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Derivatives usage, securitization, and the crash sensitivity of bank stocks☆

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ABSTRACT

We show that the information on derivatives usage and securitization activities of U.S. banks as disclosed in their pre-crisis 10-K filings explains extreme equity returns of banks during the financial crisis. Stocks of banks that had previously disclosed a more extensive use of financial derivatives and loan securitization were more likely to experience extreme losses. Our findings are consistent with investors viewing banks that used derivatives for non-hedging purposes as highly vulnerable to the crisis. Moreover, banks which had significant securitization activities and were thus potentially exposed to under-capitalized risks from conduits possess a higher vulnerability of their equity to market downturns.

1. Introduction

Many commentators of the recent financial crisis have stressed the notion that the panic of 2007–2008 was set in motion by a run on the sale and repurchase market (see, e.g., Gorton and Metrick, 2012). In particular, high uncertainty about the solvency and the involvement and risk exposure of banks in the market for securitized loans sparked a "run on repo" that ultimately caused the interbank lending market to freeze (see Kwan, 2009) and subsequently the temporary insolvency of the U.S. banking system. Additionally, ex-post analyses of the crisis have concluded that inadequate risk management at many banks contributed to the severity of the crisis.[1] Yet, the majority of both theoretical and empirical analyses on the financial crisis and systemic risk in banking have solely concentrated on the role of banks' business models (see Brunnermeier et al., 2012), their funding fragility and leverage (see Adrian and Shin, 2010; Brunnermeier and Pedersen, 2009) as well as their risk culture and corporate governance (see Fahlenbrach and Stulz, 2011; Aebi et al., 2012; Fahlenbrach et al., 2012). In this paper, we investigate whether bank transparency concerning the banks' securitization activities and risk management can explain extreme stock returns of U.S. banks during the financial crisis.[2] More precisely, we show that information on the securitization activities and risk management of U.S. banks as disclosed in their pre-crisis 10-K filings explains the sensitivity of their equity prices to market downturns during the crisis. Banks with a more elaborate use of financial derivatives and which securitized loans had significantly higher Marginal Expected Shortfall (MES) and ΔCoVaR estimates in 2007–2009. Analyzing the former (counterintuitive) result in more detail, we find the use of financial derivatives to have a particularly detrimental effect on banks' equity returns in

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[1] For example, the Financial Crisis Inquiry Commission concluded in January 2011 that "[...] dramatic failures of corporate governance and risk management at many systemically important financial institutions were a key cause of this crisis."

[2] Note that we consider banks' current rather than expected returns during the financial crisis.

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case the bank employs derivatives primarily for non-hedging purposes.

There now exists a wide consensus among financial economists that the reluctance of banks to lend in the interbank market as well as the credit crunch that ensued were at least in part due to the opacity of banks and the uncertainty of investors about banks' default risk (see Heider et al., 2010; Pritsker, 2010; Flannery et al., 2013). In fact, the importance of financial reporting transparency for market discipline and financial stability had been previously underlined well before the start of the crisis in scientific studies (see, e.g., Flannery and Thakor, 2006) and by regulators (see Basel Committee on Banking Supervision, 1998; 2001; Corporation, 2002).[3] The empirical evidence on the relation between accounting transparency and financial stability, however, is mixed at best. For example, Barth et al. (2004) find no evidence for a decreasing effect of higher bank transparency on the likelihood of a financial crisis at the country-level. In contrast, Nier (2005) shows that extreme negative stock returns become less likely with greater transparency.[4] Although overall accounting transparency is generally associated with less firm risk of banks, the opposite is true for unfavorable disclosures like, e.g., reports on a bank's risk exposure. Kothari et al. (2009) find that negative disclosures from firm and press sources increase a company's cost of capital and stock return volatility. Closely related to their finding, Liu et al. (2004) and Lim and Tan (2007) find banks' trading Value-at-Risks (VaR) to have predictive power for the banks' total risk and future stock return volatility. Investors in bank equities thus appear to act on disclosed information on the market risk exposure of banks. Following this line of argumentation, banks with a higher level of risk exposure before the financial crisis could have suffered to a greater extent from losses in stock prices than banks that had less risk exposure.

Moreover, publicly available information not only on the risk exposure but also on a bank's securitization activities could be positively related to large losses in the bank's equity. As Acharya et al. (2013) empirically show, many banks set up asset-backed commercial paper conduits prior to the financial crisis to exploit regulatory arbitrage thereby effectively securitizing assets without transferring the risks to other investors. Consequently, bank stocks could also have experienced extreme negative returns during the crisis because of available information on the banks' securitization activities that possibly made them retain under-capitalized risks on their balance sheets. This conjecture mirrors previous research indicating that securitizations impact investors' risk assessments (see Niu and Richardson, 2006; Barth et al., 2012; Dou et al., 2014).

Finally, a bank's exposure and contribution to market-wide shocks in equity prices could also have been caused by the banks' extensive use of derivatives for hedging and non-hedging purposes. While the trading volume of derivatives has increased considerably during the last three decades, the empirical evidence on the effects of derivatives usage on the performance and risk of firms is ambiguous.[5] For instance, several studies have found the intuitive result that firms predominantly employ derivatives to hedge rather than increase firm risk (see, e.g., Tufano, 1996; Guay, 1999; Allayannis and Weston, 2001; Graham and Rogers, 2002). Recently, Bartram et al. (2011) and Pérez-González and Yun (2013) found empirical evidence that the use of financial derivatives significantly reduces both total firm risk and systematic risk as well as increases firm value, respectively. Yet at the same time, several studies have also stressed the finding that derivatives usage does not significantly lower firm risk even if it is used for hedging purposes.[6] For example, Guay (1999) finds that systematic firm risk is unaffected by the use of derivatives. Underlining this result, Hentschel and Kothari (2001) find that derivatives usage is not significantly related to a firm's stock return volatility. In addition, the results by Guay and Kothari (2003) and Jin and Jorion (2006) further show that firm market values are relatively unaffected by hedging. Turning to the literature on banks' derivatives usage, the study of Venkatachalam (1996) supports the finding that banks reduce their risk exposure through hedging.[7] However, the study's results also show that only 47% of banks seem to use derivatives for hedging purposes. Building on the idea that banks could use derivatives for non-hedging purposes, many authors have argued that derivatives usage could (1) tempt bank managers to engage in excessive risk-taking (see, e.g., Franke and Krahnen, 2006) and (2) lead to a destabilizing concentration of risks (see, e.g., Stulz, 2004; Rajan, 2005).[8] Given the divergent views in both the accounting and finance literature, the question of the effects of derivatives usage on a bank's firm risk especially during times of crisis is ultimately an empirical one.

We find strong evidence that both the exposure and the contribution of U.S. banks' equity to crashes of the financial sector during the financial crisis was significantly driven by the banks' use of financial derivatives. More precisely, U.S. banks that used more financial derivatives in general and interest rates derivatives in particular had economically significantly higher MES and lower ΔCoVaR estimates. Additionally, banks which disclosed information on their securitization of loans also had a significantly higher exposure (but not a higher contribution) to equity market crashes during the crisis. Furthermore, our regression results support the hypothesis that the crash sensitivity of U.S. bank stocks critically depended on the banks' derivatives usage and securitization activities before the crisis. In particular, banks that used derivatives for non-hedging purposes have a systematically higher equity tail risk than other banks that either used less derivatives or that used derivatives for hedging. Our key results are robust to the additional inclusion of various idiosyncratic control variables proxying for the banks' business model, regulatory capital, funding fragility and size. Also, the relation between the derivatives usage and securitization of banks and the crash sensitivity of the banks' equity cannot simply be explained by the fact that larger (and thus systemically more important) banks employ a more elaborate risk management. However, our analysis should not be mistaken for a simple analysis of the causes of the financial crisis. Rather, our analysis is concerned with the way stock market investors reacted to publicly available information on a bank's potential vulnerability during the crisis.

Our study is related to several papers in the literature. For instance, Brunnermeier et al. (2012) employ the same measures of a bank's equity tail risk as we do arguing that both the MES and ΔCoVaR do not only measure the crash sensitivity of bank stocks but also the banks' exposure and contribution to systemic risk, respectively. Their empirical findings show that higher non-interest

[3] The importance of transparency in financial reports is also discussed, e.g., in Bushman and Smith (2001) who review the role of publicly reported financial accounting information in the governance processes of corporations, and Hutton et al. (2009) who show that opaque firms are more prone to stock price crashes.

[4] As Nier and Baumann (2005) show, higher transparency is also associated with more bank capital and thus higher financial stability.

[5] Theoretically, hedging should not add value to a firm in case of perfect capital markets following the famous reasoning of Modigliani and Miller (1958). However, market frictions could reverse this result as shown, e.g., by Smith and Stulz (1985), Froot et al. (1993), and Leland (1998).

[6] Perhaps most famously, Berkshire Hathaway CEO Warren Buffett referred to derivatives as "financial weapons of mass destruction" in 2003.

[7] In a related study, Purnanandam (2007) finds empirical evidence that derivatives enable banks to maintain smooth operating policies in the event of external macroeconomic shocks. Consequently, users of financial derivatives (in contrast to non-users) do not have to bear the costs of offering new terms to their relationship borrowers or depositors.

[8] Further evidence on the detrimental side-effects of (especially credit) derivatives usage on financial stability is provided by Instefjord (2005), Dewally and Shao (2013), and Nijskens and Wagner (2011).

income increases a bank's contribution to systemic risk as proxied by its ΔCoVaR. In a similar study, Anginer et al. (2014a) come to the conclusion that deposit insurance had both a beneficial effect on banks' equity tail risk during crises as well as an adverse effect caused by increased risk-taking by bank managers. The equity tail risk of banks has also been studied by Anginer et al. (2014b) and Weiß et al. (2014) in the context of bank consolidation. However, none of these studies looks at the role of derivatives usage or risk disclosure during the financial crisis. Our paper is also related to the studies by Venkatachalam (1996), Guay (1999), Purnanandam (2007), and Bartram et al. (2011) in which the effects of using financial derivatives on idiosyncratic and systematic risk are analyzed. In contrast, our paper is concerned with the effects of derivatives and risk disclosure on extreme stock returns of banks. Next, our paper is related to the work of Mayordomo et al. (2014) on the nexus between banks' derivatives holdings and systemic risk. In contrast to their paper, however, we explicitly focus on the purpose of the banks' usage of derivatives and its effect on extreme stock returns. Finally, our choice of dependent variables is related to the study of DeFond et al. (2014) who analyze the impact of mandatory IFRS adoption on firm-level crash risk which is proxied by the frequency of extreme negative stock returns.[9] They find that crash risk decreases among industrial firms and increases among financial firms after the IFRS mandate.

The paper proceeds as follows. In Section 2, we describe our data and discuss both our dependent and independent variables of interest. In Section 3, we document our main finding that the equity tail risk of U.S. banks during the financial crisis was driven by information on the banks' use of derivatives and securitization as disclosed in their pre-crisis 10-K filings. Section 4 concludes.

2. Data and methodology

The following section outlines the construction of our sample as well as data sources, defines the main dependent and independent variables used in the statistical analysis, and presents the empirical strategy for our cross-sectional regressions.

2.1. Sample construction and data sources

For the construction of our sample, we follow Fahlenbrach and Stulz (2011) and Fahlenbrach et al. (2012) and first select all banks with SIC codes between 6000 and 6300 listed in *Thomson Reuters Financial Datastream*. We then exclude all firms that are not in the traditional banking industry, i.e., we concentrate on banks whose respective two-digit SIC code equals 60 (depository banks), 61, or 62 (non-depository banks). To rule out a possible survivorship bias, we select all banks from both the active and dead-firm lists in *Datastream*. While financial accounting data is retrieved from *Thomson Reuters Worldscope*, we manually collect information on a bank's derivatives usage and securitization activities as well as risk management from the banks' respective 10-K filings with the SEC. 10-K filings are retrieved from the *Morningstar Document Research* database. We then content-analyze by hand the U.S. banks' 10-K filings from the fiscal year 2006 for two reasons. First, we are interested in testing the predictive power of a bank's pre-crisis risk management for forecasting its extreme stock returns during the crisis. Second, using explanatory variables from 2006 mitigates otherwise possible concerns of biased regression results due to endogeneity. Our initial sample comprises 1,087 U.S. banks, from which we first exclude banks for which Morningstar does not provide the 10-K filings from 2006 (159 firms). We also exclude banks with no stock price available in Datastream (79 firms) at the start of our sample and those banks with incomplete accounting data available in *Worldscope* (305 firms). Eventually, we exclude firms with U.S. OTC Bulletin Board and "Pink Sheet" listings (13 firms), secondary listings and American Depositary Receipts (ADRs) (24 firms) as well as non-primary issues (35 firms). Given that these data screens lead to 615 exclusions, our final sample consists of 472 U.S. banks. The construction of our final sample and the quantitative impact of the different data screens on the sample size are shown in Appendix IA.I. Statistics on the U.S. banking sector provided by the Federal Deposit Insurance Corporation (FDIC) reveal that the sum of total assets represented by our final sample covers 87.2% of the total sum of the FDIC insured banks' total assets in 2006. Moreover, the total market cap of our sample banks in 2006 was $1.529 trillion compared to a market cap of the *Datastream US Financials Index* of $3.061 trillion (note that the *Datastream US Financials Index* is not solely composed of banks but also includes insurers and other financial firms). Our final sample should thus be representative of the complete U.S. banking sector. For increased transparency, the names of the banks in our final sample are listed in Appendix IA.II.

In the final step of our data collection, we apply several screening procedures for the daily returns on the banks' stock prices to control for known data errors in *Datastream* and to minimize differences between returns calculated from stock prices taken from *Datastream* and the Center for Research in Security Prices (CRSP) databases (see Ince and Porter, 2006).[10] We find no significant evidence of such data errors and the additional data screens we apply lead to no further exclusions of banks from our sample.

In the following subsections, we define and discuss our set of dependent and explanatory variables. Definitions and data sources for all our variables are summarized in Appendix A.

2.2. Dependent variables: measures of equity tail risk

To measure the extent to which information on risk management and securitization affects the equity tail risk of U.S. banks, we use one metric for the exposure and one metric for the contribution of a bank to crashes in the returns on a financial sector index. As such, both measures can be viewed as measures of the crash sensitivity of a bank's stock.

As our first dependent variable, we employ the Marginal Expected Shortfall as proposed by Acharya et al. (2010) which captures the marginal *exposure* of an institution to a system-wide collapse.[11] The MES is defined as the negative mean net equity return of a bank conditional on the financial sector as a whole experiencing an extreme crash.[12] We then follow Beltratti and Stulz (2012) and Fahlenbrach et al. (2012) and define the crisis period as the time period from 1st of July, 2007 to 31st of December, 2008 and compute the MES for each sample bank for this period using the *Datastream US Financials Index* (DS code FINANUS) as a proxy for the U.S. financial sector.[13,14] To be precise, we construct our

[9] Other related studies in the literature by Beisland and Frestad (2013) and Chen et al. (2014) examine the effects of corporate governance and fair-value accounting rule changes on derivatives usage.

[10] For example, we check whether the stock prices of our sample drop at least once below a minimum price of $1 during the time period of July 2007 to December 2008 and whether monthly stock returns exist in our sample that are above 300% and which are reversed in the following month.

[11] Alternatives to the equity-based systemic risk measures comprise, e.g., the CDS spread-based measures of Oh and Patton (2013). However, measuring systemic risk via CDS spreads requires the availability of liquid CDS on the bank names in question.

[12] Acharya et al. (2010) propose to define a market crash by a market index being in its lower 5% tail. We follow their definition and estimate the MES accordingly using the 5% threshold.

[13] Note that the periods over which the dependent and independent variables are measured do not overlap.

[14] We also employed the S&P 500 as an alternative market index for computing the banks' MES in our robustness checks. The (unreported) results yielded a

dependent variable by taking the mean of the daily MES estimates computed via the dynamic model specification of Brownlees and Engle (2012) during the crisis period.[15]

As our second dependent variable, we use the ΔCoVaR measure proposed by Adrian and Brunnermeier (2010) as a measure of a financial institution's marginal *contribution* to the extreme returns on a financial sector index. They define a bank's CoVaR as the Value-at-Risk of the financial system conditional on an institution being under distress.[16] The systemic risk contribution of a bank is then proxied by the difference (referred to as ΔCoVaR) between CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution. Just like the MES, CoVaR and ΔCoVaR are based on the left tail of the joint distribution of the returns on a sector index and an individual institution's stock, and measure the externalities a bank causes on the financial system in case of default. In our analysis, we employ the conditional, time-varying version of the ΔCoVaR and estimate it using a set of state variables that capture the evolution of tail risk dependence over time.[17]

Throughout our paper, we consider the MES and ΔCoVaR to be measures of a bank's *equity tail risk* rather than *systemic risk* (as it is done, e.g., by Brunnermeier et al., 2012; Fahlenbrach et al., 2012; Hovakimian et al., 2012; Anginer et al., 2014a; 2014b; Weiß et al., 2014). Although both Acharya et al. (2010) and Adrian and Brunnermeier (2010) argue in their respective studies that both measures capture the systemic risk that emanates from an individual financial institution to the stability of the financial sector, both measures have been heavily criticized in the literature for being based solely on stock market returns.[18] For example, Benoit et al. (2013) compare several equity-based measures of systemic risk and come to the conclusion that these measures fall short in capturing the multiple facets of systemic risk. Acharya et al. (2012) argue in a similar fashion and point out the fact that both the MES and ΔCoVaR neglect the size and the leverage of financial institutions. In this paper, we do not consider the MES and ΔCoVaR as proxies for the systemic risk of banks but rather as measures of the sensitivity of the banks' equity to crashes of the financial sector. In this way, we circumvent an otherwise possible overinterpretation of both the MES and ΔCoVaR and focus on the dynamics between individual bank stock and sector returns during the financial crisis. In particular, our main research hypothesis is that extreme stock returns of banks can in part be explained by mandated disclosed information on derivatives usage and securitization in banks' 10-K filings. Nonetheless, we note that extreme bank stock returns (or equity tail risk) should of course be seen as an important part of a bank' systemic risk as shown, e.g., in the Capital Shortfall model of Acharya et al. (2012).

2.3. Main variables of interest: derivatives usage and risk management disclosure

Employing the previously described measures, we investigate if disclosures on derivatives usage and securitization activities in 10-K filings published prior to the financial crisis explain the U.S. banks' equity tail risk during the crisis. We operationalize our independent variables by using a set of five measures.

The first variable that reflects derivatives usage and risk management disclosure is the Derivatives intensity, defined as the number of the used types of financial derivatives as disclosed in the bank's 10-K filing. This proxy indicates the intensity with which firms employ financial derivatives. While banks in the United States are mandated by FAS 133 to disclose information on their derivatives positions, the amount of information disclosed by banks on the notional and/or fair values of derivative positions is quite heterogeneous across our sample banks. Consequently, we follow Bartram et al. (2011) and employ the absolute number of different derivative types used by a bank (instead of the sum of notional values) as a proxy of the bank's derivatives intensity. We argue that the sign of the coefficient is unrestricted in our regressions. On the one hand, banks may reduce their risk exposure by using derivatives for hedging (see Venkatachalam, 1996), suggesting a negative sign for the corresponding coefficient. On the other hand, more intensive usage of derivatives, as signaled by a higher derivatives intensity, may indicate that banks take higher risks (see Franke and Krahnen, 2006). This expectation implies an increasing impact on a bank's equity tail risk.

Our second variable, interest rate derivatives, is a dummy variable equaling one if a bank uses interest rate derivatives, and zero if no such statement is made. Guay (1999) finds a negative correlation between the use of interest rate derivatives and firm risk, indicating that the sign of the coefficient may be negative. However, Purnanandam (2007) provides evidence that banks with higher risk exposures manage their interest rate risk more aggressively. Therefore, interest rate derivatives usage may increase equity tail risk.

The third variable refers to the use of foreign exchange derivatives (see Guay, 1999; Graham and Rogers, 2002). Similarly to the use of interest rate derivatives, we measure the use of foreign exchange derivatives with a dummy variable that equals one for banks disclosing the usage of foreign exchange derivatives and zero for those banks that do not use such derivatives. As in the case of the use of interest rate derivatives, we argue that using derivatives related to foreign exchange risks may reduce a bank's total risk. At the same time, using FX derivatives may increase counterparty risk. Therefore, the sign of the coefficient cannot be unambiguously predicted.

Our fourth variable captures securitization activities disclosed in the banks' 10-K filings. The dummy variable equals one if a bank discloses the use of loan securitization and zero if such information cannot be found. As securitization implies the transfer of risks, we may predict that its use decreases extreme bank stock returns. However, Acharya et al. (2013) find that banks may use securitization for regulatory arbitrage without transferring the risk to outside investors. Therefore, we expect the sign of the coefficient to be unrestricted in our regressions.

Finally, our fifth variable disclosed risk types refers to the number of risk types a bank is exposed to as disclosed in its 10-K filings. On the one hand, the (mandatory) disclosure of more risk types may indicate more risk-taking by the bank, suggesting an expected increasing impact on bank stock returns during the crisis. On the other hand, more comprehensive disclosure could indicate a more alert risk management, corresponding with a decreasing impact on a bank's equity tail risk. Thus, we predict the sign of the coefficient to be unrestricted in our regressions.

correlation between the two indexes of 90.64%, thus a near perfect positive correlation between the two different sets of MES estimates, and our regression results remained qualitatively and quantitatively the same.

[15] To compute daily MES estimates, we follow Brownlees and Engle (2012) and employ the Threshold-ARCH (TARCH) (see Rabemananjara and Zakoïan, 1993) and Dynamic Conditional Correlation (DCC) (see Engle, 2002) specifications for all trading days within the crisis period. As we employ back-looking averages of daily in-sample estimates from the TARCH/DCC model, the MES estimates should not suffer from a look-ahead bias.

[16] We define a financial institution to be in distress if its stock return is in the lower 5%-tail

[17] We follow Adrian and Brunnermeier (2010) and use 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 Bond, the MSCI World Index as a proxy for the market return, 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 on interest rates are retrieved from the U.S. Federal Reserve Board's H.15.

[18] See, e.g., Bisias et al. (2012) and Giglio et al. (2013) for two recent surveys of systemic risk measures.

2.4. Control variables

In our regression analyses, we also use a comprehensive set of control variables to avoid an otherwise potential omitted-variable bias. As control variables, we use several proxies for the banks' size, profitability, business profile, capital structure and market valuation. In the following, we discuss each control variable in turn, focusing on the hypothesized effect on our two measures of banks' extreme stock returns.

As a first control variable, we employ the natural logarithm of the banks' total assets as a proxy for bank size. If a bank is deemed too big to fail, a bank might receive a subsidy from safety net policies thereby incentivizing bank managers to take on more risks than socially optimal. Consequently, large banks should contribute significantly more to extreme downturns of a financial sector index than smaller banks. At the same time, large banks should also have a higher exposure of their equity to adverse effects spilling over from the financial sector (see O'Hara and Shaw, 1990; Acharya and Yorulmazer, 2008; Anginer et al., 2014b).

Next, we include the banks' return on assets (ROA) as an explanatory variable. We expect ROA to have a decreasing effect on the extreme stock returns of banks as higher profits can shield banks from the adverse effects of a financial crisis. A similar argument applies to the banks' Tier 1 capital which we use later on in our robustness checks. Higher bank capital can serve as a cushion against external shocks to the financial system thereby stabilizing both individual banks and the financial system as a whole (see, e.g., Kashyap et al., 2008; Hart and Zingales, 2011; BIS, 2012). The opposite argument applies to the banks' leverage, which we compute using the definition of Acharya et al. (2010) who define a bank's leverage as the book value of assets minus the book value of equity plus the market value of equity, divided by the market value of equity. The expected sign of the influence of leverage on the banks' MES and ΔCoVaR is not clear ex-ante. On the one hand, higher leverage could exert a disciplining effect on bank managers thus limiting the risk-taking of banks. On the other hand, higher leverage could also lead to a more pronounced vulnerability of a bank during a financial crisis (see Adrian and Shin, 2010). For similar reasons, we also use a proxy for the banks' debt maturity which we estimate by taking the banks' ratio of their total long-term debt to total debt. We expect a less fragile funding structure of a bank to decrease our measures of equity tail risk as it makes the banks' less vulnerable to sudden shortages in liquidity during a crisis (see Brunnermeier and Pedersen, 2009).

We also use the banks' non-interest income to total interest income ratio as a control variable. Brunnermeier et al. (2012) state and confirm the hypothesis that a focus on non-core activities outside the traditional lending business increases a bank's extreme stock returns measured by their MES and ΔCoVaR. Conversely, a higher loans to total assets ratio could indicate a business model that focuses on lending rather than more risky activities like, e.g., investment banking. Both our proxies for equity tail risk could also be dependent on the banks' risk culture. Fahlenbrach et al. (2012) show in their study that banks sticked to their risk culture causing them to perform similarly during both the LTCM crisis of 1998 and the recent financial crisis. To control for persistence in the banks' risk culture, we compute and use in our regressions the banks' buy-and-hold returns in 1998. In addition, we make use of the banks' market-to-book ratio in our cross-sectional regressions. As pointed out by, e.g., Keeley (1990), greater charter value could incentivize bank managers to keep their bank's capital ratio and to limit their risk-taking.

Additionally, we also use in our robustness checks a proxy for the overall transparency and amount of information disclosed in the banks' 10-K filings. Pérignon and Smith (2010) propose in their study on a sample of international banks a simple index of the level of VaR-disclosure. We compute a similar VaR-disclosure index by taking the sum of several dummy variables that take on the value of one if a certain information on the bank's VaR-model is disclosed, and zero otherwise. The index constituents cover the questions whether a) the confidence level of the VaR is disclosed, b) whether the bank calculates a model with a confidence level of 97.5% or higher, c) discloses information on the estimation method, d) the holding period, e) the employed backtests, and f) the overall diversification effect in the bank portfolio.

Finally, we employ two standard corporate governance control variables in our regressions. As pointed out by, e.g., Diamond and Rajan (2009) and Aebi et al. (2012), poor governance at banks could have contributed to the severity of the financial crisis. Consequently, we use the size and independence of the banks' boards to proxy for the governance of insurers before the financial crisis. Board size is defined as the natural logarithm of the number of directors on a bank's board. We expect board size to be positively related to equity tail risk because larger boards have been found to destroy firm value and possibly capital buffers (see, e.g., Yermack, 1996). To proxy for the independence of the board, we use the percentage of independent outside directors on the board of directors. Because outside directors should be more concerned about the sensitivity of the bank's stock price to market shocks, we expect the board's independence to have a decreasing impact on extreme bank stock returns.

2.5. Empirical strategy

The focus of our empirical analysis is the explanation of the cross-sectional variation in the equity tail risk of U.S. banks during the financial crisis. We estimate cross-sectional regressions of the banks' MES and ΔCoVaR using ordinary least squares (OLS) with Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors. Our baseline regression models are given by

$$\begin{aligned} MES_{i,crisis} = \beta_0 &+ \beta_1 \times derivatives\ intensity_{i,pre-crisis} \\ &+ \beta_2 \times securitization_{i,pre-crisis} \\ &+ \beta_3 \times disclosed\ risk\ types \\ &+ \Omega \times bank\ controls_{i,pre-crisis} + \varepsilon_i. \end{aligned} \quad (1)$$

and

$$\begin{aligned} \Delta CoVaR_{i,crisis} = \beta_0 &+ \beta_1 \times derivatives\ intensity_{i,pre-crisis} \\ &+ \beta_2 \times securitization_{i,pre-crisis} \\ &+ \beta_3 \times disclosed\ risk\ types \\ &+ \Omega \times bank\ controls_{i,pre-crisis} + \varepsilon_i. \end{aligned} \quad (2)$$

Each explanatory variable (derivatives intensity, risk management, and control variables) is constructed using data for the end of fiscal year 2006. As we use lagged explanatory variables, we mitigate a potential endogeneity bias caused by reverse causality between risk disclosure and banks' equity tail risk. Furthermore, the definition of the crisis period and our empirical strategy of using explanatory variables from 2006 in regressions of dependent variables during the crisis parallel similar approaches used in the related studies by Fahlenbrach and Stulz (2011), Beltratti and Stulz (2012), and Fahlenbrach et al. (2012).

3. Does banks' derivatives usage increase equity tail risk?

This section provides descriptive statistics for our data sample and results from our univariate and multivariate analyses.

3.1. Descriptive statistics

Sample summary statistics of our data are shown in Table 1.

Table 1
Descriptive statistics.

	Minimum	Maximum	5% Quantile	95% Quantile	Mean	Median	Standard deviation
Panel A: Equity tail risk measures							
- MES	−0.1190	0.1728	−0.03060	0.0980	0.0336	0.0338	0.0419
- ΔCoVaR	−0.0512	0.0160	−0.0419	0.0041	−0.0172	−0.0147	0.0159
Panel B: Risk management variables							
- Derivatives intensity	0	16	0	3	0.62	0	1.51
- Interest rate derivatives	0	1	0	1	0.25	0	0.50
- FX derivatives	0	1	0	0	0.04	0	0.20
- Disclosed risk types	0	8	0	7	4.35	5	1.61
- Securitization	0	1	0	1	0.17	0	0.38
- VaR-disclosure index	0	5	0	0	0.09	0	0.52
Panel C: Control variables							
- Total assets	0.04	1884.32	0.22	34.11	22.08	0.87	147.40
- Return on assets	−0.54	6.3	0.57	2.11	1.34	1.33	0.58
- Loans	0.14	8.29	0.63	1.23	0.95	0.93	0.39
- Non-interest income	−0.02	1.41	0.04	0.40	0.18	0.14	0.15
- Buy-and-hold returns 1998	−1.00	0.20	−0.56	−0.00	−0.25	−0.24	0.19
- Debt maturity	0	1	0	0.96	0.52	0.53	0.27
- Leverage	1.77	37.36	3.92	11.39	7.00	6.42	3.02
- Market-to-book ratio	0.06	0.93	0.17	0.51	0.31	0.30	0.10
- Tier 1 capital ($n = 472$)	6.91	62.10	8.73	21.58	13.05	11.62	5.54
- Stock liquidity ($n = 408$)	−2.40	−0.00	−1.79	−0.00	−0.44	−0.13	0.63
- DtD ($n = 455$)	−501.50	23.68	−2.71	9.99	1.82	3.17	25.45
- Board size ($n = 28$)	9	24	9.4	20.8	14.11	13	3.57
- Board independence ($n = 26$)	29.33	88.26	39.32	87.71	76.30	77.49	11.62

The table presents summary statistics for the different dependent and independent variables used in the empirical study. The sample includes 477 U.S. banks for which stock price (2007 to 2008) and accounting data (2006) were available in *Thomson Reuters Financial Datastream* and *Thomson Worldscope*, respectively, and for which 10-K filings were available in the *Morningstar Document Research* database. The sample construction and used data filters are given in Appendix IA.I and the full list of sample banks is presented in Appendix IA.II. All variables and data sources are defined in Appendix A. Total assets are given in $ billion. Accounting data are measured at the end of fiscal year 2006 while the two systemic risk measures are estimated based on the time period 07/01/2007 to 12/31/2008.

The mean and median MES of U.S. banks during the crisis are 3.36% and 3.38%, respectively, while the corresponding mean and median estimates of ΔCoVaR are −1.72% and 1.47%, respectively. These results are similar to those reported, e.g., by Acharya et al. (2010) and Brunnermeier et al. (2012) for the financial crisis. Especially the 95% (MES) and 5% quantiles underline that U.S. banks did not only contribute significantly to the turmoil in the financial sector, but their stocks also suffered to a large extent from shocks to the sector index. The standard deviation of the MES is considerably higher than the standard deviation of our ΔCoVaR estimates. In addition, the difference between the minimum and maximum estimates is significantly smaller for ΔCoVaR than for the MES. These findings show that the stocks of U.S. banks reacted quite differently to the shocks to the sector index. In contrast, the influence of shocks from individual bank stocks on the sector index was less pronounced with ΔCoVaR having less variation across our sample banks.

The U.S. banks in our sample had a mean derivatives intensity of 0.6264 with the median being zero. The majority of banks used zero to three types of financial derivatives in 2006 as shown by the 5% and 95% quantiles. Almost one quarter (24.74%) of our sample banks disclosed using financial derivatives to lower their interest rate risk exposure. At the same time, only 4.2% mentioned in their 10-K filing that they were using derivatives to hedge against foreign exchange risks. U.S. banks also disclosed a considerable number of risk types in their 10-K filings. On average, a U.S. bank explicitly mentioned 4.348 different sources of risk it was exposed to. The median number of disclosed risk types was 5. Finally, on average, 16.98% of our U.S. sample banks disclosed using the securitization of loans to transfer credit risk to other market investors.

As presented in Panel C of Table 1, our sample includes a diverse set of small and large banks. The mean and median total assets of our sample banks were $22.08 billion and $0.87 billion, respectively. In addition to a large number of smaller banks, our sample also includes several very large banks with total assets of up to $1.88 trillion in 2006. The banks' mean (median) return on assets in 2006 was 1.34% (1.33%) with the vast majority of banks reporting a positive pre-crisis return on their assets. U.S. banks had a mean loans-to-deposits ratio of 94.55% and a mean non-interest income to total interest income ratio of 17.69%. In line with our expectation, banks experienced a detrimental stock performance in 1998. The banks' buy-and-hold returns for the year 1998 were −25.14% on average with the stocks of several banks losing almost all value. Moreover, 90% of our sample banks had a negative stock performance during the year of the LTCM crisis. Banks had an average ratio of long-term debt to total debt of 52.33%, a mean leverage of 7.0047, and a mean market-to-book ratio of 0.3111. Finally, U.S. banks had 14.1071 board members, on average, with 76.3% of the board's members being independent outside directors.

3.2. Univariate analysis

We now test our major hypotheses on the correlation between public information on risk management and the equity tail risk of U.S. banks during the crisis. As stated in the introduction, stock market investors could have acted on publicly available information on the use of financial derivatives and loan securitization by both investing and divesting during the crisis. Table 2 provides strong evidence for the latter.

Users of both interest rate and FX derivatives had statistically significantly higher MES and ΔCoVaR estimates in the full sample than non-users. These differences are also highly economically significant as, e.g., users of interest rate derivatives lost 1.77% more on their stocks than non-users on those days during which the market plummeted. For users of FX derivatives, this difference is even larger with derivatives users losing 7.34% on their stocks during the worst days of the financial crisis with non-users losing only 3.15%. Similar results can be seen from our estimates of the banks'

Table 2
Equity tail risk of derivatives users and non-users.

Panel A: Derivatives users and non-users in the full sample.

	Interest rate derivatives			FX derivatives			Securitization		
	Users	Non-users	Difference	Users	Non-users	Difference	Users	Non-users	Difference
n	110	367		24	453		81	396	
ΔCoVaR	−0.0258	−0.0147	−0.0111***	−0.0340	−0.0164	−0.0177***	−0.0225	−0.0162	−0.0063***
MES	0.0472	0.0295	0.0177***	0.0734	0.0315	0.0420***	0.0493	0.0304	0.0190***

Panel B: Derivatives users and matched non-users.

	Derivatives usage		
	Users	Non-users	Difference
n	114	114	
ΔCoVaR	−0.0255	−0.0219	−0.0036**
MES	0.0473	0.0346	0.0127***

The table presents comparisons of the equity tail risk of derivatives users and non-users. Panel A presents mean estimates of Marginal Expected Shortfall (MES) and ΔCoVaR separately for banks that use interest rate derivatives, foreign exchange derivatives, and banks that securitize loans in comparison to non-users and non-securitizers using the full sample. The statistical significance of the difference between the two sample means is tested using the nonparametric Wilcoxon rank-sum test. The full sample includes 477 U.S. banks for which stock price (2008 to 2009) and accounting data (2006) were available in *Thomson Reuters Financial Datastream* and *Thomson Worldscope*, respectively, and for which 10-K filings were available in the *Morningstar Document Research* database. The sample construction and used data filters are given in Appendix IA.I and the full list of sample banks is presented in Appendix IA.II. In Panel B, mean MES and ΔCoVaR estimates are presented for banks that use derivatives and matched non-using banks. The matching of users to non-users of derivatives is done using the propensity score matching technique which is also used by Bartram et al. (2011). In a first step, the banks' propensity to use derivatives is estimated based on their distance-to-default, firm size, leverage, and their quick ratio. In a second step, derivatives users are matched to those banks that do not use derivatives, based on this propensity. The statistical significance of the difference between the two sample means is tested againby the use of the nonparametric Wilcoxon rank-sum test. The sample includes 114 U.S. banks that used derivatives and matched non-users. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

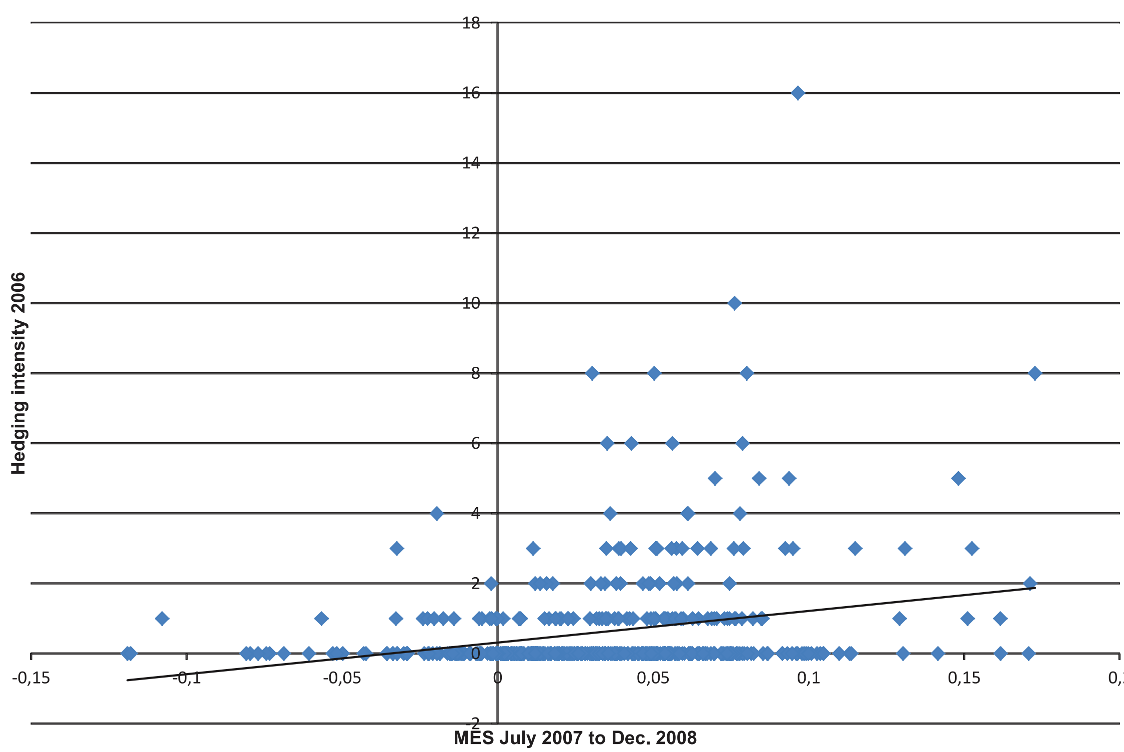

Fig. 1. Banks' exposure to equity tail risk and derivatives intensity. The figure shows a scatter plot of estimates of U.S. banks' Marginal Expected Shortfall during the financial crisis against the respective U.S. banks' derivatives intensity (defined as the number of types of financial derivatives used by the bank). The MES estimates are computed for the crisis period running from 07/01/2007 to 12/31/2008, while the values of the banks' derivatives intensity are taken from the banks' 10-K filings at the end of 2006. Variable definitions and data sources are provided in Appendix A. The sample consists of 477 U.S. banks.

ΔCoVaR. Banks that hedged their interest rate risks using financial derivatives in 2006 pulled down the U.S. financial sector by 2.58% in equity returns during the crisis. In comparison, the US Financials Index from *Datastream* lost only 1.47% on those days on which non-users of derivatives had their stock perform worst during the crisis. Further evidence on the increasing impact of a bank's derivatives intensity on our two measures of equity tail risk is presented in Figs. 1 and 2.

Both Figures show that, on average, banks that used more financial derivatives had both a higher exposure and contribution to equity tail risk. Finally, our comparison of banks that did or did not securitize loans shows a similar picture. Banks that employed loan securitization as a risk transfer tool had both statistically and economically significantly worse mean MES and ΔCoVaR estimates than banks that did not securitize loans.

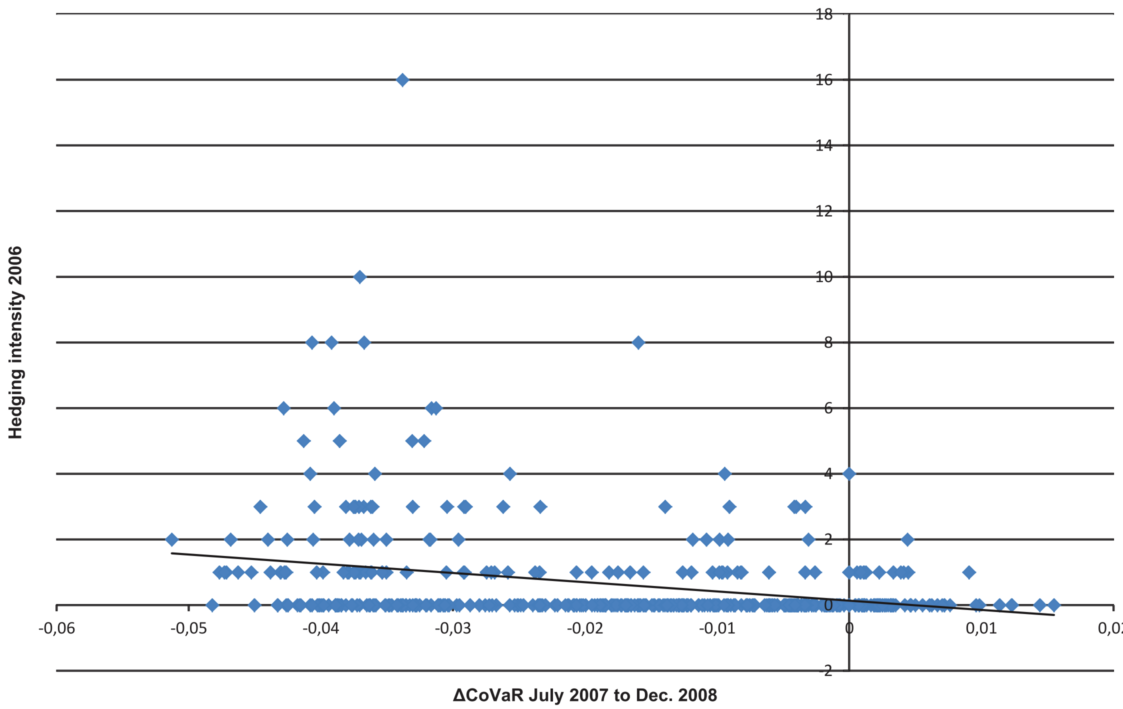

Fig. 2. Banks' contribution to equity tail risk and derivatives intensity. The figure shows a scatter plot of estimates of U.S. banks' ΔCoVaR during the financial crisis against the respective U.S. banks' derivatives intensity (defined as the number of types of financial derivatives used by the bank). The ΔCoVaR estimates are computed for the crisis period running from 01/07/2007 to 12/31/2008, while the values of the banks' derivatives intensity are taken from the banks' 10-K filings at the end of 2006. Variable definitions and data sources are provided in Appendix A. The sample consists of 477 U.S. banks.

Although these first results show strong support for systematic differences between the equity tail risk of users and non-users of derivatives, an important caveat applies to the interpretation of these univariate results. As noted, e.g., by Jin and Jorion (2006) and Bartram et al. (2011), the differences in the banks' extreme stock returns that we find may be confounded by the endogeneity of a bank's decision to hedge. To account for endogeneity concerns, we follow Bartram et al. (2011) and match users and non-users of derivatives using propensity score matching. In a first step, the banks' propensity to use derivatives is estimated based on their distance-to-default, firm size, leverage, and their quick ratio. In a second step, derivatives users are matched to those banks that do not use derivatives, based on this propensity. In Panel B of Table 2, we compare mean MES and ΔCoVaR estimates for banks that use derivatives and matched non-using banks. Again, we find derivatives users to have significantly higher MES estimates and lower ΔCoVaR estimates than matched non-users.

In Table 3, we split our sample into banks in the bottom and top quartile of MES estimates. U.S. banks in the top MES quartile had the highest exposure to shocks to the financial sector while banks in the bottom MES quartile, by construction, had the lowest exposure to equity tail risk. In Table 4, we repeat this quartile analysis for the estimates of the banks' ΔCoVaR during the financial crisis and compare the characteristics of the largest contributors (bottom ΔCoVaR quartile) with those of the weakest contributors (top ΔCoVaR quartile) to downturns of the financial sector index.

The results in Table 3 show that U.S. banks that had the largest exposure to crashes of the financial sector also had significantly lower ΔCoVaR estimates. Even more importantly, banks in the top MES quartile used more derivatives, had a higher likelihood of using interest rate and FX derivatives and were more likely to engage in loan securitization. Interestingly, banks in the top and bottom MES quartile differ from each other with respect to almost all of our control variables as well. Banks that were the most exposed to equity tail risk were significantly larger, relied more on non-interest income, performed worse in 1998, had less leverage, and a higher market-to-book ratio. Table 4 presents similar results for our analysis of the contribution to stock market downturns. Top contributing banks had a higher derivatives intensity, were more likely to use interest rate and FX derivatives and disclosed more types of risk exposure and a higher likelihood to securitize loans. Again, we find U.S. banks in the bottom ΔCoVaR quartile to be significantly larger, to have higher non-interest income to interest income ratios, and to have less leverage. Overall, our results are strongly supportive of the hypothesis that public information on a more extensive usage of financial derivatives and securitization of some banks led to the extreme losses on these banks' stocks at the height of the financial crisis.

A problem with these results is, however, that the variables we employ in our quartile analysis are obviously correlated thus further necessitating a multivariate analysis of our main hypotheses. In addition, to further mitigate concerns of endogeneity, we later employ lagged values of our explanatory variables in our multivariate analyses. Moreover, in Section IA.6 in the Internet Appendix, we perform a set of simultaneous equations regressions to control for the possibility that a bank's equity tail risk and derivatives intensity are jointly determined.

3.3. Multivariate regressions

We now turn to our cross-sectional regressions of U.S. banks' equity tail risk. Table 5 presents the results of our baseline regressions of our sample banks' MES on our main independent variables and several control variables.

Table 5 presents strong support for the hypothesis that stocks of banks whose pre-crisis 10-K filings revealed them to be more exposed to the crisis via their use of financial derivatives and loan securitization had systematically higher extreme losses than less exposed banks. Columns 1 to 5 report the results of regressions in which we test the isolated impact of our risk management

Table 3
Summary statistics for banks in the first and fourth Marginal Expected Shortfall quartile.

	Descriptive statistics of banks in the bottom quartile of the distribution of MES				Descriptive statistics of banks in the top quartile of the distribution of MES				Test for equality of means	
	Mean	5% Quantile	95% Quantile	St. dev.	Mean	5% Quantile	95% Quantile	St. dev.	*t*-statistic	*p*-Value
Panel A: Systemic risk measures										
- MES	−0.0165	−0.0745	0.0061	0.0262	0.0847	0.0597	0.1512	0.0267	−42.2585	0.00***
- ΔCoVaR	−0.0013	−0.0148	0.0096	0.0073	−0.0289	−0.0428	−0.0044	0.0122	41.1967	0.00***
Panel B: Risk management variables										
- Derivatives intensity	0.21	0.00	1.00	0.58	1.13	0.00	5.00	2.31	−17.52	0.00***
- Interest rate derivatives	0.13	0.00	1.00	0.34	0.33	0.00	1.00	0.47	−6.15	0.00***
- FX derivatives	0.00	0.00	0.00	0.00	0.14	0.00	1.00	0.35	4.43	0.00***
- Securitization	0.14	0.00	1.00	0.35	0.32	0.00	1.00	0.47	−5.47	0.00***
- Disclosed risk types	4.15	0.00	6.00	1.60	4.46	1.00	7.00	1.63	−2.11	0.14
- VaR-disclosure Index	0.01	0.00	0.00	0.09	0.20	0.00	1.05	0.88	−23.00	0.00***
Panel C: Control variables										
- Total assets	0.57	0.19	1.21	0.32	44.25	0.30	108.05	219.49	−1512.15	0.00***
- Return on assets	1.17	0.36	1.77	0.42	1.48	0.74	2.13	0.61	−8.07	0.00***
- Loans	0.91	0.65	1.20	0.18	0.93	0.61	1.19	0.18	−1.01	0.48
- Non-interest income	0.15	0.03	0.36	0.12	0.23	0.05	0.53	0.21	−6.95	0.00***
- Buy-and-hold returns 1998	−0.20	−0.48	0.00	0.15	−0.27	−0.62	−0.07	0.16	4.63	0.01***
- Leverage	7.81	4.50	11.57	2.63	6.29	3.81	10.93	2.37	6.33	0.00***
- Market-to-book	0.27	0.15	0.45	0.09	0.33	0.21	0.49	0.09	−7.12	0.00***
- Debt maturity	0.55	0.00	1.00	0.28	0.52	0.09	0.94	0.25	1.42	0.30

This table presents summary statistics comparing the characteristics of banks whose Marginal Expected Shortfall was in the bottom quartile with the characteristics of banks whose Marginal Expected Shortfall was in the top quartile. The sample includes 477 U.S. banks for which stock price (2007 to 2008) and accounting data (2006) were available in *Thomson Reuters Financial Datastream* and *Thomson Worldscope*, respectively, and for which 10-K filings were available in the *Morningstar Document Research* database. The sample construction and used data filters are given in Appendix IA.I and the full list of sample banks is presented in Appendix IA.II. All variables and data sources are defined in Appendix A. Total assets are given in $ billion. Accounting data are measured at the end of fiscal year 2006 while the two systemic risk measures are estimated based on the time period 07/01/2007 to 12/31/2008. The tests of differences between banks in the top and bottom MES are performed using the nonparametric Wilcoxon rank-sum test. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Table 4
Summary statistics for banks in the fourth and first ΔCoVaR quartile.

	Descriptive statistics of banks in the top quartile of the distribution of ΔCoVaR				Descriptive statistics of banks in the bottom quartile of the distribution of ΔCoVaR				Test for equality of means	
	Mean	5% Quantile	95% Quantile	St. dev.	Mean	5% Quantile	95% Quantile	St. dev.	*t*-statistic	*p*-Value
Panel A: Systemic risk measures										
- MES	−0.0017	−0.0690	0.0540	0.0400	0.0621	0.0347	0.0967	0.0216	32.3850	0.00***
- ΔCoVaR	0.0017	−0.0033	0.0096	0.0039	−0.0386	−0.0463	−0.0335	0.0038	−116.2432	0.00***
Panel B: Risk management variables										
- Derivatives intensity	0.26	0.00	1.00	0.60	1.39	0.00	6.00	2.36	5.42	0.00***
- Interest rate derivatives	0.15	0.00	1.00	0.36	0.43	0.00	1.00	0.50	6.24	0.00***
- FX derivatives	0.01	0.00	0.00	0.09	0.15	0.00	1.00	0.36	4.33	0.00***
- Securitization	0.12	0.00	1.00	0.32	0.25	0.00	1.00	0.43	3.36	0.01***
- Disclosed risk types	4.07	0.00	6.00	1.81	4.73	3.00	7.00	1.33	5.48	0.00***
- VaR-disclosure Index	0.03	0.00	0.00	0.02	0.29	0.00	2.05	0.97	3.00	0.00***
Panel C: Control variables										
- Total assets	1.06	0.13	1.32	5.51	75.79	1.20	232.37	278.07	2.94	0.00***
- Return on assets	1.17	0.36	1.81	0.46	1.62	0.85	2.47	0.60	8.24	0.00***
- Loans	0.90	0.59	1.25	0.19	1.01	0.61	1.26	0.70	1.75	0.10*
- Non interest income	0.15	0.04	0.32	0.12	0.25	0.04	0.68	0.22	5.23	0.00***
- Buy-and-hold returns 1998	−0.18	−0.40	0.00	0.13	−0.26	−0.60	0.00	0.17	4.−5.35	0.00***
- Leverage	7.45	4.12	11.23	2.59	5.65	3.78	7.91	1.55	−12.75	0.00***
- Market-to-book	0.28	0.15	0.45	0.09	0.38	0.26	0.59	0.11	10.68	0.00***
- Debt maturity	0.58	0.00	1.00	0.26	0.48	0.08	0.81	0.24	−4.65	0.00***

This table presents summary statistics comparing the characteristics of banks whose ΔCoVaR was in the top quartile with the characteristics of banks whose ΔCoVaR was in the bottom quartile. The sample includes 477 U.S. banks for which stock price (2007 to 2008) and accounting data (2006) were available in *Thomson Reuters Financial Datastream* and *Thomson Worldscope*, respectively, and for which 10-K filings were available in the *Morningstar Document Research* database. The sample construction and used data filters are given in Appendix IA.I and the full list of sample banks is presented in Appendix IA.II. All variables and data sources are defined in Appendix A. Total assets are given in $ billion. Accounting data are measured at the end of fiscal year 2006 while the two systemic risk measures are estimated based on the time period 07/01/2007 to 12/31/2008. The tests of differences between banks in the bottom and top ΔCoVaR quartiles are performed using the nonparametric Wilcoxon rank-sum test. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

variables on the banks' MES. With the exception of the disclosed number of risk types to which a bank is exposed, all our variables on a bank's derivatives usage and loan securitization enter the regressions with a highly statistically significant positive sign. In column 6, we estimate a regression in which we use both the banks' derivatives intensity, the dummy for the securitization of loans, and the number of disclosed risk types. Again, the banks' derivatives intensity and the dummy for loan securitization enter regression of the banks' MES during the crisis with highly statistically significant coefficients. Adding the bank-specific control variables to this model in regression (7) does not change our findings. Derivatives intensity and loan securitization remain powerful

Table 5
Baseline regressions of a bank's exposure to equity tail risk during the financial crisis.

Dependent Variable	(1) MES	(2) MES	(3) MES	(4) MES	(5) MES	(6) MES	(7) MES	(8) MES	(9) MES	(10) MES
Panel A: Risk management variables										
Derivatives intensity	**0.007*****					**0.007*****	**0.005*****		**0.005*****	
	(0.000)					**(0.000)**	**(0.000)**		**(0.002)**	
Interest rate derivatives		**0.017*****						**0.011*****		**0.013*****
		(0.000)						**(0.006)**		**(0.000)**
FX derivatives			**0.039*****					0.007		0.001
			(0.000)					(0.368)		(0.936)
Securitization				**0.019*****		**0.016*****	**0.012****	**0.011****	**0.014****	**0.013****
				(0.001)		**(0.002)**	**(0.022)**	**(0.033)**	**(0.019)**	**(0.028)**
Disclosed risk types					0.001	−0.001	−0.002	−0.001	−0.001	−0.001
					(0.377)	(0.452)	(0.194)	(0.254)	(0.588)	(0.686)
Panel B: Control variables										
Total assets ($\times 10^{11}$)							**1.996****	0.350	**2.265****	0.138
							(0.047)	(0.685)	**(0.030)**	(0.824)
Return on assets							**0.007***	0.006	−0.002	−0.004
							(0.069)	(0.109)	(0.732)	(0.517)
Loans							**−0.008****	**−0.006***	**−0.009****	**−0.007****
							(0.032)	**(0.062)**	**(0.022)**	**(0.049)**
Non interest income							**0.025****	**0.027****	**0.024****	**0.027***
							(0.011)	**(0.019)**	**(0.044)**	**(0.054)**
Buy-and-hold returns 1998									−0.019	−0.022
									(0.171)	(0.110)
Leverage							**−0.001***	**−0.001***	**−0.002****	**−0.002****
							(0.068)	**(0.083)**	**(0.047)**	**(0.042)**
Market-to-book							**0.047****	**0.049****	**0.073****	**0.075****
							(0.024)	**(0.022)**	**(0.014)**	**(0.012)**
Debt maturity							−0.003	−0.003	0.004	0.005
							(0.562)	(0.577)	(0.604)	(0.522)
Intercept	0.029***	0.029***	0.032***	0.030***	0.029***	0.031***	0.024**	0.022**	0.026*	0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.035)	(0.085)	(0.132)
R^2	0.063	0.043	0.035	0.029	0.002	0.084	0.128	0.125	0.183	0.189
Adj. R^2	0.061	0.041	0.033	0.027	0.000	0.078	0.109	0.103	0.150	0.154
Observations	477	477	477	477	477	477	463	463	286	286

This table shows results from cross-sectional regressions of the Marginal Expected Shortfall of U.S. banks on several variables related to the banks' risk management and various control variables. The dependent variable in each regression is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). All explanatory variables are based on stock market or accounting data for the year 2006. Models (1) through (5) only employ one risk management variable at a time. Regression model (6) uses all risk management variables in our sample excluding the dummy variables on the use of interest rate and foreign exchange derivatives which are highly correlated with the derivatives intensity variable. In regression (7), various bank-specific control variables are added to the regression on the risk management variables. Model (8) is equal to regression (7) but uses the dummy variables on the use of interest rate and foreign exchange derivatives instead of the derivatives intensity. Regression specifications (9) and (10) equal models (7) and (8) with the exception that we additionally employ the banks' stock performance in 1998 as a further explanatory variable (due to data availability, these regressions are performed on a sub-sample only). Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-tests. Corresponding p-values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' R-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.

** denote coefficients that are significant at the 5% level.

* denote coefficients that are significant at the 10% level.

determinants of a bank's exposure to equity tail risk. These effects are also economically significant with a one standard deviation increase in a bank's derivatives intensity in 2006 being associated with a 0.76% increase in MES (0.005 × 1.5138) during the crisis. Disclosing the securitization of loans led to a 1.2% higher MES of U.S banks.

In regression (8), we substitute our proxy for the banks' derivatives intensity with our dummy variables for the use of interest rate and FX derivatives. While the dummy for FX derivatives does not enter the regression with a statistically significant sign, the use of interest risk derivatives is both statistically and economically significantly related to a bank's exposure to a crash in the financial sector. Usage of interest rate derivatives is associated with a 1.1% higher MES during the financial crisis. Loan securitization remains both statistically and economically significant in this regression as well (1.1% increase in MES for banks that securitize). Note that, interestingly, the number of risk types a bank is exposed to does not statistically significantly affect the banks' exposure to shocks in the stock market. In columns 9 and 10, where we include the banks' buy-and-hold returns during the LTCM crisis, we find statistically and economically similar evidence.[19]

In our most comprehensive regression specifications (7)–(10), the control variables enter the regressions with the expected signs. For example, a higher non-interest income to interest income ratio is associated with a higher MES of banks. Conversely, banks that granted more loans in 2006 had lower MES estimates during the crisis. Also, larger banks exhibited higher losses on the worst days of the crisis. However, the effect of bank size on MES is attenuated in our regressions in which we employ our dummy variables for the use of interest rate and FX derivatives.[20] Finally, as in our

[19] Note that the adjusted R^2 in our regressions is comparable to (and sometimes higher than) those reported for U.S. banks buy-and-hold returns in the study of Fahlenbrach et al. (2012).

[20] We also compute for each explanatory variable the regressions' variance inflation factor (VIF) defined as $1/(1-R^2)$, where R^2 is the multiple R-squared from the regression of MES/ΔCoVaR on the remaining independent variables. For all our explanatory variables, the VIF is always below the value of 2, suggesting that multicollinearity does not significantly affect our results.

Table 6
Baseline regressions of a bank's contribution to equity tail risk during the financial crisis.

Dependent variable	(1) ΔCoVaR	(2) ΔCoVaR	(3) ΔCoVaR	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR	(9) ΔCoVaR	(10) ΔCoVaR
Panel A: Risk management variables										
Derivatives intensity	**−0.003*****					**−0.003*****	**−0.002*****		**−0.001***	
	(0.000)					**(0.000)**	**(0.001)**		**(0.054)**	
Interest rate derivatives		**−0.009*****						**−0.005*****		**−0.005*****
		(0.000)						**(0.000)**		**(0.001)**
FX derivatives			**−0.018*****					−0.001		0.001
			(0.000)					(0.762)		(0.776)
Securitization				**−0.006*****		**−0.005*****	−0.002	−0.002	−0.002	−0.001
				(0.001)		**(0.007)**	(0.278)	(0.383)	(0.475)	(0.614)
Disclosed risk types					**−0.002*****	**−0.001****	0.000	0.000	0.000	0.000
					(0.000)	**(0.014)**	(0.628)	(0.568)	(0.512)	(0.521)
Panel B: Control variables										
Total assets							0.000	0.000	0.000	0.000
							(0.386)	(0.535)	(0.643)	(0.533)
Return on assets							**−0.004****	**−0.003****	0.002	0.002
							(0.025)	**(0.039)**	(0.476)	(0.355)
Loans							0.004*	0.003	**0.004****	**0.003***
							(0.051)	(0.103)	**(0.045)**	**(0.090)**
Non interest income							−0.008	−0.008	−0.005	−0.006
							(0.102)	(0.106)	(0.357)	(0.320)
Buy-and-hold returns 1998									**0.008***	**0.009***
									(0.081)	**(0.056)**
Leverage							**0.001*****	**0.001*****	**0.002*****	**0.002*****
							(0.004)	**(0.003)**	**(0.000)**	**(0.000)**
Market-to-book							**−0.040*****	**−0.040*****	**−0.053*****	**−0.051*****
							(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Debt maturity							**0.006*****	**0.006*****	0.004	0.003
							(0.009)	**(0.010)**	(0.306)	(0.351)
Intercept	−0.015***	−0.015***	−0.017***	−0.016***	−0.010***	−0.011***	−0.008**	−0.007*	−0.017***	−0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.060)	(0.003)	(0.003)
R^2	0.087	0.079	0.050	0.022	0.030	0.108	0.251	0.256	0.261	0.278
Adj. R^2	0.085	0.077	0.048	0.020	0.028	0.102	0.234	0.238	0.231	0.247
Observations	477	477	477	477	477	477	463	463	286	286

This table shows results from cross-sectional regressions of the ΔCoVaR of U.S. banks on several variables related to the banks' risk management and various control variables. The dependent variable in each regression is the average of the daily conditional ΔCoVaR estimates for the time period 07/01/2007 to 12/31/2008 computed using the original model specification of Adrian and Brunnermeier (2010). All explanatory variables are based on stock market or accounting data for the year 2006. Models (1) through (5) only employ one risk management variable at a time. Regression model (6) uses all risk management variables in our sample excluding the dummy variables on the use of interest rate and foreign exchange derivatives which are highly correlated with the derivatives intensity variable. In regression (7), various bank-specific control variables are added to the regression on the risk management variables. Model (8) is equal to regression (7) but uses the dummy variables on the use of interest rate and foreign exchange derivatives instead of the derivatives intensity. Regression specifications (9) and (10) equal models (7) and (8) with the exception that we additionally employ the banks' stock performance in 1998 as a further explanatory variable (due to data availability, these regressions are performed on a sub-sample only). Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-tests. Corresponding p-Values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' R-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.
** denote coefficients that are significant at the 5% level.
* denote coefficients that are significant at the 10% level.

univariate analysis, results from our regression emphasize the disciplining effect of leverage as the banks' MES is found to be negatively associated with leverage. Note that the adjusted R-squared values for the regressions in Table 5 (and also in further regressions) for the most comprehensive model specifications are comparable to the ones found in related studies (see, e.g., Beltratti and Stulz, 2012; Anginer et al., 2014a;b).

Our multivariate results on the determinants of U.S. banks' MES are consistent with the hypothesis that the use of derivatives and loan securitization made some banks riskier than non-users which in turn resulted in the extreme losses on the stocks of derivatives users during the crash of the financial sector. In the next part of our analysis, we test the hypothesis that extreme negative stock returns of individual banks with a supposedly higher pre-crisis risk exposure led to extreme stock losses of the whole financial sector. Table 6 presents the results of our regressions of U.S. banks' ΔCoVaR estimates during the crisis.

Regressions (1)–(5) in Table 6 employ each of our risk management variables one at a time. Each variable enters its respective regression with a highly statistically significant coefficient. In addition, and as expected, all coefficients carry a negative sign. Banks that used more financial derivatives contributed more strongly to declines in the stocks of the financial sector. So did banks which securitized loans and which had a more pronounced risk exposure in 2006. These results carry over to regression (6), in which we employ our three main risk management variables simultaneously. However, both our dummy variables for securitization and the number of risk types lose their statistical significance after the addition of our control variables. In regressions (7) and (8), we use our full sample and find a bank's derivatives intensity and its use of interest rate derivatives to be significantly correlated with its contribution to the extreme stock returns of banks. Both effects are economically significant, although the effects are less pronounced than those from our regressions of the banks' MES.

Among our control variables, leverage and debt maturity enter regressions (7) and (8) with a highly statistically and economically significant positive sign. Banks that had lower leverage but a more fragile funding structure thus contributed more to losses on the financial sector index. Conversely, lower market-to-book ratios and return on assets were associated with higher returns on the sector index on those days an individual bank's stock plummeted. Finally, regressions (9) and (10) employ the subsample of U.S. banks for which we have data on their stocks' buy-and-hold returns in 1998. The stock performance during the LTCM crisis significantly influences the contribution of banks to the performance of the financial sector index. Banks that performed poorly in 1998 contributed more to losses of the sector index during the financial crisis. Our main finding from these regressions, however, is that the sample banks' derivatives intensity and the propensity to use interest rate derivatives are positively associated with the banks' ΔCoVaR.

3.4. Additional analyses

This section provides results of further analyses on the relation between risk management and the equity tail risk of U.S. banks during the financial crisis.

3.4.1. Does derivatives usage increase banks' equity tail risk if used for hedging?

Up to this point in our analysis, our results indicate a negative perception of derivatives usage by stock market investors. One possible explanation for this finding could be that a more elaborate risk management of a bank is indicative of a significantly higher risk exposure and higher default risk. On the other hand, banks with low risk exposure from their business operations could have experienced extreme negative stock returns if they had used derivatives and loan securitization for speculation rather than hedging.

The results from our analysis of interactions shown later in this section provide first evidence for the latter conjecture. In models (3) and (10) in Table 10, we include an interaction term between a bank's derivatives intensity and the number of disclosed risk types. While the interaction term is not statistically significant in the regression of MES, it is highly statistically significant in the regression of a bank's contribution to the banks' tail risk. A bank that reports the use of more derivatives contributes more to extreme downturns in the financial sector index, but this effect is attenuated if the bank also reports a higher actual risk exposure. This first analysis thus supports the conjecture that the use of derivatives for purposes other than hedging was negatively perceived by stock market investors during the crisis.

The disclosed number of risk types of a bank is obviously only a suboptimal proxy for a bank's true risk exposure. Therefore, we additionally estimate the banks' distance-to-default (DtD) (see Merton, 1974; Hillegeist et al., 2004; Campbell et al., 2008; Anginer et al., 2014b) during the year 2006 to proxy for the banks' pre-crisis default risk. Everything else equal, we would expect a bank's distance-to-default to be negatively correlated with the bank's MES and positively correlated with ΔCoVaR as a higher distance-to-default (and thus a lower default probability) should be reflected in a bank's equity tail risk. Table 7 presents the results of regressions in which we employ the banks' DtD as a further explanatory variable.[21]

Regressions (1), (2), (4), and (5) in Table 7 confirm both our previous findings as well as the conjecture that default risk is positively related to equity tail risk.[22] The higher a bank's pre-crisis distance-to-default is, the lower (higher) is its MES (ΔCoVaR) during the crisis. In columns 3 and 6, we interact the banks' distances-to-default with the banks' derivatives intensity and our dummy for loan securitization. In both regressions, the interaction term of the distance-to-default with the derivatives intensity is statistically significant at the 10% level. Furthermore, the sign on the coefficient of the interaction terms in both regressions supports the hypothesis stated above. The positive relation between the derivatives intensity and the equity tail risk of banks is amplified by decreases in default risk (at least during the financial crisis). Our results are thus again consistent with the notion of a risk-increasing effect of derivatives if used for non-hedging purposes. Finally, the interaction terms with loan securitization are not statistically significant in our regressions.

To get an even better understanding of the relation between derivatives usage and banks' equity tail risk, we test the hypothesis that the risk-increasing effect of derivatives usage is indeed caused by banks employing derivatives for non-hedging purposes. To this end, we extract the fair value gains and losses on derivatives and selected balance sheet items (investment securities, net loans, deposits, and long term debt) from our sample banks' 10-K filings in 2006. We then follow Venkatachalam (1996) and consider a bank's motive for using derivatives to be risk reduction and hedging if both the fair value gains/losses on derivatives and balance sheet items are of different signs. Conversely, if both variables are of the same sign, we consider this to be an indication of risk-taking being the bank's primary motive for using financial derivatives. From this information, we construct a dummy variable that takes on the value of one if derivatives are used for taking on increased risks, and zero if derivatives are used for hedging.[23] This dummy variable is then used in additional regressions in which we interact the risk-taking/hedging dummy with the banks' derivatives intensities.[24]

The results of these regressions are shown in Table 8.

The results from regressions (1), (2), (4), and (5) in Table 8 show that the use of the dummy variable for a non-hedging purpose of derivatives usage as an alternative to our main explanatory variable is in line with our predictions. Banks that use derivatives for non-hedging purposes, on average, have statistically and economically higher MES and ΔCoVaR estimates during the crisis. In regressions (3) and (6), we interact the non-hedging purpose dummy with a bank's derivatives intensity to test the hypothesis that a non-hedging purpose does indeed increase the effect of derivatives usage on equity tail risk. For the banks' MES, this hypothesis cannot be rejected based on the results from regression (3) in which the interaction term is positive and statistically significant at the 10% level. In regression (6) of the banks' ΔCoVaR, the interaction term is not statistically significant. Finally, corresponding regressions of the banks' default risk turn out unsuccessful.

It should be noted that the approach of Venkatachalam (1996) of assessing the purpose of derivatives usage by analyzing the correlation between the gains/losses on derivatives and balance sheet items at a single point in time to some extent neglects the fact that hedging operates through time for a given bank (see Skinner, 1996). To attenuate this concern, in unreported robustness checks we repeat our previous analysis using the sum

[21] We also estimate regressions in which we employ the banks' distance-to-default estimated using data from 2008 as an explanatory variable. The results from these regressions are qualitatively and quantitatively similar to those reported in the paper.

[22] In Section IA.1 in the Internet Appendix, we additionally test the hypothesis that a bank's derivatives intensity and its use of loan securitization did not only increase equity tail risk, but also the bank's default probability during the financial crisis. Complementing our findings on equity tail risk, in the regressions presented in Table IA.III, we find a bank's derivatives intensity and the dummy variable for securitization to be significantly negatively related to a bank's distance-to-default during the crisis.

[23] We find 50.77% of our sample banks to be using derivatives for non-hedging purposes. Quite interestingly, this proportion does not seem to have changed significantly over time. Almost 20 years ago, Venkatachalam (1996) found a comparable 53% of banks to have used derivatives for increased risk-taking.

[24] In an unreported robustness check, we also directly employ the ratio of the fair value gains/losses on derivatives and balance sheet items as a proxy for the degree for which a bank is a net user of derivatives for hedging purposes. Our findings remain unchanged.

Table 7
Regressions of a banks equity tail risk during the financial crisis – default risk.

Dependent variable	(1) MES	(2) MES	(3) MES	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR
Panel A: Risk management variables						
Derivatives intensity	**0.005*****		**0.005*****	**−0.002*****		**−0.002*****
	(0.003)		**(0.004)**	**(0.002)**		**(0.003)**
Interest rate derivatives		**0.010*****			**−0.005*****	
		(0.008)			**(0.000)**	
FX derivatives		0.007			−0.001	
		(0.563)			(0.811)	
DtD ($\times$ 10^4)	**−1.947****	**−2.037****	**−7.898****	**0.899*****	**0.923*****	**3.149****
	(0.020)	**(0.015)**	**(0.023)**	**(0.003)**	**(0.002)**	**(0.012)**
Securitization	**0.014*****	**0.013*****	**0.013****	−0.002	−0.002	−0.002
	(0.005)	**(0.007)**	**(0.014)**	(0.206)	(0.286)	(0.365)
Disclosed risk types	−0.002	−0.002	−0.002	0.000	0.000	0.000
	(0.149)	(0.194)	(0.143)	(0.709)	(0.662)	(0.752)
Panel B: Control variables						
Total assets	0.000	0.000	0.000	0.000	0.000	0.000
	(0.333)	(0.769)	(0.698)	(0.478)	(0.466)	(0.919)
ROA	0.006	0.005	0.005	**−0.003***	**−0.003***	−0.003
	(0.239)	(0.299)	(0.358)	**(0.059)**	**(0.088)**	(0.100)
Loans	−0.006	−0.005	−0.006	0.003	0.002	0.003
	(0.247)	(0.366)	(0.244)	(0.105)	(0.194)	(0.112)
Non interest income	**0.023***	0.023	0.021	**−0.008***	−0.008	−0.008
	(0.093)	(0.105)	(0.120)	**(0.098)**	(0.104)	(0.123)
Leverage	**−0.002*****	**−0.002*****	**−0.002****	**0.001*****	**0.001*****	**0.001*****
	(0.004)	**(0.004)**	**(0.016)**	**(0.000)**	**(0.000)**	**(0.000)**
Market-to-book	0.030	0.031	0.036	**−0.033*****	**−0.032*****	**−0.034*****
	(0.202)	(0.190)	(0.134)	**(0.000)**	**(0.000)**	**(0.000)**
Debt maturity	−0.003	−0.003	−0.003	**0.006****	**0.006****	**0.006****
	(0.655)	(0.671)	(0.614)	**(0.023)**	**(0.026)**	**(0.021)**
Panel C: Interactions						
DtD $\times$ Securitization			0.000			−0.000
			(0.226)			(0.103)
DtD $\times$ Derivatives intensity ($\times$ 10^4)			**2.176***			**−0.793***
			(0.071)			**(0.069)**
R^2	0.140	0.138	0.147	0.267	0.273	0.272
Adj. R^2	0.119	0.115	0.122	0.248	0.253	0.251
Observations	452	452	452	452	452	452

This table shows results from cross-sectional regressions of the Marginal Expected Shortfall and ΔCoVaR of U.S. banks on the banks' pre-crisis default risk measured by their distances-to-default (see Merton, 1974; Hillegeist et al., 2004; Campbell et al., 2008; Anginer et al., 2014b, for details of the computation of the DtD) and several control variables. The dependent variable in the first three regressions is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). In regressions (4) and (6), the dependent variable is the average conditional ΔCoVaR of the banks during the same period. Regressions (3) and (6) include interaction terms between the banks' distances-to-default and the banks' derivatives intensity as well as the dummy variable for loan securitization. All explanatory variables are based on stock market or accounting data for the year 2006. Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-tests. Corresponding p-Values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' R-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.
** denote coefficients that are significant at the 5% level.
* denote coefficients that are significant at the 10% level.

of the gains/losses on both derivatives and balance sheet positions for fiscal years 2004, 2005, and 2006. Our conclusions remain unchanged.

3.4.2. Does more hedging lead to higher equity tail risk?

Our analysis so far has produced evidence that is equally consistent with banks that used more derivatives having higher equity tail risk and with banks that did not use financial derivatives having lower MES and ΔCoVaR estimates. Consequently, we cannot rule out the possibility that our results are simply driven by moderate returns on the stocks of non-hedging banks during times of market turmoil. We therefore investigate possible asymmetries in the relation between a bank's derivatives intensity and its equity tail risk in the next part of our analysis. To this end, we divide our sample banks into quintiles based on their 2006 derivatives intensity. We then construct dummy variables for the membership in each of the five quintiles with the first (fifth) quintile containing banks with the lowest (highest) pre-crisis derivatives intensity. Table 9 presents the results of regressions of MES and ΔCoVaR in which the banks' derivatives intensity has been replaced with the quintile indicators.[25]

The results show that our findings are indeed driven by the banks that had the highest pre-crisis derivatives intensity. While membership in the second to fourth quintiles of derivatives intensity is not statistically significantly related to MES or ΔCoVaR, the dummy for membership in the fifth quintile enters all regressions with an economically and statistically significant sign. This effect is not significantly affected in those regressions in which we control for differences in the banks' Tier 1 capital. In the regressions of the banks' MES, our dummy variable for loan securitization remains statistically and economically highly significant. In contrast, the number of risk types disclosed in the banks' 10-K filings enters none of our regressions of MES and ΔCoVaR with a statistically significant coefficient.

[25] To avoid perfect multicollinearity, the dummy variable for membership in the first quintile is omitted.

Table 8
Equity tail risk and the motives of derivatives usage.

Dependent variable	(1) MES	(2) MES	(3) MES	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR	(7) DtD	(8) DtD	(9) DtD
Panel A: Risk management variables									
Non-hedging purpose	**0.014****	**0.013****	0.010	**−0.010*****	**−0.009*****	**−0.005***	0.195	0.846	2.240
	(0.018)	**(0.025)**	(0.225)	**(0.000)**	**(0.000)**	**(0.087)**	(0.893)	(0.632)	(0.622)
Securitization		**0.019*****	**0.012****		**−0.006*****	−0.002		−2.488	0.073
		(0.001)	**(0.019)**		**(0.001)**	(0.283)		(0.332)	(0.980)
Disclosed risk types		0.001	−0.002		**−0.001*****	0.000		−1.064	−0.859
		(0.559)	(0.178)		**(0.000)**	(0.603)		(0.176)	(0.214)
Derivatives intensity			0.001			−0.001			−0.141
			(0.701)			(0.413)			(0.935)
Panel B: Control variables									
Total assets			0.000			0.000			0.000
			(0.205)			(0.542)			(0.120)
ROA			0.007			**−0.004****			**5.531***
			(0.111)			**(0.034)**			**(0.053)**
Loans to deposit			−0.008			**0.003***			**6.781****
			(0.107)			**(0.062)**			**(0.021)**
NIItoII			**0.025***			−0.008			1.404
			(0.063)			(0.124)			(0.856)
Leverage			**−0.001***			**0.001*****			**−4.108*****
			(0.083)			**(0.004)**			**(0.000)**
Market-to-book			**0.045****			**−0.040*****			**−87.873*****
			(0.041)			**(0.000)**			**(0.000)**
Debt maturity			**−0.003**			**0.006*****			3.216
			(0.616)			**(0.008)**			(0.409)
Panel C: Interaction									
Hedging int. × Non-hedging purpose			**0.006***			−0.001			−1.956
			(0.091)			(0.423)			(0.302)
R^2	0.013	0.042	0.134	0.042	0.085	0.256	0.000	0.006	0.287
Adj. R^2	0.011	0.035	0.111	0.040	0.080	0.236	−0.002	−0.001	0.268
Observations	477	477	463	477	477	463	455	455	452

This table shows results of cross-sectional regressions of the Marginal Expected Shortfall, ΔCoVaR, and distance-to-default (see Merton, 1974; Hillegeist et al., 2004; Campbell et al., 2008; Anginer et al., 2014b, for details of the computation of the DtD) of U.S. banks on several variables related to the banks' risk management, a dummy variable for the banks' motive for using derivatives, and various control variables. The dependent variable in the first three regressions is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). In regressions (4) and (6), the dependent variable is the average conditional ΔCoVaR of the banks during the same period. Regressions (7) and (9) employ the banks' distances-to-default as the dependent variable. All explanatory variables are based on stock market or accounting data for the year 2006. Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-tests. Corresponding p-Values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' R-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.

** denote coefficients that are significant at the 5% level.

* denote coefficients that are significant at the 10% level.

3.4.3. Is the relation between derivatives usage and banks' extreme stock returns exacerbated by bank size and mitigated by bank capital?

In the next step of our analysis, we investigate whether the relation between a bank's derivatives intensity and its equity tail risk during the financial crisis depends on a bank's size and regulatory capital. Although we control for a bank's size in our baseline regressions, we nevertheless expect larger banks to use financial derivatives more extensively than smaller banks. Also, we would expect banks with more regulatory capital to have suffered less during the crisis. In Table 10, we undertake first tests of these hypotheses by running several cross-sectional regressions in which we interact our main independent variables with size and bank capital.

In columns 1 and 8 of Table 10, we interact a bank's derivatives intensity with its size measured by its total assets. This test is unsuccessful as the interaction terms in the regressions of both MES and ΔCoVaR are statistically insignificant. In regression (2), we interact the banks' Tier 1 capital ratios with their derivatives intensity. We find higher bank capital to have an attenuating effect on the positive relation between a bank's MES and its derivatives intensity. Consequently, and in line with our expectation, stock market investors view derivatives usage as less detrimental if the bank is financially healthier (we do not find a comparable result in regression (9) of the banks' ΔCoVaR).

Regression specifications (4), (5), (11), and (12) show that bank size exacerbates to some extent the negative influence of the use of interest rate derivatives on both the banks' MES and ΔCoVaR. The same result can be seen from regressions (6) and (13) which show that bank size positively affects the relation between loan securitization and equity tail risk. One explanation for this finding could obviously be that larger banks possess a more elaborate risk management than smaller banks. We address this concern in Section 3.4.4. Finally, higher Tier 1 capital is again associated with a less detrimental effect of securitization on banks' extreme stock returns. Thus, both the exposure and contribution to equity tail risk of a bank during the crisis were less pronounced in case the bank held more capital.

3.4.4. Is equity tail risk driven by the overall level of disclosure?

Although our results so far are strongly supportive of the hypothesis that banks that used more derivatives and securitized loans (especially when reporting less risk exposure and less regulatory capital at the same time) experienced more extreme negative losses on their stocks than other banks, we cannot rule out the possibility that our results are driven by differences in the amount

Table 9
Regressions of a bank's equity tail risk during the financial crisis – derivatives intensity quintiles.

Dependent variable	(1) MES	(2) MES	(3) MES	(4) ΔCoVaR	(5) ΔCoVaR	(6) ΔCoVaR
Panel A: Risk management variables						
Derivatives intensity Quintile 2	0.000	−0.001	−0.001	0.000	0.000	0.000
	(0.932)	(0.886)	(0.920)	(0.981)	(0.928)	(0.971)
Derivatives intensity Quintile 3	0.000	0.000	0.000	0.000	0.000	0.000
	(0.945)	(0.937)	(0.982)	(0.932)	(0.903)	(0.961)
Derivatives intensity Quintile 4	0.002	0.002	0.001	−0.002	−0.002	−0.002
	(0.774)	(0.767)	(0.820)	(0.304)	(0.268)	(0.329)
Derivatives intensity Quintile 5	**0.016****	**0.013****	**0.015****	**−0.010*****	**−0.009*****	**−0.010*****
	(0.012)	**(0.031)**	**(0.013)**	**(0.000)**	**(0.000)**	**(0.000)**
VaR-disclosure index			−0.007			0.002
			(0.247)			(0.327)
Securitization	**0.011****	**0.010****	**0.012****	−0.002	−0.001	−0.002
	(0.021)	**(0.042)**	**(0.018)**	(0.323)	(0.605)	(0.298)
Disclosed risk types	−0.001	−0.002	−0.002	0.000	0.000	0.000
	(0.220)	(0.179)	(0.183)	(0.792)	(0.939)	(0.865)
Panel B: Control variables						
Total assets	0.000	0.000	0.000	0.000	0.000	0.000
	(0.752)	(0.975)	(0.306)	(0.335)	(0.925)	(0.201)
Tier 1 capital ($\times 10^4$)		**−8.242****			**4.238*****	
		(0.024)			**(0.003)**	
ROA	0.006	0.006	0.007	**−0.003****	**−0.004****	**−0.003****
	(0.183)	(0.165)	(0.153)	**(0.038)**	**(0.013)**	**(0.028)**
Loans	−0.006	**−0.009***	−0.008	**0.003****	**0.005*****	**0.003*****
	(0.223)	**(0.078)**	(0.144)	**(0.015)**	**(0.000)**	**(0.009)**
Non interest income	**0.028****	**0.029****	**0.036****	−0.007	−0.008	−0.009
	(0.039)	**(0.033)**	**(0.018)**	(0.193)	(0.164)	(0.130)
Leverage	−0.001		−0.001	**0.001****		**0.001****
	(0.109)		(0.119)	**(0.017)**		**(0.019)**
Market-to-book	**0.049****	**0.073*****	**0.049****	**−0.038*****	**−0.052*****	**−0.038*****
	(0.028)	**(0.002)**	**(0.025)**	**(0.000)**	**(0.000)**	**(0.000)**
Debt maturity	−0.004	−0.006	−0.004	**0.007*****	**0.008*****	**0.007*****
	(0.532)	(0.400)	(0.579)	**(0.001)**	**(0.000)**	**(0.001)**
Intercept	0.022*	0.022**	0.021*	−0.008**	−0.007**	−0.008*
	(0.052)	(0.033)	(0.058)	(0.050)	(0.038)	(0.054)
R^2	0.128	0.131	0.130	0.278	0.281	0.279
Adj. R^2	0.102	0.106	0.103	0.257	0.260	0.257
Observations	463	462	463	463	462	463

This table shows results from cross-sectional regressions of the Marginal Expected Shortfall and ΔCoVaR of U.S. banks on dummy variables for membership in the second, third, fourth and fifth quintile of derivatives intensity. The dependent variable in the first three regressions is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). In regressions (4) and (6), the dependent variable is the average conditional ΔCoVaR of the banks during the same period. All explanatory variables are based on stock market or accounting data for the year 2006. Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-tests. Corresponding p-Values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' R-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.
** denote coefficients that are significant at the 5% level.
* denote coefficients that are significant at the 10% level.

of information disclosed by our sample banks. Especially, if larger banks allocate more resources to foster investor relations and consequently disclose more information on their risk management on top of the information mandated by regulators, our main findings could be due to spurious correlation rather than causation. To test this conjecture, we run several additional regressions in which we employ the index proposed by Pérignon and Smith (2010) on the level of VaR-disclosure of our sample banks. This index captures the level and quality of information disclosed by banks on their use of Value-at-Risk in their risk management. In contrast to our main explanatory variables which also proxy (at least in part) for a bank's risk-taking, however, the VaR-disclosure index only conveys information on the quality of a bank's risk management (and the bank's transparency concerning its risk management). Even more importantly, in contrast to the mandatory information on a bank's derivative positions, VaR-based market risk disclosures are not mandatory but only encouraged by the SEC's Financial Reporting Release Number (FRR) 48 and the Basel Accord. If our results are indeed simply driven by differences in the amount of disclosed information on a bank's risk management, we would expect the VaR-disclosure index to capture this effect in our regressions. The results of these tests are presented in Table 11.[26]

The results of the regressions show a clear picture. As expected, more information on the use and estimation of VaR is associated with a lower MES and a higher ΔCoVaR. Despite this, the VaR-disclosure index enters none of our regressions with a statistically significant coefficient. In contrast, our proxies for a bank's derivatives intensity, loan securitization, and use of interest rate derivatives remain highly statistically and economically significant determinants of a bank's equity tail risk during the financial crisis.

3.5. Robustness

In this section, we perform various additional tests to check the robustness of our main findings. We start by performing re-

[26] In essence, these regressions can be seen as placebo tests in which we expect the VaR-disclosure index to be insignificant while our main explanatory variables remain significant determinants of MES and ΔCoVaR.

Table 10
Regressions of a bank's equity tail risk during the financial crisis – interactions.

Dependent variable	(1) MES	(2) MES	(3) MES	(4) MES	(5) MES	(6) MES	(7) MES	(8) ΔCoVaR	(9) ΔCoVaR	(10) ΔCoVaR	(11) ΔCoVaR	(12) ΔCoVaR	(13) ΔCoVaR	(14) ΔCoVaR
Panel A: Risk management variables														
Derivatives intensity	0.000	**0.021*** **	0.009			**0.004*** **	**0.005*** **	−0.004	−0.005	**−0.008*** **			**−0.002** **	**−0.002** **
	(0.968)	**(0.002)**	(0.114)			**(0.003)**	**(0.001)**	(0.355)	(0.041)	**(0.000)**			**(0.012)**	**(0.012)**
Interest rate derivatives				**−0.106*** **	**0.010*** **						**0.040*** **	**−0.005*** **		
				(0.002)	**(0.007)**						**(0.001)**	**(0.000)**		
FX derivatives				−0.001	0.108						0.002	−0.066		
				(0.922)	(0.495)						(0.719)	(0.248)		
Securitization	**0.012** **	**0.009* **	**0.012** **	**0.008* **	**0.011** **	**−0.140*** **	0.031	−0.002	−0.001	−0.002	0.000	−0.001	**0.052*** **	**−0.013*** **
	(0.017)	**(0.058)**	**(0.016)**	**(0.089)**	**(0.024)**	**(0.001)**	(0.237)	(0.263)	(0.648)	(0.355)	(0.800)	(0.409)	**(0.000)**	**(0.010)**
Discl. risks	−0.002	−0.002	−0.001	−0.001	−0.001	−0.001	−0.002	0.000	0.000	−0.001	0.000	0.000	0.000	0.000
	(0.213)	(0.195)	(0.275)	(0.349)	(0.260)	(0.256)	(0.166)	(0.648)	(0.717)	(0.172)	(0.438)	(0.588)	(0.513)	(0.721)
Panel B: Control variables														
Total assets ($\times 10^{11}$)	3.023	**4.135** **	1.293	1.827	1.885	**4.072*** **	**2.234** **	0.214	1.026	−0.625	0.473	−1.340	**1.277** **	0.687
	(0.259)	**(0.031)**	(0.524)	(0.291)	(0.514)	**(0.006)**	**(0.018)**	(0.825)	(0.140)	(0.289)	(0.446)	(0.198)	**(0.049)**	(0.272)
Tier 1 capital ($\times 10^4$)		**−7.048* **					**−6.308** **		0.357					**4.422*** **
		(0.053)					**(0.023)**		(0.001)					**(0.009)**
Panel C: Interactions														
Total assets × Hedging intens.	0.000							0.000						
	(0.614)							(0.651)						
Tier 1 capital × Hedging intens.		**−0.002** **							0.000					
		(0.013)							(0.151)					
Discl. risks × Deriv. intens.			−0.001							**0.001*** **				
			(0.500)							**(0.000)**				
Total assets × IR deriv.				**0.008*** **							**−0.003*** **			
				(0.001)							**(0.000)**			
Total assets × FX derivatives					−0.006							0.004		
					(0.521)							(0.256)		
Total assets × Securit.						**0.010*** **							**−0.004*** **	
						(0.000)							**(0.000)**	
Tier 1 capital × Securit.							−0.002							**0.001** **
							(0.454)							**(0.012)**
R^2	0.129	0.144	0.129	0.147	0.125	0.160	0.137	0.251	0.259	0.267	0.278	0.258	0.276	0.266
Adj. R^2	0.108	0.123	0.108	0.125	0.102	0.140	0.115	0.233	0.241	0.249	0.258	0.238	0.259	0.248
Observations	463	462	463	463	463	463	462	463	462	463	463	463	463	462

This table shows results from cross-sectional regressions of the Marginal Expected Shortfall and ΔCoVaR of U.S. banks on several variables related to the banks' risk management and various control variables together with interaction terms. The dependent variable in the first seven regressions is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). In regressions (8) and (14), the dependent variable is the average conditional ΔCoVaR of the banks during the same period. Coefficients for the bank-specific control variables are not shown for brevity. All explanatory variables are based on stock market or accounting data for the year 2006. Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent *t*-tests. Corresponding *p*-Values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' *R*-squared and adjusted R-squared, respectively.
*** denote coefficients that are significant at the 1% level.
** denote coefficients that are significant at the 5% level.
* denote coefficients that are significant at the 10% level.

gressions using alternative estimation techniques to control for a biasing influence of outliers on our results. For this, we reestimate our main models from Tables 5 and 6 using median regressions in which the sum of the absolute value of the regression's residuals are minimized. The results from our baseline OLS regressions remain quantitatively and qualitatively the same. Additionally, we reestimate all our regressions using winsorized (1% and 99% quantiles) explanatory variables as well as standard errors clustered by derivatives intensity and total assets groups. To further control for a confounding effect caused by different definitions of derivatives due to different auditors, and the geographical core/periphery structure of the U.S. banking sector, we reestimate our baseline regressions using auditor-fixed and state-fixed effects. The results of all these robustness checks do not alter our findings.

Next, it could be argued that our proxy of a bank's derivatives intensity does not take into account the actual size of a bank's derivatives position relative to the bank's size. To address this concern, we reestimate our regressions using the ratio of a bank's total fair value of all asset and liability side derivatives holdings and the bank's total assets as an alternative proxy of the bank's derivatives intensity.[27] The results of this robustness check are presented in Section IA.4 of the Internet Appendix. The results we get from this robustness check are qualitatively and quantitatively similar to those reported in our main analysis.

Furthermore, we employ several additional explanatory variables in regressions of MES and ΔCoVaR. First, in Section IA.2 in the Internet Appendix, we substitute our proxy for a bank's leverage for the bank's Tier 1 capital ratio. In Section IA.3, we also estimate regressions in which we control for differences in the liquidity of the banks' stocks. As investors prefer assets which are either liquid (see Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996) or are at least not exposed to systematic drops in liquidity (see Acharya and Pedersen, 2005; Sadka, 2006), the differences in the banks' equity tail risk could simply be due to differences in liquidity. The results of both robustness checks show that our main conclusions remain unchanged. Second, we estimate regressions in which we use our two proxies for the corporate governance of banks (board size and board independence). Although

[27] See Mayordomo et al. (2014) for a similar approach to measure a bank's derivatives intensity.

Table 11
Robustness check – VaR-disclosure index.

Dependent Variable	(1) MES	(2) MES	(3) MES	(4) MES	(5) ΔCoVaR	(6) ΔCoVaR	(7) ΔCoVaR	(8) ΔCoVaR
Panel A: Risk management variables								
VaR-disclosure index	−0.005	−0.005	−0.009	−0.008	0.002	0.000	0.003	0.002
	(0.363)	(0.466)	(0.142)	(0.193)	(0.399)	(0.980)	(0.244)	(0.338)
Derivatives intensity			**0.006*****				**−0.002*****	
			(0.001)				**(0.001)**	
Interest rate derivatives				**0.010*****				**−0.005*****
				(0.007)				**(0.000)**
FX derivatives				0.010				−0.002
				(0.444)				(0.630)
Securitization			**0.012****	**0.012****			−0.002	−0.002
			(0.012)	**(0.019)**			(0.254)	(0.356)
Disclosed risk types			−0.002	−0.001			0.000	0.000
			(0.152)	(0.218)			(0.721)	(0.636)
Panel B: Control variables								
Total assets	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.221)	(0.404)	(0.970)	(0.329)	(0.132)	(0.508)	(0.998)	(0.280)
ROA	0.007	−0.002	**0.008***	0.007	**−0.004****	0.002	**−0.004****	**−0.004****
	(0.122)	(0.760)	**(0.094)**	(0.130)	**(0.022)**	(0.355)	**(0.019)**	**(0.032)**
Loans	−0.007	**−0.009***	**−0.009***	−0.008	**0.004***	**0.004***	**0.004****	**0.003***
	(0.192)	**(0.087)**	**(0.072)**	(0.131)	**(0.059)**	**(0.056)**	**(0.029)**	**(0.068)**
Non interest income	**0.043*****	**0.044****	**0.035****	**0.035****	**−0.015*****	−0.010	**−0.011****	**−0.011***
	(0.004)	**(0.012)**	**(0.020)**	**(0.028)**	**(0.005)**	(0.151)	**(0.047)**	**(0.063)**
Buy-and-hold returns 1998		**−0.025****				**0.010****		
		(0.045)				**(0.045)**		
Leverage	−0.001	**−0.002****	**−0.001***	−0.001	**0.001*****	**0.002*****	**0.001*****	**0.001*****
	(0.183)	**(0.050)**	**(0.099)**	(0.108)	**(0.009)**	**(0.000)**	**(0.004)**	**(0.004)**
Market-to-book	**0.064*****	**0.100*****	**0.047****	**0.049****	**−0.046*****	**−0.060*****	**−0.040*****	**−0.040*****
	(0.004)	**(0.001)**	**(0.034)**	**(0.027)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Debt maturity	−0.004	0.004	−0.003	−0.003	**0.006****	0.003	**0.006****	**0.006****
	(0.594)	(0.619)	(0.689)	(0.680)	**(0.010)**	(0.329)	**(0.011)**	**(0.011)**
Intercept	0.011	0.013	0.023**	0.021**	−0.006*	−0.018***	−0.008**	−0.007*
	(0.258)	(0.323)	(0.031)	(0.049)	(0.079)	(0.001)	(0.048)	(0.063)
R^2	0.097	0.143	0.133	0.128	0.230	0.247	0.253	0.257
Adj. R^2	0.082	0.115	0.111	0.105	0.216	0.222	0.235	0.237
Observations	463	286	463	463	463	286	463	463

This table shows results from robustness checks with cross-sectional regressions of the Marginal Expected Shortfall and ΔCoVaR of U.S. banks on several variables related to the banks' risk management and various control variables. The dependent variable in the first four regressions is the average of the daily Marginal Expected Shortfall estimates for the time period 07/01/2007 to 12/31/2008 computed using the dynamic model specification proposed by Brownlees and Engle (2012). In regressions (5) and (8), the dependent variable is the average conditional ΔCoVaR of the banks during the same period. All explanatory variables are based on stock market or accounting data for the year 2006. In contrast to our baseline regressions, we additionally employ the VaR-disclosure index in all regressions. Variable definitions and data sources are provided in Appendix A. All models are estimated with OLS. The statistical significance of the estimated coefficients is tested with Newey and West (1987) heteroskedasticity and autocorrelation consistent *t*-tests. Corresponding *p*-values are shown in parentheses. R^2 and Adj. R^2 are the estimated regression models' *R*-squared and adjusted R-squared, respectively.

*** denote coefficients that are significant at the 1% level.
** denote coefficients that are significant at the 5% level.
* denote coefficients that are significant at the 10% level.

of limited statistical value due to a small number of observations, we do not find any evidence that the significant relation between derivatives usage, securitization, and equity tail risk is attenuated by the addition of these variables. Third, we address concerns that our regressions so far neglect the possibility that MES and ΔCoVaR are indeed valid measures of systemic risk and thus influenced by the banks' interconnectedness with the rest of the banking sector. In untabulated regressions, we employ the measure of a bank's interconnectedness proposed by Billio et al. (2012) based on a principal component analysis of all banks' stock returns as an additional control variable. Doing so does not change our conclusions.

We also reestimate our measures of equity tail risk using a different index and different time periods. To be precise, we use the S&P 500 as a general market index instead of the *Datastream US Financials Index*. For both indexes, we arrived at nearly identical results for the banks' MES and ΔCoVaR. In another robustness check, we reestimated the banks' MES and ΔCoVaR using the time period from 07/01/2007 to 06/30/2009 as the crisis period. Again, our main results remain unchanged.

In further robustness checks reported in Section IA.5 in the Internet Appendix, we address concerns that our analysis of equity tail risk is rather an analysis of the banks' systematic risk. The results show that while MES and ΔCoVaR exhibit some correlation with the banks' beta, the risk measures are far from being strongly correlated with each other. Consequently, the tail risk measures we employ do indeed capture a different facet of equity risk.

Finally, in Section IA.6 in the Internet Appendix, we perform a set of simultaneous equations regressions to control for the possibility that our measures of equity tail risk and default risk as well as the banks' derivatives intensity are jointly determined. The results of these robustness checks given in Table IA.VII clearly show that a bank's derivatives intensity exerts a significant influence on the bank's MES, ΔCoVaR, and distance-to-default. We thus rule out the possibility that our main findings are subject to reverse causality.

4. Conclusion

In this paper, we find that the intensity with which U.S. banks used financial derivatives and their use of loan securitization as a tool for transferring risks as disclosed in their 10-K filings before the financial crisis explain the banks' equity tail risk during the crisis. In particular, banks that used more derivatives and securitized loans suffered greater losses on their stocks on those days the market plummeted during the crisis. In addition, the market suffered heavier losses in case the stocks of banks with a more elaborate use of derivatives were in their lower left tail. These effects are economically large and cannot be attributed to larger (and thus systemically more important) banks disclosing more information on their risk management.

The results of our empirical work are consistent with the hypothesis that derivatives usage for non-hedging purposes increases an individual bank's equity risk and potentially destabilizes the financial sector. Banks that used derivatives and loan securitization in their risk management had higher stock returns if they had a higher actual risk exposure before the crisis. The same is true for banks that had a higher default probability before the financial crisis. In contrast, derivatives usage without need led to higher losses on individual bank stocks and the sector index during the crisis.

Our paper fills an important gap in the empirical review of the financial crisis. Our results show that banks did not exit indiscriminate extreme losses on their stocks at the climax of the financial crisis. If anything, extreme stock returns were driven by a rational assessment of the banks' pre-crisis default probability and exposure to two major multipliers of the crisis: excessive usage of derivatives and loan securitization.

Regarding disclosure on the usage of derivatives and securitization, our findings appear particularly interesting in light of the arguments by Barth and Landsman (2010) suggesting that disclosure according to SFAS 133 and 140 respectively were too aggregated and incomplete to indicate the risk inherent in these activities adequately. In light of our findings that investor reaction reflected information on the usage of derivatives and loan securitization, our study puts such concerns somewhat into perspective. Nevertheless, our study cannot rule out that investor assessment could have differed if investors had more detailed information during the crisis. Obviously, this question remains unanswered empirically.

Although we find disclosed information on risk management to be a powerful determinant of a bank's extreme stock returns during the crisis, our study should not be misunderstood as an investigation into systemic risk or the causes of the crisis. Rather, our results explain how stock market investors reacted during the financial crisis. In contrast, an analysis of systemic risk would ultimately require private information on a bank's funding structure, its interconnectedness, and detailed data on its derivatives usage. However, we do not consider this to be a weakness of our study as we base all our findings on exactly the type of information that was available to investors during the crisis: disclosed bank balance sheets and risk reports. Yet at the same time, if one assumes that both MES and ΔCoVaR as proxies of banks' equity tail risk do indeed capture a significant portion of a bank's exposure and contribution to the fragility of the financial system (as it is done, e.g., by Brunnermeier et al., 2012; Anginer et al., 2014b), our results identify derivatives usage as a significant determinant of systemic risk that had previously been neglected in the empirical literature.

Appendix A. Variable definitions and data sources.

The appendix presents data sources, definitions and expected signs in our regression analyses for all dependent and independent variables that are used in the empirical study. The expected sign of each independent variable on the equity tail risk of a U.S. bank is shown in the last column with a "+" indicating an expected increasing (and a "-" a decreasing) impact on equity tail risk. The bank controls were taken from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases and the variables on the banks' derivatives usage and risk management activities were extracted from the banks' respective 10-K filings retrieved from the *Morningstar Document Research* database.

Variable name	*Definition*	*Data source*	*Hypotheses*	*Expected sign*
Panel A: Systemic risk measures				
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.	–	
Δ CoVaR	Conditional Δ CoVaR as defined by Adrian and Brunnermeier (2010), 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 Δ CoVaR, 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.	–	
Panel B: Main variables of interest (derivatives usage and risk management disclosure)				
Derivatives intensity	Proxy for the intensity with which firms employ financial derivatives. The variable is defined as the number of the used types of financial derivatives as disclosed in the bank's 10-K filing (see Bartram et al., 2011, for a similar definition).	Morningstar, 10-K filings.	Hedging for risk management purposes reduces total firm risk; hedging could increase counterparty risk; derivatives usage could be indicative of increased risk-taking. Smith and Stulz (see 1985); Bartram et al. (see 2011).	+/−

(*continued*)

Variable name	*Definition*	*Data source*	*Hypotheses*	*Expected sign*
Interest rate derivatives	Dummy variable that equals one for interest rate derivative users and zero for non-users.	Morningstar, 10-K filings.	Banks with higher probability of financial distress manage their interest rate risk more aggressively; non-user banks adopt conservative asset-liability management policies (see Guay, 1999; Purnanandam, 2007).	+/−
FX derivatives	Dummy variable that equals one for users of FX derivatives and zero for non-users.	Morningstar, 10-K filings.	The use of FX derivatives for risk management purposes reduces total firm risk; use of FX derivatives could increase counterparty risk and be due to non-hedging purposes (see Graham and Rogers, 2002; Rogers, 2002).	+/−
Securitization	Dummy variable that equals one if the bank discloses the use of loan securization and zero otherwise.	Morningstar, 10-K filings.	Securitization should decrease credit risk; banks could have employed securitization for regulatory arbitrage thereby effectively securitizing loans without transferring the risks to other market participants (see Acharya et al., 2013).	+/−
Disclosed risk types	Number of risk types a bank is exposed to as disclosed in the 10-K filing.	Morningstar, 10-K filings.	More disclosed risk types could indicate more risk-taking by the bank; more disclosure could also indicate a more alert risk management.	+/−
VaR-disclosure index	Index of the extent to which banks disclose information on their employed Value-at-Risk (VaR) models (see Pérignon and Smith, 2010, for a similar index). The index is constructed by taking the sum of several dummy variables taking on the value of one if a certain information on the bank's VaR-model is disclosed, and zero otherwise. The index constituents cover the questions whether a) the confidence level of the VaR is disclosed, b) whether the bank calculates a model with a confidence level of 97,5% or higher, c) discloses information on the estimation method, d) the holding period, e) the employed backtests, and f) the overall diversification effect in the bank portfolio.	Morningstar, 10-K filings.	More voluntary disclosure on a bank's risk management increases transparency and decreases equity tail risk caused by a panic-based contagion.	−
Panel C: Control variables				
Total assets	Natural logarithm of a bank's total assets at fiscal year end 2006.	Worldscope (WC02999).	Larger banks could become too-big-to-fail.	+
Return on assets	A bank's annual return on assets.	Worldscope (WC08326).	Higher profits shield banks from adverse effects emanating from the financial sector.	−
Tier 1 capital	Tier 1 capital representing the primary capital supporting the lending and deposit activities of a bank.	Worldscope (WC18228).	Higher regulatory bank capital acts as a buffer against losses and should stabilize both an individual bank and the financial sector.	−
Non-interest income	Non-interest income divided by total interest income.	Worldscope (WC01021 and WC01016).	Higher values of non-interest income relative to total interest income could be indicative of a business model that concentrates more on non-deposit taking activities (like, e.g., investment banking) and thus more risk-taking (see Brunnermeier et al., 2012).	+
Loans	Ratio of total loans to total assets.	Worldscope (WC02271 and WC02999).	A higher loans-to-assets ratio of a bank could indicate a business model that focuses on lending rather than more risky activities.	−
Buy-and-hold returns 1998	Annual buy-and-hold stock returns in fiscal year 1998.	Datastream, own calc.	Subsequent to the "risk culture hypothesis" of Fahlenbrach et al. (2012), a higher buy-and-hold return during the LTCM crisis in 1998 together with persistence in the bank's risk culture, could cause the bank to fare better during subsequent crises.	−

(*continued on next page*)

(*continued*)

Variable name	Definition	Data source	Hypotheses	Expected sign
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.	Disciplining effect of leverage vs. greater vulnerability during financial crises (see Adrian and Shin, 2010).	+/−
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210 and WC03501).	Greater charter value incentivizes bank managers to keep their bank's capital ratio and to limit their risk-taking (see Keeley, 1990).	−
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251 and WC03255).	A less fragile funding structure of a bank makes it less vulnerable to sudden shortages in liquidity during a crisis (see Brunnermeier and Pedersen, 2009).	−
Distance-to-default (DtD)	A bank's distance-to-default, defined as the difference between the bank's asset value and the face value of its debt, scaled by the standard deviation of the bank's asset value (see Merton, 1974). For its computation, we follow the estimation methods laid out by Hillegeist et al. (2004) and Campbell et al. (2008) using Newton's algorithm and the 1 year US treasury yield as the risk-free rate.	Datastream, Worldscope (WC05301, WC03051, and WC03251), own calc.	Higher distances-to-default imply lower default probabilities of U.S. banks and thus lower equity tail risk.	−
Stock 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.	More liquid stocks are more susceptiple and contribute more to downturns of a sector index.	+
Non-hedging purpose	Dummy variable that takes on the value of one if the fair value gains/losses on derivatives and the fair value gains/losses on selected balance sheet items (investment securities, net loans, deposits, and long term debt) are of the same sign, and zero otherwise.	Morningstar, 10-K filings, own calc.	Derivatives usage for non-hedging purpose increases equity tail risk and default risk.	+
Board size	Natural logarithm of the number of directors on an insurer's board.	ESG ASSET 4 (CGBSDP060) and Morningstar (DEF 14A filings).	Larger boards destroy value and capital buffers (see, e.g., Yermack, 1996).	+
Board independence	Percentage of independent outside directors on the board of directors.	ESG ASSET 4 (CGBSO07S) and Morningstar (DEF 14A filings).	More independent board members improve governance.	−

Appendix B. Systemic risk measures

In this appendix, we shortly discuss the details of the estimation of the measures of a bank's equity tail risk used in our empirical study.

Dynamic Marginal Expected Shortfall

As our first measure of a bank's equity tail risk, we employ the dynamic specification of the MES (see Acharya et al., 2010) proposed by Brownlees and Engle (2012). Therefore, let $R_{j,t}$ and $R_{M,t}$ be the j^{th} bank's and the log return of the financial sector on day t, respectively. The bivariate daily return process is then given by

$$R_{M,t} = \sigma_{M,t}\epsilon^1_{M,t}$$
$$R_{j,t} = \sigma_{j,t}\rho_{j,t}\epsilon^2_{M,t} + \sigma_{M,t}\sqrt{1-(\rho_{j,t})^2}\epsilon^2_{j,t}$$
$$(\epsilon^1_{M,t}, \epsilon^2_{j,t}) \sim H,$$

where $\sigma_{i,t}$ is the conditional volatility of the sector return ($i = m$) or bank j's return ($i = j$), $\rho_{j,t}$ is the conditional sector/bank correlation and $(\epsilon^1_{M,t}, \epsilon^2_{j,t})$ are i.i.d. innovations with $\mathbb{E}(\epsilon^j_{i,t}) = 0$, $Var(\epsilon^j_{i,t}) = 1$ for $n = \{1, 2\}$ and $i = \{j, M\}$ and zero covariance (although they are not necessarily independent of each other).

The one-period-ahead MES for a tail event S is denoted by

$$MES^1_{j,t-1} = \mathbb{E}_{t-1}(R_{j,t} \mid R_{M,t} < S)$$
$$= \sigma_{j,t}\mathbb{E}_{t-1}\left(\rho_{j,t}\epsilon^1_{M,t} + \sqrt{1-(\rho_{j,t})^2}\epsilon^2_{j,t} \mid S/\sigma_{M,t}\right)$$
$$= \sigma_{j,t}\rho_{j,t}\mathbb{E}_{t-1}\left(\epsilon^1_{M,t} \mid S/\sigma_{M,t}\right) + \sigma_{j,t}\sqrt{1-(\rho_{j,t})^2}\mathbb{E}_{t-1}\left(\epsilon^2_{j,t} \mid S/\sigma_{M,t}\right).$$

Furthermore, the conditional probability of the tail event is given by

$$Pr^1_{S,t}(S) = Pr_{t-1}(r_{M,t} < S) = Pr(\epsilon^1_{M,t} < S/\sigma_{M,t}).$$

Next, the *multi-period-ahead* MES is estimated by a simulation procedure to construct forecasts. First, K return paths of length h for $k = 1, \ldots, K$ are simulated on day $t-1$

$$\begin{Bmatrix} R^k_{M,t+\delta-1} \\ R^k_{j,t+\delta-1} \end{Bmatrix}^h_{\delta=1}.$$

Furthermore, pseudo-innovations are drawn from the innovation distribution H yielding

$$\left(\epsilon^{1,k}_{M,t+\delta-1}, \epsilon^2_{M,t+\delta-1}\right)^h_{\delta=1} \sim H.$$

To obtain the simulated return paths, the pseudo-innovations are used in the Dynamic Conditional Correlation (DCC) and GARCH models with the current levels of volatility and correlation as starting conditions. The MES is then estimated as the Monte Carlo average of the simulated paths

$$MES^h_{j,t-1}(S) = \frac{\sum_{k=1}^K R^k_{j,t:t+h-1} I\{R^k_{M,t:t+h-1} < S\}}{\sum_{k=1}^K I\{R^k_{M,t:t+h-1} < S\}},$$

where $R^k_{i,t:t+h-1}$ is the k^{th} simulated cumulative return of bank j or of the sector from period t to period $t+h-1$, i.e.,

$$R^k_{j,t:t+h-1} = exp\left\{\sum_{\delta=1}^h r^k_{j,t:t+h-1}\right\} - 1.$$

Finally, the multi-period probability of a tail event is given by

$$Pr^1_{S,t}(S) = Pr_{t-1}(R^k_{M,t:t+h-1} < S) = \frac{1}{K}\sum_{k=1}^K I\{R^k_{M,t:t+h-1} < S\}.$$

Following Brownlees and Engle (2012), the 6-months period MES is taken as the "long term" or "long run" MES of a bank.

$\Delta CoVaR$

The $CoVaR^{j|i}_\alpha$ of financial institution j (or the financial system) is defined as its Value-at-Risk (VaR) given by $Pr(R_i \le VaR^i_\alpha) = \alpha$ conditional on some (tail) event $\mathbb{C}(R_i)$ of institution i, where R_i is the return of institution i for which the VaR^i_α is defined. The $CoVaR^{j|i}_\alpha$ is defined implicitly by the α-quantile of the conditional probability distribution:

$$Pr\left(R_j \le CoVaR^{j|\mathbb{C}(R_i)}_\alpha \mid \mathbb{C}(R_i)\right) = \alpha.$$

Then, the contribution of institution i to the VaR of institution j (or the financial system) is given by

$$\Delta CoVaR^{j|\mathbb{C}(R_i)}_\alpha = CoVaR^{j|R_i=VaR^i_\alpha}_\alpha - CoVaR^{j|R_i=Median^i}_\alpha.$$

To measure an individual bank's contribution to the system's tail risk, j is simply set to be the financial sector. Hence, $\Delta CoVaR^{j|\mathbb{C}(R_i)}_\alpha$ or simply $\Delta CoVaR^i_\alpha$ denotes the difference between the financial system's VaR conditional on a particular financial institution i being in distress and the VaR of the financial system conditional on the median state of institution i.

The unconditional $CoVaR$ is then estimated by quantile regressions. Let $\hat{R}^{system,j}_q$ be the predicted value of a quantile regression of the financial sector on a particular institution or portfolio i for the q^{th}-quantile:

$$\hat{R}^{system,j}_q = \hat{\alpha}^j_q + \hat{\beta}^j_q \hat{R}^j_q,$$

where $\hat{R}^{system,j}_q$ is the predicted value for a particular quantile conditional on institution j. The VaR of the financial system conditional on R^j, $VaR^{system}_q \mid R^j$, is the predicted value of the quantile regression of the system on institution j, $\hat{R}^{system,j}_q$, since $VaR^{system}_q \mid R^j$ is the conditional quantile, i.e.,

$$VaR^{system}_q \mid R^j = \hat{R}^{system,j}_q.$$

If $R^j = VaR^i_q$, then the $CoVaR$ measure conditioned on the event $\{R^j = VaR^j_q\}$ is

$$CoVaR^{system|R^j=VaR^j_q}_q := VaR^{system}_q \mid VaR^j_q = \hat{\alpha}^j_q + \hat{\beta}^j_q VaR^j_q$$

and the $\Delta CoVaR^j_q$ is

$$\Delta CoVaR^j_q = VaR^{system|j}_q = \hat{\beta}^j_q (VaR^j_q - VaR^j_{50\%}).$$

Now assume that the returns $R_{i,t}$ have the linear factor structure

$$R_{j,t} = \phi_0 + M_{t-1}\phi_1 + R_{i,t}\phi_2 + (\phi_3 + M_{t-1}\phi_4 + R_{i,t}\phi_5)\epsilon^i_t$$

with M_{t-1} as a vector of state variables. Furthermore, the i.i.d. error term ϵ_t with zero mean and unit variance is independent of M_{t-1} so that $\mathbb{E}[\epsilon^j_t \mid M_{t-1}, R_{i,t}] = 0$. The returns are generated by a "location scale" process, therefore the conditional expected return $\mathbb{E}[R_{j,t} \mid M_{t-1}, R_{i,t}] = \phi_0 + M_{t-1}\phi_1 + R_{i,t}\phi_2$ and the conditional volatility $Var_{t-1}[X^j_t \mid M_{t-1}, R_{i,t}] = \phi_3 + M_{t-1}\phi_4 + R_{i,t}\phi_5$ are dependent on the set of state variables M_{t-1} and on $R_{i,t}$. The quantile regressions include estimates of the conditional mean and the conditional volatility for generating conditional quantiles. The model is then estimated by this method for different percentiles. The cumulative distribution function (cdf) of ϵ^j is given by $F_{\epsilon^j}(\epsilon^j)$ and its inverse cdf by $F^{-1}_{\epsilon^j}(q)$ for percentile q with the conditional quantile function

$$F^{-1}_{R_{j,t}}(q \mid M_{t-1}, R_{i,t}) = \alpha_q + M_{t-1}\gamma_q + R_{i,t}\beta_q,$$

where $\alpha_q = \phi_0 + \phi_3 F^{-1}_{\epsilon^j}(q)$, $\gamma_q = \phi_1 + \phi_4 F^{-1}_{\epsilon^j}(q)$ and $\beta_q = \phi_2 + \phi_5 F^{-1}_{\epsilon^j}(q)$ for quantiles $q \in (0, 1)$. We then have

$$VaR^j_q = \inf_{VaR_q}\{Pr(R_t \le VaR_q \mid M_{t-1}, R_{i,t}) \ge q\} = F^{-1}_{R_{j,t}}(q \mid M_{t-1}, R_{i,t})$$

and by conditioning on $X^i_t = VaR^i_q$ we get the CoVaR $^{j|i}_q$ by

$$\begin{aligned} CoVaR^{j|i}_q &= \inf_{VaR_q}\left\{Pr\left(R_t \le VaR_q \mid M_{t-1}, R_{i,t} = VaR^i_q\right) \ge q\right\} \\ &= F^{-1}_{R_{j,t}}(q \mid M_{t-1}, VaR^i_q). \end{aligned}$$

Here, the quantile function is estimated as the predicted value of the q-quantile regression of $R_{i,t}$ on M_{t-1} and $R_{j,t}$ by solving

$$\min_{\alpha_q,\beta_q,\gamma_q} \sum_t \begin{cases} q|R_{j,t} - \alpha_q - M_{t-1}\gamma_q - R_{i,t}\beta_q|, & \text{if } (R_{j,t} - \alpha_q - M_{t-1}\gamma_q - R_{i,t}\beta_q) \ge 0, \\ (1-q)|R_{j,t} - \alpha_q - M_{t-1}\gamma_q - R_{i,t}\beta_q|, & \text{if } (R_{j,t} - \alpha_q - M_{t-1}\gamma_q - R_{i,t}\beta_q) < 0. \end{cases}$$

In our empirical study, we employ the conditional version of CoVaR, i.e., the dynamic versions CoVaR_t and VaR_t of the static versions described above. We estimate the time variation of CoVaR conditional on a vector of lagged state variables M_{t-1}. The state variables can be interpreted as conditioning variables shifting the conditional mean and the conditional volatility of the risk measures. The previous quantile regression is now performed using weekly data with

$$\begin{aligned} R_{i,t} &= \alpha^i + \gamma^i M_{t-1} + \epsilon^i_t, \\ R_{system,t} &= \alpha^{system|i} + \beta^{system|i} R_{i,t} + \gamma^{system|i} M_{t-1} + \epsilon^{system|i}. \end{aligned}$$

The predicted values of VaR and CoVaR are given by

$$\begin{aligned} VaR^i_t(q) &= \hat{\alpha}^i + \hat{\gamma}^i M_{t-1}, \\ CoVaR^i_t(q) &= \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR^i_t(q) + \hat{\gamma}^{system|i} M_{t-1}. \end{aligned}$$

The predicted values from the regressions of $R_{i,t}$ and $R_{system,t}$ are used. In the end, ΔCoVaR ^i_t for each institution is calculated by

$$\begin{aligned} \Delta CoVaR^i_t(q) &= CoVaR^i_t(q) - CoVaR^i_t(50\%), \\ &= \hat{\beta}^{system|i}(VaR^i_t(q) + VaR^i_t(50\%)). \end{aligned}$$

The set of used state variables is mentioned in the main text.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jbankfin.2016.07.001

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