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Banks' Noninterest Income and Systemic Risk

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This paper finds noninterest income is positively correlated with the total systemic risk for U.S. banks. Decomposing total systemic risk into three components, we find that noninterest income is positively related to a bank's tail risk, positively related to a bank's interconnectedness risk, and an insignificantly related to a bank's exposure to macroeconomic and finance factors. We also find that noninterest income is more volatile and negatively related to interest income. Finally, we find trading and other noninterest income to be positively correlated with systemic risk. Other noninterest income, compared with trading income, has a slightly larger economic impact. (*JEL* G01, G18, G20, G21, G32, G38)

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

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Introduction

The financial crisis of 2007–2009 was a showcase of large risk spillovers from one bank to another heightened risk in the whole banking system. 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 noninterest income rather than interest income.[2] Noninterest income includes income from trading and securitization, investment banking and advisory fees, brokerage commissions, venture capital, fiduciary services, and gains on nonhedging derivatives. These activities are different from the traditional deposit-taking and lending function of banks. In noninterest 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 noninterest income to total assets starting around 1998. The latter panel shows that the increase in noninterest income remains when we remove investment banks in the precrisis period.[3]

This paper begins by reexamining[4] the contribution of noninterest income to *systemic* bank risk. The existing literature presents mixed evidence for U.S. banks. De Jonghe (2010), Moore and Zhou (2014), and Bostandzic and Weiss (2018) find that noninterest income is *positively* correlated with systemic risk. Engle et al. (2014), Weiss, Bostandzic, and Neumann (2014), and Saunders, Schmid, and Walter (2020) detect an *insignificant* relationship between noninterest income and systemic risk. De Jonghe, Diepstraten, and Schepens (2015) document that noninterest 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. Extrapolating their results to the

[1] This banking role 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] 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 comprise this group.

[4] See Section 2 for a more detailed description of the literature.

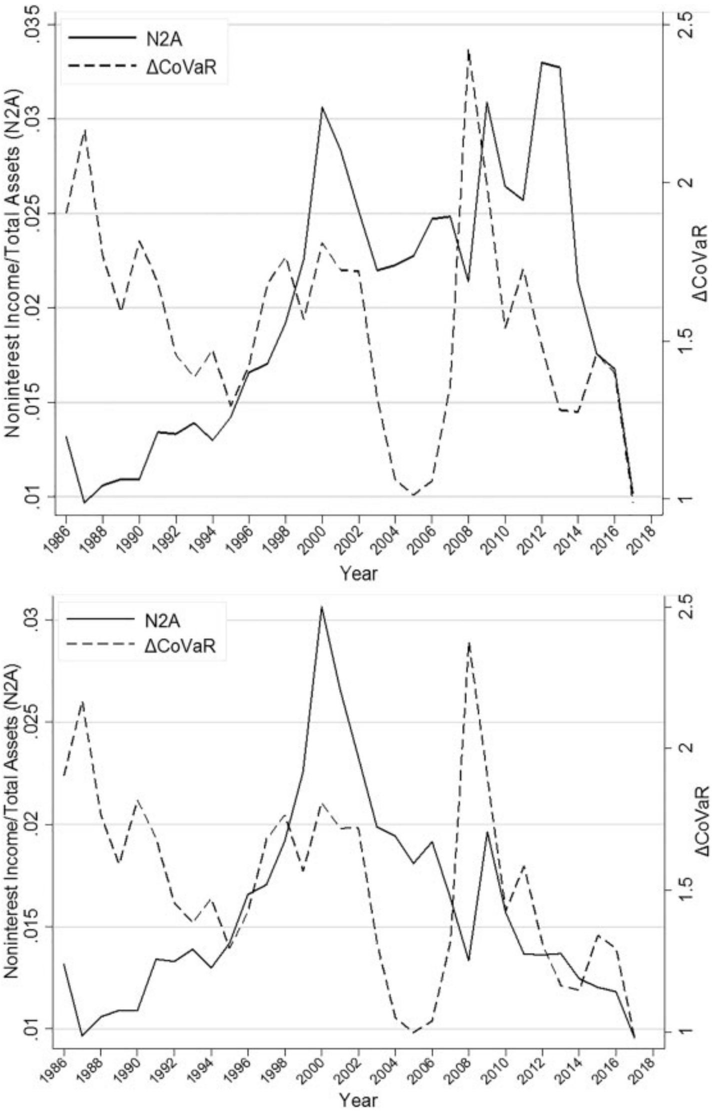

Figure 1
Ratio of average noninterest income to assets and $\Delta CoVaR$
The first (second) panel includes (excludes) bank holding companies that were investment banks prior to 2008.

United States, where such issues do not dominate, suggests a *negative* relationship for *large* banks and a *positive* relationship for *small* banks.

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 et al. (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 examines five issues. First, we reexamine the relationship between systemic risk and a bank's noninterest income. Second, we decompose systemic risk into three components, estimating the relationship of noninterest 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 noninterest income to each component. Third, we categorize noninterest income into two subgroups, trading income and other noninterest income, in order to examine whether they have a differential effect on systemic risk and its three components. Fourth, we examine the relationship between noninterest income and the traditional interest income. Fifth and finally, we examine whether large, midsize, and small banks have different relationships.

Our results are as follows:

1. Systemic risk is higher for banks with a higher ratio of noninterest income to assets. Specifically, a 1-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 et al. (2014), and Saunders et al. (2020).
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 noninterest income significantly increases *alpha*. A 1-standard-deviation increase in noninterest 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 noninterest income and a bank's return volatility. In addition, we find an insignificant relationship between noninterest income and comovements with *beta*. Finally, we find that noninterest income is positively related to a bank's *gamma*. A 1-standard-deviation increase in noninterest income results in a 10.5% rise in a bank's *gamma*.

4. We find that the above results are robust to an alternative measure of noninterest income, longer time windows of past changes in noninterest income, and whether we include a quadratic transformation of noninterest income.
5. We also find that interest and noninterest income are negatively correlated (correlation coefficient = -0.13). In a regression framework, we find that a 1-standard-deviation increase in interest income results in an average decrease of -2.53% in noninterest income. We also find noninterest income to be higher in large banks, in higher market-to-book banks, those with higher nonperforming loans, and when the dollar value of M&A transactions are higher. On the other hand, we find noninterest income to be lower for banks with higher liquidity and leverage.
6. After splitting noninterest income into two components, trading income and other noninterest income, we find both components are positively related to total systemic risk. Economically we find that other noninterest income has a slightly larger impact on $\Delta CoVaR$, *alpha*, and *gamma* than interest income. No such difference is found for *beta*.
7. Examining the impact of noninterest 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 noninterest income and systemic risk? DeYoung and Roland (2001) suggest that noninterest income is more volatile than the stable interest-income activities. We calculate the coefficient of variation (cv) of the ratio of noninterest income to assets and the ratio of interest income to assets. We find cv of noninterest 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 noninterest income (47.6%) to be significantly higher than the cv of interest income (22.5%). This confirms the DeYoung and Roland (2001) argument that noninterest income is more volatile than interest income in our sample.

But why does this more volatile noninterest 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 noninterest income when the aggregate value of M&A activity 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 banks to be highly procyclical and their performance worse than those of nonbank-affiliated private equity investments.

1. Related Literature

1.1 Noninterest income and systemic risk

The prior literature shows mixed evidence on the relationship between noninterest income and systemic risk measures. For example, De Jonghe (2010) finds that noninterest income is positively correlated with systemic risk for European banks, and Moore and Zhou (2014) find that noninterest income is positively correlated with systemic risk for U.S. banks.

[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), and 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).

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 noninterest income. De Jonghe, Diepstraten, and Schepens (2015) find that noninterest 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 United States, where such issues do not dominate, suggests a negative relationship between noninterest income and systemic risk for large banks and a positive relationship between noninterest income and systemic risk for small banks. Engle et al. (2014) find that noninterest income is higher in banks from countries with low banking market concentrations. They also find that noninterest 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 United States). Weiss et al. (2014) find no statistically significant relationship between noninterest income and systemic risk for U.S. and European banks, whereas Saunders et al. (2020) find a similar insignificant relationship for U.S. banks.

1.2 Noninterest income and individual bank risk

Other papers have examined the relationship between noninterest income and individual bank risk. Saunders and Walter (1994), DeYoung and Roland (2001), and Bisias et al. (2012) provide detailed literature reviews. While our study focuses on the effect of noninterest 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 noninterest 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 noninterest income. Williams (2016) finds that noninterest 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, De Jonghe, and Vander Vennet (2007) find that higher noninterest income decreases bank risk. Köhler (2014) finds that retail-oriented German banks lowered their bank risk when they had higher noninterest income. DeYoung and Torna (2013) find that the probability of bank failure decreased with securities brokerage and insurance sales.[7]

2. Data, Methodology, and Variables Used

2.1 Data

We focus on all publicly traded bank holding companies in the United States, 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 have been obtained from the NBER (http://www.nber.org/cycles/cyclesmain.html).

2.2 Definition of systemic risk using $\Delta CoVaR$

We will 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, to avoid procyclicality and the "volatility paradox," one should base regulation on reliably observed variables that predict future $\Delta CoVaR$s (in our regressions, by 1 year ahead).[8]

[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.

[8] The volatility paradox was introduced in Brunnermeier and Sannikov (2014).

Value at risk (VaR)[9] 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 preset horizon T:

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

Thus, by definition, the value of VaR is negative in general.[10] 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 $Probability(R^i \leq VaR^i_{1\%}) = 1\%$.

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 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:

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

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:

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

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),

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

[10] Empirically, the value of VaR also can 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.

and the second term measures the systemic risk when bank i's return is at its median level (normal state).

To estimate[11] 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[12] 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 $\beta^{i,median}$:

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

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 ($i = j = 1, 2, 3 \ldots, N$) 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.[13] We obtain the value-weighted daily market returns from the CRSP Indexes for the S&P 500 index. We use the weekly value-weighted

[11] We strictly follow the estimation method used by Adrian and Brunnermeier (2016, pp. 1718–19). Their Stata program is available from the American Economic Association's Web site (https://www.aeaweb.org/articles?id=10.1257/aer.20120555).

[12] See Koenker and Hallock (2001) and Koenker (2005) for a detailed explanation of the quantile regression estimation methodology.

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

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 3-month Libor rate and the 3-month Treasury-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 3-month Treasury-bill rate. Term structure is the change in the slope of the yield curve (the yield spread between the 10-year Treasury-bond rate and the 3-month Treasury-bill rate). Default risk is the change in the credit spread between 10-year BAA corporate bonds and the 10-year Treasury-bond rate. All interest rate data is obtained from the U.S. Federal Reserve Web site 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 $\widehat{\alpha}^i$, $\widehat{\beta}^i$, $\widehat{\alpha}^{i,median}$, and $\widehat{\beta}^{i,median}$ estimated from the quantile regressions of Equations (5) and (7):

$$VaR^i_{q,t} = \widehat{R}^i_t = \widehat{\alpha}^i + \widehat{\beta}^i Z_{t-1} \tag{10}$$

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

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

$$CoVaR^{system|i}_{q,t} = \widehat{R}^{system}_t = \widehat{\alpha}^{system|i} + \widehat{\beta}^{system|i} Z_{t-1} + \widehat{\gamma}^{system|i} VaR^i_{q,t} \tag{12}$$

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

$$CoVaR^{system|i,median}_{q,t} = \widehat{\alpha}^{system|i} + \widehat{\beta}^{system|i} Z_{t-1} + \widehat{\gamma}^{system|i} R^{i,median}_t. \tag{13}$$

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:

$$\begin{aligned}\Delta CoVaR^i_{q,t} &= CoVaR^{system|i}_{q,t} - CoVaR^{system|i,median}_{q,t}\\ &= \widehat{\beta}^{system|i}(VaR^i_{q,t} - R^{i,median}_t).\end{aligned} \tag{14}$$

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

$$\Delta CoVaR^{i}_{1\%,t} = CoVaR^{system|i}_{1\%,t} - CoVaR^{system|i,median}_{1\%,t}. \quad (15)$$

While the value of $\Delta CoVaR^{i}_{1\%,t}$ 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 $\Delta CoVaR^{i}_{q,t}$ into its three components:

$$\Delta CoVaR^{i}_{q,t} = \widehat{\gamma}^{system|i}[(\widehat{\alpha}^{i} - \widehat{\alpha}^{i,median}) + (\widehat{\beta}^{i} - \widehat{\beta}^{i,median})Z_{t-1}], \quad (16)$$

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

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

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.

2.3 Definition of systemic risk using *MES*

Acharya et al. (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.[14] 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

[14] Acharya et al. (2017) calculate the annual *realized* systemic expected shortfall using equity return data during the 2007–2008 crisis.

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 et al. (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[15] 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:

$$MES^i_{5\%} = \frac{1}{\#days_{t:\,system\,is\,in\,5\%\,tail}} \sum R^i_t. \tag{18}$$

2.4 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*).[16] Our main variable of analysis is the bank's ratio of noninterest 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 noninterest income on total systemic risk and the components of systemic risk.

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

Table 2 presents the summary statistics of our systemic risk measures. Comparing our results to those in Adrian and Brunnermeier (2016), we

[15] 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.

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

Table 1
Variable definitions and sources

Variable	Description	Calculation	Source
$\Delta CoVaR$	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 noninterest 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 noninterest 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	SD	Min	Max
$\Delta CoVaR$	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%
Noninterest 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 noninterest 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 for further details.

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 et al. (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 (median) ratio of noninterest 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%).

3. Empirical Results

3.1 Relationship between noninterest income and systemic risk

We begin by regressing our measures of systemic risk on the ratio of noninterest 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 and 2 are the $\Delta CoVaR$ regressions, and Columns 3 and 4 are the MES regressions. Table 3 gives the results of our panel regressions that include bank fixed effects and year dummies. All regressions use robust standard errors clustered at the bank level. We have included a large set of independent variables, while controlling for bank-level fixed effects, loan types, and year dummies. That said, our results on noninterest income could be possibly picking up some time-varying omitted variable correlated with both noninterest income and systemic risk but that has not been included in our regressions.

We begin by examining the relationship between total systemic risk and the ratio of noninterest income to total assets. We find that the ratio of noninterest income to total assets is strongly positively correlated with both $\Delta CoVaR$ and MES, suggesting that noninterest income adversely contributes to systemic risk. Specifically, a 1-standard-deviation shock to a bank's ratio of noninterest 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.[17] This positive relationship is consistent with the results of De Jonghe (2010), Moore and Zhou (2014), and Bostandzic and Weiss

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

Table 3
Regression of a bank's systemic risk on noninterest income

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	.379	.381	.438	.454

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 1-year-lagged values and are defined in Table 1. t-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

(2018), but different from the insignificant relationship results of Engle et al. (2014), Weiss et al. (2014), and Saunders et al. (2020).

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 nonperforming loans increase systemic risk, whereas those with 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.

3.2 Relationship between noninterest 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 noninterest income to tail risk (*alpha*), exposure to fundamental macroeconomic and finance factors (*beta*), and bank interconnectedness (*gamma*). Table 4 presents the results of these regressions.

We first examine the relationship of noninterest income to a bank's tail risk, or *alpha*. We document that noninterest income significantly

Table 4
Regression of a bank's *alpha*, *beta*, and *gamma* on noninterest income

Dependent variable	(1) $alpha_t$	(2) $beta_t$	(3) $gamma_t$
(Noninterest income/total assets) $_{t-1}$	0.376***	−0.0178	0.912***
	(9.19)	(-0.38)	(9.18)
(Interest income/total assets) $_{t-1}$	0.175***	−0.114	0.0198
	(2.68)	(-1.54)	(0.13)
log(total assets) $_{t-1}$	−0.00576***	0.00264***	0.0203***
	(-21.82)	(8.84)	(31.69)
Leverage $_{t-1}$	0.00215***	0.000405***	−0.00142***
	(19.26)	(3.20)	(-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	0.108***	0.00276	−0.216***
	(22.99)	(0.52)	(-18.92)
Controlling for loan type	Yes	Yes	Yes
N	9,631	9,631	9,631
R^2	.110	.054	.236

See Equation (17) for the definitions of *alpha*, *beta*, and *gamma*. 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, which is 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, which is the proxy for interconnectedness *gamma*. The independent variables are 1-year-lagged values and are defined in Table 1. *t*-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

increases tail risk. A 1-standard-deviation increase in noninterest 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 noninterest income and volatility of bank returns. We next examine *beta*, the relationship between noninterest income and a bank's exposure to fundamental macroeconomic and finance factors. We find that noninterest income to be statistically insignificantly related to *beta*, suggesting that noninterest income does not lead to more severe comovements with macroeconomic and finance factors. Finally, we examine the relationship between noninterest income and a bank's interconnectedness, or *gamma*. We document that noninterest income is positively related to *gamma*, suggesting that noninterest income does lead to more systemic risk due to interconnectedness. A one standard-deviation increase in noninterest income results in a 10.5% increase in a bank's systemic risk of being interconnected to other banks.

3.3 Additional tests

We now conduct three additional tests to examine the robustness of the above relationship that we found. The first test uses a different definition

Table 5
Regression of a bank's systemic risk on an alternative measure of noninterest income

Dependent variable	(1) $\Delta CoVaR_t$	(2) MES_t	(3) $alpha_t$	(4) $beta_t$	(5) $gamma_t$
(Noninterest income / noninterest income + interest income) $_{t-1}$	0.0709*	−0.178	0.0193***	−0.0284***	0.0635***
	(1.78)	(-0.52)	(5.27)	(-6.97)	(7.12)
log(total assets) $_{t-1}$	0.0139*	0.531***	−0.00625***	0.00389***	0.0194***
	(1.87)	(9.35)	(-22.69)	(12.65)	(28.79)
Leverage $_{t-1}$	0.00154	0.0422***	0.00202***	−0.00000480	−0.00156***
	(1.38)	(4.92)	(17.02)	(-0.04)	(-5.38)
Market-to-book $_{t-1}$	0.0199***	0.00912	−0.00230***	0.00464***	0.00464***
	(3.45)	(0.21)	(-4.05)	(7.34)	(3.35)
Liquidity $_{t-1}$	−0.0748**	−0.816***	0.00404	−0.0506***	0.130***
	(-2.03)	(-2.89)	(1.20)	(-13.50)	(15.89)
(Nonperforming loans/total loans) $_{t-1}$	1.386***	20.39***	0.201***	0.196***	−0.798***
	(6.15)	(11.82)	(7.68)	(6.70)	(-12.49)
Constant	0.520***	−4.874***	0.118***	−0.00811*	−0.204***
	(4.24)	(-5.19)	(29.85)	(-1.84)	(-21.19)
Controlling for loan type	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	No	No	No
N	9,195	9,195	9,195	9,195	9,195
R^2	.364	.457	.098	.051	.233

In regression model 1, 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 model 2, the dependent variable is the MES, or the marginal expected shortfall. In model 3, the dependent variable is the first component of the $\Delta CoVaR$ decomposition, namely, the proxy for tail risk *alpha*. In model 4, the dependent variable is the second component of the $\Delta CoVaR$ decomposition, which is the proxy for exposure to fundamental macroeconomic and finance factors *beta*. In model 5, the dependent variable is the third component of the $\Delta CoVaR$ decomposition, which is the proxy for interconnectedness *gamma*. Noninterest income is measured using the ratio of noninterest income and the sum of interest income and noninterest income. Other independent variables are 1-year-lagged values and are defined in Table 1. *t*-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

of noninterest income, namely, the ratio of noninterest income to the sum of interest income and noninterest income. This captures the proportion of a bank's income that arises from noninterest income, the results of which are given in Table 5. We find that noninterest income is positively related $\Delta CoVaR$, *alpha*, and *gamma*, which is consistent with those in Tables 3 and 4. But we find no statistically significant relationship to MES.

Our second test examines if past changes in noninterest income have any additional correlation with systemic risk, the results of which are given in Table 6. We include two different independent variables, the 1-year change in noninterest income, and the 3-year change in noninterest income, respectively. We still find that lagged noninterest income variable to be positively correlated with systemic risk in all four regression models. For the changes in noninterest income variables, there is no statistically significant correlation in 3 of the 4 regression models. This suggests weak evidence, if any, that longer windows of noninterest income correlate with higher systemic risk.

Table 6
Regression of a bank's systemic risk on noninterest income and changes in noninterest income

Dependent variable	(1) $\Delta CoVaR_t$	(2) MES_t	(3) $\Delta CoVaR_t$	(4) MES_t
(Noninterest income/total assets) $_{t-1}$	13.31***	6.503*	15.24***	3.566
	(5.57)	(1.84)	(5.41)	(0.90)
(1-year change in noninterest income/total assets) $_{t-1}$	−7.222**	−7.372		
	(-2.43)	(-0.93)		
(3-year change in noninterest income/total assets) $_{t-1}$			−4.904	−0.276
			(-1.36)	(-0.04)
(Interest income/total assets) $_{t-1}$	−2.923	11.74	−4.566	12.27
	(-0.63)	(1.64)	(-0.84)	(1.47)
log(total assets) $_{t-1}$	0.151***	0.290***	0.138***	0.300***
	(7.37)	(11.57)	(6.24)	(10.46)
Leverage $_{t-1}$	−0.00862	0.0335***	−0.00736	0.0345**
	(-1.34)	(2.86)	(-1.06)	(2.49)
Market-to-book $_{t-1}$	0.124***	0.108**	0.140***	0.117**
	(3.42)	(2.10)	(3.64)	(2.13)
Liquidity $_{t-1}$	0.693***	−0.604*	0.805***	−0.679*
	(3.40)	(-1.89)	(3.67)	(-1.92)
(Nonperforming loans/total loans) $_{t-1}$	−2.498**	25.65***	−2.216**	25.32***
	(-2.38)	(10.20)	(-2.05)	(9.57)
Constant	−1.864***	−1.575***	−1.001**	−1.140*
	(-5.31)	(-3.70)	(-2.49)	(-1.95)
Controlling for loan type	Yes	Yes	Yes	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	.284	.492	.306	.515

In regression models 1 and 3, 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 2 and 4, the dependent variable is the MES, or the marginal expected shortfall. Noninterest income is measured using the ratio of noninterest income to total assets. In models 1 and 2, we include the 1-year change in noninterest income, and in models 3 and 4, we include the 3-year change in noninterest income. Other independent variables are 1-year-lagged values and are defined in Table 1. t-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. $*p <$ .1; $**p < .05$; $***p < .01$.

In Table 7, we examine whether noninterest income is nonlinearly correlated with systemic risk. Accordingly, we also include the squared transformation of noninterest income. We find the squared term to be positively correlated with $\Delta CoVaR$. This suggests that the largest banks contribute even more to systemic risk when measured by $\Delta CoVaR$. However, we find no statistically significant relationship between MES and the squared term. Therefore, we find mixed evidence for a nonlinear relationship.

3.4 Determinants of noninterest income

We find that interest and noninterest income are negatively correlated (correlation coefficient = -0.13). In a regression framework, we examine the determinants of noninterest income, the results of which are given in Table 8. We again find that noninterest income is negatively related to interest income. A 1-standard-deviation increase in interest income results in an average decrease of -2.53% in noninterest income. This

Table 7
Regression of a bank's systemic risk on noninterest income with quadratic terms

Dependent variable	(1) $\Delta CoVaR_t$	(2) MES_t
(Noninterest income/total assets) $_{t-1}$	1.748***	6.833
	(3.02)	(1.54)
(Noninterest income/total assets)^2 $_{t-1}$	5.789***	−8.789
	(5.22)	(-1.03)
(Interest income/total assets) $_{t-1}$	−0.0763	−5.993
	(-0.12)	(-1.22)
log(total assets) $_{t-1}$	0.0161**	0.532***
	(2.17)	(9.35)
Leverage $_{t-1}$	0.00181	0.0419***
	(1.60)	(4.81)
Market-to-book $_{t-1}$	0.0160***	0.00723
	(2.72)	(0.16)
Liquidity $_{t-1}$	−0.0631*	−0.898***
	(-1.68)	(-3.12)
(Nonperforming loans/total loans) $_{t-1}$	1.311***	20.37***
	(5.82)	(11.78)
Constant	−0.0590	0.221
	(-1.25)	(0.61)
Controlling for loan type	Yes	Yes
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	9,631	9,631
R^2	.367	.458

In regression model 1, 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 model 2, the dependent variable is the MES, or the marginal expected shortfall. Noninterest income is measured using the ratio of noninterest income to total assets. Its squared term is also included in the regression specification. Other independent variables are 1-year-lagged values and are defined in Table 1. t-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

result suggests that when a bank sees its interest income decreasing, it increases its riskier noninterest income. After controlling for the size of interest income, we also find noninterest income to be higher in small banks, in higher market-to-book banks, and in those with higher nonperforming loans. On the other hand, we find noninterest income to be lower for banks with higher liquidity and leverage. In Column 2, we add three marketwide variables potentially correlated with trading and advisory services and therefore expected to be correlated to noninterest income. They are the lagged dollar value of all initial public offerings (IPOs) in the United States (obtained from the SDC Platinum's Global New Issues Database), the lagged dollar value of all merger and acquisition transactions in the United States (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). We find noninterest income to be positively related to the dollar value of M&A transactions.

Table 8
Determinants of noninterest income

Dependent variable: (Noninterest income/total assets) $_t$	(1)	(2)
(Interest income/total assets) $_{t-1}$	−0.0341***	−0.0370***
	(-2.84)	(-3.04)
log(total assets) $_{t-1}$	−0.000792***	−0.000781***
	(-5.67)	(-5.47)
Leverage $_{t-1}$	−0.000116***	−0.000121***
	(-5.45)	(-5.55)
Market-to-book $_{t-1}$	0.00142***	0.00141***
	(12.94)	(12.69)
Liquidity $_{t-1}$	−0.00122*	−0.00142**
	(-1.73)	(-1.98)
(Nonperforming loans/total loans) $_{t-1}$	0.00938**	0.00879**
	(2.21)	(2.05)
(Dollar value of IPOs) $_t$		0.0946
		(1.08)
(Dollar value of M&A transactions) $_{t-1}$		0.00430**
		(2.50)
(CRSP volume) $_{t-1}$		0.000821
		(0.50)
Constant	0.0188***	−0.00212
	(8.18)	(-0.07)
Controlling for loan type	Yes	Yes
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	9,195	9,195
R^2	.087	.084

The dependent variable is the ratio of noninterest income to total assets. Dollar value of IPOs is defined as the lagged dollar value of all IPOs in the United States; dollar value of M&A transactions is defined as the lagged dollar value of all M&A transactions in the United States; and CRSP volume is defined as lagged market volume. Table 1 defines all other control variables. *t*-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

3.5 Relationship of trading and other noninterest income to total systemic risk and its components

We further decompose noninterest income into trading income and other noninterest income to examine the relationship of trading and other noninterest income, with total risk $\Delta CoVaR$, and the three different components of systemic risk: *alpha*, *beta*, and *gamma*. In Table 9, the dependent variable is total systemic risk $\Delta CoVaR$. In all three regression specifications, we find that both trading and other noninterest income are positively correlated with total systemic risk. Examining the most comprehensive specification (Column 3), we find that a 1-standard-deviation increase in trading income increases $\Delta CoVaR$ by 0.94%, which is less than the 1.39% increase in $\Delta CoVaR$ associated with a 1-standard-deviation increase in other noninterest income. In Table 10, the dependent variables are *alpha*, *beta*, and *gamma*, respectively. We find that both trading and other noninterest income are positively correlated with *alpha* and *gamma*, but insignificantly related to *beta*. A 1-standard-deviation increase in trading income increases *alpha* (*gamma*) by 0.10% (0.55%), which is less than the 0.35% (0.76%) associated with 1-standard-deviation increase in other noninterest income, respectively.

Table 9
Regression of a bank's systemic risk on the type of noninterest income (trading income vs. other non-interest income)

Dependent variable	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) $\Delta CoVaR_t$
(Trading income/total assets) $_{t-1}$	14.92***		13.52**
	(2.62)		(2.37)
(Other noninterest income/total assets) $_{t-1}$		1.564***	1.428**
		(2.71)	(2.46)
(Interest income/total assets) $_{t-1}$	−0.573	−0.887*	−0.847
	(-1.09)	(-1.65)	(-1.58)
log(total assets) $_{t-1}$	0.00582	0.00645	0.00677
	(0.80)	(0.89)	(0.93)
Leverage $_{t-1}$	0.00202*	0.00207*	0.00221**
	(1.87)	(1.91)	(2.04)
Market-to-book $_{t-1}$	0.00538	0.00469	0.00372
	(0.94)	(0.82)	(0.65)
Liquidity $_{t-1}$	−0.0732**	−0.0668*	−0.0730**
	(-1.99)	(-1.82)	(-1.98)
(Nonperforming loans/total loans) $_{t-1}$	1.255***	1.259***	1.231***
	(5.72)	(5.74)	(5.61)
Constant	0.882***	0.868***	0.864***
	(8.53)	(8.36)	(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	.044	.050	.054

In all regressions, systemic risk is defined as $\Delta CoVaR$. The independent variables include the ratio of 1-year-lagged trading income to assets, the ratio of other noninterest income to assets, and other control variables defined in Table 1. *t*-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

These results suggest that other noninterest income has a slightly larger economic effect than trading income.

3.6 Differential impact of noninterest income on differently sized banks

We now check to see if noninterest 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). Table 11 gives the results of these nine regression models. We find noninterest income to be positively related to interconnectedness risk *gamma* for both large and midsize banks, but not for small banks. We also find that noninterest 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 10
Regression of a bank's *alpha*, *beta*, and *gamma* on trading income versus other noninterest income

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	.110	.055	.238

See Equation (17) for the definitions of *alpha*, *beta*, and *gamma*. 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, which is 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, which is the proxy for interconnectedness *gamma*. The independent variables are 1-year-lagged values and are defined in Table 1. *t*-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

4. 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 noninterest income, specifically from nonlending activities, such as trading, investment banking, engaging in venture capital funding, and advising. This paper examines the contribution of this noninterest income to systemic bank risk.

Using two prominent measures of systemic risk, we find that banks with higher noninterest 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. Decomposing total systemic risk into three components, we find that noninterest income has a positive relationship with a bank's tail risk, a positive relationship with a bank's interconnectedness risk, and an insignificant relationship with a bank's exposure to macroeconomic and finance factors. We also find that

Table 11
Large, midsize, and small bank regressions of *alpha*, *beta*, and *gamma* on trading income versus other noninterest income

	Large banks			Midsize banks			Small banks		
Dependent variable	(1) $alpha_t$	(2) $beta_t$	(3) $gamma_t$	(4) $alpha_t$	(5) $beta_t$	(6) $gamma_t$	(7) $alpha_t$	(8) $beta_t$	(9) $gamma_t$
(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	.124	.074	.162	.066	.074	.214	.075	.031	.067

See Equation (17) for the definitions of *alpha*, *beta*, and *gamma*. 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, which is 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, which is 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 1-year-lagged values and are defined in Table 1. t-statistics, calculated using robust standard errors, are clustered at the bank level and shown in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

noninterest income is more volatile and negatively related to interest income. Finally, we find trading and other noninterest income to be positively correlated with systemic risk, with other noninterest income having a slightly larger economic impact than trading income.

Future research might examine whether further subcategorization of noninterest income (such as proprietary trading on behalf of the bank itself vs. trading on behalf of its clients vs. market-making activities) has differential impacts on systemic research.

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