The impact of bank herding on systemic risk*

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Abstract

We examine the impact of bank herding on systemic risk. We find that the level of bank herding in real estate loans during boom periods is substantially higher than the level of bank herding in commercial and industrial loans or consumer loans. More importantly, we find that bank herding significantly increases the systemic risk. In particular, we find that herding by big banks interacts in boom periods resulting in the stronger predictive power of systemic risk in the next period beyond what is predicted by bank herding and the boom period individually. We attribute these results to evidence of *too-many-and-big-to-fail*.

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1. Introduction

Systemic risk captures the risk of a cascading failure, caused by interlinkages within the financial system, resulting severe negative externalities on the rest of the economy.[1] Of particular concern for regulators and policymakers is how to control the build-up of systemic risk and limit the occurrence and propagation of financial crises. In the banking sector, systemic risk usually stems from interconnectedness and herding behaviors by banks. Ample recent research documents that interlinkages matter for financial stability.[2] Yet relatively less empirical research has been done to examine whether bank herding poses significant threats to the financial system.[3]

Intuitively, bank herding indicates the tendency of banks to issue or close (sell) a certain loan together in the same direction more often than it is expected. Acharya and Yorulmazer (2008a) note that the likelihood of information

[1] There are various definitions of systemic risk. Billio, Getmansky, Lo, and Pelizzon (2012) note that "…systemic risk seems to be hard to define but we think we know it when we see it…a more formal definition is any set of circumstances that threatens the stability of or public confidence in the financial system." Adrian and Brunnermier (2016) note the following: "…systemic risk: the risk that the capacity of the entire financial system is impaired, with potentially adverse consequences for the real economy"

[2] See, for example, Ibragimov, Jaffee, and Walden (2011), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Greenwood, Landier, and Thesmar (2015), Giglio, Kelly, and Pruitt (2016), Calomiris, Jeremski, and Wheelock (2019), and so on.

[3] In the previous literature, Nakagawa and Uchida (2011) examine herding behaviors in Japanese banks.

contagion induces banks to herd with other banks.[4] Acharya and Yorulmazer (2008a) show that banks herd and undertake correlated investment to minimize the effect of information contagion on the expected cost of borrowing. Many previous studies show *too-many-to-fail* leads to bank herding ex-ante, indicating that banks may be more likely to lend to same sectors and take risks if they know they are less likely to fail when subsequent problems appear to be system wide. (Acharya and Yorulmazer (2007), Acharya and Yorulmazer (2008b), Brown and Dinç (2011))

In a similar light, recent literature on financial networks document that the interlinkage among banks predicts systemic risk. For example, Allen, Babus, and Carletti (2012) show that asset commonality can lead to spillover effects. Brunnetti, Harris, Mankad, and Michailidis (2019) show that correlation networks forecasts financial crises. It is noteworthy to mention that many recent papers document that lending booms end poorly and are followed by severe crises. Thakor (2015) notes that financial crises typically follow economic booms with leveraged-financed asset price bubbles. Brunnermeier, Rother, and Schnabel (2017) show that asset price bubbles increase systemic risk at the bank level. Similarly, Baron and Xiong (2017) show bank credit expansion predicts the crash risk.

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[4] In banking, information contagion is triggered by changes in market perceptions about the value of assets or the creditworthiness of particular institutions, which can feed through the system. See Acharya and Yorulmazer (2008a) for more discussion.

Based on these studies, this paper examines the impact of bank herding on systemic risk. We address the following fundamental questions. Does bank herding exist in the banking sector? If so, does bank herding contribute to more systemic risk? Does bank herding during lending booms amplify or dampen systemic risk?

We start by constructing the bank herding measure. Using the Lakonishok, Shleifer and Vishny (LSV) herding measure, we construct measures for banks' herding in real estate loans (*Herding in real estate loans*), commercial and industrial loans (*Herding in C&I loans*), and consumer loans (*Herding in consumer loans*). We find that the level of bank herding in real estate loans during a boom period is substantially higher than the level of bank herding in C&I loans or consumer loans. The mean herding in real estate loans is 0.155. Intuitively, this implies that if 100 banks issue a given loan in a given quarter, approximately 15 more banks issue loans on the same side of the market than would be expected. The mean herding in C&I loans is 0.069 and the mean herding in consumer loans is 0.082.[5] After 2010, the level of herding in real estate loans decreased to the level of bank herding in C&I loans or consumer loans.

[5] These findings are consistent with the implication of Charkraborty, Goldstein, and Mackinlay (2018, 2019) that banks benefiting from quantitative easing increase mortgage lending while decrease commercial lending. The findings are also related to the notion that monetary policy accelerate housing boom by Drechsler, Savov, and Schnabl (2019).

Next, we examine the impact of bank herding on systemic risk. Using *ΔCoVaR* (Adrian and Brunnermeier (2016)) and *MES* (Acharya, Pedersen, Philippon, and Richardson (2017)) as measures of systemic risk, we find that bank herding increases systemic risk.[6] We investigate if there is any disparate effect of herding between big banks and small banks. We find that herding in real estate loans by big banks contributes more to systemic risk than herding by small banks. Further, we examine whether bank herding interacts with a boom period to provide a stronger predictive power of systemic risk. We find that herding by big banks during a boom period predicts an interactive effect of higher systemic risk in the next period beyond what is predicted by bank herding and the boom period individually. Our findings are robust to the alternative count-based herding measure. We attribute these results to evidence of *too-many-and-big-to-fail*.

Overall, our study provides evidence that bank herding can propagate negative externalities on the economy. Our study provides an insight that regulators and policymakers need to pay special attention to herding by big banks, since they have a more crucial impact on systemic risk. Our findings are especially important if regulators want to understand which channels affect systemic risk and want to design appropriate policy responses in the context that

[6] Billio, Getmansky, Lo, and Pelizzon (2012) and Giglio, Kelly, and Pruitt (2016) show that a combination of systemic risk measures has more predictive power in explaining bank performance during crisis events than a single measure of systemic risk.

bank herding can affect the availability of credit in the economy, which is well known to be a key driver of fluctuations and crises.

Our study contributes to the existing literature in several dimensions. First, by linking bank herding to financial stability, our study contributes to the broader debate on the nature of systemic risk and its determinants. Previous literature finds that systemic risk is affected by bank size (e.g., De Jonghe (2010), Leaven, Ratnovski, and Tong (2016), Davila and Walther (2018)), by asset price bubbles (e.g., Brunnermeier, Rother, and Schnabel (2017)), by bank asset structure (e.g., Beck, De Jonghe, and Mulier (2017)), and by operational risk (e.g., Berger, Curti, Mihov, and Sedunov (2018)). In addition to these studies, we provide evidence that bank herding increases systemic risk.[7]

Our study is closely related to the literature on lending booms and financial crises. Many recent papers find that lending booms can have severe consequences on the real economy as reflected by subsequent banking crises, housing market crashes, and economic recessions (See, for example, Dell'ariccia and Marquez (2006), Schularick and Taylor (2012), Agarwal at all. (2014), Piskorski, Seru, and Witkin (2015), Thakor (2015), Baron and Xiong (2017), Becker and Ivashina (2017), Charkraborty, Goldstein, and Mackinlay (2018), Fahlenbrach, Prilmeier, and Stulz (2018)) On top of this, our study contributes by

[7] Our study is also related to recent studies on financial network. (e.g. Elliott, Golub, and Jackson (2014), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Brunnetti, Harris, Mankad, and Michailidis (2019), and Calomiris, Jeremski, and Wheelock (2019), etc).

providing evidence that bank herding during a boom period can exacerbate negative externalities on the economy. Lastly, our study contributes to the vast literature on herding. While most empirical studies investigate the herding behaviors of institutional investors in equity markets or bond markets, our study examines the herding behaviors in lending by banks.[8]

2. Data

We collect data on the market capitalization and returns for bank stocks from the Center for Research on Security Prices (CRSP). The bank accounting data are obtained from the Commercial Bank Reports of Income and Condition (Call Reports) quarterly. The Call Reports contain banks' balance sheets, income statements, and other information. Interest rate data are downloaded from FRED. By focusing on banks, we do not include insurance companies, investment banks, investment management companies, and brokers. Our focus on banks operating inside the U.S. ensures that all banks in the analysis are subject to a uniform regulatory regime. We obtain the list of all banks from the Federal Reserve Bank of New York's Federal Reserve Banks link. The entire sample consists of 1301 bank holding companies and commercial banks. The sample period runs from 1990 to 2016.

[8] For example, Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Sias, (2004), Choi and Sias (2009), Jiang and Verardo (2018), and Cai, Han, Li, and Li (2019), etc.

2.1 Herding measures

We adopt the herding measure that was proposed by Lakonishok, Shleifer and Vishny (1992) to estimate the herding behaviors in lending by banks. Using the Lakonishok, Shleifer and Vishny (LSV) measure, we capture banks' herding in certain bank loans. These loans include (1) loans for real estate (real estate loans), (2) commercial and industrial loans (C&I loans), and (3) loans to individuals for household, family, and other personal expenditures (consumer loans). We construct measures for banks' herding in real estate loans (*Herding in real estate loans*), commercial and industrial loans (*Herding in C&I loans*), and consumer loans (*Herding in consumer loans*).

Following the existing literature, our herding measure of loan *k* in quarter *t* is defined as follows:

$$H_{k,t} = \left|p_{k,t} - E\left[p_{k,t}\right]\right| - AF_{k,t} \quad (1)$$

where $p_{k,t}$ is:

$$p_{k,t} = \frac{\$amount\ of\ increased\ loan_{k,t}}{\$amount\ of\ increased_{k,t} + \$amount\ of\ decreased\ loan_{k,t}} \quad (2)$$

Alternately, $p_{k,t}$ can be defined using the number of banks that increased their issuance of loan k in quarter *t*:

$$p_{k,t} = \frac{\#number\ of banks\ increased\ loan_{k,t}}{\#number\ of\ banks\ increased\ loan_{k,t} + \#number\ of\ banks\ decresed\ loan_{k,t}} \quad (3)$$

The term $E\left[p_{k,t}\right]$ is the expected level of each loan k's issuance intensity. Following previous studies, we estimate $E\left[p_{k,t}\right]$ as $\overline{p_t}$. That is,

$$\overline{p_t} = \frac{\sum_k \$amount\ of\ increased\ loan_{k,t}}{\sum_k \$amount\ of\ increased\ loan_{k,t} + \sum_k \$amount\ of\ increased\ loan_{k,t}} \tag{4}$$

or

$$\overline{p_t} = \frac{\sum_k \#number\ of\ banks\ increased\ loan_{k,t}}{\sum_k \#number\ of\ banks\ increased\ loan_{k,t} + \sum_k \#number\ of\ banks\ increased\ loan_{k,t}} \tag{5}$$

Note that $\overline{p_t}$ varies over time only. The second term in equation (1) is an adjustment factor, which is defined as $E\left|p_{k,t} - E\left[p_{k,t}\right]\right|$. This adjustment ensures that under the null hypothesis, the herding measure for loan *k*, in quarter *t* is expected to be zero. Under the null hypothesis of no herding, all banks make independent lending decisions. Intuitively, our herding measure captures the tendency of banks to issue or close (sell) a given loan together in the same direction more often than would be expected if they issue or close loans independently.

2.2 Systemic risk measures

Our main systemic risk measure is *ΔCoVaR* that was introduced by Adrian and Brunnermeier (2016). *ΔCoVaR* represents the change in the value at risk (VaR) of the entire financial system that occurs when a given institution goes into distress. *ΔCoVaR* quantifies the contribution of a bank to the overall level of systemic risk by estimating the additional value at risk of the entire financial system that is associated with this bank experiencing distress. Jiang and Long (2018) note that *ΔCoVaR* is more in line with the "too interconnected to fail" paradigm while *MES* offers a compromise between the "too interconnected to fail" and "too big to fail" paradigms. The estimates rely on the tail dependencies between losses in the market value of the equity of individual banks and those of the entire financial system.

One of the advantages of *ΔCoVaR* is that it controls for general risk factors such that a high volatility in markets does not lead to a high level of systemic risk. We estimate *ΔCoVaR* using quantile regressions. First, we define the financial system returns as X_{system} and the individual institutional returns as X_i using equity returns. We then estimate *VaR* and *CoVaR* as a function of a vector of state variables, *M*. We define q as the q^{th} quantile of the return distribution. Following Adrian and Brunnermeier (2016), we set q equal to 0.05. In the first step, we run the following regressions using weekly data:

$$X_{i,t} = \alpha_i^q + \gamma_i^q M_{t-1} + e_{i,t}^q \tag{6}$$

$$X_{system|i,t} = a_{system|i}^q + \gamma_{system|i}^q M_{t-1} + \beta_{system|i}^q X_{i,t} + e_{system|i,t}^q \tag{7}$$

We then use the predicted values from the first step to calculate the following:

$$VaR_{i,t}^q = \widehat{\alpha_i^q} + \widehat{\gamma_i^q} M_{t-1} \tag{8}$$

$$CoVaR_{i,t}^q = \widehat{\alpha_{system|i}^q} + \widehat{\gamma_{system|i}^q} + \widehat{\beta_{system|i}^q} VaR_{i,t}^q \tag{9}$$

Finally, for each institution, we calculate *ΔCoVaR*:

$$\Delta CoVaR_{i,t}^{q} = CoVaR_{i,t}^{q} - CoVaR_{i,t}^{50} \tag{10}$$

The vector of state variables includes six variables: the change in the three-month Treasury yield, the change in the slope of the yield curve, the short-term TED spread, the change in the credit spread between Baa-rated bonds and the treasury rate, the weekly U.S. market returns, and the VIX index of stock market volatility.

The second measure of systemic risk is the marginal expected shortfall (MES), which is based on Acharya, Pedersen, Philippon, and Richardson (2017). The *MES* estimates how individual institutions' stock returns react to those of the entire market when aggregate returns are low. The *MES* is calculated using the 5% worst days of market returns over the previous quarter of return data:

$$MES_{i,t} = -\frac{1}{\#days}\sum_{t}^{t*} R_{i,t} \tag{11}$$

where $R_{i,t}$ represent the daily returns of an institution, and t to t* represent days on which the market is in the tail of its return distribution. For presentation purposes, we multiply *MES* by -1 so that higher values indicate higher contributions to the systemic risk.

2.4 Descriptive statistics

Figure 1 plots the time series of the aggregate volume of bank loans with respect to three different types of loans: Real estate loans, C&I loans, and

Consumer loans. Approximately, real estate loans are 40 to 60% of the aggregate volume, C&I loans are 30%, and consumer loans are 20%. In Figure 1, the proportion of real estate loans increases rapidly after 2002. Figure 2 captures the fluctuations of bank herding with respect to the three different types of loans. A positive and significant herding measure will be evidence of bank herding. Notably, bank herding in real estate loans has substantially increased from 2002 to 2006. In 2005, herding in real estate loans peaks and then, in 2007, it immediately plummets to close to zero. Bank herding in C&I loans or consumer loans is highly cyclical. It generally peaks in the first or second quarter, and then relatively decreases in the third and fourth quarters. Findings in Figure 2 are closely related to Charkraborty, Goldstein, and Mackinlay (2018, 2019) that banks benefiting from quantitative easing increase mortgage lending while decrease commercial lending.

Panel A of Table 1 reports the descriptive statistics of the herding measures. It shows the level of bank herding and how it varies by loan type. As shown in Panel A, the mean herding in real estate loans is 0.155. Intuitively, this implies that if 100 banks issue a given loan in a given quarter, approximately 15 more banks will issue loans on the same side of the market than would be expected. The mean herding in C&I loans is 0.069 and the mean herding in consumer loans is 0.082. In addition, we construct separate herding measures for big banks and small banks. The patterns largely mimic those means that were reported for all banks.

Panel B shows the herding in different periods. Clearly, bank herding during a boom period is higher than that in other time periods. The mean herding in real estate loans is 0.221. The level of bank herding in real estate loans during a boom period is substantially higher than the herding in C&I loans and consumer loans. After 2010, the level of herding in real estate loans is similar to the herding in C&I loans and consumer loans.

Panel C reports the descriptive statistics of the systemic risk measures and control variables. The mean of *ΔCoVaR* equals 1.203, meaning that distress at one institution is associated with an average increase in the financial system's conditional value at risk by 1.203%. The mean of the MES is 4.76 and the standard deviation is 3.08. In addition to the herding and systemic measures, we include a number of bank-level control variables. We use several bank specific variables that proxy for the key bank risk factors: bank size, bank capital, bank profitability, loans-to-assets ratio, loan growth, loan loss provisions-to-assets ratio, liquidity-to-assets ratio, deposits-to-assets ratio, and non-interest income-to-assets ratio. Panel D reports the correlations between our main variables. All variables are defined in Appendix.

3. Main Results

3.1 Bank herding and systemic risk

In this section, we examine the impact of bank herding on systemic risk. The systemic risk measure is *ΔCoVaR*. Our main interest is on bank herding in real estate loans (*Herding in Real estate Loans*). To ensure that our herding measures are predetermined, all independent variables are the one-quarter lagged values.

Panel A in Table 2 reports the regression results for *Herding in Real estate Loans*. In Panel A, column (1) starts with a pooled regression with no fixed effects. The coefficient of *Herding in Real estate Loans* is positive and statistically significant at the 1% level, indicating that higher bank herding in real estate loans contributes to more systemic risk. To mitigate the concern that the bank-level systemic risk might be jointly determined by bank characteristics, we include a large set of control variables. Columns (2) and (3) confirm the positive association between herding in real estate loans and systemic risk and the relationship is robust to the both time- and bank-fixed effects. In column (4), the robust standard errors are corrected for clustering across banks. Based on the specification in column (4), a one standard deviation increase in bank herding is associated with a $0.0168(= (0.198 * 0.070)/0.822)$ increase in *ΔCoVaR*.

Panel B reports the regressions results for *Herding in C&I Loans*. In Panel B, the coefficients of *Herding in C&I Loans* are positive and statistically significant at the 1% level. Columns (2) to (4) further show that the positive association is robust to the both time- and bank-fixed effects and clustered standard errors across banks. The result indicates that higher bank herding in C&I loans contributes to more systemic risk. Panel C reports the regressions results for *Herding in Consumer Loans*. Panel C shows the different results from Panel A and Panel B. The coefficient in column (1) is positive and statistically significant at the 1% level, suggesting that higher bank herding in consumer loans contributes to more systemic risk. However, the coefficients in columns (2) to (4) are negative and statistically significant at the 1% level.

In Panel D, to mitigate the reverse causality concerns, we examine the effect of bank herding on the systemic risk two or three quarters ahead. Panel D reports the regression results for the led values of systemic risk. In Panel D, we do not report the regression coefficients for the control variables for brevity. In columns (1) and (2), the coefficients of *Herding in Real estate Loans* are positive and statistically significant at the 1% level. These results indicate that higher bank herding in real estate loans contributes to more systemic risk. The coefficients in columns (3) and (4) of *Herding in C&I Loans* are also positive and statistically significant. An interesting pattern emerges in columns (5) and (6). In column (5), the coefficient of *Herding in Consumer Loans* is not statistically significant. In column (6), the coefficient is positive and statistically significant at the 1% level.

Overall, the results in Table 2 indicate that bank herding is positively associated with systemic risk in subsequent periods. Given that a larger value of

ΔCoVaR corresponds to a higher systemic risk contribution, a positive sign of the coefficient of the herding measure represents that bank herding increases systemic risk. Perhaps this finding is connected to the *too-many-to-fail* by Acharya and Yorulmazer (2007), Acharya and Yorulmazer (2008b), and Brown and Dinç (2011), suggesting that banks may be more likely to lend to the same sectors and take risks if they know that they are less likely to fail when subsequent problems appear to be system wide. These results are related to the notion that asset commonality can lead to spillover effects and financial crises by Allen, Babus, and Carletti (2012) and Brunnetti, Harris, Mankad, and Michailidis (2019).

3.2 Bank herding and systemic risk: big banks vs. small banks

Next, we examine if there is any disparate effect of bank herding on systemic risk between big banks and small banks. It may be expected that herding by big banks has more pronounced effects and contributes to more systemic risk given that certain large banks are so central and important such that their failure could cause devastating damage to financial markets. Table 3 shows the results for bank herding on systemic risk based on bank size. To distinguish big banks and small banks, we sort all banks into terciles based on their assets (BHCK 3368) each quarter.

In Table 3, we focus on *Herding in real estate loans* given that a lending boom and the collapse of the residential or commercial real estate markets was a key driver of the 2007 to 2008 financial crisis. Columns (1) and (2) in Table 3 confirm that herding in real estate loans increases systemic risk. More importantly, it shows that the effect of herding by big banks (coefficient: 0.312) is stronger than that by small banks (coefficient: 0.058). Based on the specification in column (1), a one standard deviation increase in herding by big banks is associated with a 0.0265(= (0.312 $*$ 0.070)/0.822) increase in $\Delta CoVaR$. In column (2), a one standard deviation increase in herding by big banks is associated with a 0.0049(= (0.058 $*$ 0.070)/0.822) increase in $\Delta CoVaR$. The results indicate that herding in real estate loans by big banks contributes to more systemic risk than herding by small banks. These findings are consistent with the implication of De Jonghe (2010), Laeven, Ratnovski, and Tong (2016) and Dávila and Walther (2018) that bank size matters for bank risk and leverage choices. Overall, the results in Table 3 indicate that herding in real estate loans by big banks increases systemic risk.

3.3 Boom period

Now, we turn our attention to the boom period. One might naturally wonder how bank herding that is associated with a boom period is related to systemic risk. This insight suggests that bank herding may interact with a boom period to provide an even stronger predictive effect of systemic risk. We start to analyze this insight by examining the effect of a boom period on systemic risk. Table 4 reports the impact of a boom period on systemic risk. We define the boom period as from 2002 to 2006. Column (1) in Table 4 reports that the coefficients of the boom period are negative and statistically significant at the 1% level. In columns (2) to (4), we specifically estimate the following specification:

$$
\begin{aligned}
&systemic\ risk_{i,t} \\
&\qquad = \alpha_i + \beta_1 Herding_{t-1} + \beta_2 Boom_t + \beta_3 Herding_{t-1} * Boom_t \\
&\qquad + \Gamma Controls_{i,t-1} + \epsilon_{i,t}
\end{aligned}
\tag{12}
$$

In equation (12), we include the interaction terms with herding in real estate loans and the boom indicators. Column (2) reports the regressions results for all banks. In column (2), the coefficient of the interaction term is 1.297. The result is sizable and statistically significant. A positive coefficient of the interaction term is what we expect. We find that a one standard deviation increase in bank herding in a boom period predicts an interaction effect with higher systemic risk in the next quarter beyond what is predicted by bank herding and a boom period individually.

Column (3) reports the regression results for big banks. In column (3), the coefficient of the interaction term is 2.038, meaning that a one standard deviation increase in herding by big banks in a boom period predicts an interaction effect of significantly higher systemic risk next quarter. Column (4) reports the regression results for small banks. In column (4), while the coefficient of herding is positively significant, the coefficient of the interaction term is negative. The results imply that the interaction effect of herding by small banks during a boom period does not contribute to systemic risk beyond what is predicted by the herding and boom period.

Overall, the results in Table 4 indicate that herding by big banks interacts with the boom period to provide stronger predictive power of systemic risk on the next period beyond what is predicted by bank herding and the boom period individually. These results are closely related to the literature on lending booms and financial crises. Many recent papers found that lending booms generally end poorly and are followed by severe crises (e.g., Dell'ariccia and Marquez (2006), Thakor (2015), Baron and Xiong(2017) and so on). On top of this literature, we provide evidence that herding by big banks during a boom period can result in negative externalities on the economy. We attribute these results to evidence of *too-many-and-big-to-fail*.

4. Robustness

4.1 Alternative systemic measure

In this section, we re-examine the main findings using an alternative systemic measure. The alternative measure of systemic risk is the marginal expected shortfall (MES), which is based on Acharya, Pedersen, Philippon, and Richardson (2017). The *MES* estimates how individual institutions' stock returns react to those of the entire market when aggregate returns are low. Jiang and Long

(2018) note that $\Delta CoVaR$ is more in line with the "too interconnected to fail" paradigm while the *MES* offers a compromise between the "too interconnected to fail" and "too big to fail" paradigms.

Panel A in Table 5 reports the regression results for *Herding in Real estate Loans*. Panel A, column (1) shows that herding in real estate loans increases systemic risk. The coefficient on *Herding in Real estate Loans* is positive and statistically significant at the 1% level, indicating that higher bank herding in real estate loans contributes to more systemic risk. The results in column (1) indicate that a one standard deviation increase in bank herding is associated with a $0.0778(= (3.425 * 0.070)/3.083)$ increase in the *MES.*

Columns (2) and (3) in Panel B show the results for big banks and small banks, respectively. Column (2) shows that the effect of herding by big banks is positive and statistically significant at the 1% level. Based on the specification in column (2), a one standard deviation increase in herding by big banks is associated with a $0.0804(= (3.541 * 0.070)/3.083)$ increase in the *MES*. However, in column (3), the coefficient for small banks is not positive and statistically significant. Consistent with Table 3, the results in Table 5 indicate that herding in real estate loans by big banks increases systemic risk.

Panel 2 in Table 5 reports the impact of a boom period on the *MES*. We include the interaction terms with herding in real estate loans and the boom indicators. Column (1) reports the regressions results for all banks. In column (1), the coefficient of the interaction term is 0.529. A positive coefficient of the interaction term implies that bank herding with a boom period predicts an interaction effect of a higher *MES* next quarter beyond the expected effects of bank herding and the boom period individually.

Column (2) reports the regression results for big banks. In column (2), the coefficient of the interaction term is 1.928, meaning that a one standard deviation increase in herding by big banks with a boom period predicts an interaction effect of significantly higher systemic risk next quarter. Column (3) reports the regression results for small banks. Consistent with Table 4, the coefficient of the interaction term is negative in column (3). Overall, the results in Panel B indicate that big bank herding in real estate loans during a boom period predicts systemic risk the next quarter.

4.2 Alternative herding measure

In this section, we re-examine the main findings using an alternative herding measure. Sias, Starks, and Titman (2006) note that count-based measures are better predictors than dollar-based measures. We recompute the herding measure using a count-based measure, as explained in Section 2. Table 6 reports the regression results using the count-based herding measure. The dependent variable in column (1) is *ΔCoVaR*. In column (1), the coefficient of *Herding in Real estate Loans* is positive and statistically significant at the 1% level, indicating that higher bank herding in real estate loans contributes to more *ΔCoVaR*. Based on the specification in column (1), a one standard deviation increase in bank herding is associated with a 0.0679(= (0.797 $*$ 0.070)/0.822) increase in *ΔCoVaR*. The dependent variable in column (2) is the *MES*. In column (2), the coefficient of *Herding in Real estate Loans* is positive and statistically significant at the 1% level. Based on the specification in column (2), a one standard deviation increase in bank herding is associated with a 0.1331(= (5.862 $*$ 0.070)/3.083) increase in the *MES*.

4.3 Bank herding vs. Bank loan portfolio similarity

In this section, we test whether *bank-level* loan portfolio similarity instead of bank herding drives the prediction of systemic risk. We construct a parsimonious measure for the bank-level loan portfolio similarity. The bank-level loan portfolio similarity of loan *k* in bank *i* in quarter *t* is defined as follows:

$$Similarity_{k,i,t} = \left|\frac{\Delta amount\ of\ certain\ loan_{k,i,t}}{\Delta amount\ of\ total\ loan_{i,t}}\right| - \frac{\Delta amount\ of\ certain\ loan_{k,t}}{\Delta amount\ of\ total\ loan_{t}} \quad (13)$$

Table 7 reports the effect of similarity on systemic risk. The dependent variable in columns (1) and (2) is *ΔCoVaR*. In column (1), the coefficient of *Similarity on Real estate Loans* is not statistically significant and, in column (2), the coefficient of *Similarity on C&I Loans* is not statistically significant. The dependent variable in columns (3) and (4) is the *MES*. In column (3), the coefficient of *Similarity on*

Real estate Loans is not statistically significant and, in column (4), the coefficient of *Similarity on C&I Loans* is not statistically significant. Overall, the results in Table 7 suggest that bank-level loan portfolio similarity does not predict systemic risk.

5. Conclusion

Ample research has been done to enhance the understanding of the systemic risk over the last decades both from a theoretical and an empirical perspective. Understanding the source of systemic risk is an important and fundamental issue in bank regulation. Bank herding can create or facilitate a number of potential problems, including the deterioration of lending standards, the misallocation of lending resources, asset price bubbles, and the exacerbation of the business cycle. We find that the level of bank herding in real estate loans during a boom period is substantially higher than herding in C&I loans and consumer loans. We find that bank herding significantly increases systemic risk. In particular, bank herding in real estate loans by big banks contributes to more systemic risk. We find that bank herding and the lending boom interact to make herding by big banks a particularly strong predictor of systemic risk. We attribute these results to evidence of *too-many-and-big-to-fail*.

Our findings are crucial if regulators want to understand which channels affect systemic risk and want to design appropriate policy responses. Our study provides a general insight that regulators and policymakers need to pay special attention to herding by big banks since they have a crucial impact on systemic risk. Our findings can be particularly important in the context that bank herding increases the availability of credit in the economy, which is well known to be a key driver of financial crises.

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Appendix

Table A1. Variable Definitions

Variable	Definition	Source
Herding in Real estate Loans	Herding in Real estate Loans measures the bank herding in real estate loans. $$H_{k,t} = \lvert p_{k,t} - E[p_{k,t}] \rvert - AF_{k,t}$$ Herding in Real estate Loans measures captures the tendency of banks to issue or close (sell) real estate loans together in the same direction more often than would be expected if they issue or close loans independently.	Call Report
Herding in C&I Loans	Herding in C&I Loans measures the bank herding in C&I loans. $$H_{k,t} = \lvert p_{k,t} - E[p_{k,t}] \rvert - AF_{k,t}$$ Herding in C&I Loans captures the tendency of banks to issue or close (sell) C&I loans together in the same direction more often than would be expected if they issue or close loans independently.	Call Report
Herding in Consumer Loans	Herding in Consumer Loans measures the bank herding in consumer loans. $$H_{k,t} = \lvert p_{k,t} - E[p_{k,t}] \rvert - AF_{k,t}$$ Herding in Consumer captures the tendency of banks to issue or close (sell) consumer loans together in the same direction more often than would be expected if they issue or close loans independently.	Call Report
ΔCoVaR	ΔCoVaR is a systemic measure proposed by Adrian and Brunnermeier (2016). It is the difference between the financial system's value-at-risk conditional on bank i being distressed at the 5% level and financial system's value-at-risk conditional on bank i being in its median state.	CRSP
MES	MES is a systemic measure proposed by Acharya, Pedersen, Philippon, and Richardson (2017). It is defined as the bank's stock returns when the market has the worst stock returns at the 5% level.	CRSP
Ln(Assets)	Banks of different sizes have different risks. To control for this possibility, we proxy for bank size by natural logarithm of bank assets.	Call Report
Bank Capital	More leveraged banks are more likely to experience a larger variation in equity values given a shock. We proxy for bank capital by the ratio of bank equity to assets.	Call Report
Profitability (ROA)	Return on assets is a measure for Profitability common in banking industry. We proxy for bank profitability by a bank's return-on-assets variables to total assets.	Call Report
Loan-to-Assets	We proxy for loan-to-assets as total loans scaled by assets.	Call Report
Loan Growth	Loan growth is the growth rate of loan-to-assets ratio.	Call Report
Loan Loss Provisions-to-Assets	We proxy for loan loss provisions-to-assets as total loan loss provisions scaled by assets.	Call Report
Liquidity-to-Assets	We proxy for liquidity-to-assets as the sum of cash and treasury securities scaled by assets.	Call Report
Deposit-to-Assets	We proxy for deposit-to-assets as total deposits scaled by assets.	Call Report
Non-interest income-to-Assets	We proxy non-interest income-to-assets as the ratio of noninterest income to assets.	Call Report

Figures

Figure 1. Aggregate volume of bank loans (in proportion)
This figure plots the time series of the bank loan amounts between 1990 to 2016 and is broken down into three different types of loans: Real estate loans, C&I loans, and Consumer loans.

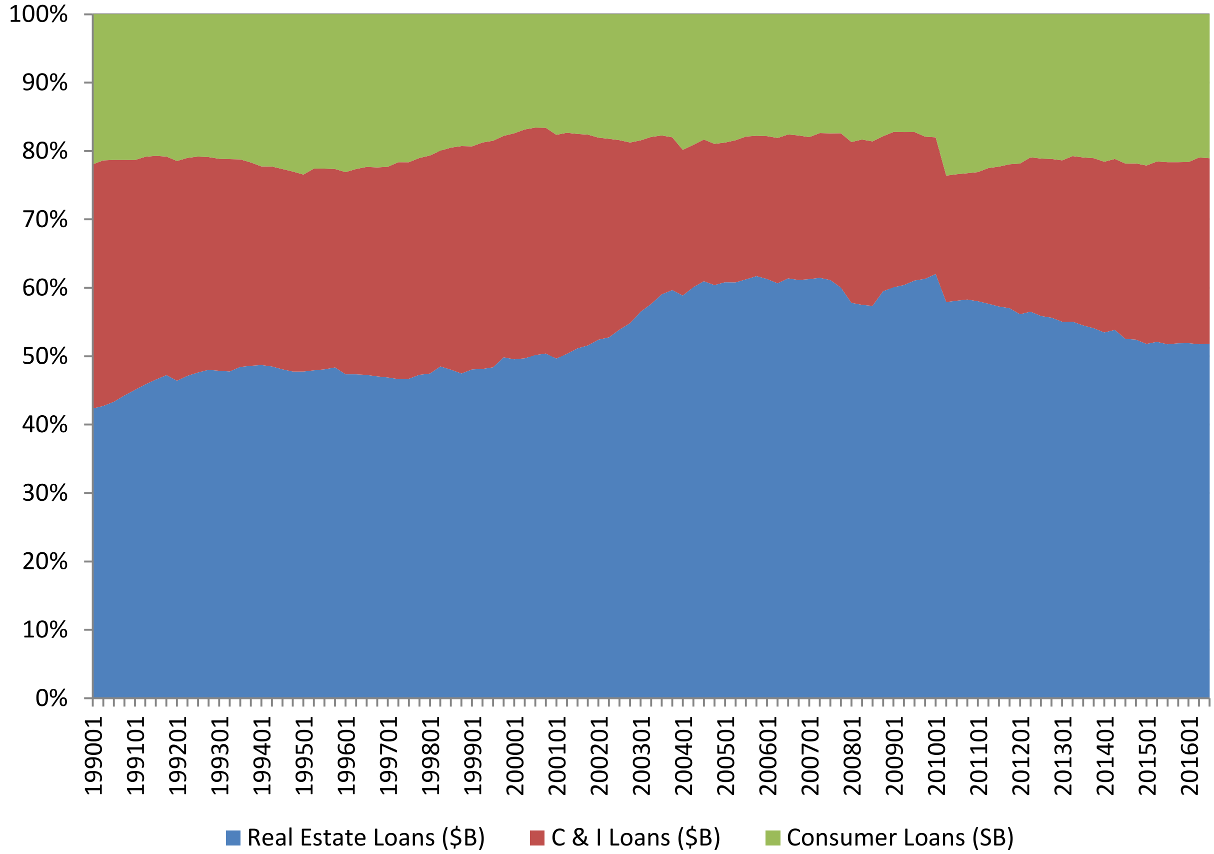
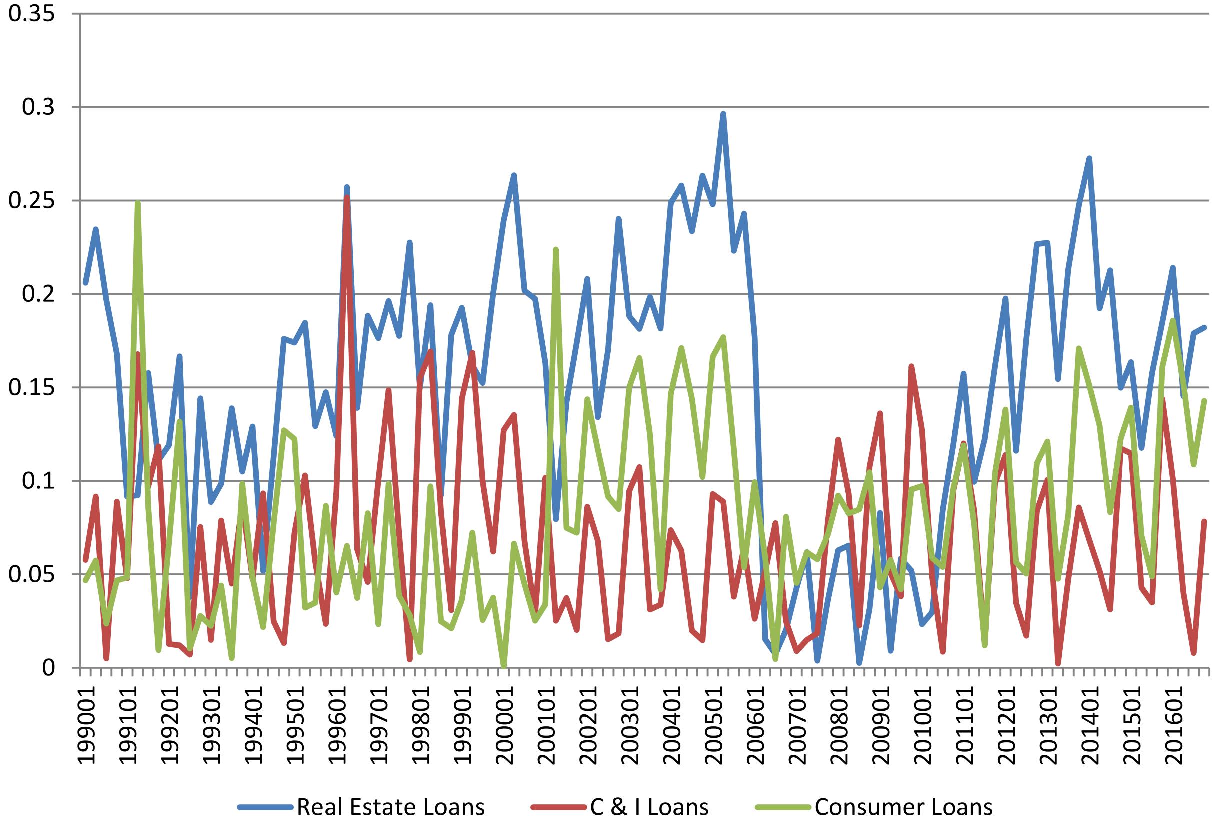


Figure 2. Bank herding measures

This figure plots the time series of the bank herding measures between 1990 to 2016 and are broken down in to three different types of loans: Real estate loans, C&I loans, and Consumer loans.



Tables

Table 1. Descriptive statistics

This table presents the descriptive statistics. Panel A reports the descriptive statistics of the herding measures. Panel B reports the herding measures of different time periods. Panel C reports the descriptive statistics of the systemic risk measures and control variables. Panel D reports the Pearson correlations for all variables. *Herding in Real estate Loans* measures the bank herding in real estate loans. *Herding in C&I Loans* measures the bank herding in C&I loans. *Herding in Consumer Loans* measures the bank herding in consumer loans. To distinguish big banks and small banks, we sort all banks into terciles based on their assets (BHCK 3368) each quarter. The *t*-statistics are shown in parentheses. All bank-level variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix.

Panel A: Herding Measures

	Mean	Std	Min	Max
All banks				
Herding in Real estate Loans	0.155***	0.070	0.003	0.296
Herding in C&I Loans	0.069***	0.047	0.002	0.252
Herding in Consumer Loans	0.082***	0.051	0.001	0.249
Big banks				
Herding in Real estate Loans	0.146***	0.073	0.001	0.339
Herding in C&I Loans	0.097***	0.064	0.002	0.241
Herding in Consumer Loans	0.080***	0.058	0.001	0.282
Small banks				
Herding in Real estate Loans	0.163***	0.071	0.001	0.306
Herding in C&I Loans	0.065***	0.045	0.001	0.251
Herding in Consumer Loans	0.093***	0.056	0.003	0.271

Panel B: Herding in boom and crisis

	Before 2002	Boom (2002-2006)	Crisis (2007-2009)	After 2009
All banks				
Herding in Real estate Loans	0.158***	0.221***	0.141***	0.088***
Herding in C&I Loans	0.077***	0.057***	0.069***	0.066***
Herding in Consumer Loans	0.058***	0.126***	0.107***	0.076***
Big banks				
Herding in Real estate Loans	0.142***	0.224***	0.130***	0.086***
Herding in C&I Loans	0.102***	0.068***	0.111***	0.106***
Herding in Consumer Loans	0.089***	0.085***	0.084***	0.052***
Small banks				
Herding in Real estate Loans	0.162***	0.226***	0.166***	0.093***
Herding in C&I Loans	0.075***	0.052***	0.060***	0.063***
Herding in Consumer Loans	0.061***	0.139***	0.120***	0.086***

Panel C: Systemic risk measure and control variables

	Mean	Median	Std	P25	P75
Systemic Risk Measures					
ΔCoVaR	1.203	1.126	0.822	0.565	0.175
MES	4.764	3.854	3.083	2.780	5.623
Controls					
Ln(Assets)	14.506	14.157	1.631	13.316	15.371
Bank Capital	0.095	0.092	0.272	0.777	0.108
Profitability (ROA)	0.0056	0.0054	0.0056	0.0028	0.0088
Loan-to-Assets	0.677	0.686	0.140	0.605	0.762
Loan Growth	0.027	0.017	0.063	-0.003	0.041
Loan Loss Provisions-to-Assets	0.0024	0.0012	0.0038	0.0005	0.0027
Liquidity-to-Assets	0.046	0.039	0.030	0.026	0.056
Deposit-to-Assets	0.661	0.680	0.140	0.599	0.752
Non-interest income-to-Assets	0.008	0.006	0.008	0.003	0.010

Panel D: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Herding in Real estate Loans	1												
(2) Herding in C&I Loans	0.5975	1											
(3) Herding in Consumer Loans	0.2648	0.2185	1										
(4) ΔCoVaR	0.0495	0.0398	0.0189	1									
(5) MES	0.0768	-0.0013	0.0102	-0.0308	1								
(6) Ln(Assets)	0.005	-0.0028	0.0368	0.5449	-0.218	1							
(7) Bank Capital	-0.0216	0.0073	0.0553	0.1003	-0.1688	0.0049	1						
(8) Profitability (ROA)	-0.1292	-0.1051	-0.2068	0.0206	-0.3813	0.0726	0.2512	1					
(9) Loan-to-Assets	-0.028	-0.0399	0.0063	0.0094	0.0474	-0.1688	0.1089	-0.0119	1				
(10) Loan Growth	-0.0589	-0.0914	-0.0447	-0.015	-0.1224	-0.0289	0.2312	0.195	0.2972	1			
(11) Loan Loss Provisions	-0.0451	0.0136	-0.0607	0.1162	0.3803	0.086	-0.1334	-0.4335	0.1011	-0.1464	1		
(12) Liquidity-to-Assets	0.0778	0.0686	-0.0094	-0.0216	0.0497	0.0026	0.0449	-0.0447	-0.1093	0.0162	0.0832	1	
(13) Deposit-to-Assets	-0.0002	-0.011	-0.0382	-0.2177	0.0982	-0.541	0.0041	-0.0796	0.4196	0.1501	0.0272	-0.0445	1
(14) Non-interest income-to-Assets	-0.1061	-0.0561	-0.1479	0.1341	-0.0739	0.3218	0.093	0.3847	-0.1522	0.0755	0.1484	0.1465	-0.3763

Table 2. Bank herding and systemic risk

This table reports the coefficients from the regressions on the systemic risk on bank herding in different loans and control variables. Panel A reports the regression results for *Herding in Real estate Loans*. Panel B reports the regressions results for *Herding in C&I Loans*. Panel C reports the regressions results for *Herding in Consumer Loans*. *Herding in Real estate Loans* measures the bank herding in real estate loans. *Herding in C&I Loans* measures the bank herding in C&I loans. *Herding in Consumer Loans* measures the bank herding in consumer loans. *ΔCoVaR* is the dependent variable. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The robust standard errors are corrected for clustering across banks. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: ΔCoVaR and Herding in Real estate Loans

	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) $\Delta CoVaR_t$	(4) $\Delta CoVaR_t$
Herding in Real estate loans$_{t-1}$	0.528***	0.512***	0.198***	0.198***
	(9.99)	(11.94)	(10.09)	(17.24)
Ln(Assets)$_{t-1}$		1.949***	-0.096***	-0.096***
		(63.25)	(-3.81)	(-2.59)
Ln(Assets)$^2_{t-1}$		-0.054***	0.003***	0.003**
		(-53.74)	(3.42)	(2.30)
Bank Capital$_{t-1}$		3.340***	-0.128	-0.128
		(25.35)	(-1.51)	(-0.84)
Profitability$_{t-1}$		2.130***	-0.235	-0.235
		(2.65)	(-0.62)	(-0.44)
Loan-to-Assets$_{t-1}$		0.342***	0.021	0.021
		(12.05)	(1.05)	(0.62)
Loan Growth$_{t-1}$		-0.311***	-0.001	-0.001
		(-5.20)	(-0.06)	(-0.04)
Loan Loss Provisions$_{t-1}$		18.458***	5.960***	5.960***
		(16.61)	(11.35)	(6.95)
Liquidity-to-Assets$_{t-1}$		-0.088	-0.109*	-0.109
		(-0.74)	(-1.72)	(-1.18)
Deposit-to-Assets$_{t-1}$		-0.034	0.014	0.014
		(-1.00)	(0.67)	(0.43)
Non-interest income-to-Assets$_{t-1}$		-3.257***	1.375***	1.375***
		(-6.07)	(4.35)	(2.58)
Bank fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Clustered by bank	No	No	No	Yes
Number of observations	37327	36309	36304	36304
Adj. R^2	0.003	0.379	0.911	0.911

Panel B: ΔCoVaR and Herding in C&I Loans

	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) $\Delta CoVaR_t$	(4) $\Delta CoVaR_t$
Herding in C&I Loans$_{t-1}$	0.251***	0.231***	0.025*	0.025***
	(8.11)	(9.28)	(1.78)	(3.67)
Ln(Assets)$_{t-1}$		1.952***	-0.095***	-0.095**
		(63.29)	(-3.78)	(-2.57)
Ln(Assets)$^2_{t-1}$		-0.054***	0.003***	0.003**
		(-53.75)	(3.41)	(2.29)
Bank Capital$_{t-1}$		3.302***	-0.131	-0.131
		(25.02)	(-1.54)	(-0.86)
Profitability$_{t-1}$		1.608**	-0.505	-0.505
		(2.00)	(-1.32)	(-0.95)
Loan-to-Assets$_{t-1}$		0.345***	0.025	0.025
		(12.15)	(1.24)	(0.73)
Loan Growth$_{t-1}$		-0.300***	-0.001	-0.001
		(-4.99)	(-0.03)	(-0.03)
Loan Loss Provisions$_{t-1}$		17.486***	5.093***	5.093***
		(15.80)	(9.77)	(6.02)
Liquidity-to-Assets$_{t-1}$		-0.037	-0.104	-0.104
		(-0.31)	(-1.64)	(-1.13)
Deposit-to-Assets$_{t-1}$		-0.032	0.013	0.013
		(-0.95)	(0.65)	(0.41)
Non-interest income-to-Assets$_{t-1}$		-3.426***	1.188***	1.188**
		(-6.38)	(3.76)	(2.26)
Bank fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Clustered by bank	No	No	No	Yes
Number of observations	37327	36309	36304	36304
Adj. R^2	0.002	0.378	0.910	0.910

Panel C: ΔCoVaR and Herding in Consumer Loans

	(1) $\Delta CoVaR_t$	(2) $\Delta CoVaR_t$	(3) $\Delta CoVaR_t$	(4) $\Delta CoVaR_t$
Herding in ConsumerLoans$_{t-1}$	0.143***	-0.115***	-0.205***	-0.205***
	(3.98)	(-3.85)	(-16.83)	(-23.36)
Ln(Assets)$_{t-1}$		1.958***	-0.092***	-0.092**
		(63.39)	(-3.68)	(-2.48)
Ln(Assets)$^2_{t-1}$		-0.055***	0.003***	0.003**
		(-53.86)	(3.25)	(2.17)
Bank Capital$_{t-1}$		3.416***	-0.070	-0.070
		(25.73)	(-0.83)	(-0.46)
Profitability$_{t-1}$		0.271	-1.734***	-1.734***
		(0.33)	(-4.51)	(-3.23)
Loan-to-Assets$_{t-1}$		0.347***	0.031	0.031
		(12.19)	(1.52)	(0.90)
Loan Growth$_{t-1}$		-0.350***	-0.010	-0.010
		(-5.84)	(-0.39)	(-0.31)
Loan Loss Provisions$_{t-1}$		16.489***	3.685***	3.685***
		(14.72)	(7.09)	(4.47)
Liquidity-to-Assets$_{t-1}$		0.037	-0.090	-0.090
		(0.32)	(-1.43)	(-0.99)
Deposit-to-Assets$_{t-1}$		-0.039	0.009	0.009
		(-1.15)	(0.44)	(0.28)
Non-interest income-to-Assets$_{t-1}$		-3.587***	0.707**	0.707
		(-6.67)	(2.24)	(1.39)
Bank fixed effects	No	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes
Clustered by bank	No	No	No	Yes
Number of observations	37327	36309	36304	36304
Adj. R^2	0.002	0.378	0.910	0.910

Panel D: Bank herding and $\Delta CoVaR$

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta CoVaR_{t+1}$	$\Delta CoVaR_{t+2}$	$\Delta CoVaR_{t+1}$	$\Delta CoVaR_{t+2}$	$\Delta CoVaR_{t+1}$	$\Delta CoVaR_{t+2}$
Herding in Real estate Loans$_{t-1}$	0.327***	0.040***				
	(19.24)	(4.16)				
Herding in C&I Loans$_{t-1}$			0.026**	0.211***		
			(2.58)	(15.23)		
Herding in ConsumerLloans$_{t-1}$					-0.003	0.225***
					(-0.42)	(19.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by bank	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	35339	34368	35339	34368	35339	34368
Adj. R^2	0.864	0.877	0.863	0.878	0.863	0.878

Table 3. Bank herding and systemic risk: Big banks vs. Small banks

This table reports the coefficients from the panel regressions of the systemic risk on bank herding in different loans and the control variables. *Herding in Real estate Loans* measures the bank herding for real estate loans. *ΔCoVaR* is the dependent variable. To distinguish big banks and small banks, we sort all banks into terciles based on their assets (BHCK 3368) each quarter. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The robust standard errors are corrected for clustering across bank. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1) *Big Banks* $\Delta CoVaR_t$	(2) *Small Banks* $\Delta CoVaR_t$
Herding in Real estate Loans$_{t-1}$	0.312***	0.058***
	(15.18)	(4.10)
Ln(Assets)$_{t-1}$	-0.112	0.725***
	(-0.97)	(2.80)
Ln(Assets)$^2_{t-1}$	0.004	-0.029***
	(1.23)	(-2.86)
Bank Capital$_{t-1}$	0.326	0.055
	(1.01)	(0.34)
Profitability$_{t-1}$	-0.494	-0.362
	(-0.49)	(-0.77)
Loan-to-Assets$_{t-1}$	0.100	0.009
	(1.29)	(0.26)
Loan Growth$_{t-1}$	-0.048	0.020
	(-0.70)	(0.55)
Loan Loss Provisions$_{t-1}$	6.085***	3.034***
	(3.50)	(3.76)
Liquidity-to-Assets$_{t-1}$	-0.250	0.120
	(-1.20)	(1.55)
Deposit-to-Assets$_{t-1}$	0.037	-0.012
	(0.62)	(-0.38)
Non-interest income-to-Assets$_{t-1}$	1.086	0.859**
	(1.22)	(2.18)
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Clustered by bank	Yes	Yes
Number of observations	12248	11865
Adj. R^2	0.827	0.945

Table 4. Bank herding and systemic risk: Boom period

This table reports the coefficients from the panel regressions of the systemic risk on bank herding in different loans and the control variables. *Herding in Real estate Loans* measures the bank herding for real estate loans. The boom period runs from 2002 to 2006. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The robust standard errors are corrected for clustering across bank. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1) All Banks $\Delta CoVaR_t$	(2) All Banks $\Delta CoVaR_t$	(3) Big Banks $\Delta CoVaR_t$	(4) Small Banks $\Delta CoVaR_t$
Herding in Real estate Loans$_{t-1}$	0.548***	0.288***	0.349***	0.328***
	(20.91)	(14.67)	(8.87)	(5.75)
Boom (2002-2006)	-0.128***	-0.283***	-0.452***	0.009
	(-21.66)	(-23.15)	(-22.14)	(1.25)
Herding in Real estate Loans$_{t-1}$* *Boom (2002-2006)*		1.297***	2.038***	-1.034***
		(18.44)	(16.12)	(-8.48)
Ln(Assets)$_{t-1}$	-0.219***	-0.199***	-0.354***	1.605***
	(-3.85)	(-3.54)	(-2.89)	(4.54)
Ln(Assets)$^2_{t-1}$	0.007***	0.007***	0.012***	-0.062***
	(3.76)	(3.53)	(3.28)	(-4.57)
Bank Capital$_{t-1}$	-0.919***	-1.004***	-1.685***	0.050
	(-4.51)	(-5.00)	(-3.53)	(0.27)
Profitability$_{t-1}$	-1.270*	-0.982	-5.019***	-1.135**
	(-1.68)	(-1.30)	(-2.97)	(-2.08)
Loan-to-Assets$_{t-1}$	0.406***	0.424***	0.693***	0.099**
	(7.60)	(7.94)	(5.01)	(2.53)
Loan Growth$_{t-1}$	-0.121***	-0.125***	-0.156	-0.054
	(-2.65)	(-2.74)	(-1.49)	(-1.36)
Loan Loss Provisions$_{t-1}$	16.528***	16.059***	25.069***	5.307***
	(13.88)	(13.63)	(10.25)	(5.34)
Liquidity-to-Assets$_{t-1}$	-0.798***	-0.804***	-1.527***	-0.069
	(-7.01)	(-7.18)	(-5.22)	(-0.84)
Deposit-to-Assets$_{t-1}$	-0.223***	-0.213***	-0.293***	-0.061*
	(-4.88)	(-4.71)	(-3.26)	(-1.85)
Non-interest income-to-Assets$_{t-1}$	2.833***	2.890***	4.530***	1.082**
	(4.18)	(4.25)	(3.95)	(2.44)
Bank fixed effects	Yes	Yes	Yes	Yes
Clustered by bank	Yes	Yes	Yes	Yes
Number of observations	36304	36304	13470	10139
Adj. R^2	0.875	0.877	0.709	0.942

Table 5. Alternative systemic measure

This table reports the coefficients from the panel regressions of the systemic risk of bank herding in different loans and control variables. *Herding in Real estate Loans* measures the bank herding in real estate loans. *MES* is the dependent variable. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The robust standard errors are corrected for clustering across bank. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A: Herding in real estate loans and MES

	(1) All Banks MES_t	(2) Big Banks MES_t	(3) Small Banks MES_t
Herding in Real estate Loans$_{t-1}$	3.425***	3.541***	-0.436
	(23.06)	(17.58)	(-0.44)
Ln(Assets)$_{t-1}$	-5.332***	-0.544	-6.497
	(-9.44)	(-0.68)	(-1.08)
Ln(Assets)$^2_{t-1}$	0.180***	0.023	0.227
	(9.39)	(0.98)	(0.98)
Bank Capital$_{t-1}$	-13.864***	-5.116***	-19.919***
	(-8.61)	(-2.86)	(-7.42)
Profitability$_{t-1}$	-76.951***	-62.783***	-96.219***
	(-12.02)	(-8.77)	(-7.67)
Loan-to-Assets$_{t-1}$	0.541	0.260	0.237
	(1.24)	(0.50)	(0.30)
Loan Growth$_{t-1}$	-0.801**	-0.737**	-0.241
	(-2.48)	(-2.18)	(-0.35)
Loan Loss Provisions$_{t-1}$	112.599***	111.267***	106.423***
	(13.78)	(10.58)	(5.66)
Liquidity-to-Assets$_{t-1}$	2.407**	2.606*	4.902**
	(2.17)	(1.70)	(2.49)
Deposit-to-Assets$_{t-1}$	0.170	0.268	0.453
	(0.40)	(0.42)	(0.62)
Non-interest income-to-Assets$_{t-1}$	30.371***	19.798***	26.825**
	(5.96)	(4.74)	(2.12)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Clustered by bank	Yes	Yes	Yes
Number of observations	36304	13470	10139
Adj. R^2	0.571	0.570	0.605

Panel B: Herding in real estate loans and MES: Boom period

	(1) All Banks MES_t	(2) Big Banks MES_t	(3) Small Banks MES_t
Herding in Real estate Loans$_{t-1}$	3.925***	2.785***	8.919***
	(20.68)	(11.45)	(6.21)
Boom (2002-2006)	-1.887***	-1.737***	-1.747***
	(-28.71)	(-22.80)	(-8.72)
Herding in Real estate Loans$_{t-1}$ Boom (2002-2006)*	0.529*	1.928***	-9.464***
	(1.71)	(4.77)	(-4.39)
Ln(Assets)$_{t-1}$	-5.433***	-1.740**	8.101
	(-9.61)	(-2.05)	(1.34)
Ln(Assets)$^2_{t-1}$	0.174***	0.060**	-0.345
	(9.33)	(2.42)	(-1.49)
Bank Capital$_{t-1}$	-21.166***	-14.646***	-24.254***
	(-12.51)	(-5.58)	(-7.75)
Profitability$_{t-1}$	-97.507***	-93.779***	-119.637***
	(-13.71)	(-9.40)	(-9.06)
Loan-to-Assets$_{t-1}$	3.188***	3.173***	3.022***
	(6.95)	(4.74)	(3.67)
Loan Growth$_{t-1}$	-1.462***	-0.878*	-1.963**
	(-4.06)	(-1.90)	(-2.54)
Loan Loss Provisions$_{t-1}$	178.983***	163.171***	193.318***
	(20.53)	(13.22)	(9.54)
Liquidity-to-Assets$_{t-1}$	-4.488***	-6.365***	1.435
	(-4.06)	(-3.74)	(0.71)
Deposit-to-Assets$_{t-1}$	-0.992**	-1.126	-0.603
	(-2.27)	(-1.51)	(-0.75)
Non-interest income-to-Assets$_{t-1}$	33.876***	34.342***	33.634**
	(5.75)	(5.91)	(2.54)
Bank fixed effects	Yes	Yes	Yes
Clustered by bank	Yes	Yes	Yes
Number of observations	36304	13470	10139
Adj. R^2	0.449	0.373	0.501

Table 6. Bank herding and systemic risk

This table reports the coefficients from the panel regressions of the systemic risk of bank herding in different loans and control variables. *Alt_Herding in Real estate Loans* measures the bank herding for real estate loans. The robust standard errors are corrected for clustering across bank. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
	$\Delta CoVaR_t$	MES_t
$Alt\_Herding\ in\ Real\ estate\ Loans_{t-1}$	0.797***	5.862***
	(19.84)	(17.00)
$Ln(Assets)_{t-1}$	-0.094**	-5.306***
	(-2.53)	(-9.40)
$Ln(Assets)^2_{t-1}$	0.003**	0.180***
	(2.26)	(9.36)
$Bank\ Capital_{t-1}$	-0.118	-13.775***
	(-0.78)	(-8.59)
$Profitability_{t-1}$	-0.667	-83.623***
	(-1.27)	(-13.11)
$Loan\text{-}to\text{-}Assets_{t-1}$	0.016	0.543
	(0.47)	(1.24)
$Loan\ Growth_{t-1}$	-0.004	-0.823**
	(-0.11)	(-2.55)
$Loan\ Loss\ Provisions_{t-1}$	5.600***	100.049***
	(6.73)	(12.55)
$Liquidity\text{-}to\text{-}Assets_{t-1}$	-0.086	2.627**
	(-0.95)	(2.37)
$Deposit\text{-}to\text{-}Assets_{t-1}$	0.018	0.197
	(0.55)	(0.46)
$Non\text{-}interest\ income\text{-}to\text{-}Assets_{t-1}$	1.131**	26.428***
	(2.17)	(5.23)
Bank fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Clustered by bank	Yes	Yes
Number of observations	36304	36304
Adj. R^2	0.911	0.569

Table 7. Bank-level loan portfolio similarity and systemic risk

This table reports the coefficients from the panel regressions of the systemic risk of bank loan similarities on different loans and control variables. *Similarity on Real estate Loans*$_{t-1}$ measures the bank loan similarity for real estate loans. *Similarity on C&I Loans*$_{t-1}$ measures the bank loan similarity for C&I loans. All independent variables are one-quarter lagged values. All variables are defined in Appendix. The robust standard errors are corrected for clustering across bank. The *t*-statistics are included in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	$\Delta CoVaR_t$	$\Delta CoVaR_t$	MES_t	MES_t
Similarity on Real estate Loans$_{t-1}$	0.002		-0.023	
	(0.62)		(-0.85)	
Similarity on C&I Loans$_{t-1}$		0.004		-0.001
		(0.64)		(-0.02)
Ln(Assets)$_{t-1}$	-0.095**	-0.095**	-5.313***	-5.313***
	(-2.57)	(-2.57)	(-9.40)	(-9.40)
Ln(Assets)$^2_{t-1}$	0.003**	0.003**	0.180***	0.180***
	(2.29)	(2.29)	(9.35)	(9.35)
Bank Capital$_{t-1}$	-0.127	-0.128	-13.825***	-13.834***
	(-0.84)	(-0.84)	(-8.59)	(-8.60)
Profitability$_{t-1}$	-0.586	-0.587	-83.021***	-83.016***
	(-1.10)	(-1.11)	(-12.91)	(-12.91)
Loan-to-Assets$_{t-1}$	0.025	0.025	0.611	0.612
	(0.74)	(0.74)	(1.40)	(1.40)
Loan Growth$_{t-1}$	-0.002	-0.002	-0.816**	-0.812**
	(-0.06)	(-0.05)	(-2.52)	(-2.51)
Loan Loss Provisions$_{t-1}$	4.963***	4.961***	95.394***	95.383***
	(5.93)	(5.93)	(11.85)	(11.85)
Liquidity-to-Assets$_{t-1}$	-0.103	-0.103	2.498**	2.503**
	(-1.12)	(-1.12)	(2.25)	(2.25)
Deposit-to-Assets$_{t-1}$	0.013	0.013	0.167	0.165
	(0.41)	(0.41)	(0.39)	(0.39)
Non-interest income-to-Assets$_{t-1}$	1.160**	1.162**	26.633***	26.642***
	(2.22)	(2.22)	(5.26)	(5.26)
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Clustered by bank	Yes	Yes	Yes	Yes
Number of observations	36303	36303	36303	36303
Adj. R^2	0.910	0.910	0.565	0.565