.078	0.195	0.031	0.102*
	(0.83)	(1.00)	(0.99)	(1.15)	(1.27)	(0.94)	(1.02)	(1.60)
MA	0.009*	0.015*	0.021	0.009	0.016**	0.028**	0.018	0.017*
	(1.67)	(1.69)	(1.51)	(1.32)	(1.74)	(1.85)	(1.43)	(1.61)
INF	0.017***	0.029**	0.009	0.023**	0.039**	0.051**	0.024*	0.084**
	(3.61)	(1.91)	(1.59)	(1.72)	(1.87)	(1.82)	(1.68)	(1.87)
GDP	0.032**	0.053**	0.041*	0.057**	0.086**	0.54*	0.063**	0.097***
	(1.88)	(1.83)	(1.69)	(1.95)	(1.83)	(1.68)	(1.85)	(2.13)
Observations	419	419	419	419	389	389	389	389
R^2	0.182	0.214	0.192	0.177	0.224	0.232	0.281	0.209
F-statistic	14.89	16.42	15.01	13.41	17.62	19.06	18.76	16.31
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen *J*-statistic	3.47	3.81			5.63	4.32		
p-value	0.324	0.351			0.464	0.398		
Hausman *p*-value	0.04	0.04	0.04	0.03	0.04	0.02	0.03	0.03

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

Table 5b

First-stage regression results. This table presents the first-stage results obtained by the 2SLS IV fixed-effects regression model with systemic risk (*CoVaR*)as the dependent variable of the second-stage. Panel A reports the results for the pre-crisis period (2002q1-2007q2) and Panel B the results for the crisis period (2007q3-2012q3). The average quarterly change in on-balance-sheet leverage (*ΔLEV1*) is instrumented with *ΔLEV2* and *ΔLEV3*, the average quarterly change in derivatives leverage (*ΔDERLEV1*) is instrumented with *ΔDERLEV2* and *ΔDERLEV3*, the average quarterly change in leverage from securitisation (*ΔSECLEV1*) is instrumented with *ΔSECLEV2*, while the average quarterly change in off-balance-sheet leverage ratio (*ΔOBSLEV1*) with *ΔOBSLEV2*. The exogenous control variables which are also included in the second-stage regressions are: asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), a dummy variable (*MA*) which accounts for M&A transactions, the rate of inflation (*INF*), and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term is included in the regression model, but is not reported in the table. The Hansen-*J* test of overidentifying restrictions tests the null hypothesis that the excluded instruments are uncorrelated with the error term of the model and are correctly excluded from the regression in the second stage. The *F*-test of instrumental variables reports the joint significance of identifying instruments. The Hausman test examines whether 2SLS and OLS coefficients are statistically different. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	Panel A: Pre-crisis period				**Panel B: Crisis period**			
	ΔLEV1	*ΔDERLEV1*	*ΔSECLEV1*	*ΔOBSLEV1*	*ΔLEV1*	*ΔDERLEV1*	*ΔSECLEV1*	*ΔOBSLEV1*
ΔLEV1		0.159**	0.064*	-0.149		0.286**	0.049	-0.179
		(1.82)	(1.65)	(1.14)		(1.91)	(1.35)	(1.04)
ΔLEV2	0.083***	0.191**	0.041	-0.130	0.101***	0.210*	0.040	-0.159
	(2.42)	(1.84)	(1.53)	(0.96)	(2.33)	(1.76)	(1.25)	(0.90)
ΔLEV3	0.139***	0.206*	0.074*	-0.192	0.150***	0.257**	0.079	-0.237
	(3.45)	(1.66)	(1.69)	(0.89)	(4.00)	(1.73)	(1.50)	(0.86)
ΔDERLEV1	0.211**		0.251	0.267*	0.196		0.284*	0.263**
	(1.79)		(1.52)	(1.66)	(1.51)		(1.66)	(1.99)
ΔDERLEV2	0.204	0.202***	0.239**	0.289***	0.224	0.198***	0.240**	0.336**
	(1.51)	(1.99)	(1.79)	(1.96)	(1.49)	(2.11)	(1.79)	(1.91)
ΔDERLEV3	0.249*	0.221**	0.301***	0.257**	0.212	0.255**	0.311**	0.362**
	(1.65)	(1.85)	(2.01)	(1.88)	(1.46)	(1.83)	(1.81)	(1.73)
ΔSECLEV1	0.092	0.061*		0.072	0.105	0.103*		0.096*
	(1.14)	(1.64)		(1.57)	(1.00)	(1.66)		(1.64)
ΔSECLEV2	0.081	0.050*	0.082***	0.084*	0.096	0.110*	0.140***	0.121*
	(1.26)	(1.66)	(2.04)	(1.65)	(0.92)	(1.67)	(1.96)	(1.68)
ΔOBSLEV1	-0.159	0.143	0.164		-0.160	0.124	0.157	
	(0.90)	(1.58)	(1.26)		(1.03)	(1.55)	(1.14)	

ΔOBSLEV2	-0.139	0.172*	0.194	0.240***	-0.160	0.103*	0.202	0.287***
	(0.87)	(1.69)	(1.48)	(2.93)	(0.88)	(1.65)	(1.50)	(3.45)
ASSETCOMP	0.250***	0.108	0.120**	0.100	0.194*	0.094	0.167*	0.104
	(2.44)	(0.94)	(1.83)	(0.91)	(1.68)	(1.32)	(1.63)	(1.21)
LIABCOMP	0.044	0.210	0.019	0.013	0.085	0.204	0.030	0.113*
	(0.76)	(0.96)	(1.06)	(1.21)	(1.21)	(1.03)	(0.96)	(1.63)
MA	0.0010**	0.013**	0.022	0.011	0.014*	0.024**	0.015	0.019*
	(1.76)	(1.75)	(1.54)	(1.39)	(1.65)	(1.86)	(1.38)	(1.65)
INF	0.019***	0.027***	0.010*	0.026**	0.042**	0.056**	0.022*	0.090**
	(3.46)	(1.98)	(1.65)	(1.76)	(1.80)	(1.89)	(1.66)	(1.90)
GDP	0.030***	0.047*	0.044*	0.059***	0.079*	0.59**	0.057**	0.102***
	(1.96)	(1.68)	(1.67)	(1.97)	(1.65)	(1.73)	(1.81)	(2.03)
Observations	406	406	406	406	375	375	375	375
R^2	0.171	0.207	0.188	0.168	0.153	0.212	0.209	0.208
F-statistic	12.45	15.80	14.89	12.97	10.20	16.86	16.12	15.88
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen *J*-statistic	3.02	3.76			2.83	4.01		
p-value	0.292	0.343			0.264	0.363		
Hausman *p*-value	0.04	0.03	0.04	0.03	0.04	0.03	0.03	0.03

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

4.2. Second-stage results

The estimation results of the second-stage regressions are presented in Tables 6a and 6b below. The former table shows the estimation output using *TOTRISK* as the dependent variable of the model; the latter relies on systemic risk (*CoVaR*) regressions. The left column in each table reports the empirical results for the time period preceding the emergence of the crisis, while the right column contains the results for the crisis period.

Table 6a

Second-stage regression results. This table presents the second-stage results obtained by 2SLS IV fixed-effects regression analysis for the pre-crisis period (2002q1-2007q2) and for the crisis period (2007q3-2012q3). The dependent variable is total bank risk (*TOTRISK*). The main explanatory variables are the average quarterly changes in: on-balance-sheet leverage (*ΔLEV1*), derivatives leverage (*ΔDERLEV1*), leverage from securitisation (*ΔSECLEV1*), and off-balance-sheet leverage ratio (*ΔOBSLEV1*). All explanatory variables are instrumented in the first stage; the instrumental variables are: *ΔLEV2*, *ΔLEV3*, *ΔDERLEV2*, *ΔDERLEV3*, *ΔSECLEV2*, and *ΔOBSLEV2*. The set of bank-specific control variables used in our analysis includes the asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), and a dummy variable (*MA*) which accounts for M&A transactions during the examined periods. Two macroeconomic control variables are also used: the level of inflation (*INF*) and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term is included in the regression model, but is not reported in the table. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	TOTRISK	
	Pre-crisis period	Crisis period
ΔLEV1	0.089***	-0.009***
	(5.07)	(-2.34)
ΔDERLEV1	1.041***	-0.784**
	(4.75)	(-1.77)
ΔSECLEV1	1.119**	-1.005***
	(1.87)	(-4.21)
ΔOBSLEV1	0.834***	-0.193***
	(2.52)	(-1.99)
ASSETCOMP	-4.767***	-3.163**
	(-2.44)	(-1.80)
LIABCOMP	-1.702**	-0.932**
	(-1.79)	(-1.73)
MA	0.012	0.016
	(1.21)	(0.98)
INF	-0.099**	-0.052***
	(-1.76)	(-2.07)
GDP	-1.165**	-0.865*

	(-1.86)	(-1.61)
Observations	419	389
R^2	0.163	0.179
F-statistic	11.54	10.88
p-value	0.00	0.00

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

Table 6b
Second-stage regression results. This table presents the second-stage results obtained by 2SLS IV fixed-effects regression analysis for the pre-crisis period (2002q1-2007q2) and for the crisis period (2007q3-2012q3). The dependent variable is systemic risk (*CoVaR*). The main explanatory variables are the average quarterly changes in: on-balance-sheet leverage (*ΔLEV1*), derivatives leverage (*ΔDERLEV1*), leverage from securitisation (*ΔSECLEV1*), and off-balance-sheet leverage ratio (*ΔOBSLEV1*). All explanatory variables are instrumented in the first stage; the instrumental variables are: *ΔLEV2*, *ΔLEV3*, *ΔDERLEV2*, *ΔDERLEV3*, *ΔSECLEV2*, and *ΔOBSLEV2*. The set of bank-specific control variables used in our analysis includes the asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), and a dummy variable (*MA*) which accounts for M&A transactions during the examined periods. Two macroeconomic control variables are also used: the level of inflation (*INF*) and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term is included in the regression model, but is not reported in the table. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	CoVaR	
	Pre-crisis period	Crisis period
ΔLEV1	0.165***	0.197**
	(2.31)	(1.69)
ΔDERLEV1	0.078***	0.286***
	(4.31)	(4.24)
ΔSECLEV1	0.552***	0.669**
	(1.99)	(1.75)
ΔOBSLEV1	0.834**	1.275***
	(1.87)	(2.03)
ASSETCOMP	1.304	0.899
	(1.29)	(1.41)
LIABCOMP	0.868	1.103
	(0.99)	(0.90)
MA	0.028	0.033
	(1.32)	(1.14)
INF	-1.106***	-1.539***

	(-2.46)	(-1.97)
GDP	-1.883**	-2.376*
	(-1.89)	(-1.76)
Observations	406	375
R^2	0.144	0.129
F-statistic	14.12	12.76
p-value	0.00	0.00

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

4.2.1. The pre-crisis period

A positive and statistically significant impact of *LEV1* on both *TOTRISK* and *CoVaR* is reported. This implies that, before the outbreak of the crisis, the on-balance-sheet leverage exerted an increasing effect not only on the degree of total bank risk, but, most importantly, on the risk exposure of the entire banking system. Along the same lines, the risk profile of individual banks was deteriorated and the level of systemic risk was raised as a result of the expansion of the off-balance-sheet business of baking institutions. These are revealed by the significantly positive relationship we document between *ΔDERLEV1*, *ΔSECLEV1* and *ΔOBSLEV1* with *TOTRISK* and *CoVaR*. In fact, by comparing the coefficient values on *ΔDERLEV1*, *ΔSECLEV1* and *ΔOBSLEV1* with that on *LEV1*, we can argue that off-balance-sheet leverage played a relatively more harmful role for both the health of individual banks and for the stability of the entire system. To sum up, in the years before the onset of the crisis, the growth in bank leverage through derivatives in association with the increase in securitisation activity, and the expansion of other off-balance-sheet undertakings seriously hurt the health of individual banks and, at the same time, produced substantial instability to the system.

Consistently, over the past decade or more, banks responded to the increased demand for credit instruments with higher yield by developing financial engineering techniques and creating modern types of products.[19] Although these developments may have come about as a result of the wider financial advances aimed at increasing the profitability of banks, strengthening their risk profile, and improving the efficiency of the system, they also provided opportunities for

[19] The banking literature provides ample empirical evidence on the upsurge in the volume of modern activities of U.S. banking institutions before the crisis (see, e.g., Rogers and Sinkey, 1999; Stiroh, 2004).

growing off-balance-sheet leverage and for shifting risks amongst market participants in highly complicated ways. Consequently, according to our findings, most of the (then) new financial instruments were indeed opaque and masked the extent of leverage and interconnectedness of risk, which appeared to be spilled-over across a wide range of institutions and markets worldwide.

4.2.2. The crisis period

Let us now turn to analyse the regression output for the crisis period. During that period, the off-balance-sheet holdings of banks were largely reduced as earlier shown in the relevant summary statistics. When asset prices and liquidity started falling in mid-to-late 2007, the collateral values of assets held by financial institutions deteriorated. This made it difficult for banking institutions to raise funds and, hence, the majority of banks were forced to decrease leverage. The shrink of leverage (deleveraging), though probably led to further asset price reductions, occurred mainly off the balance sheet of banks improving their risk profile by lowering their overall risk-taking, as revealed by the significantly negative link between *DERLEV1*, *SECLEV1* and *OBSLEV1* with *TOTRISK*. For example, by focusing on the impact of *SECLEV1* on *TOTRISK*, we can argue that the low-quality subprime loans offered by U.S. banks to their conduits and other relevant financial vehicles before the onset of the crisis put an upward pressure on their overall risk-taking. The collapse of those financial organisations when the crisis erupted led to the decrease in the off-balance-sheet leverage of banks and, hence, to the reduction of individual bank risk.

Equally strong in terms of statistical significance, but not that strong in terms of the estimated coefficient value if compared to the coefficients of the off-balance-sheet leverage variables, is the effect of the traditional leverage of banks -as captured by *LEV1*- on *TOTRISK*. On the whole, we can maintain that both the on- and the off-balance-sheet deleveraging process which commenced immediately after the outbreak of the crisis has strengthened the soundness of banking institutions on an individual basis. To the contrary, a serious threat to systemic stability was formed after the beginning of the crisis by the large number of bad assets that SIFIs used to hold (and still do, though to a decreased extent) in their portfolios as a result of the above-described on- and off-balance-sheet deleveraging process. This is reflected in the positive link we report between the on- and off-balance-sheet leverage measures and *CoVaR*.

4.2.3. Across the two periods

Both *ASSETCOMP* and *LIABCOMP* are found to have a significantly negative effect on *TOTRISK* across the two data periods under study. By contrast, the impact of these two variables on *CoVaR* is not statistically significant in any of the two periods. We can therefore sya that the banks which concentrate on traditional bank lending activities contribute less to the overall individual bank risk even though the business mix of traditional banking services is not statistically related to the stability of the whole banking system.

We can make an effort to combine the above-described positive impact of traditional banking products on total bank risk with the negative effect of off-balance-sheet business on risk as reported in the pre-crisis period. Evidently, the relationship that holds between the diversification of bank output through the production and release of modern financial items with risk could be either negative or positive. In the former case, there are at least two channels through which product diversification leads to a reduction in the overall bank risk-taking. The first is largely related to the conventional wisdom among bank scholars (see, e.g., Papanikolaou, 2009) and practitioners and shows that non-interest (fee) income, which is produced by innovative financial assets, is less sensitive to changes in the economic and business environment than interest income, which is produced by traditional assets like bank loans. This is to say that banks which rely more on the former type of income are typically exposed to less risk as they manage to reduce the cyclical variations in profits and revenues. Turning to the second channel, in case there is a negative or a weak correlation between the above two sorts of income, then -according to the traditional banking and portfolio theories (see, e.g., Diamond, 1984)- any observed increase in the share of fee-generating business in the overall portfolio of banking items reduces the volatility of total earnings via diversification effects. As a consequence, risk is again reduced.

Nevertheless, every coin has two sides: in line with our empirical findings for the pre-crisis period, DeYoung and Roland (2001) argue that non-interest income is less stable compared to its interest counterpart, implying that non-traditional products and services increase bank riskiness, while the converse holds true for the traditional banking operations. This happens mainly due to the following three reasons: the nature of bank-customer relationships, the particular input mixes, and the lower capital requirements for fee-generating activities.

To start with the first reason, traditional activities like loan issuance generate relatively stable relationships between banks and their customers in that the switching and information costs for both lenders and borrowers are high and, hence, it is not in the interest of either side to walk away from this sort of stable relationships. To the contrary, the aforementioned costs are lower in the case of modern financial products and this renders the demand for the latter lines of business far from solid and continuous. Accordingly, where interest income appears to be rather stable, non-interest income is highly likely to fluctuate over time.

Second, a banking institution can extend a lending relationship only with a burden on its variable cost (*i.e.*, interest expenses). However, if the bank takes the decision to increase the volume of non-traditional services offered to its customers, it will have to hire additional fixed labour inputs and this will inevitably lead to an increase in its operating leverage. A higher operating leverage, in turn, is expected to amplify revenue volatility into higher profit volatility. That is, the involvement in modern banking activities that produce off-balance-sheet leverage is again related to a higher degree of risk.

Finally, the banking regulatory environment, as described in Basel I and II, allowed banks to hold just a small amount of capital against fee-based activities in comparison with the amount they were required to hold for traditional items and which was much higher than the former one. These differences in capital adequacy requirements suggest an enhanced degree of financial leverage, which is related to higher earnings volatility for non-traditional banking business.

An additional finding that remains unchanged across the two periods is that *GDP* and *INF* are linked with a significantly negative relation with both *TOTRISK* and *CoVaR*. This suggests that economic growth which, as expected, is accompanied by a higher price level, boosts banking soundness and contributes to the establishment of safer financial systems regardless of the state of the economy (upturns *vs.* downturns). In this context, the macroeconomic environment is largely considered to have an impact on the risk-taking behaviour of banks as well as on the stability of the entire financial system. Lastly, we find that M&As do not significantly affect *TOTRISK* and *CoVaR* regardless of the particular time period under scrutiny.

5. Robustness analysis

To test the robustness of our results, we replace *TOTRISK* and *CoVaR* with two alternative metrics of individual bank soundness and of systemic risk. These are the *ZSCORE* and the Marginal Expected Shortfall (*MES*), respectively.

ZSCORE is a measure of bank insolvency risk and is calculated as follows:

Let failure occurs when the total equity capital (TE) of a bank is smaller than its losses (-π: negative profits):

$$TE < -\pi \tag{12}$$

Then, the bank's probability of failure can be written in the following way:

$$p(TE < -\pi) = p(\pi < -TE) = p\left(\frac{\pi}{TA} < -\frac{TE}{TA}\right) = p(ROA < -\frac{TE}{TA}) \tag{13}$$

where $p(\cdot)$ is a probability and $ROA(Returns\ On\ Assets) = \pi/TA$, with π is measured with bank's Net Income After Taxes and TA stands for Total Assets. Suppose that $r = ROA$ and $\lambda = -\left(\frac{TE}{TA}\right)$, where r and λ are two random variables. We can then write that:

$$p(r < \lambda) = \int_{-\infty}^{\lambda} \psi(r)dr \tag{14}$$

where $\psi(r)$ is a density function. If r is assumed to follow a normal distribution, we can rewrite the likelihood of bankruptcy in terms of the standard normal density $\Psi(\cdot)$ as follows:

$$p(r < \lambda) = \int_{-\infty}^{z} \Psi(\zeta)d\zeta \tag{15}$$

where $\zeta = \frac{r-\rho}{\sigma}$ and $z = \frac{\lambda-\rho}{\sigma}$ with ρ being the true mean and σ the standard deviation of r.[20] *ZSCORE* is the sample estimate of $-z$ (since z<0) and is defined in the following way for each sample bank and for each sample quarter:

$$Z_{iq} = \frac{ROA_{iq} + (TE_{iq} / TA_{iq})}{\sigma(ROA_{iq})}, \quad i = 1, 2\ldots, N=20; \; q=2002q1, 2002q2,\ldots,Q=2012q3 \tag{16}$$

[20] Normality is a rather strong assumption for the distribution of *r*. Nevertheless, because of the Chebyshev's inequality, we know that regardless of the distribution of *r*, as long as both exist, the upper bound to the bankruptcy probability is:

$$p(r \le \lambda) \le \left(\frac{\sigma}{\rho - \lambda}\right)^2 = \frac{1}{z^2}$$

where ROA_{it} stands for the Return On Assets of bank *i* calculated by the ratio of net income to total assets (TA_{iq}); (TE_{iq} / TA_{iq}) is the ratio of total equity to total assets; and $\sigma(ROA_{iq})$ is the period standard deviation of ROA which captures the volatility of bank returns. Hence, *ZSCORE* combines profitability, capital risk, and return volatility in a single measure. Evidently, it is increasing in banks' average profitability and capital strength and decreasing in return variability. Overall, larger values of *ZSCORE* imply lower probability of default and hence greater bank soundness. Since *ZSCORE* is highly skewed, we follow the recent literature (see, e.g., Laeven and Levine, 2009; Schaeck et al., 2012) and use its log transformation in our analysis.

The alternative measure of systemic risk which we construct is *MES* as proposed by Acharya et al. (2012). *MES* measures how bank *i*'s risk exposure adds to the system's overall risk and, as such, it can be viewed as a straightforward alternative of *CoVaR*. It is based upon the established in the banking literature measure of Expected Shortfall (*ES*); *ES* is defined as the expected loss of a financial institution conditional on the loss being larger than *VaR*:

$$ES_{\alpha} = -E(R \mid R \leq -VaR_{a}) \tag{17}$$

where VaR is the maximum value loss with confidence 1-*α*, that is, $Pr(R < -VaR_{a}) = \alpha$. If we decompose banking sector's return *R* into the sum of each sample bank i's returns R_i, we get that $R = \sum_i y_i R_i$ where y_i is the weight (in terms of size) given to bank i.[21] We use the formula of *ES* (see above) to get that:

$$ES_{\alpha} = -\sum_i y_i \, E(R_i \mid R \leq -VaR_{a}) \tag{18}$$

By calculating the first order conditions with respect to the weight y_i, we obtain the sensitivity of the risk of the entire system to the risk exposure of bank *i*:

$$\frac{\partial ES_{\alpha}}{\partial y_i} = -E(R_i \mid R \leq -VaR_{a}) \equiv MES_{\alpha}^{i} \tag{19}$$

[21] The notation followed here is the same with that used in the construction of *CoVaR*.

We estimate *MES* at a risk level of $\alpha = 0.05$ or 5% using daily data of Credit Default Swaps (CDS) returns from Bloomberg. Specifically, we first pick up the 5% worst days for an equally-weighted portfolio of CDS returns on the 20 banks of our sample in every quarter, and then compute the CDS return for any given sample bank for these particular days.

Apart from replacing *TOTRISK* and *CoVaR* with *ZSCORE* and *MES* respectively, we also use in our robustness analysis the two- and three-period lags of the leverage variables as alternative instruments in the 2SLS IV regressions we run (see Elsas et al., 2010). Admittedly, selecting the number of lagged differences to be smaller than the correct one distorts the size of the tests, while selecting orders greater than the correct one results in a significant loss of power. We thus consider all possible lag orders as these selected by two of the most popular model selection criteria, namely the Akaike Information Criterion and the Schwarz-Bayesian Information Criterion.

In addition, we incorporate time (quarterly) dummies in our model to allow for common factors that may have an influence on individual bank risk and on systemic risk over time. By doing so, we can capture the unobserved as well as the non-measurable time-varying characteristics of the likely omitted variables, and also of the other variables included in our model. Before estimating the model, Maddala and Wu (1999) unit root tests are carried out to ensure the stationarity of our panel data sets; all data series are found to be stationary.

Table 7a

Robustness tests. This table presents the second-stage results obtained by 2SLS IV fixed-effects regression analysis for the pre-crisis period (2002q1-2007q2) and for the crisis period (2007q3-2012q3). The dependent variable is bank insolvency risk (*ZSCORE*). The main explanatory variables are the average quarterly changes in: on-balance-sheet leverage (*ΔLEV1*), derivatives leverage (*ΔDERLEV1*), leverage from securitisation (*ΔSECLEV1*), and off-balance-sheet leverage ratio (*ΔOBSLEV1*). All explanatory variables are instrumented in the first stage. The instrumental variables are given by the two- and three-period lags of *ΔLEV1*, *ΔDERLEV1*, *ΔSECLEV1*, and *ΔOBSLEV1* according to the Akaike Information Criterion and the Schwarz-Bayesian Information Criterion. The set of bank-specific control variables employed in our analysis includes the asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), and a dummy variable (*MA*) which accounts for M&A transactions during the examined periods. Two macroeconomic control variables are also used: the level of inflation (*INF*) and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term with time (quarterly) dummies is included in the regression models, but is not reported in the table. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	ZSCORE	
	Pre-crisis period	Crisis period
ΔLEV1	-0.164***	0.032**
	(-3.21)	(1.79)
ΔDERLEV1	-0.332***	0.050**
	(-4.78)	(1.86)
ΔSECLEV1	-0.847***	0.208***
	(-2.90)	(3.44)
ΔOBSLEV1	-0.834**	0.372***
	(-1.85)	(2.13)
ASSETCOMP	4.402**	4.175**
	(1.88)	(1.78)
LIABCOMP	2.004***	2.389***
	(3.21)	(3.98)
MA	0.002	0.008
	(0.79)	(0.90)
INF	0.904*	0.673**
	(1.62)	(1.87)
GDP	0.976**	1.153*
	(1.86)	(1.58)
Observations	413	382
R^2	0.148	0.129
F-statistic	11.04	12.88
p-value	0.00	0.00

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

Table 7b

Robustness tests. This table presents the second-stage results obtained by 2SLS IV fixed-effects regression analysis for the pre-crisis period (2002q1-2007q2) and for the crisis period (2007q3-2012q3). The dependent variable is systemic risk (*MES*). The main explanatory variables are the average quarterly changes in: on-balance-sheet leverage (*ΔLEV1*), derivatives leverage (*ΔDERLEV1*), leverage from securitisation (*ΔSECLEV1*), and off-balance-sheet leverage ratio (*ΔOBSLEV1*). All explanatory variables are instrumented in the first stage. The instrumental variables are given by the two- and three-period lags of *ΔLEV1*, *ΔDERLEV1*, *ΔSECLEV1*, and *ΔOBSLEV1* according to the Akaike Information Criterion and the Schwarz-Bayesian Information Criterion. The set of bank-specific control variables employed in our analysis includes the asset composition of banks' balance sheets (*ASSETCOMP*), banks' liabilities composition (*LIABCOMP*), and a dummy variable

(*MA*) which accounts for M&A transactions during the examined periods. Two macroeconomic control variables are also used: the level of inflation (*INF*) and the level of economic growth (*GDP*). A detailed description of each variable can be found in Appendix A. A constant term with time (quarterly) dummies is included in the regression models, but is not reported in the table. Heteroskedasticity-robust *t*-statistics are reported in parentheses.

	MES	
	Pre-crisis period	Crisis period
ΔLEV1	0.202**	0.243***
	(1.88)	(2.04)
ΔDERLEV1	0.709***	0.791***
	(3.67)	(3.54)
ΔSECLEV1	0.988**	1.197**
	(1.83)	(1.79)
ΔOBSLEV1	0.754***	0.830***
	(2.64)	(2.27)
ASSETCOMP	0.489	0.786
	(1.44)	(0.63)
LIABCOMP	0.818	1.178
	(0.89)	(0.59)
MA	0.027	0.039
	(1.02)	(1.15)
INF	0.830	0.938*
	(1.32)	(1.63)
GDP	1.794*	1.754*
	(1.67)	(1.59)
Observations	402	361
R^2	0.116	0.148
F-statistic	9.64	8.18
p-value	0.00	0.00

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

Tables 7a and 7b summarise the results of the 2SLS IV second-stage regressions.[22] As we can see, the reported results are robust to the use of *ZSCORE* and *MES* as the dependent variables of

[22] The results of the first-stage regressions are not shown here for the sake of brevity, but are available upon request. It is important to mention though that the application of the Hansen *J*-test provides us with *p*-values which belong to the closed interval [0.153, 0.377]. These values mean that we fail to reject the null hypothesis that overidentifying restrictions are valid and, hence, we can provide support to the validity of the selected instrumental variables. A

the econometric analysis. More specifically, all types of leverage are found to significantly increase both insolvency risk and systemic risk in the years before the outbreak of the crisis (recall here that larger values of *ZSCORE* mean lower probability of default and hence greater bank soundness). Like it was the case in our baseline regressions, the reported impact is stronger for the off-balance-sheet leverage activities. After mid-2007, reverse leverage activity is found to be harmful for the entire system, albeit it reduces individual bank risk. Like before, the deleveraging process that takes place off the balance sheet of banks is more harmful compared to the corresponding process that occurs on the balance sheet. To continue, even though the level of statistical significance of the estimated coefficients of *ASSETCOMP* and *LIABCOMP* on *TOTRISK* are reduced by little compared to the results of the main regression, the signs of the coefficients remain unchanged. This is to say, banks' resort to traditional activities like the issuance of loans and the taking of deposits reduces individual risk and renders institutions more resilient to shocks. Lastly, no statistically significant relationship is documented between *ASSETCOMP* and *LIABCOMP* with *MES*. In summary, our results remain largely unchanged.

Since our sample of banks has been selected on the basis of several bank-specific criteria on systemic importance, it might suffer from some sort of selection bias. Therefore, a second robustness test investigates whether our empirical findings have been influenced by selection bias induced by the non-randomness of our sample. To account for this bias, we apply the traditional Heckman (1979) two-stage methodology. In the first stage, we construct a dummy, which plays the role of the selection variable in the model. This variable is named *SCAP*, and is equal to unity if bank *i* has taken part in the *SCAP* exercise, and zero otherwise. *SCAP* is linked to one of the six criteria we apply to choose our sample of banks as they analytically discussed in Section 3.1.

The first-stage (selection) model is a probit model where *SCAP* is run on *LEV1*, *DERLEV1*, *SECLEV1*, *OBSLEV1*, and on a constant term using maximum likelihood estimation. The Inverse Mills Ratio (*IMR*) is obtained, which represents the selection control variable of the first stage regression. The *IMR* is a monotonically decreasing function of the probability that an observation is selected into the sample. Moving to the second stage, we estimate our baseline model (eq. 11) by OLS incorporating the obtained *IMR* in the set of explanatory variables to correct for sample

---

robust *F*-statistic test further confirms the validity of our instruments. Furthermore, the Hausman test supports the use of 2SLS IV estimation methodology like it happened in our main regression analysis.

selection bias. In case *IMR* is not found to be statistically significant, then the null hypothesis of no sample selection bias cannot be rejected. The first- and second-stage results of the Heckman sample selection model for the two examined time periods using *SCAP* as the selection variable in the first-stage regressions are reported in Table 8.

Table 8

Sample selection bias. This table reports the marginal effects of first- and second-stage regression results of the Heckman's sample selection model. The results for both the pre-crisis period (2002q1-2007q2) and the crisis period (2007q3-2012q3) are reported. The selection variable in the first stage regression is *SCAP* that takes the value of one if a bank has taken part in SCAP. The selection regression includes the following control variables: *ΔLEV1*, Δ*DERLEV1*, Δ*SECLEV1*, and Δ*OBSLEV1*. The selection parameter obtained from the first-stage maximum likelihood regression is *IMR*. In the second stage, we estimate our baseline model (eq. 11) by OLS incorporating the *IMR* in the set of explanatory variables to correct for sample selection bias. A constant term is included in the model of each stage, but is not reported. A description of each variable can be found in Appendix A. Heteroskedasticity-robust standard errors are in parantheses.

	Pre-crisis period		Crisis period		Pre-crisis period		Crisis period	
	Stage 1 (*SCAP*)	Stage 2 (*TOTRISK*)	Stage 1 (*SCAP*)	Stage 2 (*TOTRISK*)	Stage 1 (*SCAP*)	Stage 2 (*CoVaR*)	Stage 1 (*SCAP*)	Stage 2 (*CoVar*)
ΔLEV1	0.392**	0.110**	0.404**	-0.014**	0.372***	0.098***	0.344**	0.213**
	(1.86)	(3.88)	(1.81)	(-1.89)	(2.03)	(2.13)	(1.86)	(1.71)
Δ*DERLEV1*	0.854***	0.949***	0.815***	-0.713**	0.289***	0.138***	0.252***	0.307***
	(2.67)	(4.34)	(2.43)	(-1.83)	(2.90)	(4.12)	(2.31)	(4.12)
Δ*SECLEV1*	0.765***	1.005***	0.803***	-0.956***	0.712***	0.489**	0.709***	0.702***
	(2.43)	(1.99)	(2.78)	(-4.10)	(2.65)	(1.88)	(2.45)	(1.97)
Δ*OBSLEV1*	0.934**	0.798***	0.892**	-0.208**	0.802**	0.829***	0.833**	1.211**
	1.82	(2.28)	1.78	(-1.76)	1.79	(1.98)	1.84	(1.88)
ASSETCOMP		-3.964***		-3.443***		1.208		0.954
		(-2.90)		(-1.99)		(1.33)		(1.49)
LIABCOMP		-1.598***		-1.086**		0.890		1.072
		(-1.96)		(-1.78)		(1.04)		(0.83)
MA		0.018		0.009		0.021		0.031
		(1.14)		(0.87)		(1.23)		(1.04)
INF		-0.153**		-0.092**		-1.027**		-1.410**
		(-1.72)		(-1.86)		(-1.91)		(-1.78)
GDP		-1.290***		-0.874**		-1.730***		-2.299**
		(-2.05)		(-1.84)		(-2.00)		(-1.97)
IMR		0.083		0.076		0.053*		0.059
		(1.21)		(1.14)		(1.61)		(1.43)
Observations	419	419	389	389	419	419	389	389
R^2	0.154	0.188	0.137	0.163	0.190	0.178	0.142	0.172

***, **, * correspond to 1%, 5%, and 10% level of significance respectively for a two-tailed distribution.

The first-stage results reveal that those banks which participated in the SCAP exercise in 2009 have been largely involved in both on- but, especially, off-balance-sheet activities. This can be inferred from the positive and statistically significant relationships that we document between *LEV1*, *DERLEV1*, *SECLEV1*, and *OBSLEV1* with *SCAP*. This sort of relationships remains strong and unaffected for both periods under examination. Hence, we can argue that the *SCAP* banks were much levered before the crisis, meaning that, after the outbreak of the crisis, they would be amongst the first ones to start deleveraging their portfolios. If we consider that the SCAP banks are of the biggest banks in the U.S. market (size was the main criterion for a bank to participate in SCAP), then the aforementioned results are perfectly in line with what has been earlier discussed about the positive relationship that holds between bank size and off-balance-sheet leverage exposure of banking organisations (see Section 3.1).

As regards the second-stage regression results, these broadly confirm the findings of our baseline empirical analysis. First, the Inverse Mills Ratio is not statistically significant at the 5% level in any of our regressions, indicating that selection problems are marginal in our context. Therefore, controlling for potential sample selection bias does not have an impact on our empirical findings. And, second, the estimates of the Heckman-type regression models are consistent with those obtained from our baseline analysis.

6. Concluding remarks and policy implications

In this paper we examined how modern banking that gave birth to the off-balance-sheet leverage business affected the risk profile of U.S. banks as well as the level of systemic risk before and after the onset of the late 2000s financial crisis. To achieve this, we employed a very representative data set of 20 U.S. SIFIs that covers both the pre-crisis period as well as that after mid-2007 when the crisis erupted. We appropriately modelled the relationship between individual bank soundness and systemic fragility with on-balance-sheet leverage variables but, most importantly, with several measures of off-balance-sheet leverage activities that have never been used in the relevant literature. Markedly, we paid special attention to the deleveraging process that occurred after the outbreak of the crisis, which is an additional innovative feature of our study.

Our formal evidence reliably indicates that leverage largely contributes to both total bank risk and systemic risk thus corroborating the findings that appear in the relevant literature (e.g., see

Wu et al, 2011) as well as in the popular press. To put it in a more detailed way, we lend support to the view that, before the onset of the crisis, banks accumulated leverage both on and, especially, off their balance sheets. Indeed, banks were able to expand leverage in ways that were previously impossible: by largely relying on new financial products, they managed to extend the short-term funding of their medium- and long-term assets. This increased maturity mismatch and raised the probability of bank runs and, in turn, the levels of the overall risk thus forcing the system to either fail or consider large-scale bailouts.

Accordingly, in the pre-crisis era, the positive relationship that we document between off-balance-sheet leverage and risk shows that leverage was one of the main factors responsible for the fragility of the banking system. Nevertheless, a much more tangible threat to systemic stability was formed after the beginning of the crisis when banks started to dispose the large number of bad assets they used to hold either in their portfolios or out of them. The deleveraging process, which mostly took place off the balance sheet of banks, is found to be virtuous for individual banks' health, but very harmful for the stability of the system.

We argue that the expansion of derivatives trading associated with increased securitisation activity was disregarded by national and supranational regulatory and supervisory authorities in the years running up to the crisis. The direct link between off-balance-sheet leverage and systemic risk provides the necessary condition to the current debate on stricter bank regulations through the imposition of an explicit off-balance-sheet leverage ratio as it is the case in Canada for many years now (see Bordeleau et al., 2009). A leverage ratio that does not consider off-balance-sheet items encourages banks to either further expand such kind of activities, or to innovate other activities that will also take place off their balance-sheets. Put differently, the failure to incorporate off-balance-sheet items in a measure of leverage exposure provides additional incentives to banking firms to shift these items off their balance sheets so as to avoid the traditional on-balance-sheet leverage restrictions.

We should always bear in mind that traditional capital requirements were one of the reasons that turned banks to hide part of their assets and, hence, part of their risk off their balance sheets. Therefore, two different, complementary leverage ratios need to be imposed in our view: one that targets on the on-balance-sheet items and one that aims in restricting implicit leverage (both embedded and off-balance-sheet leverage). And, in fact, the new Basel rules (*i.e.*, Basel III) are moving towards this direction.

What we also document in this paper is that the banks which concentrate on traditional activities typically carry less risk compared to those involved with modern financial instruments. To be more specific, on the asset side of banks' balance sheets, the replacement of traditional loans with tranches of Asset Backed Securities (ABS), Collateralised Debt Obligations (CDOs) and other associated derivatives increase total bank risk. Although such tranches are often AAA-rated and thus of low risk, the newer assets originated by banks are down-the-quality-curve. And, in fact, this seems not to have been taken into serious consideration by rating agencies before the crisis. Turning to the liability side of the balance sheets, the traditional business of taking deposits from households, which has been relatively declined compared to the non-interest income business is found to decrease individual bank risk.

All things considered, the aforementioned findings could play a role in the current discussion about a possible revival of the Glass-Steagall Act, which had banned commercial banks from underwriting, holding or dealing in corporate securities, hence essentially separating investment from commercial banking activities.

Acknowledgements: The authors would like to thank the participants in the 28th Symposium on Money, Banking, and Finance, the INFINITI Conference on International Finance of 2011, and the Conference on "Financial Stability, Bank Risk and Regulation in the Light of the Crisis" for their helpful comments and suggestions. In addition, the paper has benefited from the insightful discussions with Christos Agiakloglou, Giovanni Barone-Adesi, Harald Benink, Jin-Chuan Duan, Bill Francis, Federico Galizia, Gikas Hardouvelis, Iftekhar Hasan, Paolo Guarda, Charles Kahn, Georgios Karathanasis, Leo Michelis, Philip Molyneux, Francisco Nadal de Simone, Yves Nosbusch, George Pennacchi, Ingmar Schumacher, Thanassis Stengos, Wolf Wagner, Tim Zhou, and Jean-Pierre Zigrand. The usual disclaimer applies.

References

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M.P., 2012. Measuring systemic risk. CEPR Discussion Paper No. DP8824

Adrian, T., Brunnermeier, M.K., 2011. CoVar. NBER Working Paper 17454.

Adrian, T., Shin, H.S., 2010. Liquidity and leverage. Journal of Financial Intermediation 19, 418-437.

Basel Committee on Banking Supervision (BCBS), 2009. Strengthening the resilience of the banking sector. Bank for International Settlements.

Berger, A.N., Klapper, L.F., Turk-Ariss, R., 2009. Bank competition and financial stability. Journal of Financial Services Research 35, 99-118.

Bordeleau, E., Crawford, A., Graham, C., 2009. Regulatory constraints on bank leverage: Issues and lessons from the Canadian experience. Bank of Canada Discussion Paper Series 15.

Boyson, N.E., Stahel, C.W., Stultz, R.M., 2010. Hedge funds contagion and liquidity chocks. The Journal of Finance LXV, 1789-1816.Patro, D.K., Qi, M., Sun, X., 2013. A simple indicator of systemic risk. Journal of Financial Stability 9, 105-116.

Breuer, P., 2002. Measuring off-balance sheet leverage. Journal of Banking and Finance 26, 223-242.

Brissimis, S.N., Delis, M.D., Papanikolaou, N.I., 2008. Exploring the nexus between banking sector reform and performance: Evidence from newly acceded EU countries. Journal of Banking and Finance 32, 2674-2683.

Brunnermeier, M.K., 2009. Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives 23, 77-100.

Chan-Lau, J.A., 2010. The global financial crisis and its impact on the Chilean banking system. IMF Working Paper Series 10/108.

Chernozhukov, V., Umantsev, L., 2001. Conditional value-at-risk: aspects of modelling and estimation. Empirical Economics 26, 271-292.

Chow, G.C., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica 28, 591-605.

Cornett, M.M, McNutt, J.J., Strahan, P.E., Tehranian, H., 2011. Liquidity risk management and credit supply in the financial crisis. Journal of Financial Economics 101, 297-312.

Counterparty Risk Management Policy Group (CRMP) Report, 2008. Containing systemic risk: The road to reform.

Demsetz, R.S., Strahan, P.E., 1997. Diversification, size, and risk at Bank Holding Companies. Journal of Money, Credit and Banking 29, 300-313.

De Nicoló, G., Kwast, M.L., 2002. Systemic risk and financial consolidation: Are they related? Journal of Banking and Finance 26, 861-880.

DeYoung, R., Roland, K.P., 2001. Product mix and earnings volatility at commercial banks: evidence from a degree of total leverage model. Journal of Financial Intermediation 10, 54-84.

Diamond, D., 1984. Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393-414.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427-431.

Duffee, G., Zhou, C., 2001. Credit derivatives in banking: useful tools for managing risk?, Journal of Monetary Economics 48, 25-54.

Elsas, R., Hackethal, A., Holzhäuser, M., 2010. The anatomy of bank diversification. Journal of Banking and Finance 34, 1274-1287.

Engle, R., Manganelli, S., 2004. CAViaR: conditional autoregressive value at risk by regression quantiles. Journal of Business and Economic Statistics, 22, 367-381.

Fabozzi, F.J., Choudhry, M., 2004. The Handbook of European Structured Financial Products, Wiley Finance.

Flannery, M.J., Sorescu, S.M., 1996. Evidence of bank market discipline in subordinated debenture yields: 1983-1991. The Journal of Finance 51, 1347-1377.

Galloway, T.M., Winson, B.L., Roden, D.M., 1997. Banks' changing incentives and opportunities for risk taking. Journal of Banking and Finance 21, 509-527.

Girardi, G., Tolga Ergun, A., 2013. Systemic risk measurement: Multivariate GARCH estimation of CoVaR, Journal of Banking and Finance 37, 3169-3180.

Gonzalez, F., 2005. Bank regulation and risk-taking incentives: An international comparison of bank risk. Journal of Banking and Finance 29, 1153-1184.

Greenlaw, D., Hatzius, J., Kashyap, A.K., Song Shin, H., 2008. Leveraged losses: Lessons from the mortgage market meltdown – Proceedings of the US Monetary Policy Forum.

Hansen, L.P., 1982. Large sample properties of Generalised Method of Moments estimators. Econometrica 50, 1029-1054.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46, 1251-1272.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47, 153-161.

Hsiao, C., 1986, Analysis of panel data, Cambridge University Press.

Huang, X., Zhou, H., Zhu, H., 2009. A framework for assessing the systemic risk of major financial institutions. Journal of Banking and Finance 33, 2036-2049.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit root in heterogenous panels. Journal of Econometrics 115, 53-74.

Keeley, M.C., 1990. Deposit insurance, risk, and market power in banking. American Economic Review 80, 1183-1200.

Kiff, J., Kisser, M., 2013. A shot at regulating securitization. Journal of Financial Stability, *forthcoming*.

Koenker, R., Bassett, G.Jr., 1978. Regression quantiles. Econometrica 45, 33-50.

Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. Journal of Financial Economics 93, 259-275.

Levin, A., Lin, C.F. Chu, C.S. J., 2002. Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics 108, 1-24.

Maddala, G.S, Wu., S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics, Special Issue 61, 631-652.

Morrison, A., 2005. Credit derivatives, disintermediation and investment decisions. Journal of Business 78, 621-647.

O'Hara, M., Shaw, W., 1990. Deposit insurance and wealth effects: The value of being "Too Big to Fail". The Journal of Finance 45, 1587-1600.

Papanikolaou, N.I., 2009. How output diversification affects bank efficiency and risk: an intra-EU comparison study. In: Balling, M., Gnan, E., Lierman, F. and Schoder, J.P. (Eds.), Productivity in the Financial Services Sector. Central Bank of Luxembourg/SUERF Studies 4. Editions Larcier, Brussels, 2009, 229-257.

Patro, D.K., Qi, M., Sun, X., 2013. A simple indicator of systemic risk. Journal of Financial Stability 9, 105-116.

Pedroni, P., 1999. Critical values for cointegration test in heterogeneous cointegrated panels. Oxford Bulletin of Economics and Statistics 61, 653-670.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335-346.

Rime, B., Stiroh, K. J., 2003. The performance of universal banks: evidence from Switzerland. Journal of Banking and Finance 27, 2121-2150.

Rogers, K., Sinkey, J.F.Jr., 1999. An analysis of nontraditional activities at U.S. commercial banks. Review of Financial Economics 8, 25-39.

Rubia, A., Sanchis-Marco, L., 2013. On downside risk predictability through liquidity and trading activity: A dynamic quantile approach. International Journal of Forecasting 29, 202-219.

Sargan, J. D., 1958. The estimation of economic relationships using instrumental variables. Econometrica 26, 393-415.

Schaeck, K., Cihak, M., Maechler, A., Stoltz, S., 2012. Who disciplines bank managers? Review of Finance 16, 197-243.

Stiroh, K., 2004. Diversification in banking: Is non-interest income the answer? Journal of Money, Credit and Banking 36, 853-882.

Uhde, A., Heimeshoff, U., 2009. Consolidation in banking and financial stability in Europe: Empirical Evidence. Journal of Banking and Finance 33, 1299-1311.

Van Oordt, M.R.C., 2013. Securitization and the dark side of diversification. Journal of Financial Intermediation, *forthcoming*.

Wagner, W, 2010. Diversification at financial institutions and systemic crises. Journal of Financial Intermediation 19, 373-386.

Wu, D., Yang, J., Hong, H., 2011. Securitization and banks' equity risk. Journal of Financial Services Research 39, 95-117.

Appendix A: Variables and data sources

The following table presents all variables that we use in the econometric analysis. The abbreviation of each variable and the sources we use to collect the data are also reported.

Variable	Abbreviation	Definition	Data source
Risk variables			
Total bank risk	*TOTRISK*	The quarterly standard deviation of each bank's daily stock market returns	Thomson Reuters Datastream
	ZSCORE	The sum of returns on assets and book equity ratio divided by the standard deviation of returns of assets	FR Y-9C forms
Systemic risk	*CoVaR*	The Value at Risk (*VaR*) of a financial institution conditional on the other institutions of the financial system being in distress	*See CoVaR components*
	MES	First pick up the 5% worst days for an equally-weighted portfolio of CDS returns on all sample banks in every quarter of a year, and then compute the CDS returns for each sample bank for these particular days	Bloomberg
CoVaR components			
Implied Volatility Index		An index of market return volatility	Chicago Board Options Exchange Market
Liquidity risk spread		The quarterly difference between the 3-month LIBOR rate and the 3-month U.S. T-bill rate	Federal Reserve Board & GFDatabase
Yield curve		The change in the quarterly difference between the 10-year U.S. T-bill rate and the 3-month US T-bill rate	Federal Reserve Board & U.S. Department of the Treasury
Interest rate risk		The quarterly standard deviation of the day-t-day 3-month U.S. T-bill rate	
Credit risk		The quarterly change in the credit spread between the 10-year BAA-rated bonds and the 10-year U.S. T-bill rate	Federal Reserve Board & Moody's

Leverage variables

	LEV1	The ratio of total assets to book equity capital	
On-balance-sheet leverage	*LEV2*	The inverted Tier 1 leverage ratio	FR Y-9C forms
	LEV3	The ratio of total liabilities to book equity capital	
	DERLEV1	The ratio of credit equivalent amount of OTC derivatives outstanding to book equity capital	OCC Quarterly Report on Bank Derivatives Activities & FR Y-9C forms
Derivatives leverage	*DERLEV2*	The credit exposure across all OTC derivative contracts divided by regulatory capital	
	DERLEV3	The ratio of trading revenue from OTC derivative activities to total revenue	FR Y-9C forms
	SECLEV1	The outstanding principal amount of loans and other assets sold and securitised with servicing retained or with recourse or any other credit backstops provided divided by total assets	
Securitisation leverage			FR Y-9C forms
	SECLEV2	The amount of credit exposure arising from recourse or other seller-provided credit enhancements to SIVs and other conduits divided by total assets	
OBS leverage ratio	*OBSLEV1*	The sum of commitments, direct credit substitutes, acceptances, and repos divided by total equity	
			FR Y-9C forms
	OBSLEV2	The sum of standby letters of credit and guarantees, acceptances, and repos divided by regulatory capital	

Bank-specific control variables			
Asset composition	*ASSETCOMP*	The ratio of net loans and leases to total assets	FR Y-9C forms
Liability Composition	*LIABCOMP*	The ratio of demand deposits to total liabilities	FR Y-9C forms
M&A deals	*MA*	A dummy variable which is equal to unity in the quarter *q* that bank *i* has been involved in some M&A transaction	NIC/FFIEC
Macroeconomic environment			
Inflation rate	*INF*	The quarterly change in U.S. Consumer Price Index (CPI)	Bureau of Labor Statistics, U.S. Department of Labor
Economic growth	*GDP*	GDP output gap	Bureau of Economic Analysis, U.S. Department of Commerce
Heckman-type model			
Supervisory Capital Assessment Program	*SCAP*	A dummy variable that is equal to unity if bank *i* has been taken part in the SCAP	U.S. Department of Treasury
Inverse Mills Ratio	*IML*	A monotonically decreasing function of the probability that an observation is selected into the sample	Obtained by first-stage regression of Heckman

Appendix B: Quantile *vs.* OLS regressions

The purpose of this Appendix is to explain the main reasons why we use quantile regression techniques instead of standard OLS techniques to estimate the return equations (eq. 7, 8, 9, and 10) in the context of *CoVaR* measurement. We focus on the following five reasons:

a) In the framework of *CoVaR* analysis, we can make the assumption that the return equation (say eq. 8) has the following linear factor structure:

$$R_q^{system|i} = \lambda_0 + M_{q-1}\lambda_1 + R_q^i\lambda_2 + (\lambda_3 + M_{q-1}\lambda_4 + R_q^i\lambda_5)\varepsilon_q^{system|i} \qquad \text{(8a)}$$

where $R_q^{system|i}$ is the quarterly growth rate of total assets of all *N*=20 banks that comprise our banking system conditional on bank *i* being distressed; R_q^i is the quarterly growth rate of bank *i*'s total assets conditional on bank *i* being distressed; M_{q-1} is the one-quarter lag vector of the state variables that influence bank soundness as described in Section 3.3; and $\varepsilon_q^{system|i} = \eta_q\sigma_q$, with $\eta_q \sim$ i.i.d. $N(0,1)$, where η_q is independent of M_{q-1} , *i.e.*, $E[\varepsilon_q^{system|i} \mid M_{q-1}, R_q^i] = 0$.

Both the conditional expected return $E[R_q^{system|i} \mid M_{q-1}, R_q^i] = \lambda_0 + M_{q-1}\lambda_1 + R_q^i\lambda_2$, and the conditional volatility $Vol[R_q^{system|i} \mid M_{q-1}, R_q^i] = \lambda_3 + M_{q-1}\lambda_4 + R_q^i\lambda_5$ depend on M_{q-1} and R_q^i. The coefficients $\lambda_0, \lambda_1, and\ \lambda_2$ can be consistently estimated by running an OLS regression of $R_q^{system|i}$on M_{q-1} and R_q^i. However, in order the VaR and CoVaR measures to be estimated by OLS, we need to also estimate the coefficients $\lambda_3, \lambda_4,$ and λ_5. This implies that we need to make a prior distributional assumption about the error term $\varepsilon_q^{system|i}$ of our model (eq. 8a). On the other hand, quantile regression analysis incorporates estimates of the conditional mean and the conditional volatility, which are needed to produce conditional quantiles without having to make any prior distributional assumptions about the error term (see Boyson et al., 2010; Chan-Lau, 2010; Adrian and Brunnermeier, 2011; Girardi and Tolga Ergun, 2013; Rubia and Sanchis-Marco, 2013).

b) Quantile regression models can be estimated for a large range of possible quantiles (see Boyson et al., 2010; Adrian and Brunnermeier, 2011). We can therefore run a set of different quantile regressions to estimate eq. 8a for different percentiles.

c) Quantile regression techniques capture the possible non-linearities, which can be found in the default risk of some banking institutions as well as in the relationships that hold between the default risk of different banks and that of the entire banking system (Chan-Lau, 2010). In this or similar contexts, Engle and Manganelli (2004) study a large group of non-linear quantile regression models, called Conditional Autoregressive Value-at-Risk (CAViaR).

d) Quantile regression extends the OLS intuition beyond the estimation of the mean of conditional distribution of the default risk of a bank, allowing the conditional distribution to be sliced at the quantile (percentile) p of interest thus obtaining the corresponding cross-section of the conditional distribution (Chan-Lau, 2010).

e) Quantile regression techniques allow for heteroskedasticity (Boyson et al., 2010).