Banks' Non-Interest Income and Systemic Risk

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Abstract

This paper finds non-interest income to be positively correlated with total systemic risk for a large sample of U.S. banks. Decomposing total systemic risk into three components, we find that non-interest income has a positive relationship with a bank's tail risk, a positive relationship with a bank's interconnectedness risk, and an insignificant or positive relationship with a bank's exposure to macroeconomic and finance factors. These results are generally robust to endogenizing for non-interest income and for trading and other non-interest income activities.

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"These banks have become trading operations. ... It is the centre of their business."
Phillip Angelides, Chairman, Financial Crisis Inquiry Commission

1. Introduction

The financial crisis of 2007-09 was a showcase of large risk spillovers from one bank to another heightened risk in the banking system as a whole. But all banking activities are not necessarily the same. One group of activities — namely, deposit taking and lending — makes banks special to information-intensive borrowers and crucial for capital allocation in the economy.[1]

Prior to the crisis, however, banks increasingly earned a higher proportion of their profits from non-interest income rather than interest income.[2] Non-interest income includes income from trading and securitization, investment banking and advisory fees, brokerage commissions, venture capital, fiduciary services, and gains on non-hedging derivatives. These activities are different from the traditional deposit-taking and lending function of banks. In non-interest income activities, banks are competing with other capital market intermediaries such as hedge funds, mutual funds, investment banks, insurance companies, and private equity funds, none of which have federal deposit insurance. Figure 1 shows big increases in the ratio of average non-interest income to total assets starting around 1998. The latter panel shows that the increase in non-interest income remains when we remove investment banks in the pre-crisis period.[3]

*** Figure 1 ***

This paper begins by reexamining[4] the contribution of non-interest income to *systemic* bank risk. The existing literature presents mixed evidence for U.S. banks. De Jonghe (2010),

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[1] This role for banking is a focus of Bernanke (1983), Fama (1985), Diamond (1984), James (1987), Gorton and Pennacchi (1990), Calomiris and Kahn (1991), and Kashyap, Rajan, and Stein (2002). The bank lending channel for the transmission of monetary policy is studied in Bernanke and Blinder (1988), Stein (1988), and Kashyap, Stein, and Wilcox (1993).
[2] By interest income, we mean net interest income, which is defined as total interest income less total interest expense.
[3] This group comprises AIG, American Express, Ameriprise, First American Corp., First Marblehead, Franklin Templeton, Goldman Sachs, Morgan Stanley, Raymond James Financial, Sei Investment, Stifel Financial, and T. Rowe Price.
[4] See Section 2 for a more detailed description of the literature. An earlier version of this paper was submitted to SSRN on March 2011 and presented at the 2012 AFA meetings. At that time, our results on systemic risk and non-interest income were contemporaneous with those of De Jonghe (2010), who examined European banks, although we did not have many of the other results described in this version of our paper.

Moore and Zhou (2014), and Bostandzic and Weiss (2018) find that non-interest income is *positively* correlated with systemic risk. Engle et al. (2014), Weiss, Bostandzic, and Neumann (2014), and Saunders, Schmid, and Walter (2018) detect an *insignificant* relationship between non-interest income and systemic risk. De Jonghe, Diepstraten, and Schepens (2015) document that non-interest income decreases (increases) the systemic risk of large (small) banks. They also find that the benefits of lower systemic risk for large banks disappear in countries with more corruption, concentrated banking markets, and asymmetric information. Interpreting their results to the U.S., where such issues do not dominate, suggests a *negative* relationship for *large* banks and a *positive* relationship for *small* banks.

In order to capture systemic risk in the banking sector, we use two prominent measures of systemic risk. The first is the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2016), who define $CoVaR$ as the value at risk of the banking system conditional on an individual bank being in distress. More formally, $\Delta CoVaR$ is the difference between the $CoVaR$ conditional on a bank being in distress and the $CoVaR$ conditional on a bank operating in its median state. The second measure of systemic risk is *MES,* or the marginal expected shortfall measure of Acharya, Pedersen, Philippon, and Richardson (2017), who define *MES* as a bank's stock returns when the market has its worst performance at the 5% level in a year. They show that one can infer what happens to a bank's capital in a real crisis (what they call the systemic expected shortfall) when the market is in "moderately bad days," or *MES*. Note that $\Delta CoVaR$ measures the externality a bank causes on the system, while *MES* focuses on how much a bank is exposed to a potential systemic crisis.

This paper makes five points. First, we reexamine the relationship between systemic risk and a bank's non-interest income. Second, we decompose systemic risk into three components, estimating the relationship of non-interest income to a bank's tail risk (*alpha*)*,* exposure to fundamental macroeconomic and finance factors (*beta*)*,* and interconnectedness (*gamma*), respectively. No prior paper has performed this decomposition of systemic risk and then examined the relationship of non-interest income to each component. Third, we categorize non-interest income into two sub-groups, trading income and other non-interest income, in order to examine if they have a differential effect on systemic risk and its three components. Fourth, we endogenize for non-interest income using aggregate statistics on IPOs, mergers and acquisitions, and trading volume that should, a priori, be related to non-interest income. Finally, we examine if there are different relationships for large, midsize, and small banks.

Our results are as follows:

1. Systemic risk is higher for banks with a higher ratio of non-interest income to assets. Specifically, a one standard deviation increase in this ratio raises a bank's exposure to systemic risk by 1.80% in $\Delta CoVaR$ and 4.31% in *MES*. This positive relationship is consistent with the results of De Jonghe (2010), Moore and Zhou (2014), and Bostandzic and Weiss (2018), but inconsistent with the insignificant relationship results of Engle et al. (2014), Weiss, Bostandzic, and Neumann (2014), and Saunders, Schmid, and Walter (2018).
2. Examining the bank-specific control variables, we find that banks with higher leverage and a greater number of nonperforming loans increase systemic risk, whereas those with more liquidity and higher interest income lower systemic risk.
3. After decomposing systemic risk into three components—a bank's tail risk (*alpha*), exposure to fundamental macroeconomic and finance factors (*beta*), and interconnectedness (*gamma)*—we find that non-interest income significantly increases *alpha*. A one standard deviation increase in non-interest income results in a 7.24% rise in a bank's *alpha*. Although we focus on tail risk, our results are consistent with those of Stiroh (2004), 2006), who finds a positive relationship between non-interest income and a bank's return volatility. In addition, we find an insignificant relationship between non-interest income and co-movements with *beta*. Finally, we find that non-interest income is positively related to a bank's *gamma*. A one standard deviation increase in non-interest income results in a 10.5% rise in a bank's *gamma*.
4. When we endogenize for non-interest income using three instrumental variables (the lagged dollar values of all IPOs and M&A transactions, plus total market volume) we find that non-interest income increases all three components of systemic risk. Specifically, a one standard deviation increase in non-interest income results in a 73.7% increase in a bank's *alpha*, a 187% increase in a bank's *beta*, and a 73.3% increase in a bank's *gamma*.
5. After splitting non-interest income into two components, trading income and other non-interest income, we find both components are positively related to total systemic risk. This result suggests a similar relationship for both trading income and other non-interest income.
6. Examining the impact of non-interest income on large, midsize, and small banks, we find that *gamma* is higher for both large and midsize banks, but not for small banks. *Alpha* is higher for both large and small banks, whereas *beta* is higher only for midsize banks.

What economic rationale would suggest a positive relationship between non-interest income and systemic risk? DeYoung and Roland (2001) suggest that that non-interest income is more volatile than the stable interest-income activities. We calculate the coefficient of variation (cv) of the ratio of non-interest income to assets and the ratio of interest income to assets. We find cv of non-interest income to be 117.9%, which is significantly higher than 29.7% the cv of interest income. But this could be driven by cross-sectional differences between banks. We therefore calculate the within-firm coefficient of variation. Once again, we find the cv of non-interest income (47.6%) to be significantly higher than the cv of interest income (22.5%). This confirms the DeYoung and Roland (2001) argument that non-interest income is more volatile than interest income in our sample.

But why does this more volatile non-interest income correlate with higher systemic risk? Is it because many banks earn income in the same correlated activities of trading and advisory services? We find that banks earn higher non-interest income when the aggregate value of IPO/M&A plus trading volume is higher. Can such correlated activities result in higher systemic risk? A number of theoretical papers suggest it can. [5] Acharya (2009) provides a model wherein correlated assets and the limited liability of banks creates the presence of a negative externality from one bank to another that increases systemic risk. Wagner (2010) suggests that systemic risk can be higher when one bank's premature liquidating of assets increases the failure probability of another bank. Ibragimov, Jaffee and Walden (2011) suggest that systemic risk increases when one bank hedges its idiosyncratic risk with another bank's risk portfolio. Allen, Babus and Carletti (2012) suggest that asset commonality and short-term debt can result in higher systemic risk.

Our finding that procyclical nontraditional activities (such as trading and private equity income) can increase systemic risk is consistent with a number of papers. In the model of Shleifer and Vishny (2010), activities in which bankers have less "skin in the game" are overfunded when asset values are high, which leads to higher systemic risk.[6] Similarly, Song and Thakor (2007) suggest that these transaction-based activities can lead to higher risk. Our results are also consistent with those of Fang, Ivashina, and Lerner (2013), who find private equity investments by

[5] For more detailed explanations of various direct and indirect channels by which systemic risk is increased, see for example, Goldstein and Pauzner (2004), Allen and Gale (2004), Allen and Carletti (2006), and the papers surveyed in Allen, Babus, and Carletti (2009) and Brunnermeier (2009).

[6] Our nontraditional banking activities are similar to loan securitizations or syndications, where the bank does not own the entire loan ($d < 1$ in the Shleifer-Vishny model).

banks to be highly procyclical and their performance worse than those of nonbank-affiliated private equity investments.

The structure of our paper is as follows. Section 2 describes the related literature, and Section 3 explains our data and methodology. Section 4 presents our empirical results, and Section 5 concludes.

2. Related Literature

2.1 Non-interest income and systemic risk

The prior literature shows mixed evidence on the relationship between non-interest income and systemic risk measures. For example, De Jonghe (2010) finds that non-interest income is positively correlated with systemic risk for European banks, and Moore and Zhou (2014) find that non-interest income is positively correlated with systemic risk for U.S. banks. Bostandzic and Weiss (2018) find that European banks contribute more to systemic risk than U.S. banks do, and this increase in systemic risk is higher when banks have more non-interest income. De Jonghe, Diepstraten, and Schepens (2015) find that non-interest income decreases (increases) the systemic risk of large (small) banks. They also find that the benefits of reducing systemic risk for large banks disappear in countries with more corruption, concentrated banking markets, and asymmetric information. Applying their results to the U.S., where such issues do not dominate, suggests a negative relationship between non-interest income and systemic risk for large banks and a positive relationship between non-interest income and systemic risk for small banks. Engle et al. (2014) find that non-interest income is higher in banks from countries with low banking market concentrations. They also find that non-interest income is positively correlated with systemic risk in countries with highly concentrated banking markets and is uncorrelated in countries with low-concentration banking markets (like the U.S.). Weiss, Bostandzic,and Neumann (2014) find no statistically significant relationship between non-interest income and systemic risk for U.S. and European banks, whereas Saunders, Schmid, and Walter (2018) find a similar insignificant relationship for U.S. banks.

2.2 Non-interest income and individual bank risk

Other papers have examined the relationship between non-interest income and individual bank risk. Saunders and Walter (1994) and DeYoung and Roland (2001) provide detailed literature reviews. While our study focuses on the effect of non-interest income on a bank's exposure to systemic risk, the literature on individual bank risk shows mixed evidence. On the one hand, Demsetz and Strahan (1997), Stiroh (2004, 2006), Fraser, Madura, and Weigand (2002), and Stiroh and Rumble (2006) find that non-interest income is associated with more volatile bank returns. DeYoung and Roland (2001) find fee-based activities are associated with increased revenue and earnings variability. In a sample of international banks, Demirguc-Kunt and Huizinga (2010) find that higher fee income increases bank risk. Acharya, Hasan, and Saunders (2006) find diseconomies of scope when a risky Italian bank expands into additional sectors. DeYoung and Torna (2013) find that the probability of bank failure increases with venture capital, investment banking, and asset securitization. Köhler (2014) finds that investment-oriented German banks increased their bank risk when they had higher non-interest income. Williams (2016) finds that non-interest income is positively related to bank risk for Australian banks. On the other hand, White (1986) finds that banks with a security affiliate in the pre-Glass Steagall period had a lower probability of default. Examining a sample of international banks, Baele et. al (2007) find that higher non-interest income decreases bank risk. Köhler (2014) finds that retail-oriented German banks lowered their bank risk when they had higher non-interest income. DeYoung and Torna (2013) find that the probability of bank failure decreased with securities brokerage and insurance sales.

2.3 Other measures of systemic risk

Recent papers have proposed measures of systemic risk other than $\Delta CoVaR$ and *MES.* Bisias, Flood, Lo, and Valavanis (2012) provide an overview of the growing numbers of systemic risk measures.[7] Some papers, such as those by Lehar (2005) and Jobst and Gray (2013), have employed a structural approach using contingent claim analysis. Given the strong assumptions that have to be made about a bank's liability structure, other papers have used market data to back out reduced-form measures of market risk. Allen, Bali, and Tang (2012) propose the *CATFIN* measure, which is the principal component of the 1% *VaR* and expected shortfall, using estimates of the generalized Pareto distribution, skewed generalized error distribution, and a non-parametric distribution. Tarashev, Borio, and Tsatsaronis (2010) suggest that Shapley values, based on a

[7] Giglio, Kelly, and Pruitt (2016) find that systemic risk measures have a strong association with the downside risk of future macroeconomic shocks, whereas Benoit et al. (2017) and Kupiec and Guntay (2016) find these systemic risk measures have limited ability to accurately estimate financial distress risks.

bank's default probabilities, size, and exposure to common risks, could be used to assess regulatory taxes on each bank, whereas Drehmann and Tarashev (2013) differentiate between a bank's participation versus its exposure to systemic risk. Billio et al. (2012), using principal components analysis and linear and nonlinear Granger causality tests, find interconnectedness between the returns of hedge funds, brokers, banks, and insurance companies. Zhou (2010) uses extreme value theory rather than quantile regressions to obtain a measure of *CoVaR*. Chan-Lau (2010) proposes the *CoRisk* measure, which captures the extent to which the risk of one institution changes in response to changes in the risk of another institution while controlling for common risk factors. Huang, Zhou, and Zhu (2009) derive the price of insurance against distress as the bank's expected loss, conditional on the financial system being in distress, exceeds a threshold level. Brownlees and Engle (2016) define (*SRISK*) as the capital shortfall of a firm, conditional on a severe market decline, and a function of size, leverage, and risk. Geraci and Gnabo (2018) use time-varying vector autoregressions to capture systemic risk between banks. Dungey, Luciani, and Veredas (2018) use shocks to daily stock market volatilities and Google PageRank algorithms to calculate a generalized systemic risk measure.

3. Data, Methodology, and Variables Used

3.1 Data

We focus on all publicly traded bank holding companies in the U.S.—namely, those with SIC codes 60 to 67 (financial institutions) that file a FR Y-9C report with the Federal Reserve each quarter. This report collects basic financial data from a domestic bank holding company on a consolidated basis in the form of a balance sheet, an income statement, and detailed supporting schedules, including a schedule of off-balance-sheet items. By focusing on commercial banks, we do not include insurance companies, investment banks, investment management companies, and brokers. Our sample is from 1986 to 2017 and consists of an unbalanced panel of 796 unique banks. We obtain a bank's daily equity returns from CRSP, which we then convert into weekly returns. Financial statement data is from Compustat and from Federal Reserve form FR Y-9C. Treasury bill and Libor rates are from the Federal Reserve Bank of New York, and real estate market returns are from the Federal Housing Finance Agency. The dates of recessions are obtained from the NBER (http://www.nber.org/cycles/cyclesmain.html). Detailed sources for each specific variable used in our estimation are given in Table 1.

*** Table 1 ***

3.2 Systemic risk definition using $\Delta CoVaR$

We describe below how we calculate the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2016). Such a measure is calculated one period forward and captures the marginal contribution of a bank to the financial sector's overall systemic risk. Adrian and Brunnermeier stress that—rather than using a bank's risk in isolation, which is typically measured by its VaR—regulation should also include the bank's contribution to systemic risk measured by its $\Delta CoVaR$. Importantly, in order to avoid procyclicality and the "volatility paradox," regulation should be based on reliably observed variables that predict future $\Delta CoVaR$s (in our regressions, by one year ahead).

Value at risk (VaR)[8] measures the worst expected loss over a specific time interval at a given confidence level. In the context of this paper, VaR_q^i is defined as the percentage R^i of asset value that bank i might lose with $q\%$ probability over a pre-set horizon T:

$$Probability(R^i \leq VaR_q^i) = q\,. \tag{1}$$

Thus, by definition, the value of VaR is negative in general.[9] Expressed another way, VaR_q^i is the $q\%$ quantile of the potential asset return in percentage term (R^i) that can occur to bank i during a specified time period T. Consistent with the previous literature and with Adrian and Brunnermeier, we reverse the sign for easy interpretation. The confidence level (quantile) q and the time period T are the two major parameters in a traditional risk measure using VaR. We consider 1% quantile and weekly asset return/loss R^i in this paper, and the VaR of bank i is $Probability(R^i \leq VaR_{1\%}^i) = 1\%$.

Let $CoVaR_q^{system|i}$ denote the value at risk of the entire financial system (portfolio) conditional upon bank i being in distress (in other words, the loss of bank i is at its level of

[8] See Jorion (2006) for a detailed definition, discussion, and application of VaR.

[9] Empirically, the value of VaR can also be positive. For example, VaR is used to measure the investment risk in a AAA coupon bond. Assume that the bond was sold at a discount and the market interest rate is continuously falling, but never below the coupon rate during the life of the investment. Then the q% quantile of the potential bond return is positive, because the bond price increases when the market interest rate is falling.

VaR_q^i). That is, $CoVaR_q^{system|i}$, which essentially is a measure of systemic risk, is the q% quantile of this conditional probability distribution:

$$Probability(R^{system} \leq CoVaR_q^{system|i} \mid R^i = VaR_q^i) = q\,. \tag{2}$$

Similarly, let $CoVaR_q^{system|i,median}$ denote the financial system's VaR conditional on bank i operating in its median state (in other words, the return of bank i is at its median level). That is, $CoVaR_q^{system|i,median}$ measures the systemic risk when business is normal for bank i:

$$Probability(R^{system} \leq CoVaR_q^{system|i,median} \mid R^i = median^i) = q\,. \tag{3}$$

Bank i's contribution to systemic risk can be defined as the difference between the financial system's VaR conditional on bank i in distress ($CoVaR_q^{system|i}$) and the financial system's VaR conditional on bank i functioning in its median state ($CoVaR_q^{system|i,median}$):

$$\Delta CoVaR_q^i = CoVaR_q^{system|i} - CoVaR_q^{system|i,median}\,. \tag{4}$$

In the above equation, the first term on the right-hand side measures the systemic risk when bank i's return is in its q% quantile (distress state), and the second term measures the systemic risk when bank i's return is at its median level (normal state).

To estimate[10] this measure of an individual bank's systemic risk contribution $\Delta CoVaR_q^i$, we need to calculate two conditional VaRs for each bank, namely $CoVaR_q^{system|i}$ and $CoVaR_q^{system|i,median}$. For the systemic risk conditional on bank i in distress ($CoVaR_q^{system|i}$), we run a 1% quantile regression[11] using the weekly data to estimate the coefficients α^i, β^i, $\alpha^{system|i}$, $\beta^{system|i}$, and $\gamma^{system|i}$:

$$R_t^i = \alpha^i + \beta^i Z_{t-1} + \varepsilon^i \tag{5}$$

$$R_t^{system} = \alpha^{system|i} + \beta^{system|i} Z_{t-1} + \gamma^{system|i} R_{t-1}^i + \varepsilon^{system|i} \tag{6}$$

and run a 50% quantile (median) regression to estimate the coefficients $\alpha^{i,median}$ and $\beta^{i,median}$:

$$R_t^i = \alpha^{i,median} + \beta^{i,median} Z_{t-1} + \varepsilon^{i,median}, \tag{7}$$

[10] We strictly follow the estimation method used by Adrian and Brunnermeier (2016, pp. 1718-19). Their Stata program is available from the AER web site http://www.aeaweb.org/articles?id=10.1257/aer. 20120555.
[11] See Koenker and Hallock (2001) and Koenker (2005) for a detailed explanation of the quantile regression estimation methodology.

where R_t^i is the weekly growth rate of the market-value equity of bank i at time t:

$$R_t^i = \frac{MV_t^i}{MV_{t-1}^i} - 1 \tag{8}$$

and R_t^{system} is the weekly growth rate of the market-value equity of all N banks ($i = j = 1,2,3...,N$) in the financial system at time t:

$$R_t^{system} = \sum_{i=1}^{N} \frac{MV_{t-1}^i \times R_t^i}{\sum_{j=1}^{N} MV_{t-1}^j}. \tag{9}$$

In equations (8) and (9), MV_t^i is the market value of bank i's equity at time t. When we calculate the equity return of the entire financial system in equation (9), the individual bank's equity return is value-weighted by its equity market value (MV).

Z_{t-1} in equation (7) is the vector of macroeconomic and finance factors in the previous week, including market return, equity volatility, liquidity risk, interest rate risk, term structure, default risk, and real estate returns.[12] We obtain the value-weighted daily market returns from the CRSP Indexes for the S&P 500 Index. We use the weekly value-weighted equity returns (excluding ADRs) with all distributions to proxy for the market return. Volatility is the standard deviation of log market returns. Liquidity risk is the difference between the three-month Libor rate and the three-month T-bill rate. For the next three interest rate variables, we calculate the changes from this week *t* to *t-1*. Interest rate risk is the change in the three-month T-bill rate. Term structure is the change in the slope of the yield curve (the yield spread between the 10-year T-bond rate and the three-month T-bill rate). Default risk is the change in the credit spread between 10-year BAA corporate bonds and the 10-year T-bond rate. All interest rate data is obtained from the U.S. Federal Reserve website and the Compustat Daily Treasury database. The real estate return is proxied by the Federal Housing Finance Agency's FHFA House Price Index for all 50 U.S. states.

Hence we predict an individual bank's *VaR* and median equity return using the coefficients $\hat{\alpha}^i$, $\hat{\beta}^i$, $\hat{\alpha}^{i,median}$, and $\hat{\beta}^{i,median}$ estimated from the quantile regressions of equations (5) and (7):

$$VaR_{q,t}^i = \hat{R}_t^i = \hat{\alpha}^i + \hat{\beta}^i Z_{t-1} \tag{10}$$

[12] None of our results changed significantly if we only use market returns (results not reported).

$$R_t^{i,median} = \hat{R}_t^i = \hat{\alpha}^{i,median} + \hat{\beta}^{i,median} Z_{t-1} \,. \tag{11}$$

The vector of state (macroeconomic and finance) variables Z_{t-1} is the same as in equations (5) and (7). After obtaining the unconditional *VaR*s of an individual bank i ($VaR_{q,t}^i$) and that bank's asset return in its median state ($R_t^{i,median}$) from equations (10) and (11), we predict the systemic risk conditional on bank i in distress ($CoVaR_q^{system|i}$) using the coefficients $\hat{\alpha}^{system|i}$, $\hat{\beta}^{system|i}$, and $\hat{\gamma}^{system|i}$ estimated from the quantile regression of equation (6) . Specifically,

$$CoVaR_{q,t}^{system|i} = \hat{R}_t^{system} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} VaR_{q,t}^i \,. \tag{12}$$

Similarly, we can calculate the systemic risk conditional on bank i functioning in its median state ($CoVaR_q^{system|i,median}$) as

$$CoVaR_{q,t}^{system|i,median} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} Z_{t-1} + \hat{\gamma}^{system|i} R_t^{i,median} \,. \tag{13}$$

Bank i's contribution to systemic risk is the difference between the financial system's *VaR* if bank i is at risk and the financial system's *VaR* if bank i is in its median state:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^{system|i} - CoVaR_{q,t}^{system|i,median} = \hat{\beta}^{system|i} (VaR_{q,t}^i - R_t^{i,median}) \,. \tag{14}$$

Note that this is the same as equation (4) but with an additional subscript *t* to denote the time-varying nature of the systemic risk in the banking system. As shown in the quantile regressions of equations (5) and (7), we are interested in the *VaR* at the 1% confidence level. Therefore the systemic risk of individual bank *i* at q=1% can be written as

$$\Delta CoVaR_{1\%,t}^i = CoVaR_{1\%,t}^{system|i} - CoVaR_{1\%,t}^{system|i,median} \,. \tag{15}$$

While the value of $\Delta CoVaR_{1\%,t}^i$ for bank *i* at time *t* is estimated using the time-series of a bank's weekly equity returns and the vector of macroeconomic and finance factors (Z_{t-1}), we will use the annual average of this systemic risk measure for each bank in the following empirical analysis.

We also split $\Delta CoVaR_{q,t}^i$ into its three components:

$$\Delta CoVaR_{q,t}^i = \hat{\gamma}^{system|i} [(\hat{\alpha}^i - \hat{\alpha}^{i,median}) + (\hat{\beta}^i - \hat{\beta}^{i,median}) Z_{t-1}] \,, \tag{16}$$

wherein we define $alpha = (\hat{\alpha}^i - \hat{\alpha}^{i,median})$, $beta = (\hat{\beta}^i - \hat{\beta}^{i,median}) Z_{t-1}$, and $gamma = \hat{\gamma}^{system|i}$. Then

$$\Delta CoVaR_{q,t}^i = gamma \times (alpha + beta) \,. \tag{17}$$

We can further interpret *alpha, beta,* and *gamma* as follows: *alpha* captures bank *i*'s idiosyncratic tail risk that is independent of the (time-varying) macroeconomic and finance factors *Z*; *beta* captures the time-varying component between tail dependency and central dependency that is driven by the macroeconomic and finance risk factors; and g*amma* measures the bank's interconnectedness. Accordingly, *alpha* and *beta* measure a bank's micro-prudential risk, whereas g*amma* measures a bank's macro-prudential risk per unit of micro-prudential risk.

3.3 Systemic risk definition using *MES*

Acharya, Pedersen, Philippon, and Richardson (2017) propose a model-implied measure of systemic risk that they call marginal expected shortfall (*MES*), which captures a bank's exposure assuming a moderate systemic crisis in a given year. They show that the *MES* measure is able to predict the systemic expected shortfall that a bank faces in a real crisis.[13] In general, *MES* increases in the bank's expected losses during a crisis. Note that the *MES* reverses the conditioning. Instead of focusing on the return distribution of the banking system conditional on the distress of a particular bank, *MES* focuses on bank *i*'s return distribution given that the whole system is in distress. The *CoVaR* framework of Adrian and Brunnermeier (2016) refers to this form of conditioning as "exposure *CoVaR,*" as it measures which financial institution is most exposed to a systemic crisis and not which financial institution contributes most to a systemic crisis.

Following the empirical analysis of Acharya, Pedersen, Philippon, and Richardson (2017), we estimate bank *i*'s *MES* at the 5% risk level using daily equity returns. The systemic crisis event is the 5% worst days for the aggregate equity return of the entire banking system[14] in any given year, and the average equity return of bank *i* during these "worst" market days is defined as bank *i*'s *MES* at the 5% level:

$$MES^{i}_{5\%} = \frac{1}{\#days_{t:\, system\ is\ in\ 5\%\ tail}} \sum R^{i}_{t}\ . \qquad (18)$$

[13] Acharya, Pedersen, Philippon, and Richardson (2017) calculate the annual *realized* systemic expected shortfall using equity return data during the 2007-08 crisis.

[14] To make an easy comparison with our regressions using the $\Delta CoVaR$ measure, we define systemic risk as stock returns earned by all banks. Similar results are obtained for *MES* when we define systemic risk as stock returns earned by the entire market.

3.4 Regression specifications and summary statistics

Given our panel data, we estimate a bank-level fixed-effects model to control for time-invariant unobservable heterogeneity, as well as year dummies to control for macroeconomic effects. Our standard errors are robust and clustered at the bank-level. The dependent variables are the two measures of total systemic risk ($\Delta CoVaR$ or *MES*) and the three measures of individual bank risk: tail risk (*alpha*), exposure to macroeconomic and financial factors (*beta*), and interconnectedness (*gamma*).[15] Our main variable of analysis is the bank's ratio of non-interest income to total assets. In doing so, we also control for the lagged values of the following bank-specific variables: ratio of interest income to total assets, natural logarithm of total assets, financial leverage, market-to-book, liquidity, ratio of nonperforming loans to total loans, and the type of loans (C&I loans to total loans, real estate loans to total loans, agriculture loans to total loans, and consumer loans to total loans—the results of which are not reported). Our focus is the impact of a bank's non-interest income on total systemic risk and the components of systemic risk.

We further split the ratio of non-interest income to total assets into two components, namely, trading income to total assets, and other non-interest income to total assets. Trading income includes trading revenue, capital income, net securitization income, gains/losses of loans, and real estate sales. Other non-interest income is total non-interest income minus trading income. The detailed definitions and sources of data are listed in Table 1.

Table 2 presents the summary statistics of our systemic risk measures. Comparing our results to those in Adrian and Brunnermeier (2016), we find the average $\Delta CoVaR$ of individual banks to be slightly higher. Our average (median) $\Delta CoVaR$ is 1.02% (0.87%), where Adrian and Brunnermeier's average $\Delta CoVaR$ is 1.17% (median not reported). Comparing our results to those of Acharya, Pedersen, Philippon, and Richardson (2017), we find an average (median) *MES* of 3.48% (3.04%) for the years 1986-2017, whereas they find an average (median) *SES* of 1.63% (1.47%) for the crisis period July 2007 to December 2008. The correlation between the two systemic risk measures $\Delta CoVaR$ and *MES* is 0.21, suggesting that these two measures capture similar but not identical patterns in systemic risk. As in the previous literature, we also find that banks are highly levered with an average debt-to-asset ratio of approximately 88%. The average asset size of the banks is \$21 billion and the median asset size is \$1.9 billion. We find the average

[15] Note that we are able to define *alpha, beta,* and *gamma* only when we use the systemic risk measure $\Delta CoVaR$.

(median) ratio of non-interest income to total assets across all bank years to be 0.9% (0.7%), whereas the average (median) ratio of interest income to total assets is a much larger 2.2% (2.2%).

*** Table 2 ***

4. Empirical Results

4.1 Relationship of non-interest income and systemic risk

We begin by regressing our measures of systemic risk on the ratio of non-interest income to total assets while controlling for a number of bank-specific variables. The dependent variables are the two measures of systemic risk $\Delta CoVaR$ and *MES*. Columns 1-2 are the $\Delta CoVaR$ regressions, and columns 3-4 are the *MES* regressions. The results of our panel regressions that include bank fixed-effects and year dummies are given in Table 3. All regressions use robust standard errors that are clustered at the bank-level.

*** Table 3 ***

We begin by examining the relationship between total systemic risk and the ratio of non-interest income to total assets. We find that the ratio of non-interest income to total assets is strongly positively correlated with both $\Delta CoVaR$ and *MES*, suggesting that non-interest income contributes adversely to systemic risk. Specifically, a one standard deviation shock to a bank's ratio of non-interest income to total assets increases systemic risk defined as $\Delta CoVaR$ by 1.80%, but by 4.31% when systemic risk is defined as *MES*.[16] This positive relationship is consistent with the results of De Jonghe (2010), Moore and Zhou (2014), and Bostandzic and Weiss (2018), but different from the insignificant relationship results of Engle et al. (2014), Weiss, Bostandzic, and Neumann (2014), and Saunders, Schmid, and Walter (2018).

Interest income marginally decreases systemic risk at the 10% level of statistical significance when we define systemic risk as $\Delta CoVaR$, but is statistically insignificant when we define systemic risk as *MES*. Examining the bank-specific control variables, we document that banks with higher leverage and non-performing loans increase systemic risk, whereas those with

[16] None of our results changed significantly if we only use market variables, namely, market returns and market volatility (results not reported in the paper).

more liquidity and interest income lower systemic risk. We find a statistically insignificant relationship between systemic risk measures and a bank's asset size and market-to-book ratio.

4.2 Relationship between non-interest income and the different components of systemic risk

We now use the decomposition of systemic risk into its three components (equation (17)). Specifically, we estimate the relationship of non-interest income to tail risk (*alpha*), exposure to fundamental macroeconomic and finance factors (*beta*), and bank interconnectedness (*gamma*). The results of these regressions are presented in Table 4.

*** Table 4***

We first examine the relationship of non-interest income to a bank's tail risk, or *alpha*. We document that non-interest income significantly increases tail risk. A one standard deviation increase in non-interest income (1.02%) results in a 7.24% increase in a bank's tail risk. Although not focused on tail risk, these results are consistent with those of Stiroh (2004, 2006), who presents a positive relationship between non-interest income and volatility of bank returns. We next examine *beta*, the relationship between non-interest income and a bank's exposure to fundamental macroeconomic and finance factors. We find that non-interest income is statistically insignificantly related to *beta*, suggesting that non-interest income does not lead to more severe co-movements with macroeconomic and finance factors. Finally, we examine the relationship between non-interest income and a bank's interconnectedness, or *gamma*. We document that non-interest income is positively related to *gamma*, suggesting that non-interest income does lead to more systemic risk due to interconnectedness. A one standard-deviation increase in non-interest income results in a 10.5% increase in a bank's systemic risk of being interconnected to other banks.

But it is possible that the ratio of non-interest income to total assets is itself endogenously determined. To address this issue, we estimate a system of equations wherein we use three instrumental variables that might be highly correlated with the ratio of non-interest income to total assets. More specifically, we use as instrumental variables the lagged dollar value of all IPOs in the U.S. (obtained from the SDC Platinum's Global New Issues Database), the lagged dollar value of all merger and acquisition transactions in the U.S. (obtained from the SDC Platinum's Mergers and Acquisitions Database), and lagged market volume, which is defined as the total trading volume of all stocks recorded (obtained from CRSP's monthly stock files). As these are market-wide variables that are potentially correlated with trading and advisory services, we expect these variables to be related to non-interest income. Table 5 presents the results of the first- and second-stage regressions.

*** Table 5 ***

The first column in Table 5 shows that non-interest income is strongly correlated with bank characteristics and the three instrumental variables. An *F*-test on the null hypothesis that the three instrumental variables are jointly equal to zero is strongly rejected at the 1% level (*F*-statistic = 10.78). Examining their economic impact, we find that a one standard deviation increase in the dollar value of all IPOs issued increases non-interest income by 2.9%, a one standard deviation increase in the dollar value of M&A transactions increases non-interest income by 8.5%, and a one standard deviation increase in market volume increases non-interest income by 5.7%. Interestingly, we find that non-interest income is negatively related to interest income. This result suggests that when a bank sees its interest income decreasing, it increases its non-interest income to keep profits level. We also find non-interest income to be higher in large banks, in higher market-to-book banks, and in those with higher nonperforming loans. On the other hand, we find non-interest income to be lower for banks with higher liquidity and leverage.

The second-stage regression uses the predicted values of non-interest income from the first-stage regression. All *t*-statistics adjust for estimation error in the predicted values. The next four columns of Table 5 show the results from the second-stage regression. As in Table 3, a strong positive relationship exists between non-interest income and systemic risk. Similarly, we find a positive relationship between non-interest income and a bank's tail risk (*alpha)* and interconnectedness risk (*gamma)*. But unlike Table 4, which shows an insignificant relationship between non-interest income and exposure to macroeconomic and finance factors (*beta),* we now find a positive relationship. This last finding is consistent with that of Baele, et. al (2007) and De Jonghe (2010). These results suggest that the endogeneity of non-interest income does not generally change the results when we assume non-interest income is an exogenous independent variable in the regression.

4.3 Relationship of trading and other non-interest income to total systemic risk and its components

We further decompose non-interest income into trading income and other non-interest income to examine the relationship of trading and other non-interest income, with total risk $\Delta CoVaR$, and the three different components of systemic risk: *alpha*, *beta*, and *gamma*. In Table 6 the dependent variable is total systemic risk. In all three regression specifications, we find that both trading and other non-interest income are positively correlated with total systemic risk. This suggests that the impact of trading income on systemic risk is not substantially different from the impact of other non-interest income on systemic risk. In Table 7, the dependent variables are *alpha*, *beta*, and *gamma*, respectively. We find that both trading and other non-interest income are positively correlated with *alpha* and *gamma*, but insignificantly related to *beta*. This again suggests no differential impact between trading income and other non-interest income.

*** Tables 6 and 7***

4.4 Differential impact of non-interest income for banks of different sizes

We now check to see if non-interest income has a differential impact on the three components of systemic risk according to bank size—large, midsize, and small. Large banks are defined as those in the top tercile of total assets in each year, midsize banks are in the middle tercile of total assets in each year, and small banks are those in the bottom tercile of total assets in each year. For each group, we run three regressions (where the dependent variable is equal to *alpha, beta,* and *gamma*, respectively). The results of these nine regression models are given in Table 8. We find non-interest income to be positively related to interconnectedness risk *gamma* for both large and midsize banks, but not for small banks. We also find that non-interest income positively related to tail risk *alpha* and the effect is higher for both large and small banks, whereas *beta* is higher only for midsize banks.

*** Table 8***

5. Conclusions

The recent financial crisis showed that negative externalities from one bank to another can create significant systemic risk, which resulted in significant infusions of funds from the Federal Reserve and the U.S. Treasury. But banks have increasingly earned a higher proportion of their profits from non-interest income—specifically, from activities such as trading, investment banking, venture capital, and advisory fees. This paper examines the contribution of this non-interest income to *systemic* bank risk.

Using two prominent measures of systemic risk — the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2016) and the *MES* measure of Acharya, Pedersen, Philippon, and Richardson (2017) — we find that banks with higher non-interest income have a higher contribution to systemic risk. We also find that banks with higher leverage and nonperforming loans increase systemic risk, whereas those with more liquidity and interest income lower systemic risk. These results are robust to banks endogenously choosing non-interest income and controlling for bank-level time-invariant factors.

Additionally, we document that non-interest income increases idiosyncratic tail and interconnectedness risks, but has either an insignificant or positive relationship with a bank's exposure to macroeconomic and finance factors. These results are robust to trading and other non-interest income activities. Finally, we document some differences when examining the impact of non-interest income on large, midsize, and small banks.

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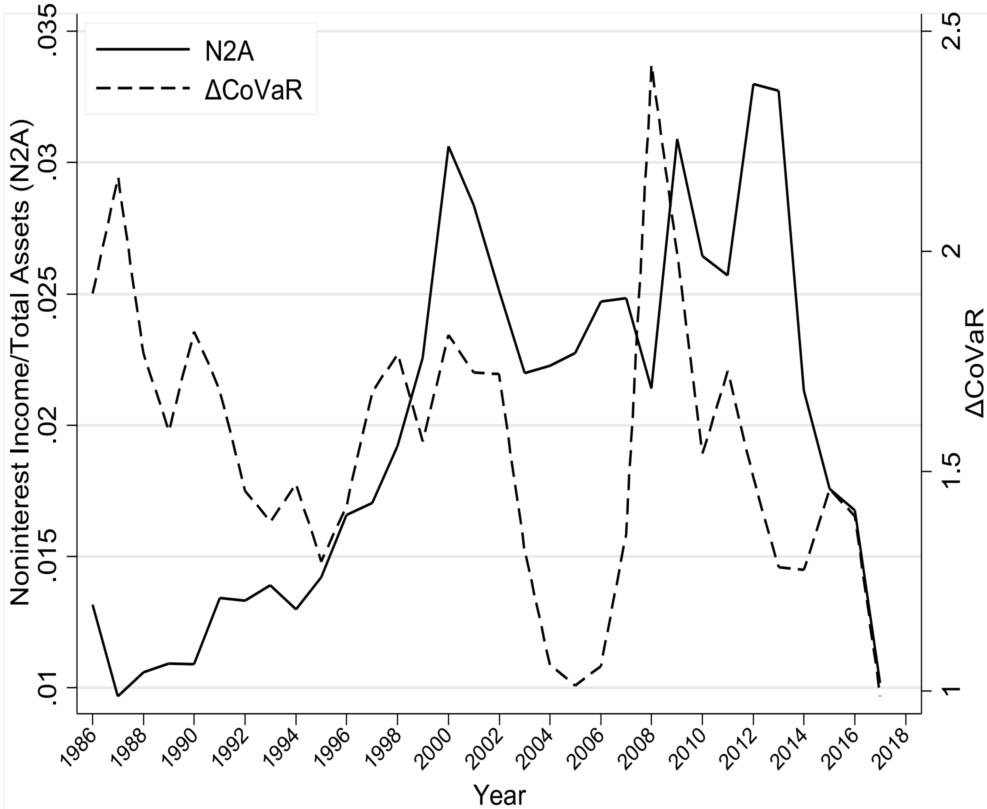
Figure 1. Ratio of average non-interest income to assets and *ΔCoVaR*

The first (second) panel includes (excludes) bank holding companies that were investment banks prior to 2008.



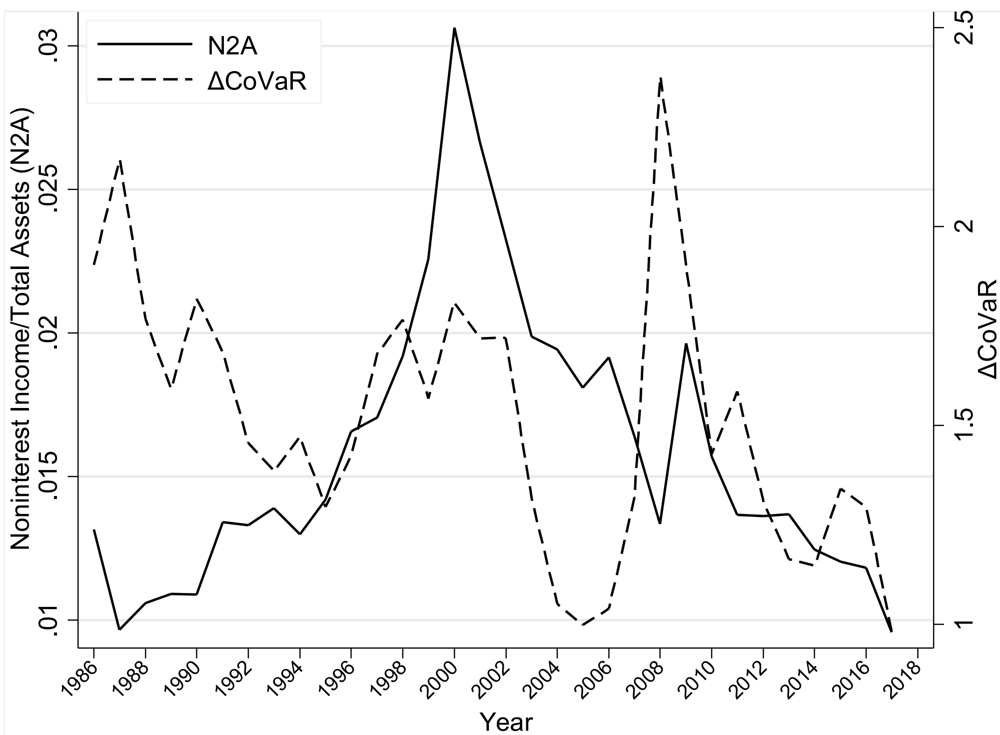


Table 1: Variable definitions and sources

Variable	Name	Calculation	Sources
ΔCoVaR	Financial institution's contribution to systemic risk	From equation (15)	Estimated
MES	Marginal expected shortfall	From equation (18)	Estimated
R^i	Weekly equity return of individual bank	$\frac{MV_t^i}{MV_{t-1}^i}-1$	CRSP Daily Stocks
R^s	Weekly equity return of all banks	$\sum_i \frac{MV_{t-1}^i}{\sum_j MV_{t-1}^j} R^i$	CRSP Daily Stocks
Total assets	Total asset value	Book value of total assets	U.S. Federal Reserve FRY-9C Report
Noninterest income/total assets	Ratio of non-interest income to total assets	Noninterest income / total assets	U.S. Federal Reserve FRY-9C Report
Trading income/total assets	Ratio of trading income to total assets	Trading income includes trading revenue, capital income, net securitization income, gain (loss) of loan sales, and gain (loss) of real estate sales / total assets	U.S. Federal Reserve FRY-9C Report
Other noninterest income/total assets	Ratio of other non-interest income to total assets	(Noninterest income minus trading income) /total assets	U.S. Federal Reserve FRY-9C Report
Interest income/total assets	Ratio of interest income to total assets	Interest income / total assets	U.S. Federal Reserve FRY-9C Report
Log(total assets)	Logarithm of total book assets	Log (total assets)	U.S. Federal Reserve FRY-9C Report
Leverage	Financial leverage	Total assets / book value of equity	Compustat Fundamentals
Market-to-book	Market-to-book ratio	Market value of equity / book value of equity	CRSP Daily Stocks, Compustat Fundamentals
Liquidity	Liquidity ratio	(Cash + held-to-maturity securities + available-for-sale securities + trading assets + repos) / total assets	U.S. Federal Reserve FRY-9C Report
Nonperforming loans/total loans	Ratio of nonperforming loans to total assets	Nonperforming loans / total loans	U.S. Federal Reserve FRY-9C Report

Table 2: Summary statistics

Variable	N	Mean	Median	Standard deviation	Min	Max
ΔCoVaR	9,631	1.02%	0.87%	0.79%	-0.87%	3.92%
MES	9,631	3.49%	3.04%	2.41%	-1.25%	15.8%
Non-interest income/total assets	9,631	0.009	0.007	0.010	0.000	0.101
Trading income/total assets	9,631	0.000	0.000	0.001	0.000	0.006
Other non-interest income/total assets	9,631	0.008	0.006	0.010	0.000	0.099
Interest income/total assets	9,631	0.022	0.022	0.007	0.005	0.047
Log(total assets)	9,631	14.76	14.45	1.658	12.09	20.89
Leverage	9,631	11.89	11.47	3.472	3.838	27.46
Market-to-book	9,631	1.521	1.400	0.754	0.201	4.901
Liquidity	9,631	0.268	0.256	0.119	0.029	0.690
Nonperforming loans/total loans	9,631	0.012	0.006	0.017	0.000	0.111

See Table 1 for data definitions and Section 3 of the paper for further details.

Table 3: Regression of a bank's systemic risk on non-interest income

In regression models (1) and (2), the dependent variable is $\Delta CoVaR$, which is the difference between *CoVaR* conditional on the bank being under distress and the *CoVaR* in the median state of the bank. In models (3) and (4), the dependent variable is the *MES,* or the marginal expected shortfall. The independent variables are one-year lagged values and are defined in Table 1.

Dependent variable:	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) MES_t	(4) MES_t
(Noninterest income/total assets) $_{t-1}$	1.794***	1.592***	14.76***	10.92**
	(3.19)	(2.83)	(3.34)	(2.50)
(Interest income/total assets) $_{t-1}$	-0.926*	-0.890*	-5.252	-5.190
	(-1.72)	(-1.66)	(-1.24)	(-1.25)
Log(total assets) $_{t-1}$	0.00895	0.00633	0.407***	0.367***
	(1.23)	(0.87)	(7.13)	(6.52)
Leverage $_{t-1}$	0.00363***	0.00208*	0.104***	0.0734***
	(3.45)	(1.93)	(12.51)	(8.73)
Market-to-book $_{t-1}$	-0.00327	0.00446	-0.205***	-0.0369
	(-0.59)	(0.78)	(-4.67)	(-0.83)
Liquidity $_{t-1}$	-0.0809**	-0.0682*	-1.119***	-0.869***
	(-2.21)	(-1.86)	(-3.89)	(-3.04)
(Nonperforming loans/total loans) $_{t-1}$		1.258***		26.03***
		(5.74)		(15.28)
Constant	0.789***	0.869***	-4.074***	-3.249***
	(7.77)	(8.39)	(-5.10)	(-4.04)
Controlling for loan type	No	Yes	No	Yes
Bank fixed-effects	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
N	9,631	9,631	9,631	9,631
R^2	0.379	0.381	0.438	0.454

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 4: Regression of a bank's *alpha*, *beta*, and *gamma* (defined in equation 17) on non-interest income

In regression models (1) and (2), the dependent variable is the first component of the $\Delta CoVaR$ decomposition—namely, the proxy for tail risk *alpha*. In models (3) and (4), the dependent variable is the second component of the $\Delta CoVaR$ decomposition—the proxy for exposure to fundamental macroeconomic and finance factors *beta*. In models (5) and (6), the dependent variable is the third component of the $\Delta CoVaR$ decomposition—the proxy for interconnectedness *gamma*. The independent variables are one-year lagged values and are defined in Table 1.

Dependent variable:	(1) $alpha_t$	(2) $alpha_t$	(3) $beta_t$	(4) $beta_t$	(5) $gamma_t$	(6) $gamma_t$
(Noninterest income/total assets) $_{t-1}$	0.273***	0.376***	-0.0712	-0.0178	1.286***	0.912***
	(7.17)	(9.19)	(-1.64)	(-0.38)	(13.39)	(9.18)
(Interest income/total assets) $_{t-1}$	-0.0360	0.175***	-0.165**	-0.114	0.512***	0.0198
	(-0.60)	(2.68)	(-2.43)	(-1.54)	(3.41)	(0.13)
Log(total assets) $_{t-1}$	-0.00594***	-0.00576***	0.00268***	0.00264***	0.0219***	0.0203***
	(-24.23)	(-21.82)	(9.62)	(8.84)	(35.52)	(31.69)
Leverage $_{t-1}$	0.00210***	0.00215***	0.000148	0.000405***	-0.000200	-0.00142***
	(19.48)	(19.26)	(1.20)	(3.20)	(-0.74)	(-5.25)
Market-to-book $_{t-1}$		-0.00301***		0.00185***		0.00467***
		(-5.33)		(2.90)		(3.41)
Liquidity $_{t-1}$		0.00819**		-0.0482***		0.135***
		(2.45)		(-12.76)		(16.61)
(Nonperforming loans/total loans) $_{t-1}$		0.193***		0.339***		-0.753***
		(7.79)		(12.13)		(-12.55)
Constant	0.114***	0.108***	0.000785	0.00276	-0.219***	-0.216***
	(26.51)	(22.99)	(0.16)	(0.52)	(-20.19)	(-18.92)
Controlling for loan type	No	Yes	No	Yes	No	Yes
N	9,631	9,631	9,631	9,631	9,631	9,631
R^2	0.089	0.110	0.013	0.054	0.165	0.236

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 5: 2SLS regression of a bank's systemic risk, *alpha*, *beta*, and *gamma* (defined in equation 17) on non-interest income

In the first-stage regression, we endogenize for the ratio of non-interest income to total assets using three instrumental variables. The first instrumental variable is the lagged dollar value of IPOs in the U.S.; the second instrumental variable is the lagged dollar value of M&A transactions in the U.S.; and the third instrumental variable is the lagged market volume. In the second-stage regression, the dependent variables are the three components of the $\Delta CoVaR$ decomposition: tail risk *alpha*, exposure to fundamental macroeconomic and finance factors *beta*, and interconnectedness *gamma*. Non-interest income to total assets uses the fitted value from the first-stage regression. All control variables are defined in Table 1.

	First stage	Second stage			
		$\Delta CoVaR_t$	$alpha_t$	$beta_t$	$gamma_t$
(Noninterest income/total assets) $_{t-1}$	N/A	26.37** (2.03)	3.083*** (3.35)	6.945*** (4.78)	9.000*** (4.08)
(Interest income/total assets) $_{t-1}$	-0.0846*** (-4.83)	-2.105 (-1.08)	-0.125 (-1.06)	-0.659*** (-3.55)	0.640** (2.27)
Log(total assets) $_{t-1}$	0.00100*** (16.43)	0.193*** (10.70)	-0.00189* (-1.74)	0.0105*** (6.11)	0.0110*** (4.22)
Leverage $_{t-1}$	-0.0004*** (-12.32)	-0.00411 (-0.66)	0.000831** (2.20)	-0.00214*** (-3.59)	0.00157* (1.73)
Market-to-book $_{t-1}$	0.00327*** (22.19)	0.160*** (3.27)	0.00782*** (2.64)	0.0232*** (4.96)	-0.0201*** (-2.83)
Liquidity $_{t-1}$	-0.00194** (-2.18)	0.701*** (8.85)	0.00295 (0.62)	-0.0621*** (-8.23)	0.149*** (12.99)
(Nonperforming loans/total loans) $_{t-1}$	0.0393*** (5.65)	-0.790 (-0.83)	0.370*** (6.48)	0.682*** (7.57)	-1.149*** (-8.39)
(Dollar value of IPOs) $_t$	0.0154** (2.14)	N/A	N/A	N/A	N/A
(Dollar value of M&A transactions) $_{t-1}$	0.0020*** (5.54)	N/A	N/A	N/A	N/A
(CRSP volume) $_{t-1}$	0.00007*** (3.23)	N/A	N/A	N/A	N/A
Constant	-0.0089*** (-6.74)		0.0762*** (7.21)	-0.0637*** (-3.82)	-0.136*** (-5.36)
Controlling for loan type	Yes	Yes	Yes	Yes	Yes
Bank fixed-effects	Yes	No	No	No	No
Year fixed-effects	Yes	No	No	No	No
N	9,195	9,195	9,195	9,195	9,195
R^2	0.170	0.070	0.105	0.110	0.206

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 6: Regression of a bank's systemic risk on the type of non-interest income (trading income versus other non-interest income)

In all regressions, systemic risk is defined as $\Delta CoVaR$. The independent variables include the ratio of one-year lagged trading income to assets, the ratio of other non-interest income to assets, and other control variables defined in Table 1.

Dependent variable:	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) $\Delta CoVaR_t$
(Trading income/total assets) $_{t-1}$	14.92*** (2.62)		13.52** (2.37)
(Other noninterest income/total assets) $_{t-1}$		1.564*** (2.71)	1.428** (2.46)
(Interest income/total assets) $_{t-1}$	-0.573 (-1.09)	-0.887* (-1.65)	-0.847 (-1.58)
Log(total assets) $_{t-1}$	0.00582 (0.80)	0.00645 (0.89)	0.00677 (0.93)
Leverage $_{t-1}$	0.00202* (1.87)	0.00207* (1.91)	0.00221** (2.04)
Market-to-book $_{t-1}$	0.00538 (0.94)	0.00469 (0.82)	0.00372 (0.65)
Liquidity $_{t-1}$	-0.0732** (-1.99)	-0.0668* (-1.82)	-0.0730** (-1.98)
(Nonperforming loans/total loans) $_{t-1}$	1.255*** (5.72)	1.259*** (5.74)	1.231*** (5.61)
Constant	0.882*** (8.53)	0.868*** (8.36)	0.864*** (8.33)
Controlling for loan type	Yes	Yes	Yes
Bank fixed-effects	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes
N	9,631	9,631	9,631
R^2	0.044	0.050	0.054

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 7: Regression of a bank's *alpha*, *beta*, and *gamma* (defined in equation 17) on the type of noninterest income (trading income versus other non-interest income)

In regression model (1), the dependent variable is the first component of the $\Delta CoVaR$ decomposition—namely, the proxy for tail risk *alpha*. In model (2), the dependent variable is the second component of the $\Delta CoVaR$ decomposition—the proxy for exposure to fundamental macroeconomic and finance factors *beta*. In model (3), the dependent variable is the third component of the $\Delta CoVaR$ decomposition—the proxy for interconnectedness *gamma*. The independent variables are one-year lagged values and are defined in Table 1.

Dependent variable:	(1) $alpha_t$	(2) $beta_t$	(3) $gamma_t$
(Trading income/total assets) $_{t-1}$	1.398**	-1.376	7.854***
	(2.33)	(-1.03)	(5.40)
(Other noninterest income/total assets) $_{t-1}$	0.359***	0.0127	0.782***
	(8.44)	(0.27)	(7.59)
(Interest income/total assets) $_{t-1}$	0.186***	-0.127*	0.0871
	(2.84)	(-1.71)	(0.55)
Log(total assets) $_{t-1}$	-0.00587***	0.00279***	0.0195***
	(-21.49)	(9.03)	(29.47)
Leverage $_{t-1}$	0.00214***	0.000422***	-0.00150***
	(19.12)	(3.33)	(-5.53)
Market-to-book $_{t-1}$	-0.00298***	0.00180***	0.00482***
	(-5.28)	(2.81)	(3.52)
Liquidity $_{t-1}$	0.00742**	-0.0470***	0.128***
	(2.20)	(-12.29)	(15.68)
(Nonperforming loans/total loans) $_{t-1}$	0.192***	0.340***	-0.759***
	(7.78)	(12.15)	(-12.66)
Constant	0.110***	0.000317	-0.203***
	(22.72)	(0.06)	(-17.34)
Controlling for loan type	Yes	Yes	Yes
N	9,631	9,631	9,631
R^2	0.110	0.055	0.238

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 8: Large, midsize, and small bank regressions of *alpha*, *beta*, and *gamma* (defined in equation 17) on the type of non-interest income (trading income versus other non-interest income)

In regression models (1), (4), and (7), the dependent variable is the first component of the $\Delta CoVaR$ decomposition—namely, the proxy for tail risk *alpha*. In models (2), (5), and (8), the dependent variable is the second component of the $\Delta CoVaR$ decomposition—the proxy for exposure to fundamental macroeconomic and finance factors *beta*. In models (3), (6), and (9), the dependent variable is the third component of the $\Delta CoVaR$ decomposition—the proxy for interconnectedness *gamma*. Large banks are defined as those in the top tercile of total assets in each year, midsize banks are in the middle tercile of total assets in each year, and small banks are those in the bottom tercile of total assets in each year. The independent variables are one-year lagged values and are defined in Table 1.

	Large banks			Midsize banks			Small banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	$alpha_t$	$beta_t$	$gamma_t$	$alpha_t$	$beta_t$	$gamma_t$	$alpha_t$	$beta_t$	$gamma_t$
(Noninterest income/total assets) $_{t-1}$	0.304***	-0.0106	1.584***	0.0803	0.298***	0.529**	0.423***	-0.105	-0.162
	(6.85)	(-0.16)	(10.06)	(0.88)	(2.90)	(2.44)	(4.17)	(-1.06)	(-0.87)
(Interest income/total assets) $_{t-1}$	-0.283**	0.251	-0.723*	-0.123	0.0312	1.235***	0.420***	-0.435***	0.259
	(-2.55)	(1.54)	(-1.84)	(-0.90)	(0.20)	(3.82)	(3.86)	(-4.08)	(1.29)
Log(total assets) $_{t-1}$	-0.00552***	0.00216***	0.00814***	-0.00707***	-0.00554***	0.0475***	-0.0102***	-0.00452***	0.0196***
	(-13.80)	(3.69)	(5.75)	(-6.14)	(-4.28)	(17.45)	(-6.83)	(-3.10)	(7.14)
Leverage $_{t-1}$	0.00189***	0.00059***	0.000834*	0.00198***	0.00057***	-0.00213***	0.00238***	0.000461**	-0.00312***
	(13.25)	(2.80)	(1.65)	(10.19)	(2.61)	(-4.62)	(9.97)	(1.97)	(-7.09)
Market-to-book $_{t-1}$	-0.00233***	0.00195**	0.00179	-0.00284***	-0.000760	0.00301	-0.00425***	-0.00116	0.00702***
	(-3.51)	(2.01)	(0.76)	(-2.64)	(-0.63)	(1.18)	(-3.16)	(-0.88)	(2.83)
Liquidity $_{t-1}$	0.0191***	-0.0426***	0.121***	-0.0122**	-0.0580***	0.205***	0.0152**	-0.0550***	0.0788***
	(4.12)	(-6.27)	(7.37)	(-2.19)	(-9.29)	(15.60)	(2.15)	(-7.92)	(6.04)
(Nonperforming loans/total loans) $_{t-1}$	0.167***	0.510***	-0.944***	0.175***	0.338***	-0.763***	0.222***	0.151***	-0.456***
	(5.16)	(10.76)	(-8.24)	(3.98)	(6.86)	(-7.33)	(4.41)	(3.07)	(-4.91)
Constant	0.109***	0.00766	-0.0245	0.144***	0.119***	-0.638***	0.158***	0.108***	-0.176***
	(13.97)	(0.67)	(-0.89)	(7.91)	(5.86)	(-14.86)	(7.46)	(5.18)	(-4.49)
Control for loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,210	3,210	3,210	3,211	3,211	3,211	3,210	3,210	3,210
Adj. R^2	0.124	0.074	0.162	0.066	0.074	0.214	0.075	0.031	0.067

t-statistics calculated using robust standard errors that are clustered at the bank-level are shown in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.