Systemic risk and the U.S. financial system – The role of banking activity

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Abstract

We demonstrate that U.S. banks that are highly exposed to systemic risk are predominantly more likely to contribute to systemic risk than other banks. We find that banks' systemic risk exposure can be explained by bank size, while banks' contribution to systemic risk is also determined by interconnectedness and banking activity. Moreover, we find that after the introduction of the Gramm-Leach-Bliley Act, non-interest income became a significant driver of systemic risk contribution. These findings reveal that the diversification of banks' income sources does not coincide with a decrease in systemic risk.

Keywords: Systemic risk, non-interest income, diversification, financial crises, bank regulation.

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"Investment banks manage to go bankrupt through their investment-banking activities, commercial banks manage to go bankrupt through their commercial-banking activities."
Ben Bernanke, Chairman of the Federal Reserve

1 Introduction

Systemic risk in the U.S. financial sector has attracted the attention of policymakers and regulators, particularly since the recent financial crisis that began in the U.S. Subprime sector in 2007. The Subprime crisis was strongly characterized by the simultaneous failure of several banks in the financial system. As the direct costs of a bank failure are much greater than the costs of a failure of a non-financial company (see James (1991) and Kaufman (1994)), regulators are faced with the primary tasks of reducing banks' exposure and limiting banks' contribution to systemic risk. The most prominent example of a threat to global financial stability, however, was the collapse of the investment bank *Lehman Brothers* on September 15, 2008, then the fifth-largest investment bank in the world. Lehman Brothers' collapse imposed significant negative externalities on global financial markets, as numerous financial institutions became bankrupt. Several government programs, e.g., the Troubled Asset Relief Program (TARP), were intended to contain the spillover effects of the recent financial crisis through the infusion of taxpayer funds. Differentiating between exposure and contribution to systemic risk is therefore of the utmost importance necessitating their measurement, regulation and the identification of their determinants. In recent studies, both banks' exposure and contribution to systemic risk have been analyzed in isolation, and both terms have been used synonymously for systemic risk.[1] However, not all banks in the U.S. banking sector are equally exposed or contribute similarly to systemic risk. This paper fills the gap in the literature

[1] Systemic financial risk is defined as the risk that an exogenous shock will trigger a loss of economic value in a substantial portion of a financial system, which consequently has adverse effects on the real economy, see Group of Ten (2001). In depending on this definition, we differentiate between a bank's exposure and contribution to systemic risk. We relate the definition of a bank's exposure to systemic risk to the work of Acharya et al. (2010) and measure an individual bank's exposure to systemic risk as the negative mean net equity return of the bank conditional on the financial market experiencing extreme downward movements. The definition of a bank's contribution to systemic risk, however, is closely related to the work of Adrian and Brunnermeier (2011). The authors define a bank's contribution to systemic risk as the extent to which an individual bank adds to the overall risk in a financial system.

by analyzing the nexus between banks' exposure and contribution to systemic risk. We investigate the determinants of both systemic risk specifications and document that bank size, banks' interconnectedness through the interbank market and banks' engagement in non-traditional banking activities determine their contribution to systemic risk. Banks' systemic risk exposure is primarily driven by bank size.

U.S. banks' exposure and contribution to systemic risk could be explained by differences in banks' sources of income. The Gramm-Leach-Bliley Act of 1999, which repealed the Glass-Steagall Act of 1933, imposed a separation between commercial and investment banking industries. The justification for the statue was to rescue the commercial banking industry, which was thought to be obsolete (see Macey (2000)). The result was that banks were allowed to engage in a greater extent of non-traditional banking activities such as investment banking, security brokerage and asset securitization (see DeYoung and Torna (2013) and Boot and Thakor (2010)). As banks became more integrated with the financial markets, their non-traditional banking activities increased. Figure 1 depicts the increase in FDIC-insured banks' non-interest income in net operating revenue for the period from 1984 through 2012. In 1984, the banks' average share of non-interest income in net operating revenue (net interest income plus non-interest income) accounted for 29% and peaked at 43% in the second quarter of 2007. By the introduction of the Gramm-Leach-Bliley Act in 1999, the average share of non-interest income accounted for 41% of net operating revenue. In this context, Brunnermeier et al. (2012) show that non-traditional banking activities in the form of non-interest income significantly increase a bank's contribution to systemic risk. The authors analyzed U.S. banks between 1986 and 2008 and found that non-core banking activities, such as investment banking, differ from the traditional deposit-taking and lending functions of banks, thereby leading to greater fragility in the financial market (see, e.g., Mercieca et al., 2007; Baele, 2005; De Jonghe, 2010).

This paper addresses the need for a comprehensive analysis of the relationship between a bank's non-traditional banking activity and both its contribution and exposure to systemic risk. More precisely, using a sample of U.S. banks in the period from 1990 to 2012, we employ two different models to measure an individual bank's exposure and contribution to systemic risk. First, we follow Acharya et al. (2010) and measure a bank's *exposure* to possible under-capitalization in the financial sector using a bank's Marginal Expected Shortfall (MES), estimated in a static fashion. Brownlees and Engle (2012) extend this measure and propose a dynamic specification of the estimation of a bank's MES (dynamic MES). For our main analysis, we focus on the dynamic MES, as the dynamic specification accounts for time-varying volatility and correlation and nonlinear tail dependence in the banks' and the financial sector's returns.[2] Second, we use the ΔCoVaR measure developed by Adrian and Brunnermeier (2011) to measure a bank's *contribution* to systemic risk.[3]

Using these measures of systemic risk, we test several hypotheses from the financial intermediation and financial market stability literature regarding the question of what factors determine both a bank's exposure and contribution to systemic risk. The Basel Committee on Banking Supervision (2013) identifies bank size, interconnectedness, substitutability, cross-jurisdictional activity and the bank's complexity as the key drivers of financial instability. Bank size is often cited as the main driver of systemic risk.[4] Specifically, large banks are exposed to systemic risk via direct and indirect contagion channels. While the direct contagion channel implies greater interconnectedness with and exposure to banks through the interbank market, the indirect channel comprises an increase in systemic risk exposure, e.g., through the information channel.[5] Further, O'Hara and Shaw (1990) and Acharya and Yorulmazer (2008) argue that larger banks could provide managers with incentives for excessive risk-taking, as the probability of a government bailout increases in the event of a bank's default. Similarly, Gandhi and Lustig (forthcoming) find that stock market investors price a bank's size in its stock returns, as the probability of receiving a bailout is determined by bank size, indicating a positive relationship between bank size and systemic risk contribution. The relationship between bank size and banks' share of

[2] We also estimate the results on the static MES. We find the results on MES to be similar to those of the dynamic MES.

[3] Giglio et al. (2013) shows the need to differentiate between several distinct measures of systemic risk.

[4] For example, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 uses the $ 50 billion of totals assets threshold for defining systemic importance. Also Beltratti and Stulz (2012) focus in their analysis on systemically important banks and use the $ 50 billion of totals assets threshold for a bank to be included in their final sample.

[5] A detailed overview of these channels is presented in Barth and Schnabel (2013).

non-interest income in net operating revenue is presented in Figure 2. The figure reveals that large banks with total assets in excess of $ 1 billion have a significantly higher share of non-interest income in total income than smaller banks with total assets below the threshold of $ 1 billion. Demirgüç-Kunt and Huizinga (2013) argue that larger banks have the ability to enter new businesses, as they enjoy easier access to capital and infrastructure. Additionally, larger banks can more easily diversify their income streams than smaller banks. Figure 2 also illustrates that during the Subprime crisis, a significant decrease in large banks' non-interest income share can be detected, while small banks exhibit a relatively constant level of non-interest income to net operating revenue of approximately 25% for the entire observation period from 1997 through 2012. This result implies that non-interest income tends to be a more volatile source of revenue, especially for larger banks. In periods of financial distress, e.g., the Subprime crisis, banks could face a decline in the sources of revenue from fees and brokerage services (see, e.g., Altunbas et al. (2011)). Moreover, the global trend towards greater diversification in bank income sources and consequently an expansion of non-interest income revenues has provided banks with additional sources of income. In this context, recent studies in the banking literature report a positive relationship between diversification and systemic risk.[6] DeYoung and Torna (2013) argue that banks that have greater reliance on non-interest income have higher betas and are consequently more sensitive to extreme market and macroeconomic changes than traditional banks. Similarly, Stiroh (2006) argues that banks relying on non-core banking activities to a greater extent exhibit higher return volatility. In contrast, Stiroh (2004) find some evidence for diversification gains and conclude that banking-strategies that predominantly rely on generating non-interest income are highly risky. Whether a bank's exposure or contribution to systemic risk is related to a bank's banking activity, its size or to crisis periods is of major importance for both regulators and policy makers to ensure global financial market stability. We contribute to this strand of the literature and demonstrate that banking

6 Prior studies have analyzed the effect of banks' involvement in non-core banking activities on bank risk (see, e.g., Kwast (1989) and Uzun and Webb (2007)). The authors find that income diversification does not result in decreased bank risk. In recent studies, Fahlenbrach et al. (2012), Brunnermeier et al. (2012) and Adrian and Brunnermeier (2011) demonstrate that a higher level of systemic risk can be related to larger banks' tail risk, while Boot and Ratnovski (2013), De Jonghe (2010), DeYoung and Torna (2013) and De Jonghe et al. (2014), however, focus on economies of scope and their relationship with systemic risk.

activities and particularly greater reliance on non-core activities determine a bank's contribution to systemic risk. However, during the Subprime crisis, we find no evidence of a positive relationship between non-interest income and either systemic risk specification.

The Basel Committee on Banking Supervision (2013) also identifies interconnectedness as a key driver of systemic risk. The interbank market serves as a liquidity provider for financial institutions. A bank that is highly interconnected through the interbank market could thus contribute more to systemic risk, as an adverse shock, e.g., a bank becoming insolvent, could be transmitted through the interbank lending channel to the entire interbank market (see, e.g., Iyer and Peydrò (2011)). Moreover, as banks enter into further contractual obligations with other banks, they are likely to increase in size. Consequently, we expect bank size and banks' interconnectedness to be positively correlated and positively related to a bank's contribution to systemic risk. Other commentators share the insight that systemic risk is not solely driven by banks' sizes or interconnectedness. For example, Adrian and Shin (2010) find that leverage among banks is strongly pro-cyclical, implying that they take on additional risk in good times and sell off risky assets in bad times. Additionally, Hovakimian et al. (2012) analyze quarterly data on U.S. banks over the period from 1974 to 2010. The authors find bank size, leverage and asset risk to be the main drivers of systemic risk. Furthermore, DeYoung and Torna (2013) determine that a bank's default probability is significantly driven by higher stakeholder income from non-traditional banking activities that require banks to make asset investments. Other commentators, however, argue that banks' reliance on short-term funding contributes to the accumulation of systemic risks, especially prior to crisis (see, e.g., Diamond and Rajan, 2009; Adrian and Shin, 2010; Gorton, 2010). Interestingly, Fahlenbrach et al. (2012) use a bank's stock return performance during the LTCM crisis to predict both a bank's performance and its default probability during the recent financial crisis. The authors relate this finding to a bank's risk culture.

Financial market stability, however, could also be influenced by the extent to which national regulators prohibit banks from engaging in certain business activities. As a theoretical justification for such banking activity restrictions, the diversification of banks into trading, underwriting and investment banking is often argued to produce conflicts of interest (see John et al., 1994) and increased risk-taking (see Boyd et al., 1998; Brunnermeier et al., 2012). Moreover, the presence of a deposit insurance scheme can have both stabilizing and destabilizing effects on the financial system (see Merton (1977)). While in their classical model, Diamond and Dybvig (1983) argue that deposit insurance can prevent self-fulfilling bank runs by depositors, deposit insurance, however, may provide bank managers with incentives to engage in excessive risk taking, thus increasing a bank's default probability (see Kane, 2000; Demirgüç-Kunt and Detragiache, 2002). In this context, Anginer et al. (2013) find that deposit insurance dominates during financial crises, while moral hazard seems to predominate during calm periods.

Analyzing a sample of 11,425 bank-year observations from 1990 through 2012, our first contribution is that a bank's high systemic risk exposure coincides with a high systemic risk contribution. We also investigate which factors determine each systemic risk specification. We find that banks' exposure and contribution to systemic risk are primarily driven by bank size. Additionally, banks' contribution to systemic risk is also positively related to banks' interconnectedness through the interbank market. These results are both statistically and economically significant. As the Gramm-Leach-Bliley Act of 1999 allowed banks to engage in non-traditional banking activities, e.g., investment banking, to a greater extent, we investigate the effect of banks' engagement in non-core banking activities and the ensuing effect on systemic risk. Our second contribution is that for our sample of large banks, we find that banks' engagement in non-traditional banking activities is significantly related to banks' systemic risk contribution. This result can be related to the fact that larger banks can diversify their income sources more easily than smaller banks, as they have easier access to capital and infrastructure, which enables them to enter new businesses (see also Demirgüç-Kunt and Huizinga (2013)). These diversification benefits on the mircrolevel, however, result in a significant increase in systemic risk contribution to the overall banking sector. We also perform additional analyses regarding the nexus of bank size, banking activities and both systemic risk specifications. We find that both systemic risk measures increase following an increase in a bank's size. This effect is more pronounced following an increase in a bank's non-core activities.

In addition, we also use quantile-regressions to investigate which bank-specific factors can explain extreme values in banks' exposure or contribution to systemic risk. We find that the dynamic MES, as a measure of banks' systemic risk exposure, is primarily driven by bank size. Using ΔCoVaR as a measure of banks' contribution to systemic risk, we obtain results consistent with those of our baseline regressions.

To the best of our knowledge, our paper fills a gap in the literature, as we are the first to analyze the nexus between a bank's exposure and contribution to systemic risk. Moreover, we investigate the question of whether banks' banking activities are also a main driver of systemic risk, which at a minimum has important implications for both regulators and politicians. This paper is related to several recent papers on systemic risk, the financial crisis and banking activity. Demirgüç-Kunt and Huizinga (2013) analyze the effect of banking activity on bank risk and return using an international sample. In our work, we follow Demirgüç-Kunt and Huizinga (2013) and use a bank's banking activity to analyze the effect of banking activity on systemic risk. Brunnermeier et al. (2012) find that a bank's non-core banking activities are positively related to its contribution to systemic risk. Here, we complement their analyses by also using a bank's dynamic MES as a measure of the bank's exposure to systemic risk as proposed by Acharya et al. (2010) and extended by Brownlees and Engle (2012). In our additional analyses, we follow Koenker and Hallock (2001) and employ quantile-regression analyses to investigate which factors determine extreme values of systemic risk.

The paper proceeds as follows. In Section 2, we describe our data and the methodology used to develop our systemic risk measures. In Section 3, we analyze the nexus between banks' systemic risk exposure and contribution to systemic risk. We also investigate which bank-specific variables determine our systemic risk measures. To validate our main findings, we perform additional analyses and robustness checks. Section 4 concludes.

2 Data

This section describes the construction of our sample, defines the different systemic risk measures and presents the choice of our main independent variables as well as descriptive statistics of our data.

2.1 Sample construction

We construct our primary sample using all publicly traded U.S. banks included in the *Thompson Reuters Financial Datastream* country and dead firm list from 1990 through 2012. As we consider only U.S. banks with primary listings in the U.S., we exclude banks with non-primary issues and secondary listings. We select all bank-year observations for banks with Standard Industry Classification (SIC) codes between 6000 and 6100 in the fiscal year end 1989. Following Fahlenbrach and Stulz (2011), we exclude non-depository banks with the two-digit SIC code 62. Additionally, we manually go through the list of banks with the SIC code 6199 (Finance Services) and exclude pure brokerage houses.

We use two sources to construct bank-level data from 1990 through 2012. While daily share price data are retrieved from *Thompson Reuters Financial Datastream*, financial accounting data are taken from the *Worldscope* database. We winsorize our balance sheet data at the 1% and 99% quantile in order to limit the biasing effect of outliers in our sample. We apply several screening procedures which are commonly applied in the empirical literature, e.g., as provided by Hou et al. (2011) and Ince and Porter (2006). First, we drop all banks from our sample with missing Worldscope data and banks with missing Datastream codes. Furthermore, we control for the known Datastream practice of rounding prices excluding banks with an average share price below $1. Also, we treat any return above 300% that is reversed within a month as missing. According to Hou et al. (2011), we also exclude bank-years if the number of zero-return days exceeds 80% in a given year. Additionally, non-trading days are excluded if 90% or more days are zero-return days. Moreover, we do not consider U.S. Bulletin Boards and ”Pink Sheet” stocks. For each bank, we require available share price data for the full observation year, to ensure the daily estimation of our systemic risk measures.

We also control for possible opaqueness in our data. Excluding some banks-years from our analysis due to missing or incomplete data can implicate a selection bias problem. We control in a two-step manner for this issue. First, we manually check, if for any excluded bank at least one annual report and stock quote are available from any data source, if Datastream does not provide any data. Moreover, we rule out a selection bias problem for those banks omitted from our analysis for which the data extracted from Datastream or Worldscope is only incomplete and for which key data items are available. Therefore, the possibility of a selection bias due to bank opacity can be ruled out.

In addition, we control for mergers in our sample. More precisely, we manually search in the *Thomson One Banker Database* to identify banks that merged during our observation period. Several authors (see, e.g., Weiß et al. (2014) and De Nicolò and Kwast (2002)) argue that mergers in the banking sector result in an increase in the acquiring banks' as well as in the combined banks' contribution to systemic risk. Furthermore, these analyses show that the number of overall takeover activities, also in the U.S., increased over the last two decades. In order to avoid distortive effects of possible mergers in our sample, we exclude both acquiring and target banks in the year they merged. Our final sample consists of 11,425 bank-year observations of 1,126 U.S. banks. The distribution of banks by year is shown in Figure 3. In 1991, the total number of banks in our sample is 295. The number of banks increases up to 666 in 2000 and decreases to 448 in 2012. While 55 banks enter our sample only once for the entire sample period, 59 banks enter our sample in each observation year.

2.2 Systemic risk measures

We use two different measures of systemic risk that are proposed in the empirical banking literature. Both measures are based on daily stock market data and have extensively been used by regulators for monitoring financial market stability (see Benoit et al., 2013). We begin with the estimation of the Marginal Expected Shortfall (MES) as proposed by Acharya et al. (2010). Using this static structural form approach, we can measure an individual bank's exposure to systemic risk. More precisely, the MES is defined as the negative mean net equity return of the bank conditional on the financial market experiencing extreme downward movements.[7] As we are interested in bank's local exposure and contribution to systemic, we use the *Datastream U.S. Bank Index* (DS code BANKSUS) as a proxy for the U.S. financial sector.[8] Further, we follow Brownlees and Engle (2012) and employ the daily MES estimates using a dynamic model instead of a static one. These authors account in their approach for time varying volatility and correlation as well as nonlinear tail dependence in the banks' and the sector's returns thus indicating that this approach is economically more challenging than the static MES. We begin with the TARCH (see Rabemananjara and Zakoïan, 1993) and Dynamic Conditional Correlation (DCC) (see Engle, 2002) specifications to compute a bank's daily MES estimates for all trading years within one year. Averaging these daily MES estimates for each individual bank yields our dependent variable.[9]

As a second approach to measure a bank's contribution to systemic risk, we follow Adrian and Brunnermeier (2011) and employ the ΔCoVaR method. This measure is based on the tail co-variation between financial institutions and the financial system. While the dynamic MES can be viewed as a measure of a bank's exposure to financial market turmoil, the ΔCoVaR approach attempts to measure a bank's contribution to systemic risk. In this study, we implement both the conditional and unconditional ΔCoVaR for our entire sample. Adrian and Brunnermeier (2011) criticize the MES measure as not being able to adequately address the procyclicality that arises from contemporaneous risk measurement. While the unconditional ΔCoVaR estimates are constant over time,[10] the conditional ΔCoVaR is time-varying and estimated using a set of state

[7] We measure a bank's MES for the entire period. The results are reported in the descriptive statistics.

[8] We use this index to estimate both systemic risk measures.

[9] Note that annual estimates of the daily dynamic MES are used to yield the dependent variable used in our main regressions, while we consider quantile estimations for our additional analyses.

[10] We do not report the results for the unconditional ΔCoVaR estimations. They are available from the authors upon request.

variables that capture the evolution of tail risk dependence over time.[11]

2.3 Main independent variables

We hypothesize that the drivers of our systemic risk measures can be explained by a set of idiosyncratic bank characteristics. Therefore, we collect a set of bank-specific variables. The data sources and definitions of each variable are reported in the Appendix I.

To proxy for bank size we use the natural logarithm of a bank's total assets. As the Basel Committee on Banking Supervision (2013) recognizes bank size as an important dimension of systemic risk, we expect bank size to be an economically significant driver of systemic risk. The too-big-to-fail hypothesis supports this view; bank size increases the probability of a bank receiving a bailout from the government, as confidence in the interbank market and possibly the financial system as a whole would be damaged in the event of the bank's failure. Banks' increased contribution to systemic risk, however, could provide managers with incentives to engage in excessive risk-taking. In accordance, larger banks should also be more exposed to systemic risk in the financial sector (see, e.g., Gandhi and Lustig (forthcoming), O'Hara and Shaw (1990) and Acharya and Yorulmazer (2008)).

We also consider a bank's return on assets ratio as a further explanatory variable. We expect banks with a higher return on assets ratio to be less exposed to systemic risks, as higher profitability generally reduces the likelihood of banks becoming insolvent. However, a bank having higher profits could be explained by the bank having a higher portion of riskier investments, consequently increasing a bank's systemic risk exposure.

Moreover, we consider a leverage variable, which is defined as the ratio of the book value of assets minus the book value of equity plus the market value of equity, divided by the market value of equity (see Acharya et al. (2010)). For example, Shleifer and Vishny (2010) confirm that

[11] We follow Adrian and Brunnermeier (2011) in using the change in the three-month Treasury bill rate, the difference between the ten-year Treasury Bond and the three-month Treasury bill rate, the change in the credit spread between BAA-rated bonds and the Treasury bill rate, the return on the Case-Shiller Home Price Index, and implied equity market volatility from VIX as state variables in the estimation of the conditional ΔCoVaR. Data are taken from the U.S. Federal Reserve Board.

highly leveraged banks contribute more to both systemic risk and economic volatility. Similarly, Brunnermeier et al. (2012) and Beltratti and Stulz (2012) demonstrate that highly leveraged banks contribute more to systemic risk and perform worse than less leveraged banks. In contrast, a less leveraged bank could lead to a higher likelihood of default and thus to a higher contribution to systemic risk because bank managers could be inclined to commit free cash flows to risky projects (see Berger and Bonaccorsi di Patti (2006)).

Additionally, we use the bank's non-interest income as a proxy for banking activity. While Brunnermeier et al. (2012) define non-traditional income as the share of non-interest income divided by net interest income, Demirgüç-Kunt and Huizinga (2013) use banks' non-interest income to total operating income as a proxy for banking activity. Following these studies, we construct a bank's non-interest income share as the share of non-interest income divided by the sum of total interest income and non-interest income. Brunnermeier et al. (2012) argue that a bank's non-traditional banking activities are positively related to the bank's contribution to systemic risk. Similarly, DeYoung and Torna (2013) argue that a bank's default probability is driven by relying on non-core banking activities to a greater extent. Moreover, Mercieca et al. (2007) and Baele (2005) find a positive relationship between non-interest income banking activities and systemic risk. As a consequence, we expect the non-interest income share variable to be positively related to banks' systemic risk contribution.

In line with the argumentation advanced in connection with the non-interest income variable, we include a loans variable, which is defined as the ratio of total loans to total assets. A higher ratio could therefore indicate that banks engage in traditional bank lending activities to relatively a greater extent. During the Subprime crisis, however, banks with higher loan ratios could have been more exposed to systemic risks, as the crisis in real estate markets resulted in substantial credit losses, thus increasing the likelihood that the banks will suffer credit losses due to credit contagion effects (see, e.g., Jorion and Zhang (2007)).

Additionally, we include the variable loan loss provisions. This variable is a proxy for the quality of a bank's loan portfolio and represents the losses that the bank expects to take due to uncollectable or troubled loans. In this context, Foos et al. (2010) argue that a higher loan growth coincides with a higher loan loss provision. A higher loan loss provision, however, could therefore be positively related to both banks' exposure and contribution to systemic risk.

We also consider the Tier 1 capital ratio, which is defined as the ratio of Tier 1 capital to total risk-weighted assets. Tier 1 capital represents the highest quality component of a banking firm's capital. It can fully absorb losses without interrupting a bank's business in any way. As a lower Tier 1 capital ratio could mean that the bank is unable to fully cover its losses in event of default, we expect Tier 1 capital to have a negative effect on banks' systemic risk (see, e.g., Kashyap et al. (2008), Hart and Zingales (2011)).

Deposits represent the total deposits to total liabilities ratio. Following the argumentation regarding the non-interest income and loans variables, banks that rely on traditional banking activities have higher deposit ratios. Moreover, the deposits variable illustrates that banks with a larger share of deposits in total assets have stable funding and contribute less to systemic risk relative to banks that rely on non-core banking activities to a greater extent (see Brunnermeier et al. (2012)).

We follow Fahlenbrach et al. (2012) and integrate a bank's lagged buy-and-hold returns as a proxy for bank performance. We expect this variable to be a predictor of the presence in bank's risk culture and therefore expect that banks that performed well in the past intend to perform well in the future, thereby contributing less to systemic risk.

One important dimension of systemic risk that the Basel Committee on Banking Supervision (2013) also identifies is the interconnectedness of a bank. Memmel and Sachs (2013) argue that a bank's interconnectedness together with bank size is the primary driver of systemic risk. These authors have access to detailed supervisory data and hence determine a bank's interconnectedness based on the interbank market. For highly interconnected banks, contagion effects in the event of a bank's default can easily be transmitted throughout the interbank market. Though information on banks' interbank loans are available from public sources, this variable does not provide any information about a bank's interconnectedness through the interbank market. Therefore, to analyze the interconnectedness of a bank within the global financial sector, we use the variable interconnectedness as introduced by Billio et al. (2012). This measure concentrates both the degree of connectedness between financial institutions and the directionality of banks' relationship based on Granger-causality estimations. We assume that a higher level of interconnectedness through the interbank market increases a bank's systemic risk contribution, as in the event of a bank's failure negative externalities are transmitted directly through the interbank lending channel. Conversely, a higher level of interconnectedness could reduce a bank's exposure to systemic risk. This could be because a bank can diversify its credit exposure through the interbank market, thereby being less exposed to substantial credit losses.

2.4 Descriptive Statistics

Table I presents annual mean estimates of our systemic risk measures and bank-specific variables.

— insert Table I here —

Beginning with the analysis of the systemic risk measures, we observe that the annual mean estimates register significant increases in both banks' exposure and contribution to systemic risk, especially during periods of financial market turmoil. An overview of the trends in our systemic risk measures over time is presented in Figure 4 and Figure 5. Figure 4 plots banks' annual mean dynamic MES for the full sample and for banks in the top and bottom quartile of dynamic MES.[12] Correspondingly, in Figure 5 the estimates of ΔCoVaR are plotted for the full sample and for the top and bottom quartiles of the distribution of ΔCoVaR. The analysis of our systemic risk measures reveals that, on average, banks' exposure to systemic risk, as measured by the dynamic MES, is clearly higher during periods of financial turmoil, e.g., during the Dotcom crash and the Subprime crisis.

[12] Banks that are in the first quartile of the distribution of dynamic MES represent banks that are on average highly exposed to systemic risk, while banks in the fourth quartile of the distribution of dynamic MES represent banks that are on average less exposed to systemic. In accordance, top quartile ΔCoVaR banks represent banks that are in the first quartile of the full sample's systemic risk contribution, and bottom quartile ΔCoVaR banks that are in the fourth quartile of the full sample's systemic risk contribution, i.e. banks with a high contribution to systemic risk.

Beginning with the analysis of a bank's exposure to systemic risk, we observe that the average dynamic MES exhibits an upward trend during the Dotcom crash in the year 2000 and during the Subprime crisis in 2008. More precisely, banks in the top dynamic MES quartile have an average dynamic MES of 6.01 %, while banks' average dynamic MES for the full sample is 2.03%. Especially during periods of financial market turmoil, banks in the top quartile of the distribution of dynamic MES exhibit significantly higher peaks than the average dynamic MES. Additionally, the analysis of ΔCoVaR, which is a proxy for a bank's contribution to systemic risk, indicates that banks' average contribution to systemic risk increased during financial crises. Again, banks in the bottom ΔCoVaR (i.e. banks with a high systemic risk contribution) quartile present a higher contribution with an average of minus 3% ΔCoVaR in comparison to the full sample average ΔCoVaR of minus 1%.

The analysis of the bank-specific variables in Table I reveals that bank size, as proxied by total assets, grew steadily over the observation period. The variable ranges from $ 94.5 billion in 1990 up to $ 256.6 billion in 2012. Analyzing banks' return on assets, we can observe that their average profitability increased during the pre-Subprime period and drastically decreased in the aftermath of the Subprime crisis in 2009. The analysis of banks' leverage reveals that at the beginning of the 1990s, banks were highly leveraged, while leverage decreased during the pre-Subprime crisis period. An increase in banks' leverage can again be observed after 2009.

The average bank performance varies widely across all years in our sample. While the minimum average bank performance is -41.9% in 1991, banks realized the best performance of 46.6% in 1998. For the period before and during the Subprime crisis, banks' yearly buy and hold returns range from 31.9% in 2004 to minus 38.3% in 2009.

To proxy for banking activity, we follow Brunnermeier et al. (2012) and Demirgüç-Kunt and Huizinga (2010). While Brunnermeier et al. (2012) define non-traditional income as the share of non-interest income divided by net interest income, Demirgüç-Kunt and Huizinga (2010) use a bank's operating income in the denominator. We construct a bank's non-interest income share as the share of non-interest income divided by the sum of total interest income and non-interest income. Non-interest income includes a bank's income from trading, fees and commissions. As these activities are not related to traditional banking activities, i.e., deposit-taking and lending, however, we investigate whether a bank's non-interest income share is a key determinant of systemic risk.

Figure 6 depicts the yearly average of the non-interest income share for all banks. The average non-interest income share ranges between 11% in 1990 up to 19.8% in 2004. With the beginning of the Subprime crisis in 2007, however, the non-interest income share decreased by 3 percentage points and in the aftermath of the financial crisis remains at a nearly constant level of 18%. This result is in line with the findings of Brunnermeier et al. (2012), who show that banks earned a higher portion of their profits from non-interest income than from interest income during the pre-crisis period. Following the introduction of the Gramm-Leach-Bliley Act in 1999, an increase in banks' non-interest income share for the post-1999 period can be observed.

In Figure 6, we further plot the non-interest income share when dividing our sample between large banks with total assets in excess of $ 1 billion and small banks with total assets below this threshold.[13] The figure shows, that larger banks rely more on non-traditional banking activities than smaller banks. For both bank categories, however, we nevertheless observe a decrease in non-interest income during the Subprime crisis. We also plot the frequency distribution of the banks' non-interest income share for the entire sample using a histogram (see Panel A of Figure 7). We use five intervals of size 0.2 between zero and one to depict the frequent observations for each of these intervals. For the full sample, the distribution of this variable indicates that banks have an average non-interest income share of 15%, while a non-interest income share of nearly one can only be observed for a very small portion of the sample. We further plot the frequency distribution of banks' non-interest income for banks in the first quartile distribution of dynamic MES (Panel B) and the fourth ΔCoVaR quartile (Panel C). Panel B of Figure 7 indicates that the non-interest income distribution is skewed to the left with only a small number of banks reporting a non-interest income share of zero. Similarly, in Panel C, the distribution of banks' non-interest income is also

[13] We use the threshold of $ 1 billion total assets in accordance to the FDIC and to check their findings as presented in Figure 2.

slightly left skewed. The average non-interest income for banks in the first dynamic MES quartile is 17% and that of banks in the fourth ΔCoVaR quartile is 18 %.

The analysis of the loans and loan loss provisions variables reveals that, on average, banks' loan ratios increased during the financial crisis and banks' loan loss provisions increased, even during the post-crisis period. However, the banks' total deposits ratio is on average 83%. During the Subprime crisis, the findings reveal a decrease in the banks' deposit ratios, while during the post-crisis period the banks' average deposit ratio again exceeds the full sample average.

The descriptive statistics on banks' foreign loans reveal that banks steadily decreased their positions in foreign loans. Similarly, the analysis of the entire period reveals that banks' cash and receivables from banks also decreased steadily in all years. Further, the banks' idiosyncratic volatility exhibits substantial variation over time. The average idiosyncratic volatility is approximately 28% and peaked during the Subprime crisis at 52%.[14]

Banks' average Tier 1 capital increases from the beginning of the 1990s, which at least in part reflects regulators' efforts to improve overall financial stability.

The interconnectedness variable, which was introduced by Billio et al. (2012), concentrates both the degree of connectedness between financial institutions and the directionality of banks' relationship based on Granger-causality estimations. The analysis of the variable illustrates that banks' interconnectedness increases during times of market turmoil. However, during the post-crisis period, banks returned to their pre-crisis interconnectedness-level.

In addition to our measures of systemic risk, we also estimate each bank's equity beta factor. The authors of several studies, e.g., Benoit et al. (2013) and Giglio et al. (2013), address the issue that the systemic risk measures, as employed in our empirical study, substitute for banks' beta factors. More precisely, Benoit et al. (2013) demonstrate that a bank's MES corresponds to the market's tail risk and a bank's tail risk, while ΔCoVaR can be related to the product of a bank's Value at Risk (VaR) and the linear projection coefficient of the market return of the bank's return.

[14] We also employ a bank's idiosyncratic volatility as a measure of ex-ante risk. We follow Beltratti and Stulz (2012) and estimate the idiosyncratic volatility as the annualized standard deviation of the residuals from the market model estimated using weekly bank returns and the Datastream U.S. Bank Index.

To address the concern voiced by the abovementioned studies, we estimate correlations between our systemic risk measures and banks' beta factors. In unreported results, we find an average correlation between banks' beta factors and dynamic MES of 23% and that between banks' beta factors and ΔCoVaR of minus 56%. We also estimate the correlations between the two systemic risk measures to address any concern that the dynamic MES and ΔCoVaR capture similar aspects of systemic risk. We find a correlation of minus 26% between the measures, which indicates that they measure distinct aspects of systemic risk.

3 Systemic risk and the U.S. financial system – The role of banking activity

In this section, we first analyze the nexus between banks' exposure and contribution to systemic risk. We estimate several regressions to investigate which factors determine a bank's exposure or contribution to systemic risk. Additional analyses are provided in the third part of this section. We briefly discuss the robustness of our analyses in the final subsection.

3.1 Univariate analysis

To analyze whether a bank's high systemic risk contribution also coincides with a high exposure to systemic risk, we apply several univariate analyses to investigate the nexus between the two systemic risk measures. In Panel A of Table II, we divide banks' systemic risk contribution as measured by ΔCoVaR into quartiles and present corresponding mean estimates of banks' dynamic MES. To investigate differences between the two measures in different time periods, we present results for the full sample, the Subprime crisis period and the pre- and post-1999 periods.

— insert Table II here —

The analysis of the full sample in Panel A indicates that an increase in banks' systemic risk contribution coincides with an increase in banks' dynamic MES. While banks in the first quartile of ΔCoVaR have a dynamic MES of 0.8%, banks in the fourth quartile of ΔCoVaR exhibit a mean dynamic MES of 4.9%. This effect is more pronounced during the Subprime crisis, where an average dynamic MES of 6.7% can be observed for banks in the fourth quartile of ΔCoVaR. With the introduction of the Gramm-Leach-Bliley Act in 1999, U.S. banks were allowed to engage in non-traditional banking activities to a greater extent. Many commentators argue that since its introduction in 1999, banks' increased engagement in non-core banking activities also resulted in an increase in systemic risk (see, e.g., Brunnermeier et al. (2012) and DeYoung and Torna (2013)). Dividing the full sample into the pre-and post-1999 periods consequently allows us to control for differences in banks' systemic risk exposure and contribution during both time periods. Again, with an increase in banks' systemic risk contribution, we can observe an increase in banks' systemic risk exposure. While for the pre-1999 period, banks' average mean dynamic MES is 1.5%, for the post-1999 period an average dynamic MES of 2.4% can be observed.

Based on Panel A of Table II, we divide banks with respect to their level of systemic risk exposure, i.e., dynamic MES, into quartiles and present corresponding mean estimates of ΔCoVaR. The main findings in Panel A of Table II can be confirmed, i.e., an increase in banks' exposure to systemic risk coincides with an increase in banks' systemic risk contribution. While the full sample analysis yields a mean estimate of banks' ΔCoVaR of minus 1.2%, the analysis of the Subprime crisis period from 2007 through 2009 yields an average ΔCoVaR of minus 1.9%. Differentiating between the pre-1999 period and the post-1999 period, the pre-1999 period exhibits a higher mean ΔCoVaR than the post-1999 period. More precisely, for the period before the introduction of the Gramm-Leach-Bliley Act in 1999, banks have a mean ΔCoVaR of minus 0.9%, and for the period following the introduction of the act (1999 through 2012), we observe a mean ΔCoVaR of minus 1.3%. Thus, an increase in the overall systemic risk contribution can be observed after 1999.[15]

To investigate whether banks in both the first and fourth of the quartile distribution of dynamic MES and ΔCoVaR differ in their bank-characteristics, we provide summary statistics in Table III.

[15] Which factors determine these increases and whether these increases can be directly associated with the introduction of the Gramm-Leach-Bliley Act will be analyzed in the following sections.

Panel A of Table III presents summary statistics for banks in the first and fourth quartiles of the distribution of banks' dynamic MES, while Panel B provides summary statistics for banks in the first and fourth ΔCoVaR quartiles. Beginning with Panel A of Table III, we note that banks in the first dynamic MES quartile differ significantly from banks in the fourth dynamic MES quartile in the systemic risk measures and several bank-specific characteristics. As in Table II, greater exposure to systemic risk coincides with a greater contribution to systemic risk. This effect is statistically significant.

— insert Table III here —

The analysis of the bank-specific variables reveals that banks in the first dynamic MES quartile, i.e., banks with a high exposure to systemic risk, have average total assets of $ 187 billion while the fourth dynamic MES quartile banks have average total assets of $ 16 billion over the entire period. Moreover, the analysis of the return on assets variable indicates that banks that are highly exposed to systemic risk are more profitable than banks that are less exposed. We also note that less exposed banks have higher leverage than banks that are highly exposed to systemic risk. The analysis of banks' banking activity reveals that banks in the first dynamic MES quartile rely on non-traditional banking activities to a greater extent than banks in the fourth dynamic MES quartile. More precisely, highly exposed banks have a non-interest income share of 17%, while less exposed banks have a non-interest income share of 14%. This result is also indirectly supported by the finding that the sample of highly exposed banks is characterized by a significantly higher reliance on traditional banking activities such as loan-making and deposit-taking. Moreover, average performance, as measured by the lagged annual buy and hold returns, reveals that highly exposed banks performed 2 percentage points better on average than less exposed banks. Additionally, we find that banks in the first quartile of the dynamic MES distribution are more interconnected through the interbank market. However, the Tier 1 capital ratio is significantly lower for these banks than for those in the fourth quartile of the dynamic MES distribution.

The analysis in Panel B of Table III reports the differences between banks in the first and fourth ΔCoVaR quartiles with respect to the systemic risk measures and several bank-specific characteristics.[16] Again, our findings from Table II and Panel A of Table III are supported with respect to the systemic risk measures. The analysis of the bank-specific variables, however, indicates that the sub-sample of banks that contribute highly to systemic risk (fourth ΔCoVaR quartile) have average total assets of $ 244 billion while the sub-sample of banks that contribute to a less extent to systemic risk (first ΔCoVaR quartile) have average total assets of $ 12 billion over the sample period. Further, the sub-sample of banks that make substantial contributions to systemic risk have a higher return on assets ratio and better performance than the sub-sample of banks that contribute less to systemic risk. Comparing the two groups with respect to their engagement in banking activities, we observe that banks that contribute to systemic risk to a greater extent on average have a non-interest income share of 18%, while the sub-sample of banks with a less contribution to systemic risk have a non-interest income share of 13%. This result can indirectly be supported by the findings that the latter banks also rely on deposit-taking and loan-making activities to a relatively greater extent. Moreover, banks in the fourth ΔCoVaR quartile, and hence a higher average contibution to systemic risk, are also more interconnected through the interbank market. Interestingly, the two bank groups do not significantly differ in their mean levels of ex-ante risk, as measured by the idiosyncratic volatility variable. Interestingly, the analysis of the Tier 1 capital ratio reveals that banks that contribute more to systemic risk have a significantly lower Tier 1 capital ratio than banks that contribute on average less to systemic risk.

Additionally, we compare banks in the first dynamic MES quartile with banks in the fourth ΔCoVaR quartile to investigate whether banks that are, on average, more exposed and those that contribute substantially to systemic risk differ in their systemic risk measures and bank-specific variables (see Panel C of Table III). The results indicate that the two samples have statistically significantly different means in their systemic risk and certain bank-specific variables. Specifically, banks that contribute highly to systemic risk are on average larger, more profitable and less leveraged than banks that are highly exposed to systemic risk. However, the two groups do not statistically significantly differ in their banking activities as proxied by the non-interest income

[16] Banks in the first ΔCoVaR quartile represent banks that do not contribute highly to systemic risk, while banks in the fourth ΔCoVaR quartile represent banks that contribute highly to systemic risk.

share and loans variables.

3.2 Which factors explain banks' exposure and contribution to systemic risk?

In this section, we present the results of our baseline regressions to investigate which factors determine banks' exposure and contribution to systemic risk. The dependent variables are the annual mean dynamic MES, which is a proxy for banks' exposure to systemic risk, and the annual mean ΔCoVaR to proxy for banks' contribution to systemic risk. Using Fama-MacBeth style regressions, we regress our dependent variable on a set of bank-specific characteristics.

As our dependent variables stem from a first-stage-estimation, we correct standard errors for heteroscedasticity and possible autocorrelation following Newey and West (1987) and therefore use Newey-West standard errors. Further, our dependent variable and some of our independent variables could be determined simultaneously. Therefore, we lag all explanatory variables by one year. To analyze both the economic and statistical significance of our estimated coefficients, all regression coefficients are standardized with zero mean and unit standard deviation. An increase in an estimated coefficient implies the effect of a one-standard-deviation increase in the explanatory variable on the respective systemic risk measure.[17]

— insert Table IV here —

The dependent variable in models (1) through (5) is banks' annual mean dynamic MES and in models (6) through (10) is banks' annual mean ΔCoVaR. Beginning with the analysis of the full sample in Table 6, we observe that bank size enters our regression with a significant, positive sign. This result supports the view of the Basel Committee on Banking Supervision (2013) that bank size is an important dimension of systemic risk. More precisely, bank size is positively related to banks' exposure to systemic risk, as larger banks have higher direct exposures to other banks

[17] In unreported results, we analyzed whether our estimations could suffer from multicollinearity. Testing the models' variance inflation factors reveals that our regressions do not suffer from multicollinearity.

through the interbank market. Moreover, larger banks are also indirectly exposed to systemic risk through information contagion (see, e.g., Barth and Schnabel (2013)). A one-standard-deviation increase in banks' total assets thus increases the annual dynamic MES by 100 basis points. Moreover, leverage has both a statistically and economically significant effect on dynamic MES. This result supports the view of Berger and Bonaccorsi di Patti (2006), who argue that more leveraged banks have a lower default probability and therefore are less exposed to systemic risk. Moreover, we find that high profitability, as proxied by the return on assets variable, decreases a bank's systemic risk exposure.

As in Table III, we divide our sample into the first and fourth quartiles of the distribution of dynamic MES to investigate which bank-specific variables determine banks' systemic risk exposure. Model (2) provides the estimation results of our sub-samples of banks in the first dynamic MES quartile while model (3) does so for banks in the fourth dynamic MES quartile.

In line with our findings for the full sample, model (2) indicates that bank size is positively related to banks' systemic risk exposure. However, the leverage variable now enters our regression with a statistically significant positive sign. This result supports the findings of Shleifer and Vishny (2010), Brunnermeier et al. (2012) and Beltratti and Stulz (2012), who demonstrate that highly leveraged banks contribute more to systemic risk. More interestingly, the non-interest income share variable enters our regression with a statistically significant sign. This result implies that non-interest income is a significant driver of dynamic MES for our sample of high exposed banks. Moreover, we find that the loans variable is negatively related to dynamic MES. As the loans variable represents banks' engagement in traditional banking activities, the argumentation advanced regarding the non-interest variable can be confirmed. Although the analysis of the sub-sample of banks in the fourth dynamic MES quartile in model (3) shows that leverage and non-interest income share do not enter the regression with statistically significant signs, a higher loan ratio coincides with a significant decrease in banks' systemic risk exposure. In models (4) and (5), we perform further sub-sample analyses and divide our full sample into two samples of large and small banks. We follow the argumentation of the Dodd-Frank Act of 2010 that considers banks to be systemically important if they have total assets in excess of \$ 50 billion. Therefore, we define our sample of large banks to include banks with total assets in excess of \$ 50 billion and our sample of small banks those having total assets below \$ 50 billion. For both sub-samples, we observe that bank size is positively related to banks' systemic risk exposure. Again, and in line with the full sample analysis, bank profitability, as measured by the return on assets variable, is negatively related to systemic risk. Additionally, for small banks we find that higher leverage significantly decreases banks' systemic risk exposure (see, e.g., Berger and Bonaccorsi di Patti (2006)).

Model (6), performing the full sample analysis of banks' contribution to systemic risk, as measured by ΔCoVaR, reveals that bank size and interconnectedness are key drivers of ΔCoVaR. These findings support the argument of the Basel Committee on Banking Supervision (2013), which argue that contagion effects in the banking system are easily transmitted throughout the banking system, especially for highly interconnected and large banks. On the one hand, larger banks contribute more to systemic risk because a shock, e.g., the default of a bank or negative information about the bank, is more likely to be transmitted through the interbank market directly, via the credit-channel, and indirectly via the information-contagion channel. Model (6) also indicates that bank leverage is not positively related to a bank's contribution to systemic risk. More precisely, we cannot find support for the findings of Shleifer and Vishny (2010), Brunnermeier et al. (2012) and Beltratti and Stulz (2012), who report that highly leveraged banks contribute more to systemic risk. Instead, our results support the findings of Berger and Bonaccorsi di Patti (2006), who show that highly leveraged banks are able to reduce their default probability in contrast to less leveraged banks, thus reducing their contribution to systemic risk.

As we are interested in whether the determinants of a bank's contribution to systemic risk differ between banks, we again divide our sample into the first and fourth quartile of the distribution of ΔCoVaR. For our sub-sample of banks in the first quartile of ΔCoVaR, we only find bank size to be positively related to a higher contribution to systemic risk. The coefficient on total assets enters our regression with a statistically and economically significant sign, yielding a decrease in ΔCoVaR of 11 basis points and hence an increase in the contribution to systemic risk. The findings from model

(8) (fourth ΔCoVaR quartile) support the results of our full sample analysis, where we found bank size to be positively related and leverage negatively related to banks' contributions to systemic risk. Further, we find that including banks' lagged performance decreases their contribution to systemic risk.

Again, we use the threshold of \$ 50 billion in total assets to divide our sample into large and small banks. The estimates from model (9) reveal that bank size and interconnectedness are again the key drivers of banks' contributions to systemic risk. These findings support the argument advanced by the Basel Committee on Banking Supervision (2013) that banks' interconnectedness is also a driver of systemic risk. Moreover, banks' banking activity is also a main driver of systemic risk, although this is only statistically significant for large banks. However, this result supports the notion that greater reliance on non-core banking activities such as trading income, fees and commissions increases banks' contributions to systemic risk. Specifically, larger banks have the ability to enter new businesses because they have easier access to capital and infrastructure (see, e.g., Demirgüç-Kunt and Huizinga (2013)). However, banks that expand their non-interest income sources could be more exposed to risk than banks that rely more on traditional banking activities. This can also be related to banks' lack of experience in non-traditional banking activities. Moreover, the deposits variable enters model (9) with a statistically significant positive sign. This result supports the argument regarding the non-interest income variable that traditional banking activities, i.e., deposit-taking, significantly reduces banks' contributions to systemic risk. Additionally, for the sub-sample of small banks, we find that a high performance in the previous year has a significant effect on ΔCoVaR, i.e. that banks' contribution to systemic risk decreases (see, e.g., Fahlenbrach et al. (2012)). Our findings imply, that larger banks that diversify their income sources into more non-traditional banking activities contribute significantly more to systemic risk.

We repeat our baseline regressions for the period of the Subprime crisis to assess whether the determinants of both systemic risk measures remain unchanged. As conducting estimates for the period of the Subprime crisis via Fama-MacBeth style regressions is not appropriate, we use Ordinary Least Squares (OLS) regressions. Following Beltratti and Stulz (2012) and Fahlenbrach et al.

(2012), we estimate the dynamic MES and ΔCoVaR for the period from January 2007 through December 2008. The mean estimates are then used as our dependent variables. As our dependent variables stem from a first-stage estimation, the regression could suffer from both heteroscedasticity and inconsistent standard error estimates. To mitigate this issue, we follow Lewis and Linzer (2005). The authors use heteroscedasticity-consistent Huber-White standard errors to correct for inconsistent OLS standard errors.[18]

— insert Table V here —

Table V presents the results of our baseline regression for the full sample of banks.[19] The dependent variable in model (1) is banks' mean annual dynamic MES and in model (2) is banks' mean annual ΔCoVaR. The two models yield similar results with respect to the determinants of systemic risk during the Subprime crisis. For both models, the coefficient total assests is highly economically and statistically significant. Moreover, and in line with our full sample analysis in Table IV, higher leverage coincides with a decrease in systemic risk. Banks' interconnectedness through the interbank market is only a significant driver of banks' contributions to systemic risk. The pre-crisis performance of banks, however, measured in model (1) indicates that high pre-crisis performance coincides with an increase in banks' systemic risk exposure. Tier 1 capital does not enter our regressions in either model with a statistically significant sign.[20] In conclusion, we find that the determinants in the two systemic risk specifications do not significantly differ during the Subprime crisis, with exception of banks' interconnectedness and performance.

3.3 Additional analyses

In the previous subsection, we find that bank size and banking activities are determinants of both systemic risk specifications. To investigate the nexus between bank size, banking activity

[18] We also repeat the regressions using Newey-West standard errors. Our main findings remain unchanged. Moreover, we divide our sample into the periods of 2007 and 2008 and repeat the OLS-regressions using White-Huber standard errors. However, we believe our results in Table V to be robust.

[19] Additionally, we consider the Tier 1 capital variable as a further explanatory variable in our OLS-regressions.

[20] The results are estimated using the full sample. However, our main findings do not change significantly when considering sub-samples of top and bottom quartiles of the exposed or contributing banks.

and both banks' exposure and contribution to systemic risk, respectively, we split our sample into quartiles.

— insert Table VI here —

Panel A of Table VI reports banks' mean dynamic MES for double-sorts of bank size and banking activity, while Panel B presents banks' mean ΔCoVaR. The results in Panel A illustrate that banks' exposure to systemic risk increases with an increase in bank size. For banks below the median bank size level, higher levels of non-interest income do not result in an increase in dynamic MES. In contrast, for banks in the first and second quartiles of the distribution of total assets, an increase in dynamic MES can be observed together with an increase in banks' non-interest income share. Similar results can be observed for Panel B. The systemic risk contribution of banks increases in bank size. A higher non-interest income share, in contrast, does not coincide with an increase in ΔCoVaR. Only a higher bank size level together with an increase in banks' non-traditional banking activity results in a higher systemic risk contribution. The results illustrate that larger and more diversified banks are systemically more important than smaller and less diversified banks, underlining the findings of previous studies (see, e.g., De Jonghe et al. (2014), Brunnermeier et al. (2012) and Adrian and Brunnermeier (2011)). This too-big-to-fail paradigm, however, requires regulators and policymakers to assess, amongst other factors, a bank's optimal size to limit its systemic importance. [21]

As a further additional analysis, we employ the quantile-regression technique to reveal whether extreme values in banks' exposure and contribution to systemic risk are determined by the same set of bank-specific characteristics as investigated in our baseline regressions. Koenker and Bassett (1978) first introduced quantile-regression analyses, while a recent survey is presented in Koenker and Hallock (2001). This technique allows us to perform a more comprehensive analysis of the extreme values of our systemic risk measures and our set of bank-specific

[21] We repeat these analyses for the periods before and after 1999 (introduction of the Gramm-Leach-Bliley Act) as well as for the Subprime crisis. We find similar results, though and not surprisingly both systemic risk measures increase during the Subprime crisis but do not change our conclusions.

variables. Therefore, we use the 95%-quantile of each bank's dynamic MES as the dependent variable to capture extreme values in banks' systemic risk exposure and the 5%-quantile of ΔCoVaR to capture extreme values in banks' systemic risk contributions. We re-estimate our baseline regression using Fama-MacBeth style regressions with Newey-West standard errors to control for possible autocorrelation and heteroscedasticity in the standard errors. Table VII presents the results of our estimations. Models (1) to (3) use the 95%-quantile of each bank's dynamic MES, while models (4) to (6) use the 5%-quantile of ΔCoVaR as dependent variables. Again, all explanatory variables are lagged by one year and standardized with zero mean and unit standard deviation. In accordance with our baseline estimations, we again use the full sample and sub-samples of large and small banks to detect any differences in the determinants of systemic risk.

Beginning with the analysis of banks' extreme values in dynamic MES, we find for the full sample that bank size is significantly positively related to extreme values in banks' dynamic MES. This result is in line with the findings in our baseline regressions, thereby supporting the Bank for International Settlements' argument that larger banks can explain extreme values in banks' systemic risk exposure. The analysis of large banks in model (2) reveals that only bank size enters our regression with a statistically significant sign, which implies that extreme values in dynamic MES can only be explained by bank size in our sample of large banks. For small banks, however, we fail to confirm that bank size is an important driver of systemic risk. We find that higher profitability decreases and higher lagged buy and hold return and higher loan loss provision increase extreme values in dynamic MES and hence banks' exposure to systemic risk for our sample of small banks.

The analysis of ΔCoVaR reveals that in all three models, bank size and interconnectedness significantly increase a bank's systemic risk contribution. In contrast to our baseline regressions, we also find for the full sample that a high loan loss provision increases a bank's extreme value in ΔCoVaR. Comparing the sub-samples of large and small banks, we find that banks' non-interest income share remains a significant driver of ΔCoVaR for our sample of large banks. This result is in line with the findings of De Jonghe et al. (2014), who argue that larger banks diversify their income sources and greater diversification coincides with an increase in systemic risk. In line with the argument advanced regarding the non-interest income variable, we find that the deposits variable enters our regression with a statistically significant positive sign, which reveals that a higher reliance on deposit-taking and hence traditional banking activities significantly decreases banks' contribution to systemic risk. The findings for the sample of small banks are qualitatively similar to those found in our baseline regressions.

3.4 Robustness checks

In this section, we present the results of a number of robustness checks. Our main findings indicate that both the statistical and economic significance of our main findings in the previous sections are robust. We begin with a robustness check on banking activity. We also repeat our baseline regressions using additional explanatory variables. Finally, we investigate alternative systemic risk measures and some further robustness checks.

3.4.1 Robustness checks on banking activity

As a first robustness check, we divide the non-interest income variable into its constituents. As the non-interest income share variable incorporates various constituents of non-traditional banking, we perform further analyses to assess the relationships between these constituents and both systemic risk specifications. Following DeYoung and Rice (2004), DeYoung and Torna (2013) and Demirgüç-Kunt and Huizinga (2010), we categorize banks' non-interest income share into two components: a trading component and a non-trading component. DeYoung and Torna (2013) argue that trading activities place equity capital at risk, as movements in market prices can result in a profit or loss. Conversely, they argue that banking activities that are based on fees and commissions are not subject to capital losses.[22] Following this line of argumentation, we hypothesize that disaggregating banks' non-interest income into its constituents can reveal the importance and

[22] The authors extend this notion and argue that non-trading activities, however, can place capital at risk, as revenue streams may not cover their associated fixed costs.

hence the significance of each constituent in banks' exposure or contribution to systemic risk.

We use the first quartile of the distribution of dynamic MES and the fourth quartile of ΔCoVaR and again employ Fama-MacBeth style regressions.[23] Beginning with the dynamic MES as the dependent variable, the analysis of the constituents reveals that neither banks' trading share nor the share of fees and commissions enters our regression with a statistically significant sign. In contrast, the analysis using ΔCoVaR as the dependent variable reveals that disaggregating the non-interest income share into trading and non-trading activities indicates that fee-based activities are not significant determinants of banks' systemic risk contribution, while trading-based activities appear to decrease ΔCoVaR. Put differently, this finding indicates that diversification into liquid, non-core banking activities increases a bank's contribution to systemic risk.

We also investigate whether the enactment of the Gramm-Leach-Bliley Act in 1999 and hence banks' ability to engage in non-traditional banking activities to a greater extent contributed to an increase in systemic risk. Specifically, our main findings in the previous subsections are that with an increase in both bank size and banks' engagement non-traditional banking activities entails an increase in both systemic risk measures. Therefore, we divide the sample of large banks into the pre- and post-1999 periods to assess whether the determinants of the two systemic risk measures (i.e., dynamic MES and ΔCoVaR) differ during both periods.[24] Table VIII presents the results of our estimations. The dependent variable in model (1) and model (2) is banks' annual mean dynamic MES and in model (3) and (4) is banks' annual mean ΔCoVaR. Models (1) and (3) represent the sub-sample for the pre-1999 period, while models (2) and (4) refer to the post-1999 period.[25] Beginning with the analysis of models (1) and (2), as for our sub-sample of large banks, we again find that the main driver of systemic risk exposure is bank size. Comparing the pre-1999 and post-1999 periods, we find that banks' interconnectedness and lagged bank performance are the main

[23] Again, we use Newey-West standard errors to correct for possible autocorrelation or heteroscedasticity that might stem from using a first-stage estimation of our dependent variables. Moreover, all explanatory variables are lagged by one year and standardized with a unit standard deviation and zero mean on an annual basis.

[24] In accordance with our baseline regressions, we use Fama-MacBeth style regressions with Newey-West standard errors to control for possible autocorrelation and heteroscedasticity in the standard errors.

[25] In unreported results, we also excluded the Subprime crisis from 2007 through 2009 for the post-1999 period to eliminate any biasing effect in our results due to the financial crisis. Our main findings, however, are qualitatively robust.

drivers of dynamic MES for the pre-1999 period. In contrast, for the post-1999 period, neither variable is statistically significant. Additionally, we find no evidence that banks' exposure to systemic risk is determined by their involvement in non-traditional banking activities, which reflects the robustness of our findings on large banks. Interestingly, we find that for the period 1990-1998, a large loan ratio decreased banks' exposure to systemic risk, while for the post-1999 period, a larger loan ratio coincides with an increase in systemic risk. When considering ΔCoVaR as our dependent variable, we find for the pre-1999 period that bank size and interconnectedness enter our regressions with negative signs, thus indicating that both variables are key drivers of banks' contributions to systemic risk (see Basel Committee on Banking Supervision (2013)), while increased leverage coincides with a decrease in banks' contribution to systemic risk for the period 1990-1998. Interestingly, for the post-1999 period, we further find that banks' non-interest income share, which is a proxy for banks' involvement in non-traditional activities, is positively related to banks' contribution to systemic risk; however, for the period 1990-1998, non-traditional banking activities are not significantly related to banks' systemic risk contributions. This implies that following the enactment of the Gramm-Leach-Bliley Act in 1999, banks' involvement in non-traditional banking activities and hence substantial diversification in their income sources increased their systemic risk contributions. This result is especially pronounced for large banks, which emphasizes the need for a comprehensive regulation on bank size and banking activity in future political and regulatory decisions.

As a further robustness check, we refer to the argument advanced by Kim et al. (2008) that banks engaged in non-traditional banking activities to a greater extent far before the enactment of the Gramm-Leach-Bliley Act in 1999. The Fed allowed banks to undertake such activities, which were called Section 20 subsidiaries. We control for this argument and use a Welch two-sample *t*-test to examine differences in the means of banks' non-interest income surrounding the period of the enactment of the Gramm-Leach-Bliley Act. The results reveal that between 1997 and 1998, no significant difference in the sample means of non-interest income can be observed, while the Welch two-sample *t*-test for 1998 and 1999 shows that the sample means in non-interest income, in contrast, are statistically significantly different from zero. This suggests that an increase in banks' non-traditional banking activities can be related to the introduction of the Gramm-Leach-Bliley Act in 1999.

Moreover, we employ additional definitions of banks' non-interest income share to proxy for non-core banking activities. Following the definition of the non-interest income share advanced by Brunnermeier et al. (2012), we find that using this definition of the variable supports the main findings from our regressions. Moreover, we also use the definition of the FDIC, i.e., non-interest income in total net operating income. We believe our results to be robust.[26]

3.4.2 Robustness checks for the baseline regressions

To complement our previous findings from the regression analyses, we consider several additional explanatory variables to investigate their impact on systemic risk. We begin with the Tier 1 capital variable and investigate the effect of Tier 1 capital on dynamic MES. We include this variable to determine whether a higher Tier 1 capital ratio can reduce banks' systemic risk exposure. However, the variable is neither statistically nor economically significant. Interestingly, we find that for our sample of large banks, a higher Tier 1 capital ratio can significantly decrease banks' contribution to systemic risk. This effect can be explained by banks' ability to absorb possible losses when they enjoy a higher Tier 1 capital ratio, thereby reducing the banks' default probability and possible contagion effects through the financial market. This result illustrates the need to consider this capital ratio to improve overall financial stability, as the variable enables banks to absorb losses and hence reduce their contributions to systemic risk. Again, we find a nearly identical set of variables to be significant determinants of ΔCoVaR as in our baseline regressions.

We also consider the foreign loans and cash and due from banks variables. A higher share of foreign loans in total assets in banks' credit portfolios indicates that banks engage in cross-jurisdictional activities to a greater extent, which the Basel Committee on Banking Supervision (2013) identifies as a further driver of systemic risk. A greater cross-jurisdictional loan-

[26] The correlation between our definition of banks' non-interest income share with the non-interest income ratio used by Brunnermeier et al. (2012) is 79%, while the correlation with the variable used by the FDIC is 90%.

diversification, however, could result in lower exposure or contribution to systemic risk. A higher share of cash and receivables can be a driver of systemic risk, especially during crisis periods, as a bank cannot easily absorb losses from the interbank market during periods of financial market turmoil. However, neither variable enters our regressions with a statistically or economically significant sign.

We also assess whether bank liquidity has influences on banks' systemic risk exposure or contribution to systemic risk. More precisely, we find that banks in the first dynamic MES and fourth ΔCoVaR quartiles are more liquid than banks in the fourth, respectively, first quartile of the respective systemic risk measure. As a measure of an individual stock's liquidity, we use a variant of the Amihud measure proposed by Karolyi et al. (2012). They adjust the Amihud liquidity measure by adding a constant and taking the natural logarithm of the original Amihud measure to minimize the effect of outliers. The resulting measure is multiplied by negative 1 to yield a measure that increases in the stock's liquidity. We then estimate a regression in which we include the annual mean of the daily-adjusted Amihud measures as a further explanatory variable. The coefficient of the adjusted Amihud measure of liquidity is not significant, and its inclusion does not affect our conclusions.

3.4.3 Alternative measures of systemic risk

Both systemic risk measures, dynamic MES and ΔCoVaR, are estimated using stock market data and not accounting data. Therefore, we also estimate the SRISK, as proposed by Acharya et al. (2012). Using this alternative measure helps to concentrate bank-specific characteristics, e.g., size, leverage and the downside risk effect of equity, in a single risk measure. Therefore, this systemic risk measure represents a bank's contribution to systemic risk. We compare the results of our SRISK estimation to our previous results using ΔCoVaR. However, our main results remain qualitatively robust.

We also estimate the Marginal Expected Shortfall in a static fashion, as proposed by Acharya et al. (2010). Comparing the static MES with the dynamic MES, we find that our main findings are robust.

Moreover, it could be argued that our results are primarily driven by averaging the daily dynamic MES and ΔCoVaR. To control for this potential bias, we consider the maximum daily dynamic MES and the minimum ΔCoVaR in a year as further dependent variables in our robustness checks. Again, our results are not affected, and our main conclusions remain unchanged.

3.4.4 Further robustness checks

As a further robustness check, we use panel-estimations with time-fixed effects and robust clustered standard errors to assess the robustness of our results using Fama-MacBeth style regressions. We believe our results to be robust, as our results remain qualitatively unchanged.

As the Basel Committee on Banking Supervision (2013) does not directly differentiate between systemic risk exposure and contributions to such risk, we construct a sample of banks that are highly exposed to systemic risk and simultaneously contribute substantially to systemic risk. We assess whether the two measures have the same determinants with respect to systemic risk and could therefore justify the synonymous use of systemic risk per se. However, we do not find support for this conjecture, as the results from our previous regressions remain qualitatively unchanged.

We also check the robustness of our results to a change in the index we employ to estimate our measures of systemic risk. To this end, we re-estimate the dynamic MES and ΔCoVaR using the *MSCI World Financials* index as a proxy for the global financial sector portfolio. We find that our conclusions remain qualitatively unchanged.

4 Conclusion

Systemic risk in the U.S. financial sector has been of substantial interest to regulators and policymakers, even prior to the recent financial crisis. The Subprime crisis demonstrated relevance of identifying systemic risks and, from a regulatory perspective, the necessity of limiting them. However, an explicit differentiation between banks' exposure and contribution to systemic risk has yet to be performed. This paper represents the first attempt to fill this gap. We analyze the nexus between a bank's exposure and contribution to systemic risk. Our findings indicate that a high level of exposure to systemic risk coincides with a high contribution to systemic risk.

To investigate whether the two systemic risk specifications are determined by the same set of bank-specific characteristics, we conduct several estimations. We find that bank size is a significant driver of both banks' exposure and contribution to systemic risk. As the enactment of the Gramm-Leach-Bliley Act in 1999 allowed banks to engage in non-traditional banking activities to a greater extent, we are interested in whether banks' non-interest income share became a significant determinant of systemic risk. We find that banks' engagement in non-traditional banking activities results in an increase in their contributions to systemic risk. This effect becomes more detrimental as bank size increases. Furthermore, we also demonstrate that a bank's interconnectedness through the interbank market is positively related to a bank's contribution to systemic risk. Among other factors, the Basel Committee on Banking Supervision (2013) has identified banks' interconnectedness as a main driver of systemic risk. However, we can only support their finding regarding banks' contributions to systemic risk. During the Subprime crisis however, both systemic risk measures are primarily driven by the same set of bank characteristics.

Our findings have relevant implications for both regulators and politicians. First, we demonstrate that beneficial regulation of systemic risk should account for both systemic risk specifications, i.e., a bank's exposure and contribution to systemic risk. On this basis, the effect of a bank's contribution to systemic risk, as the failure of *Lehman Brothers* in 2008 demonstrated, should have attracted the attention of regulators and politicians, as the collapse resulted in a drastic increase in systemic risk contributions and had consequences for overall financial stability. Second, this paper documents that an increase in size is positively related to systemic risk, and hence a reduction in bank size can decrease systemic risk. From a regulatory perspective, diversification into non-core banking activities can increase banks' ability to cope with negative externalities in the financial system. However, the implications for banking activity are unclear. While an increase in banking activity does not affect banks' exposure to systemic risk, this effect is more important with respect to banks' contributions to systemic risk. Consequently, forcing banks, particularly larger ones, to disclose their banking activities and limit their involvement in non-core banking activities could reduce their systemic risk contributions and hence lead to a higher overall financial stability.

However, the findings in our paper should be interpreted with caution. First, we only examine the U.S. financial market and do not investigate the effect of non-core banking activities among an international sample of banks. Moreover, the analysis of the determinants of systemic risk exposure and contribution could also be driven by country-specific characteristics or the regulatory environment faced by a specific bank. Second, we controlled for the effect of the constituents of the non-interest income variable and found that trading activities are positively related to a bank's contribution to systemic risk. However, a finer disaggregation of the non-interest income variable and its effects on systemic risk would be desirable, although this was not possible in this paper due to data availability. We leave both aspects for future research.

Appendix I: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The bank characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Dependent variables		
MES	Annual Marginal Expected Shortfall as defined by Acharya et al. (2010) as the average return on an individual bank's stock on the days the *World Datastream Bank* index experienced its 5% worst outcomes.	Datastream, own. calc.
Dynamic MES	Dynamic Marginal Expected Shortfall as defined by Acharya et al. (2010) and calculated following the procedure laid out by Brownlees and Engle (2012).	Datastream, own. calc.
ΔCoVaR	Conditional ΔCoVaR as defined by Adrian and Brunnermeier (2011), measured as the difference between the Value-at-Risk (VaR) of a country-specific financial sector index conditional on the distress of a particular bank and the VaR of the sector index conditional on the median state of the bank. As state variables for the computation of conditional ΔCoVaR, we employ the change in the three-month Treasury bill rate, the difference between the ten-year Treasury Bond and the three-month Treasury bill rate, the change in the credit spread between BAA-rated bonds and the Treasury bill rate, the return on the Case-Shiller Home Price Index, and implied equity market volatility from VIX.	Datastream, Chicago Board Options Exchange Market, Federal Reserve Board's H.15, S&P, own. calc.
SRISK	Average annual estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2012). The SRISK estimate for bank i at time t is given by $SRISK_{i,t} = k\,(Debt_{i,t}) - (1-k)\,(1 - LRMES_{i,t})\,Equity_{i,t}$ where k is set to 8% to denote the regulatory capital ratio, $Debt_{i,t}$ is the bank's book value of debt, $LRMES_{i,t}$ is the long run Marginal Expected Shortfall defined as $1 - \exp(-18 \cdot dynMES)$, $dynMES$ is the dynamically estimated MES and $Equity_{i,t}$ is the banks's market value of equity.	Datastream, own. calc.
Bank characteristics		
Total assets	Natural logarithm of a bank's total assets at fiscal year end.	Worldscope (WC02999).
Return on assets	Ratio of banks return on assets.	Worldscope (WC08326).
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210 and WC03501).
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity (see Acharya et al., 2010).	Worldscope (WC02999, WC03501, WC08001), own calc.
Non-interest income share	Non-interest income divided by the sum of total interest income and non-interest income.	Worldscope (WC01021 and WC01016)
Loans	Ratio of total loans to total assets	Worldscope (WC02271 and WC02999).
Loan loss provisions	Natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans.	Worldscope (WC01271).
Foreign loans	Ratio of foreign loans to total assets.	Worldscope (WC02271 amd WC02999).
Cash & due from banks	Ratio of cash & due from banks to total assets	Worldscope (WC02004 and WC02999).
Idiosyncratic volatility	Annualized standard deviation of residuals from the market model estimated with bank weekly returns as dependent variable. The market portfolio is the Datastream U.S. bank index.	own. calc.

Appendix I: Variable definitions and data sources. (continued)

Variable name	*Definition*	*Data source*
Tier 1 capital	Ratio of Tier 1 capital to total risk-weighted assets	Worldscope (WC18157).
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251 and WC03255).
Deposits	Total deposits divided by total liabilities.	Worldscope (WC03019 and WC03351).
Performance	Buy-and-hold returns of a bank lagged by one year.	Datastream, own. calc.
Liquidity	Amihud measure of an individual stock's illiquidity adjusted following the procedure proposed by Karolyi et al. (2012). The adjusted Amihud measure is defined as $-\ln\left(1+\frac{\lvert R_{i,t}\rvert}{P_{i,t}VO_{i,t}}\right)$ where $R_{i,t}$ is the return, $P_{i,t}$ is the price and $VO_{i,t}$ is the trading volume of stock i on day t.	Datastream, own calc.
Interconnectedness	The number of connections of each banking firm to other banks (sum of in and out connections) as defined by Billio et al. (2012).	Datastream, own calc.

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Figures and Tables

Figure 1: Development of the share of non-interest income in net operating revenue, 1990-2012.

This figure plots the quarterly share of non-interest income in net operating income revenue from 1984-2012. Data source: Aggregate data from FDIC.

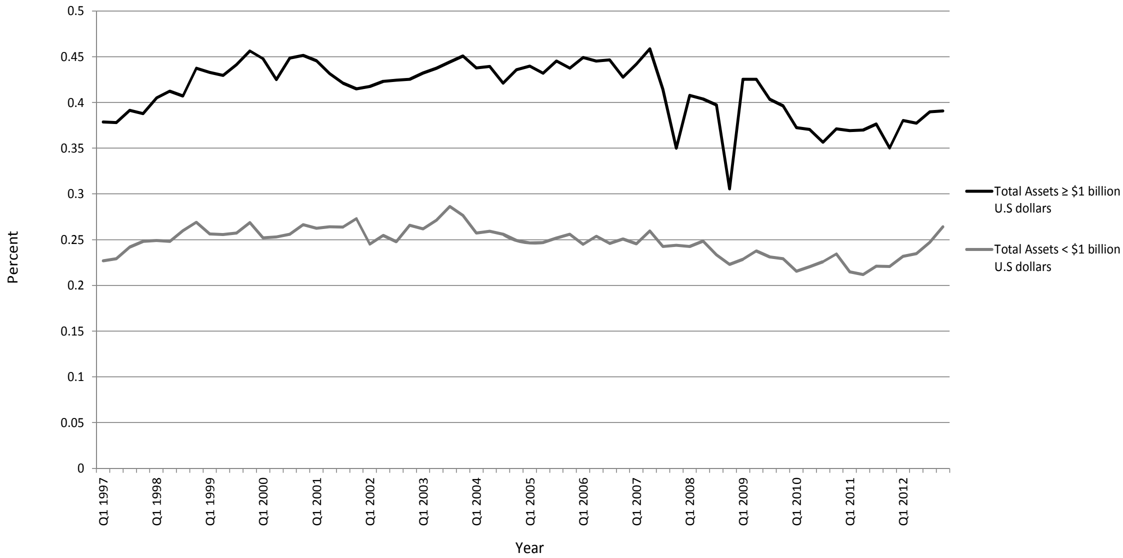

Figure 2: Development of the share of non-interest income in net operating revenue categorized by bank size, 1997-2012.

This figure plots the quarterly share of non-interest income in net operating income revenue from 1997-2012 for banks with total assets in excess of $ 1 billion U.S. dollars and for banks with total assets below $ 1 billion U.S. dollars. Data source: Aggregate data from FDIC.

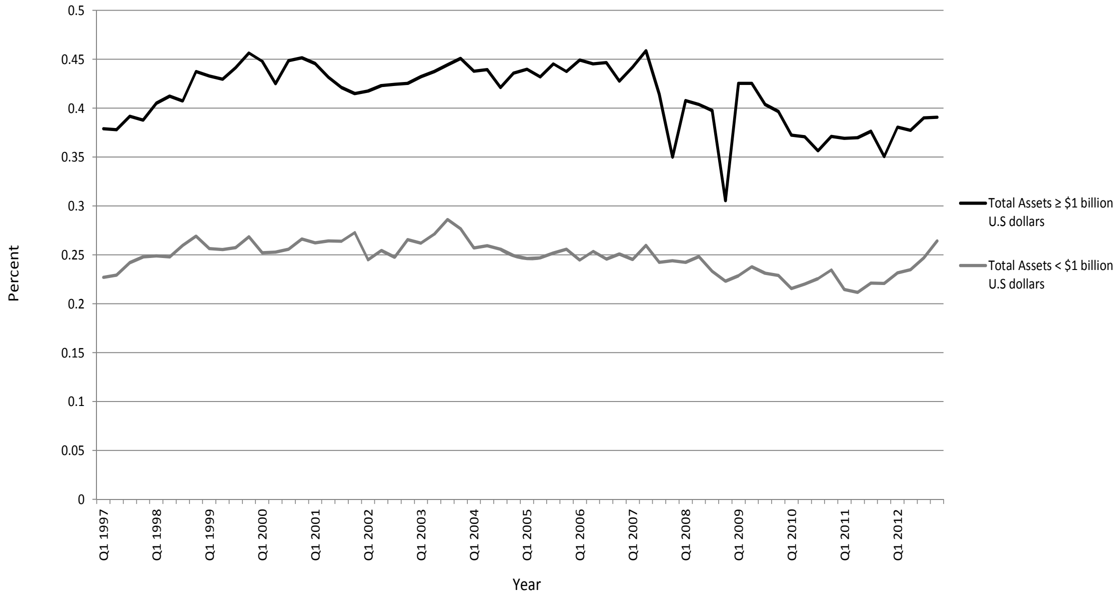

Figure 3: Banks in sample by year, 1990-2012.

This figure shows the total number of banks included in our sample by year.

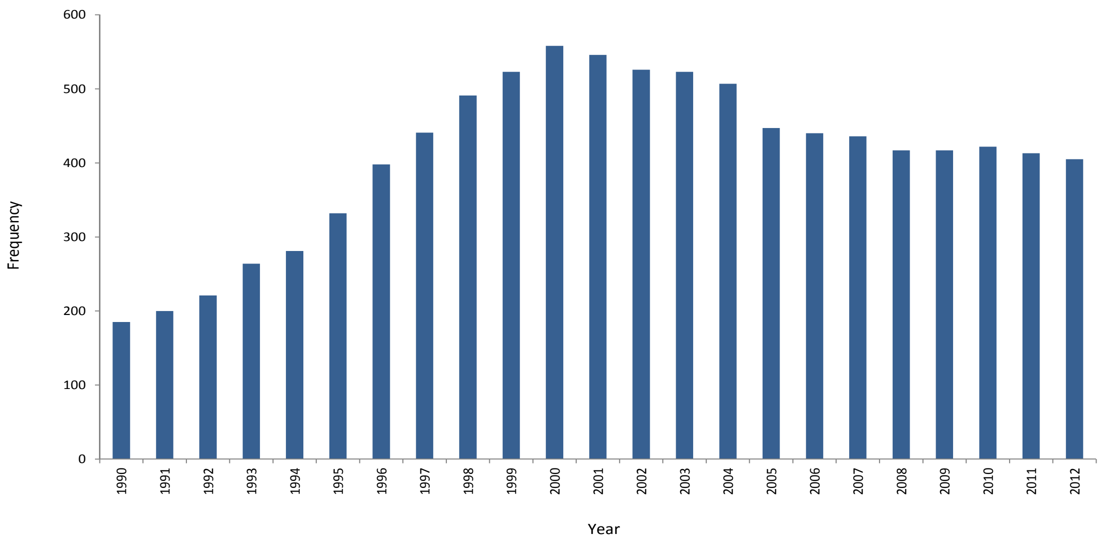

Figure 4: Development of banks' systemic risk exposure, 1990-2012.

This figure plots the annual mean dynamic Marginal Expected Shortfall (MES) of banks included in our sample between 1990 and 2012. Further, this figure plots the annual mean dynamic MES of banks in both the first and fourth quartile of the distribution of dynamic MES. The dynamic MES estimates are averaged annually from daily MES estimates computed by the use of the dynamic model proposed by Brownlees and Engle (2012).

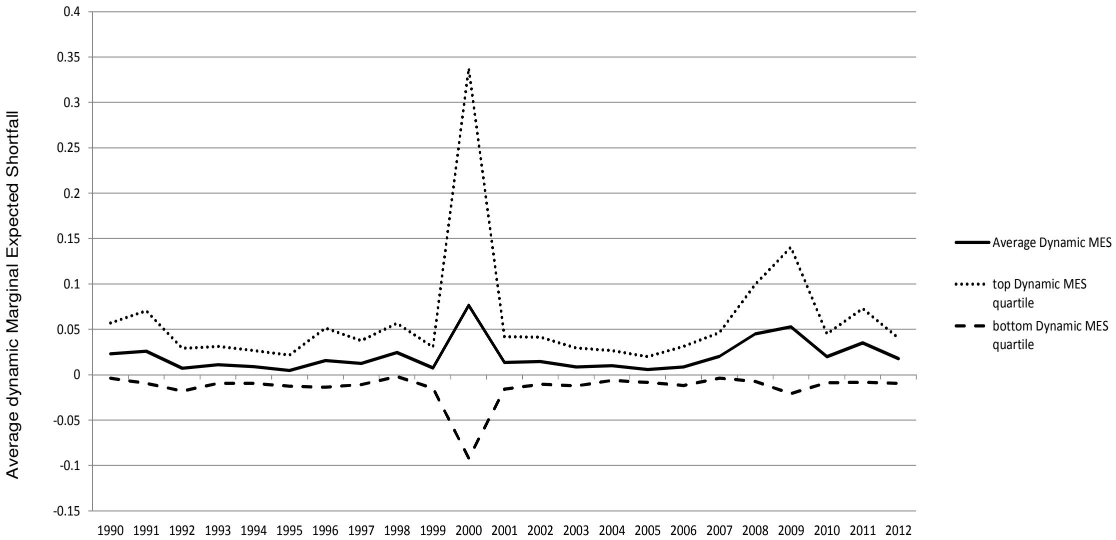

Figure 5: Development of banks' systemic risk contribution, 1990-2012.

This figure plots ΔCoVaR of banks included in our sample between 1990 and 2012. Further, this figure plots the annual mean ΔCoVaR of banks in both the first and fourth quartile of the distribution of ΔCoVaR. The conditional ΔCoVaR is estimated as proposed by Adrian and Brunnermeier (2011).

Figure 6: Development of the non-interest income share, 1990-2012.

This figure shows the development of banks' non-interest income share between 1990 and 2012. This figure also presents the average non-interest income for banks with total assets in excess of $ 1 billion U.S. dollars and banks with total assets below $ 1 billion U.S. dollars.

Figure 7: Distribution of the non-interest income share, 1990-2012.

This figure plots histograms of banks' non-interest income share between 1990 and 2012. Panel A shows the distribution of the non-interest income share of banks for the full sample. Panel B and Panel C present the distribution of the non-interest income share of banks in the first quartile of dynamic MES and fourth quartile of ΔCoVaR, respectively. The non-interest income share is measured as the share of non-interest income divided by the sum of total income and non-interest income.

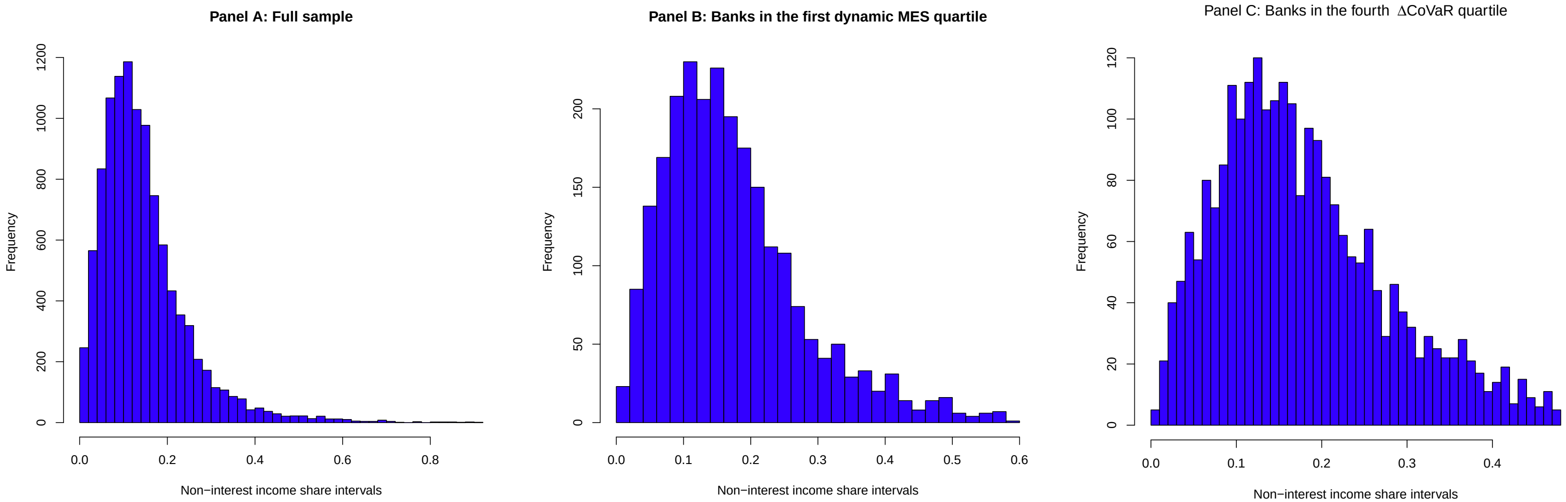

Table I: Descriptive statistics by year.

This table presents annual mean values of systemic risk measures and bank-specific variables for the entire sample we use in our empirical study. The mean values of the variables are computed from data covering the time period from 1990 to 2012. All variables are created using U.S. dollar denominated data. Total assets is given in billion U.S. dollars. Definitions of variables as well as descriptions of the data sources are given in Table I in the Appendix.

Year	MES	Dynamic MES	ΔCoVaR	Total assets	Return on assets	Market-to-book	Leverage	Non-interest income share	Loans
1990	0.0157	0.0231	-0.0124	94.5884	1.0024	1.2161	14.7049	0.1098	0.6464
1991	0.0101	0.0258	-0.0082	110.5562	0.7906	0.8725	27.4998	0.1140	0.6338
1992	0.0061	0.0070	-0.0079	99.8995	0.8207	1.1225	19.3954	0.1252	0.6178
1993	0.0102	0.0109	-0.0126	99.2839	0.9735	1.3637	12.8028	0.1455	0.5976
1994	0.0077	0.0087	-0.0064	107.6476	1.1629	1.3920	13.4509	0.1510	0.6042
1995	0.0036	0.0046	-0.0039	99.8386	1.2334	1.2445	11.2790	0.1282	0.6183
1996	0.0056	0.0154	-0.0071	99.3604	1.3128	1.4328	8.2359	0.1113	0.6240
1997	0.0075	0.0122	-0.0085	95.6898	1.3466	1.6372	7.0911	0.1121	0.6396
1998	0.0177	0.0245	-0.0092	95.3847	1.3835	2.2521	4.8007	0.1156	0.6416
1999	0.0056	0.0075	-0.0040	87.7399	1.4006	1.9156	7.1539	0.1261	0.6273
2000	0.0080	0.0763	-0.0190	86.7937	1.3581	1.6259	8.8065	0.1292	0.6522
2001	0.0094	0.0135	-0.0133	93.6296	1.4594	1.4540	10.7003	0.1193	0.6692
2002	0.0115	0.0147	-0.0097	101.8151	1.3915	1.5933	8.8807	0.1401	0.6568
2003	0.0068	0.0084	-0.0094	108.0774	1.4694	1.6434	8.1423	0.1689	0.6388
2004	0.0082	0.0101	-0.0050	121.5232	1.4020	2.0933	6.4919	0.1981	0.6404
2005	0.0058	0.0058	-0.0047	143.4763	1.3683	2.1399	6.2031	0.1867	0.6585
2006	0.0072	0.0086	-0.0023	154.2643	1.3751	1.8926	6.8613	0.1617	0.6718
2007	0.0166	0.0203	-0.0120	179.8191	1.3560	1.8602	6.6848	0.1435	0.6857
2008	0.0432	0.0451	-0.0371	211.5472	1.1451	1.3385	8.9601	0.1391	0.7010
2009	0.0397	0.0526	-0.0248	193.0713	0.4439	1.0323	15.9672	0.1464	0.7078
2010	0.0188	0.0198	-0.0142	237.0435	0.0028	0.8801	21.7138	0.1747	0.6785
2011	0.0285	0.0349	-0.0248	248.3686	0.3908	1.0091	17.8296	0.1852	0.6552
2012	0.0132	0.0177	-0.0097	256.6731	0.6488	0.8848	19.0489	0.1883	0.6369
Average	0.0130	0.0207	-0.0115	135.7226	1.1453	1.5362	10.8376	0.1455	0.6502

Table I: Descriptive statistics by year. (continued)

Year	Loan loss provision	Foreign loans	Cash and due	Idiosyncratic volatility	Tier 1 capital	Debt maturity	Deposits	Performance	Inter-connectedness
1990	0.0079	0.0088	0.0585	0.3395	NA	0.2325	0.8707	0.0316	0.1060
1991	0.0115	0.0098	0.0553	0.3584	NA	0.2464	0.8726	-0.4185	0.1030
1992	0.0118	0.0069	0.0467	0.3285	NA	0.2896	0.8882	0.3139	0.0730
1993	0.0097	0.0055	0.0465	0.2927	5.2000	0.3236	0.8886	0.3523	0.0906
1994	0.0053	0.0066	0.0393	0.2457	5.7000	0.3291	0.8763	0.1760	0.0773
1995	0.0030	0.0049	0.0404	0.2325	6.4000	0.2871	0.8576	-0.0232	0.0762
1996	0.0033	0.0048	0.0373	0.2169	6.7000	0.3165	0.8589	0.3033	0.0687
1997	0.0031	0.0042	0.0359	0.2495	6.7000	0.3385	0.8515	0.1779	0.0860
1998	0.0037	0.0047	0.0333	0.2954	7.2000	0.3572	0.8431	0.4648	0.1144
1999	0.0036	0.0033	0.0326	0.2811	7.8867	0.4733	0.8401	-0.0888	0.0630
2000	0.0035	0.0023	0.0330	0.3210	0.1668	0.4002	0.8208	-0.1587	0.0831
2001	0.0036	0.0020	0.0319	0.2771	1.4099	0.4402	0.8240	-0.0121	0.0828
2002	0.0041	0.0017	0.0327	0.2441	1.5004	0.5410	0.8198	0.2279	0.0719
2003	0.0048	0.0015	0.0323	0.2160	8.0075	0.5774	0.8202	0.1613	0.0615
2004	0.0035	0.0014	0.0297	0.1933	10.7383	0.5695	0.8096	0.3185	0.0678
2005	0.0024	0.0015	0.0258	0.1888	32.6936	0.5567	0.8103	0.0896	0.0648
2006	0.0024	0.0007	0.0269	0.1775	12.3963	0.5419	0.8152	-0.0157	0.0688
2007	0.0017	0.0008	0.0279	0.2223	12.6345	0.5372	0.8232	0.0809	0.0739
2008	0.0032	0.0009	0.0246	0.4416	12.3688	0.5222	0.8049	-0.2655	0.1119
2009	0.0092	0.0006	0.0212	0.5248	12.5269	0.5749	0.7928	-0.3829	0.0903
2010	0.0185	0.0005	0.0238	0.3757	12.7813	0.6019	0.8321	-0.2195	0.0708
2011	0.0149	0.0005	0.0242	0.3030	14.2069	0.6131	0.8560	0.0927	0.0908
2012	0.0096	0.0006	0.0270	0.2627	15.8114	0.6180	0.8654	-0.1591	0.0714
Average	0.0057	0.0027	0.0325	0.2808	13.5521	0.4665	0.8362	0.0505	0.0801

Table II: The nexus between banks' exposure and banks' contribution to systemic risk.

This table presents the nexus between banks' exposure and contribution to systemic risk for the full sample, the period during the Subprime crisis (2007-2009) as well as for the period before and after the introduction of the Gramm-Leach Bliley Act in 1999. Panel A illustrates mean dynamic MES estimates for banks in the first through fourth quartile of the distribution of ΔCoVaR. Panel B presents mean annual estimates of banks' ΔCoVaR for banks in the fourth through first quartile of the distribution of dynamic MES. Variable definitions and data sources are provided in Table I in the Appendix.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: Dynamic MES	Fullsample		Subprime		pre 1999		post 1999	
1 first ΔCoVaR quartile	0.008		0.013		0.007		0.009	
2	0.010		0.011		0.011		0.009	
3	0.019		0.035		0.017		0.021	
4 fourth ΔCoVaR quartile	0.049		0.067		0.026		0.058	
	0.022	***	0.031	***	0.015	***	0.024	***
	(0.000)		(0.000)		(0.000)		(0.000)	

Panel B: ΔCoVaR	Fullsample		Subprime		pre 1999		post 1999	
4 fourth dynamic MES quartile	-0.003		-0.004		-0.003		-0.004	
3	-0.007		-0.006		-0.006		-0.007	
2	-0.012		-0.019		-0.011		-0.013	
1 first dynamic MES quartile	-0.026		-0.046		-0.015		-0.030	
	-0.012	***	-0.019	***	-0.009	***	-0.013	***
	(0.000)		(0.000)		(0.000)		(0.000)	

Table III: Summary statistics of banks' first and fourth quartile of systemic risk exposure and systemic risk contribution.

This table reports annual mean values of our set of systemic risk measures and bank-specific variables for banks in the first and fourth quartile of the distribution of dynamic MES and ΔCoVaR, respectively. Panel A presents mean values for banks in the top and bottom dynamic MES quartile and a Welch two-sample t-test to test for equality of means for each variable between both sub-samples. Panel B presents mean values for banks in the top and bottom ΔCoVaR quartile and a Welch two-sample t-test to test for equality of means for each variable between both sub-samples. We present the corresponding p-values and of the Welch two-sample t-est. In the last column, we also provide a Welch t-test to test for equality of means between top dynamic MES and bottom ΔCoVaR quartile banks.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	Panel A: Dynamic MES				Panel B: ΔCoVaR				Panel C: Differences	
Variable	Mean of banks in the top quartile of the distribution of dynamic MES	Mean of banks in the bottom quartile of the distribution of dynamic MES	Test for equality of means		Mean of banks in the top quartile of the distribution of Delta CoVaR	Mean of banks in the bottom quartile of the distribution of Delta CoVaR	Test for equality of means		Test for equality of means	top dynamic MES and bottom ΔCoVaR
Systemic Risk Measures										
MES	-0.03	0.00	0.000	***	-0.01	-0.02	0.000	***	0.000	***
Dynamic MES	0.06	-0.01	0.000	***	0.01	0.04	0.000	***	0.000	***
ΔCoVaR	-0.02	0.00	0.000	***	0.01	-0.03	0.000	***	0.000	***
SRISK	149.53	10.89	0.000	***	8.35	227.27	0.000	***	0.000	***
Bankspecific Variables										
TotalAssets	1873.65	165.77	0.000	***	124.26	2449.67	0.000	***	0.000	***
LOGTA	6.55	5.79	0.000	***	5.80	6.71	0.000	***	0.000	***
ROA	1.14	1.06	0.007	***	1.03	1.29	0.000	***	0.000	***
Market-to-book	1.72	1.37	0.000	***	1.39	1.76	0.000	***	0.099	*
Leverage	10.75	11.57	0.025	**	11.94	9.00	0.000	***	0.000	***
Non-interest income share	0.17	0.13	0.000	***	0.13	0.18	0.000	***	0.141	
Idiosyncratic volatility	0.35	0.29	0.000	***	0.31	0.31	0.724		0.000	***
Loans	0.65	0.67	0.000	***	0.67	0.64	0.000	***	0.247	
Loan loss provisions	0.01	0.01	0.000	***	0.01	0.01	0.011	**	0.000	***
Foreign loans	0.01	0.00	0.000	***	0.00	0.01	0.000	***	0.070	*
Cash and due from banks	0.03	0.03	0.001	***	0.03	0.03	0.000	***	0.083	*
Tier 1 caital	11.02	11.71	0.005	***	11.92	11.46	0.060	*	0.061	*
Debt maturity	0.44	0.50	0.000	***	0.49	0.42	0.000	***	0.003	***
Deposits	0.81	0.86	0.000	***	0.86	0.80	0.000	***	0.003	***
Performance	0.05	0.03	0.065	*	0.03	0.07	0.000	***	0.046	**
Liquidity	0.00	0.00	0.000	***	0.00	0.00	0.000	***	0.000	***
Interconnectedness	0.09	0.07	0.000	***	0.07	0.09	0.000	***	0.001	***

Table IV: Regression of banks' exposure and contribution to systemic risk.

This table shows results from firm-level Fama-MacBeth style regressions using mean annual daily MES estimates from the model of Brownlees and Engle (2012) and ΔCoVaR as dependent variables. Regressions are estimated at the firm-level annually with the independent variables listed in the first column. The estimated coefficients are then used in a second regression that determines the relation over time (1990-2012). Results of this second regression together with corresponding p-values and cross-sectional averages of the number of observations are reported in the table. Standard errors are corrected for autocorrelation and heteroscedasticity following Newey and West (1987) using Newey-West standard errors and all explanatory variables are lagged by one year. All explanatory variables are yearly standardized to have zero mean and unit standard deviation to evaluate the economic significance of the coefficients. An estimated coefficient thus represents the effect of a one standard deviation increase in the explanatory variable on the difference in the respective systemic risk measure. Variable definitions and data sources are provided in Table I in the Appendix. The dependent variable in regression (1) through (5) is banks' dynamic Marginal Expected Shortfall and in regression (6) through (10) banks' ΔCoVaR. Regression (1) and (6) constitute the baseline-regression that include the full sample of banks. Regression (2) and (7) use the sub-sample of banks in the first quartile of the distribution of dynamic Marginal Expected Shortfall and ΔCoVaR, while regression (3) and (8) use the sub-sample of banks in the fourth quartile of the distribution of dynamic Marginal Expected Shortfall and ΔCoVaR, respectively. In regression (4) and (9), we use a sub-sample of banks with total assets in excess of $ 50 billion U.S. dollar and regression (5) and (10) banks with total assets below this threshold with the corresponding systemic risk measure as the dependent variable.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared. Both adj. R^2 and the number of observations are averages across the cross-sectional regressions.

Dependent variable	Dynamic MES					ΔCoVaR				
	Full sample	first quartile	fourth quartile	Large banks	Small banks	Full sample	first quartile	fourth quartile	Large banks	Small banks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Return on assets	-0.001***	0.000	0.001	-0.003*	-0.001***	0.000	0.000	0.000	0.000	0.000
	(0.007)	(0.559)	(0.110)	(0.070)	(0.001)	(0.717)	(0.713)	(0.762)	(0.212)	(0.802)
Total assets	0.010***	0.008*	0.003***	0.005***	0.006***	-0.008***	-0.0011***	-0.002***	-0.003***	-0.004**
	(0.000)	(0.080)	(0.002)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.027)
Leverage	-0.002*	0.001*	-0.001	-0.003	-0.001*	0.002**	0.000	0.000*	0.001**	0.001*
	(0.073)	(0.072)	(0.141)	(0.304)	(0.082)	(0.010)	(0.540)	(0.072)	(0.042)	(0.078)
Non-interest income share	0.000	0.001*	0.000	0.001	0.000	0.000	0.000	0.000	-0.001*	0.000
	(0.688)	(0.054)	(0.718)	(0.244)	(0.919)	(0.458)	(0.733)	(0.475)	(0.068)	(0.201)
Interconnectedness	0.005	0.004	-0.002	0.004	0.004	-0.002***	0.000	0.000	-0.002**	-0.001***
	(0.149)	(0.426)	(0.365)	(0.202)	(0.178)	(0.001)	(0.346)	(0.928)	(0.031)	(0.001)
Performance	0.000	-0.001	0.000	0.000	0.000	0.000	0.000	0.000*	0.000	0.000*
	(0.967)	(0.312)	(0.437)	(0.814)	(0.661)	(0.138)	(0.747)	(0.067)	(0.590)	(0.068)
Loans	0.000	-0.001**	-0.001**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.626)	(0.017)	(0.030)	(0.814)	(0.625)	(0.570)	(0.806)	(0.757)	(0.347)	(0.904)
Deposits	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001**	0.000
	(0.673)	(0.726)	(0.320)	(0.614)	(0.664)	(0.440)	(0.454)	(0.819)	(0.013)	(0.600)
Loan loss provisions	0.001	0.001	0.000	0.000	0.001*	0.000	0.000	0.000**	0.000	0.000
	(0.215)	(0.566)	(0.673)	(0.885)	(0.062)	(0.289)	(0.911)	(0.017)	(0.484)	(0.528)
Intercept	0.021***	0.059***	-0.013***	0.042***	0.016***	-0.012***	0.009***	-0.032**	-0.027***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)
Observations	9393	2203	2475	1874	7503	9393	2227	2516	1874	7503
R^2	0.238	0.157	0.166	0.275	0.160	0.345	0.131	0.215	0.258	0.173
Adj. R^2	0.219	0.070	0.066	0.183	0.132	0.328	0.025	0.137	0.163	0.145

Table V: Regression of banks' exposure and contribution to systemic risk during the Subprime crisis.

This table shows results from Ordinary Least Squares (OLS) regression using White-Huber standard errors to correct for inconsistent OLS standard errors. We estimate this regression using the dynamic MES and ΔCoVaR as dependent variables. In dependence on Beltratti and Stulz (2012) and Fahlenbrach et al. (2012), we estimate the dynamic MES and ΔCoVaR for the period of January 2007 through December 2008. The mean estimates are then used as our dependent variables. As our dependent variables stem from a first-stage estimation, we use heteroscedasticity-consistent Huber-White standard errors in order to correct for inconsistent OLS standard errors (see, e.g., Lewis and Linzer (2005)). Results of the regression together with corresponding p-values and the number of observations are reported in the table. All explanatory variables are lagged by one year. Variable definitions and data sources are provided in Table I in the Appendix. Regression (1) employs the banks' dynamic Marginal Expected Shortfall as the dependent variable and regression (2) uses the banks' ΔCoVaR as the dependent variable.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable	Dynamic MES (1)		ΔCoVaR (2)	
Return on assets	0.000		0.000	
	(0.935)		(0.931)	
Total assets	0.020	***	-0.018	***
	(0.000)		(0.000)	
Leverage	-0.005	**	0.003	**
	(0.011)		(0.030)	
Non-interest income share	-0.001		0.002	
	(0.405)		(0.108)	
Interconnectedness	0.001		-0.002	*
	(0.506)		(0.066)	
Performance	0.004	**	-0.001	
	(0.011)		(0.195)	
Loans	0.001		-0.001	
	(0.548)		(0.471)	
Deposits	0.002		-0.001	
	(0.251)		(0.540)	
Loan loss provisions	0.001		0.001	
	(0.610)		(0.398)	
Tier 1 capital	-0.001		0.002	
	(0.612)		(0.132)	
Intercept	-0.026	***	0.039	***
	(0.001)		(0.000)	
Observations	401		401	
R^2	0.356		0.418	
Adj. R^2	0.339		0.403	

Table VI: The nexus between bank size, non-core banking activities and systemic risk.

This table presents the nexus between bank size, non-core banking activities and systemic risk for the full sample. First, we split each systemic risk measure into quartiles. Panel A shows banks' mean dynamic MES estimates for double-sorts of non-interest income and bank size. Panel B shows banks' mean ΔCoVaR estimates for double-sorts of non-interest income and bank size. For both variables, bank size and banking activity (which is proxied by the non-interest income share) mean estimates of both systemic risk measures are provided in the last row and column, respectively. Variable definitions and data sources are provided in Table I in the Appendix.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

Panel A: Full sample									
DynMES	1 low NII		2		3		4 high NII		Average
1 small banks	0.015		0.007		0.009		0.007		0.010
2	0.012		0.009		0.012		0.012		0.011
3	0.024		0.022		0.025		0.027		0.024
4 large banks	0.037		0.041		0.039		0.046		0.041
	0.022	***	0.020	***	0.021	***	0.023	***	0.022
	(0.000)		(0.000)		(0.000)		(0.000)		

Panel B: Full sample									
CoVaR	1 low NII		2		3		4 high NII		Average
1 small banks	-0.004		-0.004		-0.004		-0.004		-0.004
2	-0.006		-0.007		-0.006		-0.004		-0.006
3	-0.012		-0.011		-0.012		-0.013		-0.012
4 large banks	-0.023		-0.024		-0.027		-0.029		-0.026
	-0.011	***	-0.012	***	-0.012	***	-0.012	***	-0.012
	(0.000)		(0.000)		(0.000)		(0.000)		

Table VII: Quantile-regressions of banks' exposure and contribution to systemic risk

This table shows results from firm-level Fama-MacBeth style regressions using the 95% quantile of banks' annual daily MES estimates from the model of Brownlees and Engle (2012) and the 5% quantile of banks' annual ΔCoVaR as dependent variables. Regressions are estimated at the firm-level annually with the independent variables listed in the first column. The estimated coefficients are then used in a second regression that determines the relation over time (1990-2012). Results of this second regression together with corresponding p-values and cross-sectional averages of the number of observations are reported in the table. Standard errors are corrected for autocorrelation and heteroscedasticity following Newey and West (1987) using Newey-West standard errors and all explanatory variables are lagged by one year. All explanatory variables are yearly standardized to have zero mean and unit standard deviation to evaluate the economic significance of the coefficients. An estimated coefficient thus represents the effect of a one standard deviation increase in the explanatory variable on the difference in the respective systemic risk measure. Variable definitions and data sources are provided in Table I in the Appendix. The dependent variable in regression (1) through (3) is banks' 95% quantile of dynamic Marginal Expected Shortfall and in regression (4) through (6) banks' 5% quantile of banks's ΔCoVaR. Regression (1) and (4) include the full sample of banks. Regression (2) and (5) use the sub-sample of large banks, while regression (3) and (6) use the sub-sample of small banks. As the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 uses the $ 50 billion of totals assets threshold for defining systemic importance, we categorize large banks as those banks with total assets in excess of $ 50 billion U.S. dollar and small banks with total assets below $ 50 billion U.S.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared. Both adj. R^2 and the number of observations are averages across the cross-sectional regressions.

Dependent variable	Dynamic MES			ΔCoVaR		
	Full sample (1)	Large banks (2)	Small banks (3)	Full sample (4)	Large banks (5)	Small banks (6)
Return on assets	-0.005	-0.018	-0.002 ***	0.000	-0.001	0.000
	(0.037)	(0.196)	(0.003)	(0.250)	(0.394)	(0.540)
Total assets	0.012 **	0.009 *	0.006	-0.012 ***	-0.006 ***	-0.006 **
	(0.043)	(0.097)	(0.115)	(0.003)	(0.000)	(0.028)
Leverage	-0.002	-0.007	-0.001	0.003 **	0.003	0.002 *
	(0.116)	(0.359)	(0.226)	(0.035)	(0.173)	(0.075)
Non-interest income share	0.003	0.013	0.000	0.000	-0.002 *	0.001
	(0.331)	(0.296)	(0.128)	(0.753)	(0.051)	(0.219)
Interconnectedness	0.010	0.004	0.010	-0.003 ***	-0.003 *	-0.002 ***
	(0.214)	(0.282)	(0.225)	(0.002)	(0.073)	(0.002)
Performance	0.001	0.006	0.001 ***	0.000	0.000	-0.001 *
	(0.469)	(0.520)	(0.000)	(0.726)	(0.800)	(0.065)
Loans	0.000	0.013	0.000	0.000	-0.001	0.000
	(0.515)	(0.377)	(0.955)	(0.590)	(0.525)	(0.693)
Deposits	-0.001	-0.011	0.001	0.000	0.001 **	0.000
	(0.350)	(0.327)	(0.473)	(0.116)	(0.034)	(0.695)
Loan loss provisions	0.000	-0.006	0.002 **	-0.000 ***	0.000	0.000
	(0.969)	(0.307)	(0.043)	(0.000)	(0.778)	(0.197)
Intercept	0.042 **	0.073 ***	0.035 ***	-0.026 ***	-0.051 ***	-0.020 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9393	1874	7503	9393	1874	7503
R^2	0.174	0.251	0.127	0.342	0.238	0.165
Adj. R^2	0.153	0.156	0.098	0.326	0.141	0.137

Table VIII: Robustness check: The introduction of the Gramm-Leach Bliley Act.

This table presents the results of our robustness checks controlling for the introduction of the Gramm-Leach Bliley Act. The table shows results from firm-level Fama-MacBeth style regressions using mean annual daily MES estimates from the model of Brownlees and Engle (2012) and ΔCoVaR as dependent variables for the sample of large banks. Regressions are estimated at the firm-level annually with the independent variables listed in the first column. The estimated coefficients are then used in a second regression that determines the relation over time (1990-2012). Results of this second regression together with corresponding p-values and cross-sectional averages of the number of observations are reported in the table. Standard errors are corrected for autocorrelation and heteroskedasticity following Newey and West (1987) using Newey-West standard errors and all explanatory variables are lagged by one year. All explanatory variables are yearly standardized to have zero mean and unit standard deviation to evaluate the economic significance of the coefficients. An estimated coefficient thus represents the effect of a one standard deviation increase in the explanatory variable on the difference in the respective systemic risk measure. Variable definitions and data sources are provided in Table I in the Appendix. The dependent variable in regression (1) and (2) is banks' dynamic Marginal Expected Shortfall and in regression (3) through (4) banks' ΔCoVaR. Regression (1) and (3) are sub samples for the period before the introduction of the Gramm-Leach Bliley Act, i.e. 1990-1998. Regression (2) and (4) analyze the effect for the period 1990-2012. As we analyze the sample of large banks, we define large banks to be those with total assets in excess of $ 50 billion U.S. dollar.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared. Both adj. R^2 and the number of observations are averages across the cross-sectional regressions.

Dependent variable	Dynamic MES				ΔCoVaR			
	1990-1998 (1)		1999-2012 (2)		1990-1998 (3)		1999-2012 (4)	
Return on assets	0.001		-0.005	**	-0.001		0.000	
	(0.792)		(0.043)		(0.287)		(0.571)	
Total assets	0.005	**	0.005	**	-0.003	***	-0.003	***
	(0.022)		(0.043)		(0.000)		(0.002)	
Leverage	0.000		-0.005		0.001	**	0.002	
	(0.726)		(0.235)		(0.013)		(0.115)	
Non-interest income share	0.000		0.002		0.000		-0.001	***
	(0.622)		(0.172)		(0.941)		(0.002)	
Interconnectedness	0.002	*	0.006		-0.003	**	-0.001	
	(0.095)		(0.285)		(0.012)		(0.333)	
Performance	0.002	***	-0.002		0.000	*	0.000	
	(0.008)		(0.510)		(0.087)		(0.109)	
Loans	-0.002	**	0.002	*	0.001		-0.001	**
	(0.043)		(0.094)		(0.291)		(0.022)	
Deposits	0.001		-0.002		0.001		0.001	*
	(0.271)		(0.139)		(0.217)		(0.094)	
Loan loss provisions	0.002		-0.001		0.000		-0.001	
	(0.122)		(0.375)		(0.361)		(0.247)	
Intercept	0.028	***	0.051	***	-0.020	***	-0.032	***
	(0.000)		(0.001)		(0.000)		(0.001)	
Observations	671		1203		671		1203	
R^2	0.297		0.261		0.312		0.222	
Adj. R^2	0.197		0.173		0.215		0.130	