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

Denefa Bostandzic [*]
Fakultät für Wirtschaftswissenschaft, Ruhr-Universität Bochum

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We show that investment banks on average are more exposed and contribute more to systemic risk than commercial banks or savings institutions. We find that larger banks engage more in non-traditional banking activities. We also find that a bank's size and a bank's interconnectedness are main drivers of systemic risk, though we cannot confirm that banking activity is a main driver of systemic risk. As we match investment banks and commercial bank on bank size we find that investment banks still contribute more to systemic risk during the Subprime crisis. Also, commercial banks engaging more in non-traditional banking activities increased their systemic risk contribution during the Subprime crisis though the difference to investment banks is not statistically significant.

Keywords: Financial crises, systemic risk, risk culture, bank regulation, non-interest income.
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[*] Universitätsstraße 150, D-44780 Bochum, Germany, telephone: +49 234 32 29437, e-mail: *denefa.bostandzic@rub.de*.

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Abstract

We show that investment banks on average are more exposed and contribute more to systemic risk than commercial banks or savings institutions. We find that larger banks engage more in non-traditional banking activities. We also find that a bank's size and a bank's interconnectedness are main drivers of systemic risk, though we cannot confirm that banking activity is a main driver of systemic risk. As we match investment banks and commercial bank on bank size we find that investment banks still contribute more to systemic risk during the Subprime crisis. Also, commercial banks engaging more in non-traditional banking activities increased their systemic risk contribution during the Subprime crisis though the difference to investment banks is not statistically significant.

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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

Since the recent financial crisis that started in the U.S. subprime sector in 2007 there has been considerable discussion about the importance of the U.S. banking sector throughout the world. The Subprime crisis was strongly characterized by the simultaneous failure of several banks in the financial system. As 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 task of limiting systemic risks and bank contagion effects in the banking sector. Several government programs, e.g. the Troubled Asset Relief Program (TARP), tried to restrain the spillover effects of the recent financial crisis by the infusion of taxpayer funds to both commercial as well as investment banks. Traditionally, the too-big-to-fail rationale has been used as a justification for the government to rescue commercial banks as their failure could coincide with an increase of systemic risk in the overall banking system. Since the rescue of Long-Term Capital Management by the U.S. Federal Reserve in 1998, however, the too-big-to-fail rationale has been extended also to nonbanks in order to ensure the overall financial stability. The most prominent example of a threat on the global financial stability, however, shows the collapse of the investment bank Lehman Brothers on September 14 2008, then the fifth largest investment bank in the world. Merill Lynch, Morgan Stanley and Goldman Sachs experienced all liquidity restrains and changed their business models in the aftermath of Lehman Brothers' failure. However, not all banks in the U.S. banking sector contribute equally to systemic risk. In this paper, we document that U.S. investment banks contribute significantly more to systemic risk than commercial banks or savings institutions, especially during the Subprime crisis. Also, we carefully test if a bank's non-core banking activity is related to systemic risk and which factors also help explain the banks' contribution to systemic risk.

Investment banks could be more globally systemically important than commercial banks or savings institutions because of their different sources of income. The Gramm-Leach-Bliley Act of 1999 which repealed the Glass-Steagall Act of 1933, has imposed a seperation between commercial and investment banking industries. The justification for the statue was to rescue the commerical banking industry which was thought to be obsolete (see Macey (2000)). The result was that banks were allowed to engange more in 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 also more integrated with the financial markets their nontraditional banking actitvity increased. Figure 1 shows the increase of the FDIC-insured banks' noninterest income in net operating revenue for 1984 through 2012. In 1984, the average banks' noninterest income in net operating revenue (net interest income plus noninterest income) accouted 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 noninterest income accounted for 41% of net operating revenue. In this context, Brunnermeier et al. (2012) confirm in their findings that non-traditional banking activities in the form of noninterest income significantly increase a bank's contribution to systemic risk. The authors analyzed U.S. banks between 1986 and 2008 and show that non-core banking activities like, e.g. investment banking are different from the traditional deposit-taking and lending functions of banks thus leading to a greater fragility of the financial market, (see, e.g., Mercieca et al., 2007; Baele, 2005) and De Jonghe (2010).

This paper addresses the need for a comprehensive analysis of the relation between a bank's non-traditional banking activity, its bank business model and both its contribution and exposure to systemic risk. More precisely, using a sample of U.S. banks in the period from 1999 to 2012, we employ three different models for measuring an individual bank's exposure and contribution to systemic risk. First, we follow Acharya et al. (2010) and measure a banks *exposure* to a possible under-capitalization of 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 as well as nonlinear tail dependence in the banks' and the financial sector's returns. [1] Second, we compute the banks' SRISK proposed by Acharya et al. (2012) and Brownlees and Engle (2012) which combines a measure of a bank's stock price sensitivity together with its leverage. Finally, we use the ΔCoVaR measure of Adrian and Brunnermeier (2011) to measure a bank's *contribution* to systemic risk.[2]

Using these three measures of systemic risk, we test several hypotheses from the financial intermediation and international finance literature on the question why investment banks have a higher exposure and contribution to the fragility of the global financial sector and how banking activity is related to systemic risk. The Basel Committee on Banking Supervision (2013) identifies bank size, interconnectedness, substitutability, cross-jurisdictional activity and its complexity as key drivers of financial instability. Particularly, bank size is often cited as the main driver of systemic risk.[3] O'Hara and Shaw (1990) and Acharya and Yorulmazer (2008) argue that larger banks could provide managers with incentives for excessive risk-taking as in case of a bank's default the probability of a government bailout increases. In this context, 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 its size. Similarly, Brunnermeier et al. (2012) confirm that non-core banking activities of banks in form of noninterest income have a significant effect on banks' systemic risk contribution. Furthermore, the authors document a strong and positive correlation between MES and bank size. Panel B of Figure 1 shows the relation between bank size and the banks' share of noninterest income in net operating revenue. Evidently, large banks with total assets in excess of $ 1 billion have a significantly higher noninterest income share 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 have an easier access to capital and infras-

[1] We also estimate but do not report the results on the static MES. We find the results on MES to be similar to those of the dynamic MES.

[2] Giglio et al. (2013) stress the need for several distinct measures of systemic risk.

[3] 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.

tructure. Additionally, larger banks can easier diversify their income streams than smaller banks. The Figure also shows that during the Subprime crisis a significant decrease in bank's noninterest income share for large banks can be determined while small banks indicate a relatively constant level of noninterest income to net operating revenue of approximately 25% for the entire oberservation period from 1997 through 2012. This result implicates, that noninterest income tends to be a more volatile source of revenue than traditional interest rate income 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 Altunbas et al. (2011)). Also, the global trend towards more diversification in bank income sources and consequently an expansion of noninterest income revenues has provided banks with additional sources of income thus extending the noninterest income revenues. However, diversifications can help to ensure the stability in overall bank income Stiroh (2011). Additionally, DeYoung and Torna (2013) show that banks with a higher reliance on noninterest income have higher betas and are consequently more sensitive than traditional banks to extreme market and macroeconomic changes. Whether a bank's contribution to systemic risk is either related to a bank's banking activity, its size, its business model or to crisis periods is of major importance for regulators and policy makers in order to ensure the global financial market stability.

Further, the Basel Committee on Banking Supervision (2013) also identifies a bank's interconnectedness as a key driver of systemic risk. As banks enter more contractual obligations with other banks they are likely to increase in size. At the same time, banks that become larger also tend to increase their contractual obligations with other banks. Consequently, we expect bank size and banks'interconnectedness to be positivly correlated and to be positively related to a bank's contribution to systemic risk. The insight that systemic risk is not solely driven by banks' size or banks' interconnectedness is also shared by other commentators. E.g. Adrian and Shin (2010) find that leverage among investment banks is strongly procyclical implying that they take on more risk in good times and sell off risky assets in bad times. Additionally, Hovakimian et al. (2012) analyze quarterly data of U.S. banks over the period of 1974 to 2010. The authors find bank size, leverage and asset risk to be the main drivers of systemic risk. Also, DeYoung and Torna (2013) determine that a bank's default probability is significantly driven by higher stakeholder income from non-traditional activity that require banks to make asset investments. Similarly, Demirgüç-Kunt and Huizinga (2013) find some evidence for diversification gains from their levels and conclude that banking-strategies that rely prominently on generating noninterest income are very risky. Other commentators, however, argue that the reliance of some banks on short-term funding contributes to the build-up of systemic risks, especiallly prior to the 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 refer this finding to a bank's risk culture. Applying this argumentation on the analysis of systemic risk, U.S. investment banks could contribute more to systemic risk due to their aggressive business model. Moreover, depository institutions enaging more in nontraditonal banking activities could also show a similar contribution to systemic risk as investment banks. Consequently, investment banks could ceteris paribus be more systemically relevant than commercial banks and savings institutions because of a stronger activity in non-core businesses. Also, commercial banks engaging more in non-tradtional banking businesses could also show a higher contribution to systemic risk than comparable commerical banks engaging in traditional banking activities.

Financial market stability, however, could also be influenced by the extent to which national regulators restrict banks from engaging in certain business activities. As theoretical justification for such bank activity restrictions, it is often argued that diversification of banks into trading, underwriting and investment banking causes conflicts of interest (see John et al., 1994), increased risk-taking (see Boyd et al., 1998; Brunnermeier et al., 2012). For example, the presence of a deposit insurance scheme (Merton (1977)) can have both stabilizing and destabilizing effects on the financial system. While Diamond and Dybvig (1983) argue in their classical model that deposit insurance can prevent self-fullfilling bank runs by depositors, deposit insurance, on the other hand, may provide bank managers with incentives of excessive risk taking, thus increasing a bank's default probability ((see Kane, 2000; Demirgüç-Kunt and Detragiache, 2002)). Anginer et al. (2013) find that deposit insurance dominates during times of financial crises while moral hazard seems to be dominating during calm periods. These findings could help explain the differences in systemcic risk contribution between FDIC insured banks and investment banks. The empirical banking literature has also focused on the relation between banks' non-core activities and systemic risk. DeYoung and Torna (2013), Song and Thakor (2007) and Shleifer and Vishny (2010) confirm a positive relation between banks' non-traditional banking activities and their contribution to systemic risk. Following this line of argumentation, commerical banks could contribute to systemic risk in almost the same manner as investment banks, conditional that they engange more in non-traditional banking activities.

Analyzing a sample of 8863 bank-year observations from 1999 through 2012, we find that investment banks contribute on average more to systemic risk than commerical banks or savings instituions. Especially, during the recent financial crisis, investment banks contribute significantly more to systemic risk. This results is statistically and economically significant. Further, the Gramm-Leach-Bliley Act of 1999 allowed to engage more in non-traditional banking activities like e.g. investment banking. We find, that depository banks increased their noninterest income share as used to proxy for a bank's non-traditional banking activity. We also find, that a bank's non-core banking activity is positively driven by bank size and also by the banks' business model. We also investigate further analyses to determine which bank-specific variables determine systemic risk. Again, we find bank size to be one main driver of systemic risk. Follwing these results, we propose the propensity-score matching technique and match each investment bank to a commerical bank using the banks' natural logarithm of total assets as our main matching variable. In our additional analyses we show that investment banks still contribute more to systemic risk than comparable commercial banks. Most notably, when looking at commerical banks that engage more heavily in non-traditional banking activity,no significant differences in regard to their systemic risk contribution between investment banks and commercial banks can be determined.

To the best of our knowledge, our paper fills a gap in the literature, as we are the first to analyze the nexus between banking activity and both a bank's contribution and its exposure to systemic risk. Moreover, we investigate the question if a bank's business model is also a main driver of systemic risk which at least 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) found that banks non-core banking actitivies are positively related to a bank's contribution to systemic risk. In our analyses, we complement their analyses using also a bank's dynamic MES and SRISK as further measures for a bank's exposure to systemic risk. In our final analyses, we follow Bartram et al. (2012) and use the propensity score matching technique to match investment banks to commercial banks. We also follow Kahle and Stulz (2013) and use the difference-in-difference approach to investigate differences between both groups for each period of the subprime crisis.

The paper proceeds as follows. In Section 2, we describe our data and the methodology for our systemic risk measures. In Section 3, we investigate the determinants of both banking activity as well as systemic risk. To validate our main findings, we investigate some additional analyses as well as 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 1999 through 2012. As we consider only U.S. banks with primary listings in the U.S., we exlcude banks with nonprimary issues and secondary listings. We select all bank-year observations for banks with Standard Industry Classification (SIC) codes between 6000 and 6300 in the fiscal year end 1998. In contrast to Fahlenbrach and Stulz (2011), we do not exclude non-depository banks with the two-digit SIC code 62 as we are interested in analyzing differences between deposit-taking and non deposit-taking banks and their contribution to systemic risk. Also, we follow Fahlenbrach and Stulz (2011) and manually go through the list of banks with SIC codes 6199 (Finance Services) and 6211 (Securitiy Brokers and Dealers) excluding pure brokerage houses.

We use two sources to construct bank-level data from 1999 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 outliners 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 Worlscope 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 from any data source available, 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.

Also, we control for mergers in our sample. More precisely, we manually search in the *Thomson One Banker Database* to identifiy banks that either merged or that were acquired during our observation period. Several authors (see, e.g., Weiß et al. (forthcoming) 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 target 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 aviod distortive effects of possible mergers in our sample, we exlcude both acquiring and target bank in the year they mergered. As a result, we can rule out that any non-deposit bank was acquired by a deposit-taking bank and vice versa during each observation year.

Our final sample consists of 8863 bank-year observations of 1109 U.S. banks. The distribution of bank-years with regard to the different bank classifications is shown in Figure 3. Evidently, commercial banks and savings institutions represent the highest portion of banks accorfing to both the full-sample and as well as over all years. The number of investment banks in our sample ranges from a minimum of 47 banks up to 72 banks in a observation year. The classified "other" banks, which are predominantly non-deposit taking banks, however, represent the lowest portion in the final sample.

2.2 Systemic risk measures

We use three different measures of systemic risk that are proposed in the empirical banking literature. All these measures are based on daily stock market and financial accounting data and have been extensively been used by regulators for monitoring financial 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 global financial market experiencing extreme downward movements. In contrast to this definition, we do not use a global financial sector as our reference, as we are interested in bank's local exposure to systemic risk. Therefore, we use the *Datastream US Bank Index*(DS code BANKSUS) to proxy for the U.S. financial sector.[4] Following this method, 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 variying 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. [5]

As a second approach to measure a bank's exposure to systemic risk, we follow Acharya et al. (2012) and employ their Systemic Risk Index (SRISK) approach. The authors argue that the MES approach does not account for the leverage of a financial institutions. Therefore, the authors complement the previous MES approach including a bank's leverage to measure its SRISK. SRISK considers both, a bank's liabilities as well as its exposure to shocks in equity prices. More precisely, the SRISK is the capital that a firm is expected to need conditional on a crisis, i.e., $SRISK =_{i,t} [CapitalShortfall_i \mid Crisis]$. Acharya et al. (2012) argue that the expected capital shortfall captures several important characteristics for systemic risk and thus merges size, leverage, interconnectedness and the 'comovement' (see Acharya et al., 2012) of the firm's assets with the total financial sector in a single measure. We use daily stock prices and the number of shares

4 We measure a bank's MES for the entire period but do not report our results.

5 Note that annual estimates of the daily dynamic MES are used to yield the dependent variable used in our main regressions, while we consider quarterly estimates for our additional analyses (see also Hovakimian et al. (2012)

outstanding to proxy for the daily market value of equity (due to data availability) yearly data on debt.

The SRISK estimate for bank i at time t is given by

$$SRISK_{i,t} = k\,(Debt_{i,t}) - (1-k)\,(1 - LRMES_{i,t})\,Equity_{i,t} \tag{1}$$

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 previously described dynamically estimated MES and $Equity_{i,t}$ is the banks's market value of equity. Technical details of the methods used for estimating the different measures of systemic risk are described in Appendix

As a third 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 covariation between financial institutions and the financial system. While the dynamic MES and SRISK 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,[6] the conditional ΔCoVaR is time-varying and estimated using a set of state variables that capture the evolution of tail risk dependence over time.
[7]

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

[7] 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.

2.3 Main independent variables

We hypothesize that banking activities and 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 Appendix I.

The first set of variables includes idiosyncratic bank characteristics. To proxy for bank size we use the natural logarithm of a bank's total assets. As the Bank for International Settlements (2013) recognizes bank size as one 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, as larger banks increase the bailout probability through the government in case of a default, thus damaging the confindence in the interbank market and at least the financial system as a whole. This problem, however, engages managers with incentives of excessively risk-taking (see e.g. Gandhi and Lustig (forthcoming), O'Hara and Shaw (1990), Acharya and Yorulmazer (2008)). Moreover, Demirgüç-Kunt and Huizinga (2010) show that bank size is also positively related to the bank's noninterest income share and thus to the non-traditional banking activity of a bank. We control for this an consider bank size as an independent variable in our regressions.

Next, we use a bank's market-to-book ratio which is defined as the market value of common equity divided by the market value of common equity to proxy for a bank's valuation. A greater charter value of a bank could provide managers with incentives to increase their capital ratio thus limiting their risk-taking activity. However, this could reduce possible losses in charter value in case the bank defaults, see e.g. Keeley (1990). Therefore, a bank's valuation and systemic risk contribution could be negatively correlated.

Also, we consider the variable Leverage which is defined as the quasi-market value of assets divided by the market-value of assets divided by the market-value of equity in which the quasi-market value of assets is given by the book value of assets minus the book value of equity plus the market value of equity (see e.g. Acharya et al. (2010)). For example, Shleifer and Vishny (2010) confirm that highly levered banks contribute more to both systemic risk and econonomic volatility. Similarly, Brunnermeier et al. (2012) as well as Beltratti and Stulz (2012) show that highly levered banks contribute more to systemic risk and perform worse than lower levered banks. In contrast, a lower levered bank could lead to a higher likelihood of a bank's default and this is contribution to systemic risk due to the fact that these bank managers commit free cash flows to risky projects, see Berger and Bonaccorsi di Patti (2006). Therefore, we expect the sign of leverage to be unrestrices in our regressions.

One important dimension of systemic risk which is also identified by the Basel Committee on Banking Supervision (2013) is the interconnectedness of a bank. Memmel and Sachs (2013) argue that a bank's interconnectedness is together with bank size a main driver of systemic risk. These authors have access to detailed supervisory data thus identifiying a bank's interconnectivity through the interbank market. While larger banks have a higher probability to increase their interconnectedness, contagion effects in case of a bank's default can steadily be transmitted through the interbank market. To analyze the interconnectedness of a bank with the global financial sector, we use the variable Interconnectedness as introduced by Billio et al. (2012). This variable represents the sum of in and out connections of a bank to other banks in the financial system.

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

Also, we argue that a bank's activity, as proxied by the noninterest income share is also positively correlated with a bank's performance. Additionally, we use the bank's non-interest income share as a proxy for bank activity. While Brunnermeier et al. (2012) define non-traditional income as the share of noninterest income divided by net interest income, Demirgüç-Kunt and Huizinga (2013) use the banks noninterest income to total operating income. We follow Demirgüç-Kunt and Huizinga (2013) and construct a bank's noninterest income share as the share of noninterest income divided by the sum of total interest income and noninterest income. Brunnermeier et al. (2012) argues that a bank's non-traditional banking activities are positively related to the bank's conribution to systemic risk. Similarly, DeYoung and Torna (2013) argue that a bank's default probability is driven by higher non-core banking activities. Also, Mercieca et al. (2007) and Baele (2005) find a positive relation between noninterest income banking activities and systemic risk.

In our additional analyses, we investigate the question whether commercial banks with a low Tier 1 capital ratio have a similar contribution to systemic risk as comparable investment banks during the Subprime crisis. The Tier 1 capital ratio is defined as as the ratio of 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 absorbe losses without interrupting a bank's business in any way. As a lower Tier 1 capital ratio could not fully cover the losses in case of a bank's default, we expect that commercial banks with a low Tier 1 capital ratio to have both a similar exposure and contribution to systemic risk.

2.4 Descriptive Statistics

Panel A of Table II presents annual mean estimates of our systemic risk measures an bank-specific variables. Panel B of Table III provides summary statistics of the mean estimates of our systemic risk measures and bank-specific variables for each bank classification.

— insert Tables II and III here —

The ananlysis of our systemic risk measures shows that on average the banks' exposure to systemic risk, as measured by the dynamic MES and SRISK, is evidently higher during times of financial turmoil, e.g. during the Dotcom crash and the Subprime crisis. Similarly, the average banks' contribution to systemic risk also significantly increased during the recent financial crisis. For our four bank classifications, we can see that on the one hand investment banks on average are more exposed to systemic risk. More precisely, on average they have a dynamic MES of 4.39% and on the other hand also contribute more to systemic risk (2.28%), as measured by ΔCoVaR. The average estimates of dynamic MES, SRISK and ΔCoVaR, however, do not significantly differ between commercial banks and savings institutions. Figure 4, 5 and 6 show the course of our three systemic risk measures over time. All plots show the average of the individual yearly measure of systemic risk accounting for our four bank categories. Beginning with the analysis of a bank's exposure to systemic risk, we can see that the average dynamic MES shows an upward trend for the Dotcom crash in the year 2000 as well as for the Subprime crisis in 2008. More precisely, investment banks and the fourth category ”Others”, i.e. mostly non-depository banks, have for most of the time a higher exposure to systemic risk than commercial banks or savings institutions. Similar results can be determined for SRISK which is also a proxy for a bank's exposure to systemic risk. In this figure, we can see that investment banks always have a higher exposure to systemic risk than banks of other bank categories. In the aftermath of the financial crisis, SRISK declined dramatically for investment banks, even under the commerical banks' level of SRISK. Analyzing the average ΔCoVaR, which is a bank's contribution to systemic risk, we can see that investment banks have a significant higher contribution to systemic risk than any other bank category. Put differently, investment banks contribute signficantly more to systemic risk, especially during crisis periods. Not surprisingly, savings institutions show the lowest contribution to systemic risk for the entire observation period.

The analysis of the bank-specific variables shows that banks's size proxied by total assets steadily has grown over the oberservation period. The variable ranges from $ 94.5 billion in 1999 up to $ 258 billion in 2012. The mean bank size is higher for investment banks than for any other bank category. More precisely, while investment banks have an average size of $ 400 billion commercial banks have an average of total assets of $ 202 billion. Not surprisingly, savings institutions are on average the smallest banks in the sample with average total assets of $ 30 billion.

The average bank performance varies widely across the all years in our sample. While the minimum average bank performance is -44.5% in 2009, banks realized the best bank performance of 33.7% in 2004. Most notably, investment banks realized a positive average bank performance of 2.7% while both savings institutions and commercial banks show a negative bank performance of approximately -1%.

To proxy for the different banking activities, we follow Demirgüç-Kunt and Huizinga (2010) and Brunnermeier et al. (2012). While Brunnermeier et al. (2012) define non-traditional income as the share of noninterest income divided by net interest income, Demirgüç-Kunt and Huizinga (2010) use a bank's operating income in the denominator. We follow Demirgüç-Kunt and Huizinga (2010) and construct a banks's noninterest income share as the share of noninterest income divided by the sum of total interest income and noninterest income. Noninterest income includes a bank's income from trading, fees and commissions. As these activities are not related to the traditional banking activities, i.e, deposit-taking and lending, however, we investigate the question whether a bank's noninterest income share is a good proxy for a bank's business model. Panel A of Figure 7 shows the yearly average noninterest income share for all banks. The average noninterest share ranges between 21% in 1999 up to 32% in 2005. With the beginning of the Subprime crisis in 2007 the noninterest income share level decreased for 3% points and shows in the aftermath of the financial crisis a nearly constant level of 31 %. This result is inline with the findings of Brunnermeier et al. (2012) who show that banks have earned a higher portion of their profits from noninterest income compared to interest income in the pre-crisis period. Due to the fact that we are interested in the analysis of non-tradiontional banking activities for different bank business models, we also report the average noninterest income share for all four bank categories, i.e, (1) commercial banks, (2) savings institutions, (3) investment banks and (4) others (which are predominatly non-deposit taking institutions). [8] Again, the time trends for all bank categories are shown in Panel B of Figure 7. Not surprisingly, commercial banks and savings institutions show a similar and nearly constant trend in their noninterest income share. More precisely, even before and in the aftermath of the Subprime crisis, no significant changes can be determined. On the other hand, investment banks show a high noninterest income share in the pre-crisis period, i.e., nearly one, though a decrease in the noninterest income share for investment banks is higher than for the other bank categories.

[8] We categorize these four bank business models using each bank's SIC code.

We also plot the frequency distribution of the banks' noninterest income share for the entire sample using a histogram (see Panel C of Figure 7). We use five intervals of size 0.2 between zero and one to show the frequent observations for each of these intervals. The distribution of this variable shows that most banks have an average noninterest income share of 23%, while a higher portion of observations have lower noninterest income shares. A noninterest income share of one can be determined for a very high portion of the sample, i.e. predominatly investment banks.

The analysis of the varianle interconnectedness as introduced by Billio et al. (2012) shows that banks' interconnectedness which they define as the sum of in- and out-connections of a bank increases in times of market tourmoil than in tranquil time periods. Most notably, investment banks have on average a higher interconnectedness through the entire financial system than banks of the other bank categories in our sample.

3 Why do Investment banks contribute more to systemic risk?

In this section, we analyze which factors determine a bank's banking activity. Moreover, we investigate in a panel-regression what determines both a bank's contribution and exposure to systemic risk. We investigate several additonal analyses and check the robustness of our results in the final subsection of this chapter.

3.1 Which factors determine banking activity?

As we are interested in relation between banking activity and systemic risk, we first aim to determine which bank-specific factors can help explain non-core banking activities. More precisely, we use the banks' noninterest income share as our main dependent variable and include several bank-specific variables as our explanatory variables. Moreover, we include three dummy variables, to capture the effect of different business models on the banks' non-traditional banking activity. We use a panel regression with time-fixed effects and robust standard errors. Table IV presents the results of our estimations.

— insert Table IV here —

Regression (1) constitutes our baseline regression estimated using the full sample. We proxy bank size using the natural logarithm of a banks total assets and see that bank size is a significant driver of banking activity. This result is not only statistically but also economically large as a one standard deviation increase in bank size increases a bank's noninterest income share by 112 basis points. This result is in line with the findings of Demirgüç-Kunt and Huizinga (2013). The authors also find a positive impact of total assets on banking activity. Also, this result confirms the trend in 7 indicating that larger banks engage significantly more in non-traditional banking than smaller banks. [9] Moreover, we can confirm our previous findings from Panel B Figure 7. We find that investment banks rely more on noninterest income than the other bank businesses. More precisely, commerical banks and savings institutions are negatively related to the dependent variable. Regression (2) restricts our sample to large banks with total assets in excess of $ 10 billion. Agian, total assets enter our regressopm woth a sigmnificnat positive sign. Moreover, noninterest income share generating activities are also associated with greater equity. Similar to regression (1), investment banks rely more on non-traditional banking activities than commercial banks or savings institutions. According to our findings in Figure 1, we see that during the Subprime crisis a significant decrease in noninterest income to net operating income of FDIC insured banks can be determined. Therefore, we repeat our baseline regression considering the crisis period from 2006 through 2009. The results in regression (3) mostly confirm the findings of our baseline regression. Additionally, we find that bank performance as measured by its lagged buy and hold returns, which indicates that banks that performed better significantly rely more on non-core banking activities.

Regression (4) is only restricted to depository institutions to control for the determinants of banking activity. Most notably, we again find, that total assets is a significant driver of banking activity. This result maintains the findings in Figure 2 where larger FDIC insured banks have a significant higher portion of noninterest income than smaller banks.

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[9] Note, that this figure only considers FDIC insured banks. While small banks are defined using total assets below 1 $ billion, large banks present those banks with total assets in excess of 1 $ billion.

3.2 Which factors explain the contribution to systemic risk?

In this section, we present the results of our panel estimation to examine which factors determine both a bank's contribution and exposure to systemic risk. To mitigate the problem that our dependent variables and some of our explanatory variables might be determined simoultaeously, we lag all independent variables by one year. For an easy interpretation of our estimated regression coefficients, we standardize our explanatory variables with a zero mean and a one standard deviation in order to interpret the economical significance of the estimated coefficients.

— insert Table V here —

Table V reports the results of our panel estimation using time-fixed effects and robust standard errors. Model (1) through (3) use the banks' dynamic MES as the dependent variable. Regression (1) constitutes our baseline regression for the full sample. Bank size which is proxied by the lag of total assets is significantly positive related to the dependent variable. A one standard deviation increase in total assets is associated with an increase of 97 basis points in dynamic MES. Moreover, this result maintains the idea of Basel Committee on Banking Supervision (2013) that bank size is a significant driver of systemic risk. Also, the variable MTBV, which gives information about a bank's valuation is positively related to a bank's exposure to systemic risk. A greater charter value coincides thus with a greater exposure to systemic risk. We also include the variable interconnectedness which describes the in and out bank connections. This variable is positively related to the dynamic MES as a one standard deviation increase in MTBV results in an increase of 87 basis points in dynamic MES. Banks that are highly interconnected through the interbank market are more exposed to shocks in the financial systmem that are transmitted through bank contagion through the entire interbank market. Interestingly, we find that the bank's noninterest income share is also significantly positive related to a bank's exposure to systemic risk. More precisely, banks that engage more in non-traditional banking activities like trading and generate profit through fees and commissions, are more exposed to systemic risk than bank engaging more bank income related activities.

We also control for a subsample of large banks in our sample, with total assets in excess of $ 10 billion. The estiamtion on regression (2) shows that bank size is no longer significantly related to a bank's exposure to systemic risk. The MTBV is still positively related to the dependent variable. In contrast to our findings in regression (1), we now find that a bank's debt maturity, which is defined as the total long term debt devided by total debt, enters our regression with a significant negative sign. This result maintains the findings of Beltratti and Stulz (2012) and Gorton (2010) that funding fragility of banks is a critical driver of systemic risk. Put differently, short-term funded banks are more exposed to systemic risk. Surprisingly, the noninterest-income share is no longer a significant driver of systemic risk.

Figure 4 shows that during the subprime crisis banks of each banking business experienced a peak in their dynamic MES. Therefore, we repeat our baseline regression considering only the period of the subprime crisis from 2006 through 2009. The results of this estimation are in line with the findings in the full sample analysis and show that bank size is positively related to dynamic MES. We also find that the variable Leverage, as defined by Acharya et al. (2010) is positively related to a bank's exposure to systemic risk. More precisely, highly levered banks are more exposed than lower levered bank. This result is also in line with the findings of Brunnermeier et al. (2012) and Beltratti and Stulz (2012). Moreover, we find banks that perfomed well in the pre-observation year have statistically significant decreased their exposure to systemic risk.

We repeat our regressions using the banks' SRISK as our main dependent variable in regression (4) through (6). Again, our regression model (4) constitutes our baseline regression for our full-sample analysis. The results show that total assets enters our regression with a significant and positive sign. Also, banks noninterest income share is statistically significant and positive supporting our previous results in regression (1) using the banks' dynamic MES as our main dependent variable. The variables MTBV, however, now enter our regression with a significant negative sign. This implicates that banks with a higher valuation decrease their systemic risk exposure. Analyzing both subsample of large banks and the period during the financial crisis, only banks' size enters our regression with a significant positive sign. This result indicates that bank size is a significant driver of systemic risk even during times of financial market turmoil. All other variables, however, do not enter our regression models with a statistically significant sign.

We also intend to analyze which factors determine a banks' contribution to systemic risk as measured by ΔCoVaR. Regression (7) through (9) constitute our results using ΔCoVaR as our main dependent variable. Regression (7) represents our baseline regression for the analysis of our full-sample. Again, we find that bank's size is positively related to a bank's contribution to systemic risk. A one standard deviation increase in bank size leads to an increase of 57 basispoints in ΔCoVaR. Put differently, larger banks contribute more to systemic risk. Also, banks' valuation proxied by the variable MTBV enters our our regression with a significant negative sign. This indicated that banks that are higher valuated, contribute more to systemic risk. In contrast to the findings in our previous regressions, banks' leverage enters now our regression with a statistically significant positive sign. This result implicates that banks with a higher leverage contribute less to systemic risk. Also, banks' lagged bank performance and interconnectedness are significantly related to ΔCoVaR. This means, that banks that performed better and banks that are highly interconnected contribute more to systemic risk. In contrast to our previous findings, banks' noninterest income share is no significant driver of ΔCoVaR. Analyzing our subsample of large banks in regression (8), we find similar results as in regression-model (7). More precisely, banks' size is positively related to a bank's contribution to systemic risk. Also, leverage enters our regression with a statistically significant sign. Surprinsingly, the variable noninterest income share ist negatively related to a bank's contribution to systemic risk. Hence, we cannot confirm the findings of Hovakimian et al. (2012) that a higher leverage leads also to a higher systemic risk exposure.

3.3 Additional Analyses

The results of the previous sections show that bank size is a significant driver of both banks' noninterest income share and systemic risk. Also, the analysis of Figure 6 shows that investment banks have a significantly higher contribution to systemic risk than banks of the other bank categories. More precisely, they contribute more to systemic risk especially during crisis periods in comparison to commercial banks, while savings institutions do not show any significant change during the entire sample period. Therefore, we investigate additional analyses in order to analyze if investement banks and commercial banks only differ in their contribution to systemic risk because of their different bank size. For this reason, we match each investment bank to a commercial bank using bank size, i.e. proxied by log total assets using the end of 2005 as our reference year. We employ a matching procedure and follow (Drucker and Puri, 2005), citetBartramBrownConrad, Bartram et al. (2012) and Weiß et al. (forthcoming) using the propensity-score (p-score) matching technique to compare banks of both bank categories along their bank size. First, we estimate a logit-regression of an indicator function of the banks' category on bank size. Then, investment banks and commercial banks are matched using the propensity-scores from our first estimation, minimizing the difference of propensity-scores between both bank categories, thus following the ”nearest-neighbor” technique with replacement. More precisely, investment banks are matched to commercial banks with replacement in order to improve the quality of our matching. [10] Moreover, we use the pre-crisis peroid as of year end 2005 and control if changes in our systemic risk measures can be determined when analyizing the crisis period. For instance, we follow Kahle and Stulz (2013) and perform a difference-in-difference (DiD) estimation in which we compare our systemic risk measures of interest along both groups. This procedure enables us to control for the fact that the systemic risk measures between treated and control groups could be different prior to the financial crisis and continue to be different in the aftermath of the Subprime crisis.

— insert Table VI here —

Table VI reports the results of our difference-in-difference estimation in which we compare the changes in our systemic risk measures across treatment and control groups. We focus on four different time periods i.e. the pre-crisis period, beginning in the third quarter of 2006 through the second quarter of 2007 as used in Ivashina and Scharfstein (2008) and Kahle and Stulz (2013). The first year of the Subprime crisis is defined as the third quarter of 2007 through the second quarter of 2008, following Duchin et al. (2010). With the collapse of Lehman Brothers in Septermber

[10] Delta P-score is not statistically significant and therefore implicates a high matching quality.

2008 which is commoly defined as the peak of the financial crisis, we define the post-Lehman period beginning in the last quarter of 2008 through the last quarter of 2009 as well as the post-crisis period in the last quarter of 2009 through the third quarter of 2010. These crises-period classifications, however, allow us to compare our systemic risk measures along all periods with the same length along our two bank-classifications.

Comparing the changes of our risk measures between treated and control groups for the pre-crisis and the first year of the crisis, we can see that investment banks on average have a higher dynamic MES in the pre-crisis than comparable non-investment banks, although the difference in their changes between pre-crisis and first crisis are not statistically significant. Similarly, the results for SRISK show that on average the difference between both groups is not statistically significant. In column (1) we see, that on average investment banks and comemrcial banksdo not significantly differ in their dynamic MES between the pre-crisis and the first year of the Subprime crisis. Nevertheless, in the post-Lehman period, we find that investment banks experienced a significant higher increase in dynamic MES than commercial banks. For the post-crisis period, however, we find no significant difference between treated and control group.

Using the same approach, we turn to SRISK as our second systemic risk measure. Investment banks experienced changes in SRISK between the pre-crisis period and the first year og the crisis that are not statistically significant different from the changes commerical banks experienced. However, for the post-Lehman period, investment banks have a larger increase in SRISK from the pre-crisis period than comparable commercial banks. This result holds, when we analyze the post-crisis period. Further, we use the ΔCoVaR method to analyze differences between investment banks and commercial banks according to differences in their systemic risk contribution. Beginning with the changes between the pre-crisis period and the first year of the crisis, no significant changes between treated and control group can be affirmed. However, ΔCoVaR increases for investment banks from the pre-crisis period to both the post-Lehman as well as the post-crisis period in comparison to comparable commercial banks. These difference are statistically significant, which means that even in the aftermath of the financial crisis, investment banks have a higher level of systemic risk contribution in comparison to the pre-crisis period. While commercial banks also experienced an increase in their systemic risk contribution which was not statistically significant, we can observe that in the aftermath of the financial crisis their systemic risk contribution almost decreased at their pre-crisis-level.

We further investigate some subsample analyses to check the difference between commercial banks and investment banks with regard to their systemic risk exposure and contribution. For this reason, we use bank-specific variables to build these subsamples (see table VII). More precisely, we consider only commerical banks that are in the upper quartile of our sample according to noninterest income share controlling for bank activity and total assets controlling for bank size. Moreover, we use the commercial banks' tier 1 capital ratio as we expect that banks being in the loest quartile in our sample do not differ in their systemic risk contribution to comparable investment banks.

— insert Table VII here —

The results show that commercial banks experienced changes in their dynamic MES that are not statistically different from those of their matched investment banks for any crisis period. This result is interesting as we see a significant increase in dynamic MES for commercial banks that engage more in non-traditional banking activities. In contrast to table VI no significant differences between the pre-crisis and post-Lehman period can be dermined between both groups. Analyzing differences in dynamic MES for the subsample of large commercial banks, we see that significant differences between treated and control group among all crisis-periods can be determined. Put differently, this result also indicates that larger investement bank on the other hand, have a higher exposure to systemic risk than their matched commerical banks. The third variable we use for our subsample is the commerical banks' Tier 1 capital ratio. The Tier 1 Capital ratio is defined as the ratio of Tier 1 Capital to total risk-weighted assets. As Tier 1 capital is the highest component of a banking firms capital and is capable to fully absorbe losses, we consider in this subsample only commercial banks being in the lower quatile of tier 1 capital in our sample. Therefore, banks with a low tier 1 capital ratio are not able to fully cover their losses which consequently leads to in the banks' default probabilty. Again, a higher default probability could coincide with a higher exposure to systemic risk. The results show that commercial banks have changes in their dynamic MES that is different to investment banks between the pre-crisis and the first-year of the crisis. More interestingly, according to the post-Lehman and the post-crisis period no significant differences between treated and control group can be determined. This result shows on the hand that commerical banks with a low Tier 1 capital ratio significantly increased their dynamic MES and on the other hand that these increases during the crisis are not significant from those of investment banks.

Nevertheless, the comparison to the post-Lehman period shows that investment banks still contrinbuted more to systemic risk than commerical banks, though this effect is no longer significant when analyzing the post-crisis period. We also test if relatively larger banks are more exposed to systemic risk than smaller banks in our sample. Therefore, we use all commerical banks with total assets in the upper quartile and compare these to their matched investment banks. The results show that in the pre-crisis to first year period significantly differences in dynamic MES between commerical banks and investment banks can be determined. These differences hold, when looking at the other time periods and our DiD estimations. More notably,we use the Tier 1 Capital ratio. Our results show that commerical banks with a lower Tier 1 capital ratio have a lower exposure to systemic risk than comparable investment banks. But more interestingly, the difference between both control and treated group almost vanishes, when controlling for the post-Lehman period. This means that commerical banks that had a low Tier 1 capital ratio at the end of 2005 do not significantly differ in their change in dynamic MES compared to investment banks.

Again, we use the difference-in-difference estimation and use SRISK as our main variable. The results show that commercial banks with a high noninterest income share have a change SRISK between the pre-crisis period and the post-crisis period that is significantly smaller than those of investment banks. This result changes for the other periods. More precisely, commerical banks report a significant higher SRISK than comparable investment banks when analyzing the effects between each period. This result could be explained by the fact, that SRISK combines both a banks liabilities as well as the banks exposure to shocks in equity prices. Similar results can be affirmed when analyzing only commercial banks with a low Tier 1 capital ratio and their matched investment banks. However, the analysis of large commercial banks shows that they have a significant lower SRISK only between the pre-crisis and the first crisis period relative to investment banks. For the other periods, however, no significant differences between both groups accroding to thier SRISK can be determined.

Finally, we use again the same subsample of banks and analyze ΔCoVaR for all periods. The results in column (7) show that commerical banks with a high noninterest income share have a systemic risk contribution that is not different from those of their matched investment banks. More interstingly, we test the findings of Brunnermeier et al. (2012) who argue that banks engaging more in non-core banking activities have a significantly higher contribution to systemic risk. As we are interested if commerical banks with a high noninterest income share also contribute more or similary to systemic risk as comparable investement banks, we find that in the aftermath of the financial crisis, i.e. the post-Lehman period and the post-crisis period, investment banks still contribute more to systemic risk than commercial banks.

4 Conclusion

In this paper, we document that investment banks are more exposed and contribute significantly more to systemic risk than banks with other business models. One main result is that investment banks have on average a higher annual dynamic MES, SRISK and ΔCoVaR than commercial banks or savings institutions. These findings can especially be maintained for the aftermath of the LTCM crisis as well as for the Subprime crisis. Since the Gramm-Leach-Bliley Act an increase in bank' non-tradtional banking activity can be determined. We investigate the question whether these increases in non-core banking activities also result in a higher exposure or contribution to systemic risk. We proxy for banking activity using the banks' noninterst income divided by the sum of total interest income and noninterest income. In our first analyses using a panel regression, we find that banking activity is mainly driven by the banks' business model as well as by bank size. Further, we analyze the determinants of systemic risk and find that bank size and a bank's interconnectedness are main drivers of systemic risk, thus underlining the notion of Basel Committee on Banking Supervision (2013) who argue that bank size and a bank's interconnectedness through the interbank market are significant drivers of systemic risk. However, the findings of the Brunnermeier et al. (2012) who find a positive relation between banking activity and systemic risk contibution can not be confirmed. We employ additional analyses to investigate differences in the exposure or contribution between commerical banks and investment banks analyzing the Subprime crisis. We employ the propensity-score matching technique using bank size to match investment banks to commercial banks. Using the difference-in-difference approach, we find that between the pre-crisis period and the first year of the crisis investment banks and commercial banks show no differences in their systemic risk measures. For the post-Lehman period and even in the post-crisis period, however, investment banks are more exposed and contribute more to systemic risk than their matched banks. Moreover, we investigate further subsample analyses in which we analyzed whether commercial banks with a high noninterest income share show similar systemic risk levels as comparable investment banks. Our key result is, that commercial banks engaging more in non-traditional banking activities did not show any significant differences to investment banks according to their systemic risk contribution, though significant differences according to their systemic contribution still maintain.

Our findings have relevant implications for both regulators as well as politicians. Especially the collapse of the U.S. investment banking sector shows the relavance of these banks for the entire financial stability. This paper shows that commerical banks and savings institution, that are subjects regulations on capital adequacy and an explicit deposit-insurance schemes have a significant lower contribution and exposure to systemic risk than investment banks. However, a higher non-traditional banking activity coincides with a higher exposure to systemic risk. A universal banking model, however, could be a good way to conduct investment banking businesses in a safe and sound manner.

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. The country control variables are taken from the World Bank's World Development Indicator (WDI) database. Data on the banks' regulatory environment and deposit insurance schemes are taken from Barth et al. (2006) and Demirgüç-Kunt et al. (2008), respectively.

Variable name	*Definition*	*Data source*
Dependent variables		
Buy-and-hold returns	Annual buy-and-hold stock returns computed from the first and last trading day in a year.	Datastream, own. calc.
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.
Bank characteristics		
Total assets	Natural logarithm of a bank's total assets at fiscal year end.	Worldscope (WC02999).
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	Non-interest income divided by the sum of total noninterest income and total interest income.	Worldscope (WC01021 and WC01016).
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251 and WC03255).
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.

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Figures and Tables

Figure 1: Development of the share of noninterest income in net operating revenue, 1984-2012

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

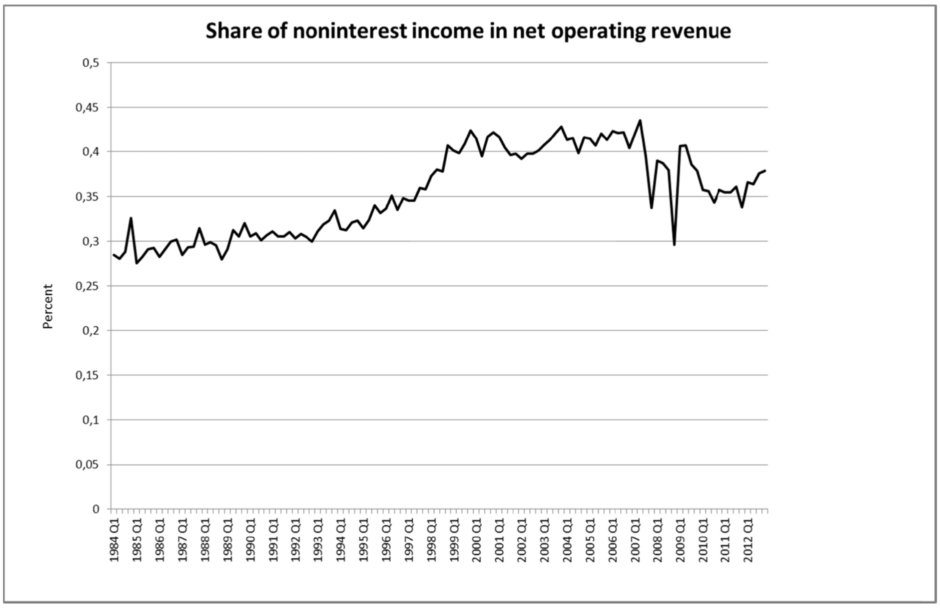


Figure 2: Development of the share of noninterest income in net operating revenue categorized by bank size, 1997-2013

This figure plots the quarterly share of noninterest income in net operating income revenue from 1997-2013 for banks in excess of $ 1 billion total assets and for banks with total assets below $ 1 billion. Data source: Aggregate data from FDIC.

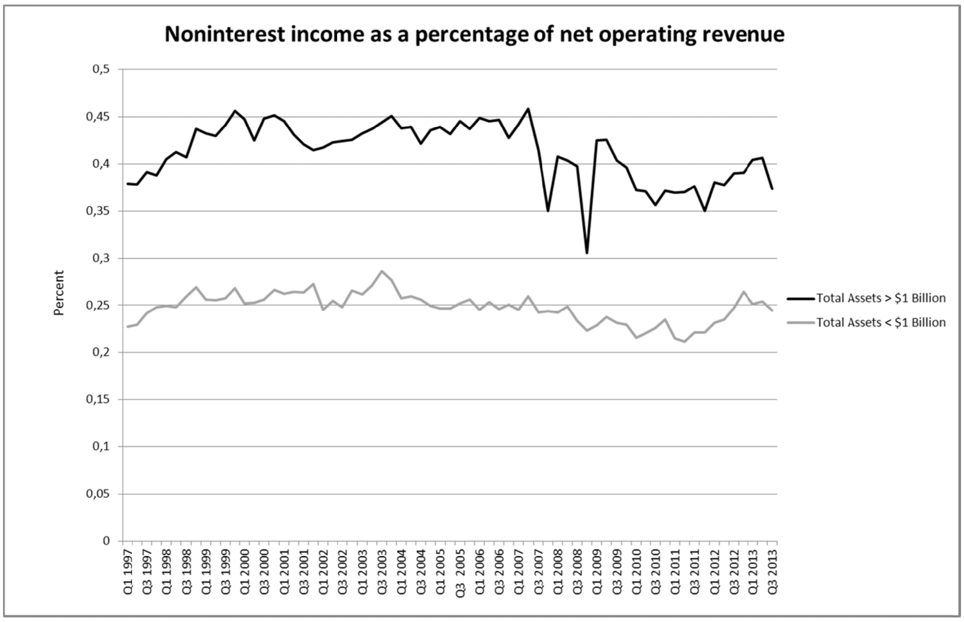


Figure 3: Banknumbers sorted by bank type

This figure shows the portion of each bank category on the total number of bank-year observations .

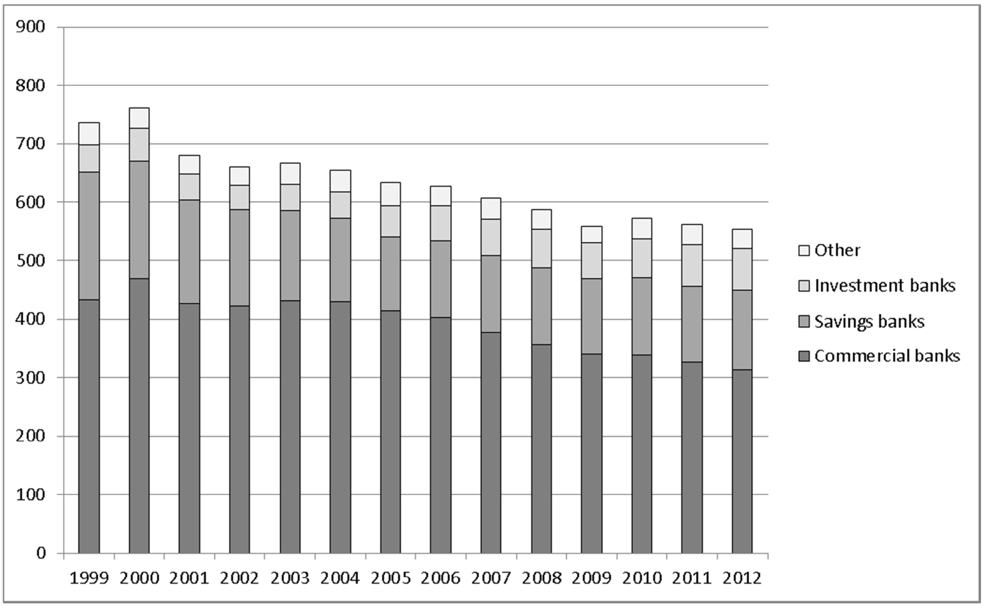


Figure 4: Development of the average Dynamic MES categorized by bank type, 1999-2012

This figure plots the average dynamic Marginal Expected Shortfall (MES) for all banking categories between 1999 and 2012. 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).

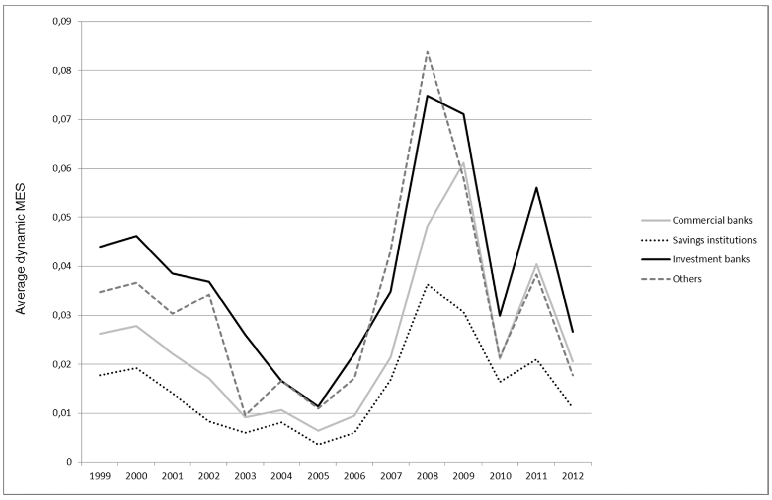


Figure 5: Development of the average SRISK categorized by bank type, 1999-2012

This figure plots the average SRISK for all banking categories between 1999 and 2012. The SRISK estimates are computed using the methodology laid out by Brownlees and Engle (2012) and Acharya et al. (2012).

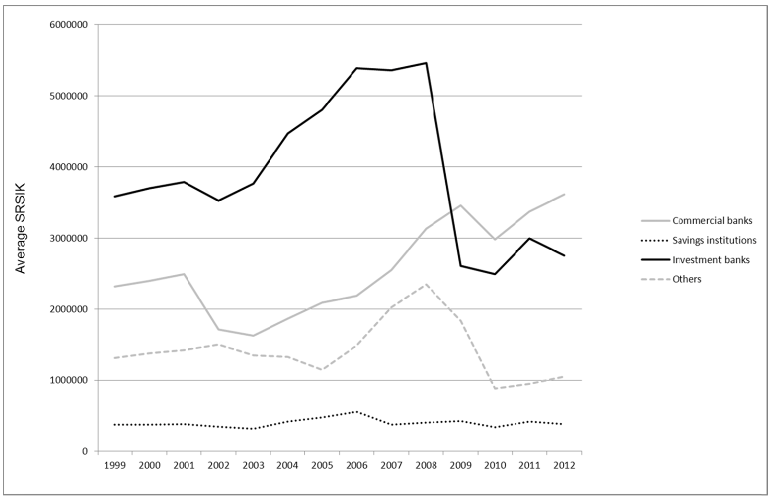


Figure 6: Development of the average delta CoVaR categorized by bank type, 1999-2012

This figure plots the average delta CoVaR for all banking categories between 1999 and 2012.

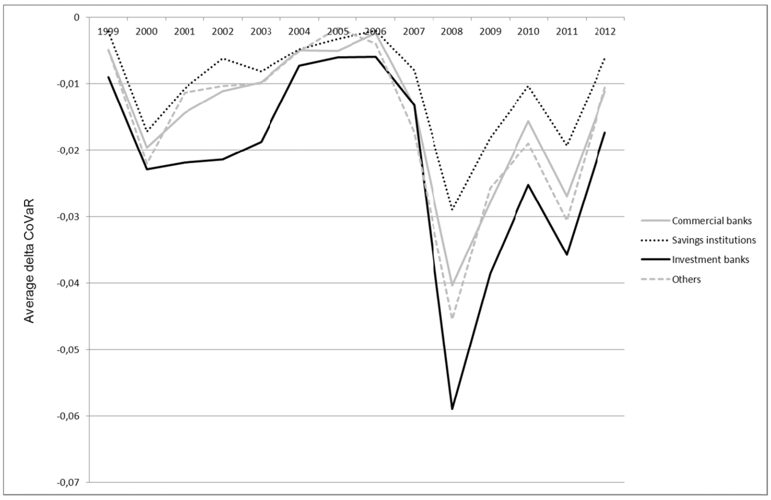
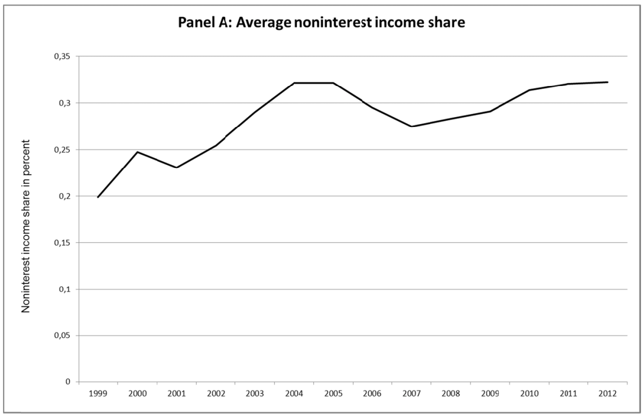
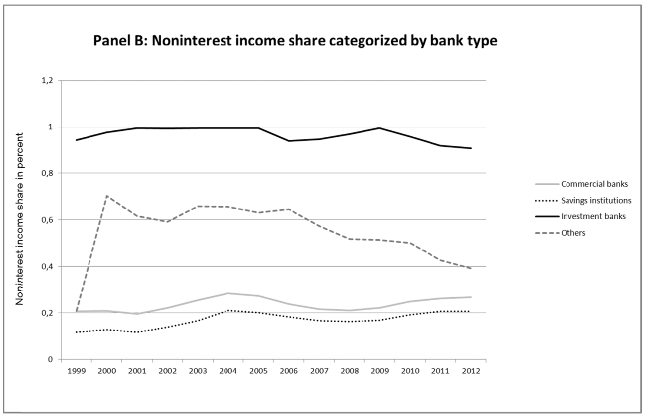


Figure 7: Development of the noninterest income share

Panel A shows the development of the average noninterest income share beween 1999 and 2012. Panel B represents the average noninterest income share categorized by bank type. Panel C reports the noninterest income share intervals for the entire sample.





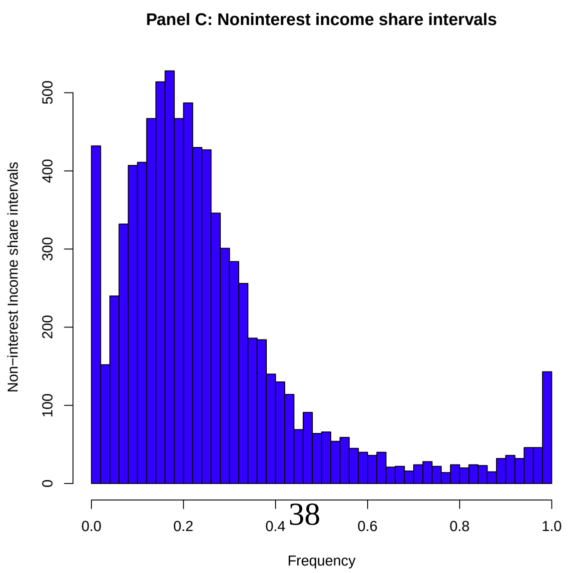


Figure 8: Differences in the systemic risk exposure and contribution of investment banks and commercial banks during the Subprime crisis

This figure plots histograms of the differences in the estimates of the dynamic MES as well as delta CoVaR measures for investment banks and commercial banks for each crisis period. The MES estimates are computed by the use of the dynamic model proposed by Brownlees and Engle (2012). Panel A represents the pre-crisis period, Panel B the first-year of the crisis. Panel C represents the post-Lehman period and Panel D the last year of the crisis.

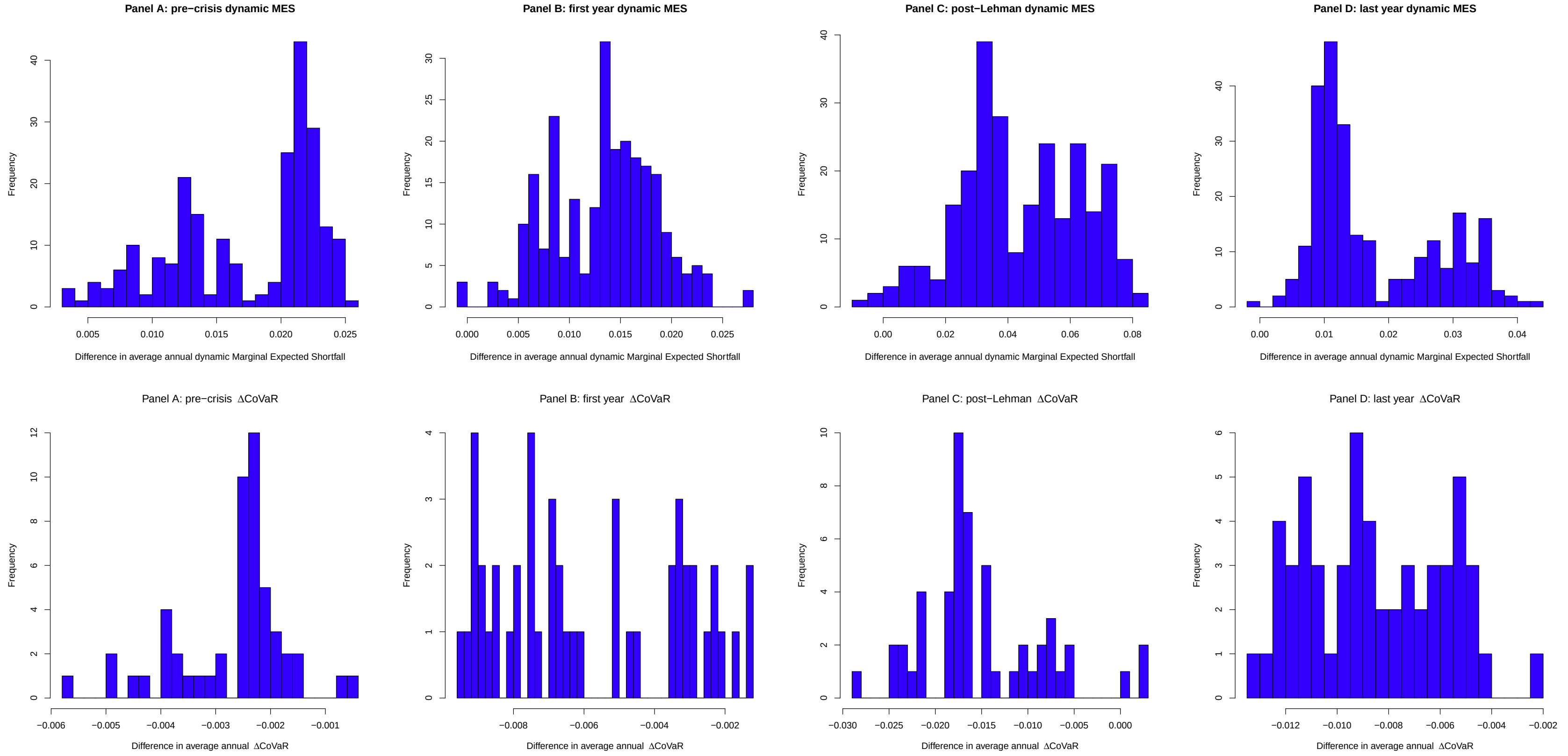


Table II: Descriptive statistics by year

This table presents annual mean values of all bank-level values 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 1999 to 2012. All variables are created using U.S. dollar denominated data. SRISK and Total assets are 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	Bank-year-Obs.	Dynamic MES	ΔCoVaR	SRISK	Buy-and-hold returns	Total Assets	Market-to-book	Leverage	Inter-connected-ness	Debt-maturity	Performance	Noninterest income share	Liquidity	Cash & Due
1999	736	0.0078	-0.0044	1.0489	-0.0880	94.964	2.1137	7.3849	0.0630	0.4755	-0.0935	0.1763	-0.0013	0.0324
2000	762	0.0822	-0.0193	1.1293	0.0167	98.578	1.8861	8.7417	0.0831	0.4109	-0.1124	0.2269	-0.0018	0.0291
2001	680	0.0156	-0.0138	1.2848	0.2198	109.499	1.7231	10.3786	0.0835	0.4539	-0.0010	0.2072	-0.0020	0.0284
2002	661	0.0170	-0.0105	1.5446	0.1220	120.355	1.7667	8.7985	0.0722	0.5424	0.2046	0.2293	-0.0020	0.0291
2003	667	0.0096	-0.0100	1.5164	0.3361	127.465	1.7054	8.3354	0.0624	0.5752	0.1207	0.2656	-0.0016	0.0286
2004	656	0.0108	-0.0051	1.7640	0.1242	142.345	2.2253	6.6411	0.0685	0.5680	0.3377	0.2963	-0.0008	0.0262
2005	633	0.0066	-0.0045	2.0389	-0.006	169.719	2.3563	6.0987	0.0642	0.56779	0.1330	0.2878	-0.0011	0.0222
2006	627	0.0103	-0.0027	2.2565	0.1072	187.978	2.1799	6.5880	0.0692	0.5517	-0.0095	0.2545	-0.0005	0.0232
2007	607	0.0231	-0.0124	2.5694	-0.2403	221.729	2.2129	6.3984	0.0747	0.5473	0.1018	0.2405	-0.0005	0.0236
2008	587	0.0505	-0.0401	3.0325	-0.4575	259.792	1.5947	8.6839	0.1123	0.5422	-0.2571	0.2365	-0.0006	0.0205
2009	559	0.0551	-0.0266	2.7645	-0.1268	241.522	1.1717	15.9582	0.0942	0.5896	-0.4450	0.2391	-0.0020	0.0181
2010	573	0.0211	-0.0157	2.3160	0.0829	240.236	2.4747	21.0664	0.0719	0.6145	-0.1105	0.2648	-0.0041	0.0202
2011	561	0.0378	-0.0265	2.6896	-0.1511	253.382	1.3457	17.7139	0.0897	0.6258	0.0810	0.2729	-0.0021	0.0201
2012	554	0.0189	-0.0107	2.7433	0.1924	258.775	1.1350	16.6850	0.0715	0.6303	-0.1573	0.2677	-0.0017	0.0222
Avergage	633	0.0262	-0.0144	2.0499	0.0097	180.4532	1.8494	10.6766	0.0772	0.5497	-0.0148	0.2475	-0.0016	0.0246

Table III: Descriptive statistics by bank type

This table presents average mean values of all bank-level values for the entire sample we use in our empirical study categorzied by bank type. The mean values of the variables are computed from data covering the time period from 1999 to 2012. All variables are created using U.S. dollar denominated data. SRISK and Total assets are 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.

Business type	Bank-year-Obs.	Dynamic MES	ΔCoVaR	SRISK	Buy-and-hold returns	Total Assets	Market-to-book	Leverage	Inter-connected-ness	Debt-maturity	Performance	Noninterest income share	Liquidity	Cash & Due
Commercial banks	392	0.0262	-0.0142	2.3196	0.0050	20.2106	0.7706	10.2701	0.0765	0.4945	-0.0164	0.2549	-0.0015	0.0318
Savings institutions	150	0.0178	-0.0102	0.3747	0.0388	3.0011	1.2718	11.5226	0.0745	0.6394	-0.0115	0.1690	-0.0019	0.0199
Investment banks	57	0.0440	-0.0228	3.5848	0.0131	40.0062	4.7320	4.1425	0.0847	0.5981	0.0272	0.6364	-0.0013	0.0001
Others	35	0.0347	-0.0151	1.3172	0.0300	14.4497	1.9329	18.2852	0.0759	0.6348	0.0384	0.1559	-0.0025	0.0056
Avergage	159	0.0307	-0.0156	1.8991	0.0217	19.4169	2.1768	11.0551	0.0779	0.5917	0.0094	0.3040	-0.0018	0.0144

Table IV: Regression on banking activity

This table shows results from our panel regression using time-fixed effects and clustered standard errors. The dependent variable is the banks noninterest income share which is used as a proxy for banking activity. Regressions are estimated at the firm-level annually with the independent variables listed in the first column. 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. Model (1) constitutes our baseline regression that includes all banks in our sample. Model (2) uses only bank-year observations of large banks with total assets in excess of $ 10 billion. Regression (3) uses only observations from during the financial crisis from 2006 through 2009. Model (4) considers only depository institutions.
***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

	Fulls sample		Large banks		2006-2009		Depository institutions	
Total Assets	0.087	***	0.084	***	0.086	***	0.089	***
	(0.000)		(0.000)		(0.000)		(0.000)	
Equity	0.002		0.701	***	-0.007		0.031	
	(0.939)		(0.001)		(0.844)		(0.261)	
Performance	-0.004		-0.015		0.027	**	0.006	
	(0.389)		(0.456)		(0.011)		(0.147)	
Interconnectedness	-0.060		-0.184		-0.070		-0.051	
	(0.181)		(0.434)		(0.316)		(0.155)	
Investment bank dummy	0.379	***	0.173	***	0.396	***		
	(0.000)		(0.000)		(0.000)			
Commercial Bank dummy	-0.298	***	-0.269	***	-0.307	***		
	(0.000)		(0.000)		(0.000)			
Savings institution dummy	-0.347	***	-0.448	***	-0.336	***		
	(0.000)		(0.000)		(0.000)			
Observations	7401		879		1971		6923	
R^2	0.529		0.366		0.558		0.248	
Adj. R^2	0.528		0.358		0.554		0.246	
Time fixed effects	Yes		Yes		Yes		Yes	

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

This table shows results from our panel regression using time-fixed effects and clustered standard errors. The dependent variables we use are the annual averaged daily MES estimates from the model of Brownlees and Engle (2012), SRISK and in ΔCoVaR as dependent variables. Regressions are estimated at the firm-level annually with the independent variables listed in the first column. 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. Regressions (1) through (3) employ the banks' Marginal Expected Shortfall as the dependent variable. Regressions (4) to (6) use the banks' SRISK as the regressand and models (7) to (9) use the difference in ΔCoVaR as the dependent variable. Models (1), (4) and (7) constitute our baseline regressions that include all banks in our sample. Models (2), (5) and (8) only use bank-year observations of large banks with total assets in excess of $ 10 billion. Models (3), (6) and (9) estimate separate regressions for the period during the financial crisis from 2006 through 2009. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable	Dynamic MES						SRISK						CoVaR					
Sample:	Full sample		Large banks		2006-2009		Full sample		Large banks		2006-2009		Full sample		Large banks		2006-2009	
Total Assets	0.018	***	-0.013		0.027	***	7792046.477	***	96508333.663	***	10098505.318	***	-0.013	***	-0.009	***	-0.019	***
	(0.000)		(0.503)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.004)		(0.000)	
Market-to-book	0.004	***	0.035	**	0.001		-813593.600	***	-1647689.438		-410254.285		-0.001	***	0.005	**	-0.002	**
	(0.000)		(0.013)		(0.573)		(0.000)		(0.407)		(0.178)		(0.000)		(0.046)		(0.018)	
Leverage	0.000		0.000		0.000	***	13948.569		279237.177		7802.880		0.000	***	0.001	***	0.000	***
	(0.412)		(0.994)		(0.003)		(0.297)		(0.124)		(0.848)		(0.000)		(0.000)		(0.000)	
Performance	-0.004		-0.022		-0.020	***	790069.704		-4580021.173		-245363.043		-0.002	**	-0.006		0.001	
	(0.132)		(0.529)		(0.000)		(0.121)		(0.364)		(0.843)		(0.033)		(0.285)		(0.699)	
Interconnectedness	0.210	***	0.534		0.030		-6038252.053		53029255.881		-2417533.523		-0.044	***	-0.050		-0.036	***
	(0.000)		(0.103)		(0.192)		(0.136)		(0.251)		(0.748)		(0.000)		(0.335)		(0.009)	
Debt maturity	0.002		-0.080	*	-0.005		125226.407		6072771.839		609860.626		0.000		0.008		0.004	
	(0.398)		(0.093)		(0.213)		(0.802)		(0.367)		(0.601)		(0.784)		(0.323)		(0.107)	
Noninterest income	0.016	***	0.021		0.012	**	2136181.859	***	-8101136.075		2196340.793		0.002		0.009		0.008	**
	(0.001)		(0.606)		(0.033)		(0.005)		(0.155)		(0.182)		(0.126)		(0.145)		(0.025)	
Observations	7170		187		1928		4591		187		1218		7170		187		1928	
R^2	0.066		0.073		0.179		0.268		0.893		0.312		0.211		0.205		0.209	
Adj. R^2	0.066		0.065		0.178		0.267		0.792		0.309		0.210		0.182		0.208	
Time fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Table VI: Difference-in-Differences (DiD) results of banks' contribution and exposure to systemic risk

This table shows the difference-in-difference results using the propensity-score technique to match investment banks to comparable commercial banks. Differences in banks' exposure and contribution to systemic risk between the treated (commercial banks) and control (investment banks) groups are reported for each crisis period. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

	Dynamic MES	**SRISK**	**Delta CoVaR**	**Buy-and-hold returns**
Precrisis (2006Q3-2007Q2) versus First year (2007Q3-2008Q2)				
Treated firms				
precrisis	0.0056	681885	-0.0068	0.0114
First year	0.0201	762339	-0.0203	-0.5154
Difference	-0.0145	-80454	0.0135	0.5268
Control firms				
precrisis	0.0222	565197	-0.0091	0.2664
First year	0.0350	611734	-0.0239	-0.2350
Difference	-0.0128	-46537	0.0149	0.5014
DID	-0.0017	-33916	-0.0013	0.0254
p-value for t-test	(0.114)	(0.211)	(0.158)	(0.499)
P-score	0.0000	0.0000	0.0000	0.0000
p-value for t-test	(0.156)	(0.015)	(0.156)	(0.156)
Number of observations	405	273	405	405
Precrisis (2006Q3-2007Q2) versus post Lehman (2008Q4-2009Q3)				
Treated firms				
precrisis - post Lehman	-0.0607	-117694	0.0307	0.4103
Control firms				
precrisis - post Lehman	-0.0936	-744041	0.0502	0.3323
DID	0.0329 ***	626347 ***	-0.0195 ***	0.0781 *
p-value for t-test	(0.000)	(0.000)	(0.000)	(0.073)
Number of observations	405	273	405	405
Precrisis (2006Q3-2007Q2) versus post crisis (2009Q4-2010Q3)				
Treated firms				
precrisis - post crisis	-0.0230	-140605	0.0081	0.1037
Control firms				
precrisis - post crisis	-0.0237	-1036807	0.0179	0.4916
DID	0.0007	896203 ***	-0.0098 ***	-0.3879 ***
p-value for t-test	(0.666)	(0.000)	(0.000)	(0.000)
Number of observations	405	273	405	405

Table VII: Subsample anlysis of the difference-in-difference estimations

This table shows the difference-in-difference results using the propensity-score technique to match investment banks to comparable commercial banks. Differences in banks' exposure and contribution to systemic risk between the treated (commercial banks) and control (investment banks) groups are reported for each crisis period. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

	Dynamic MES			**SRISK**			**Delta CoVaR**		
	High noninterest income share	Large banks	Low Tier 1 capital ratio	High noninterest income share	Large banks	Low Tier 1 capital ratio	High noninterest income share	Large banks	Low Tier 1 capital ratio
Precrisis (2006Q3-2007Q2) versus First year (2007Q3-2008Q2)									
Treated firms									
precrisis	0.0068	0.0088	0.0059	1.6450	1.860936	1.3768	-0.0103	-0.0139	-0.0089
First year	0.0230	0.0305	0.0227	1.843331	2.085677	1.5343	-0.0267	-0.0419	-0.0271
Difference	-0.0162	-0.0217	-0.0169	-0.1983	-0.224741	-0.1576	0.0164	0.0280	0.0182
Control firms									
precrisis	0.0195	0.0204	0.0197	1.2750	1.416652	1.0450	-0.0105	-0.0113	-0.0100
First year	0.0340	0.0382	0.0327	1.2884	1.441917	1.0674	-0.0293	-0.0271	-0.0278
Difference	-0.0145	-0.0177	-0.0130	-0.0135	-0.025265	-0.0224	0.0188	0.0158	0.0178
DiD	-0.0017	-0.0040 *	-0.0039 **	-0.1848 **	-0.199476 ***	-0.1352 *	-0.0024	0.0122 ***	0.0005
p-Wert	(0.331)	(0.070)	(0.046)	(0.026)	(0.010)	(0.071)	(0.194)	(0.000)	(0.770)
Precrisis (2006Q3-2007Q2) versus post Lehman (2008Q4-2009Q3)									
Treated firms									
precrisis	0.0068	0.0088	0.0059	0.0000	1.860936	1.3768	-0.0103	-0.0139	-0.0089
post Lehman	0.0960	0.1306	0.0926	0.0000	2.181164	1.5884	-0.0525	-0.0764	-0.0505
Difference	-0.0892	-0.1218	-0.0868	0.0000	-0.320228	-0.2117	0.0423	0.0625	0.0416
Control firms									
precrisis	0.0195	0.0204	0.0197	1.2750	1.416652	1.0450	-0.0105	-0.0113	-0.0100
post Lehman	0.1178	0.1165	0.1187	2.1923	1.579236	1.6765	-0.0668	-0.0716	-0.0652
Difference	-0.0983	-0.0961	-0.0990	-0.9174	-0.162584	-0.6315	0.0562	0.0603	0.0552
DiD	0.0091	-0.0257 ***	0.0122	0.6512 **	-0.157644	0.4198 *	-0.0140 ***	0.0022	-0.0136 ***
p-Wert	(0.410)	0.0060	(0.228)	(0.032)	(0.122)	(0.085)	(0.001)	0.4947	(0.000)
Precrisis (2006Q3-2007Q2) versus post crisis (2009Q4-2010Q3)									
Treated firms									
precrisis	0.0068	0.0088	0.0059	1.6450	1.860936	1.3768	-0.0103	-0.0139	-0.0089
post crisis	0.0378	0.0476	0.0329	1.959146	2.244264	1.5958	-0.0206	-0.0272	-0.0181
Difference	-0.0310	-0.0388	-0.0270	-0.3141	-0.383328	-0.2191	0.0103	0.0133	0.0092
Control firms									
precrisis	0.0195	0.0204	0.0197	1.2750	1.416652	1.0450	-0.0105	-0.0113	-0.0100
post crisis	0.0466	0.0449	0.0462	2.6384	1.745515	2.0110	-0.0297	-0.0265	-0.0277
Difference	-0.0271	-0.0245	-0.0265	-1.3634	-0.328863	-0.9659	0.0191	0.0152	0.0177
DiD	-0.0039	-0.0143 ***	-0.0005	1.0493 ***	-0.054465	0.7469 **	-0.0089 ***	-0.0019 ***	-0.0085 ***
p-Wert	(0.303)	0.0000	(0.893)	(0.009)	(0.685)	(0.021)	(0.000)	0.0000	(0.000)
Nobs.	103	103	101	79	91	77	103	103	103