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Bank of Finland  
Research Unit

PO Box 160  
FIN-00101 Helsinki

Phone: +358 9 1831

Email: [research@bof.fi](mailto:research@bof.fi)

Website: [www.suomenpankki.fi/en/research/research-unit/](http://www.suomenpankki.fi/en/research/research-unit/)

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# Lone (Loan) Wolf Pack Risk

Mingze Gao, Iftexhar Hasan, Buhui Qiu and Eliza Wu

## Abstract

This paper proposes an early-warning bank risk measure based on the syndicate concentration of recent syndicated loans that a bank participates in. At the bank level, higher values of the measure predict greater risks (i.e., loan loss provisions, idiosyncratic return volatility, default probability, and frequency of lawsuits) and lower profitability at least three years ahead, especially for opaque and complex banks. Banks failing the Federal Reserve's forward-looking stress tests subsequently exhibit a reduction in the syndicate concentration measure. At the aggregate level, higher values of the measure predict both greater financial sector risks and economic slowdowns measured by private-sector investment, business activity, total factor productivity, industrial production, and gross domestic product.

*JEL classification:* G21, E02.

*Keywords:* syndicate concentration; early-warning; bank risks; financial sector risks; economic slowdowns

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Mingze Gao: University of Sydney Business School, University of Sydney, NSW 2006, Australia; Email: [mingze.gao@sydney.edu.au](mailto:mingze.gao@sydney.edu.au). Iftexhar Hasan: Fordham University and Bank of Finland, 45 Columbus Avenue, New York, NY 10023; Email: [ihasan@fordham.edu](mailto:ihasan@fordham.edu). Buhui Qiu: University of Sydney Business School, University of Sydney, NSW 2006, Australia; Email: [buhui.qiu@sydney.edu.au](mailto:buhui.qiu@sydney.edu.au). Eliza Wu: University of Sydney Business School, University of Sydney, NSW 2006, Australia; Email: [eliza.wu@sydney.edu.au](mailto:eliza.wu@sydney.edu.au). We thank participants at the 2022 FIRN Banking and Financial Stability Meeting and seminar participants at Curtin University, Massey University, National Central University, University of Essex and University of Sydney for helpful comments and suggestions. We gratefully acknowledge the financial support from the Australian Research Council (ARC) under the ARC Discovery Projects (grant DP210102611).

# 1. Introduction

Bank failures and financial-sector risks can lead to significant economic and social costs (e.g., [Bernanke, 1983](#); [Diamond and Dybvig, 1983](#); [Calomiris and Mason, 2003](#); [Ivashina and Scharfstein, 2010a](#); [Jermann and Quadrini, 2012](#), among others). One of the most important businesses of banks around the world is syndicated lending, with the total value of global syndicated lending amounted to US\$3.5 trillion in 2020 according to Refinitiv. A bank's involvement in syndicated lending may significantly affect its future risks. In this paper, we examine how a bank's involvement in syndicated lending, as gleaned from its bank-level syndicate concentration, is related to future bank risks and profitability. We show that bank-level syndicate concentration, measured as the loan-size-weighted-average of the inverse of syndicate size based on all recently originated syndicated loans that a bank participates in, serves as a reliable early-warning predictor for future bank risks and bank profitability for at least three years ahead. Moreover, higher levels of aggregate syndicate concentration within the financial system, as more banks start to lend in smaller syndicates with fewer lenders, reliably foreshadow greater financial-sector risks and real-sector economic slowdowns.

The level of syndicate concentration can be both a manifestation of and a source of information frictions and thereby relate to lenders' riskiness. *How* syndicate concentration may impact future bank risks is unclear and remains largely an empirical question, however. In theory, the relation can be either positive or negative. On the positive side, heavy syndicate concentration may be reflective of higher future risks for banks. While banks have the incentive to diversify their risk exposures through co-lending via loan syndication to reduce bank risks (e.g., [Simons, 1993](#); [Ivashina, 2009](#)), such syndication is functioning crucially on the perceived quality and reputation of the lead bank (arranger) (e.g., [Holmstrom and Milgrom, 1987](#); [Dennis and Mullineaux, 2000](#); [Pichler and Wilhelm, 2001](#); [Gopalan, Nanda, and Yerramilli, 2011](#)). It is well known that information asymmetry exists between the lead arranger and other lenders within a syndicated loan, as the latter participants are typically not actively involved in the screening and monitoring of borrowers - they are merely fund

providers. If non-lead lenders have greater concerns on the perceived quality of the loans arranged by a bank, fewer lenders will participate in these loans, resulting in lower participant number and greater syndicate concentration. Thus, higher syndicate concentration may indicate poorer loan quality and hence greater bank-level syndicate concentration may indicate greater future risks and lower future profitability for the bank.<sup>1</sup>

An opposing view, however, is that to alleviate the information problems between the lead bank and other lenders, the former needs to retain a large share of the loan on its balance sheet to ensure sufficient ‘skin in the game’ (Leland and Pyle, 1977; Ivashina, 2009) to tangibly signal high loan quality to participant lenders in the syndicate. Since lead share and participant number are highly negatively correlated in loan syndication (e.g., Ivashina, 2009; Ivashina and Scharfstein, 2010b), higher syndicate concentration may actually indicate higher loan quality and lower credit risk exposure for lenders, giving rise to a negative relation between bank-level syndicate concentration and future bank risks.

To empirically investigate the relation between bank-level syndicate concentration and future bank risks, we compile an extensive dataset on the details of all syndicated bank loans sourced from the Thomson Reuters LPC DealScan database (DealScan) with a sample period spanning three decades from 1990 to 2020. We measure loan-level syndicate concentration as the reciprocal of the number of lenders in the syndicate rather than lender-share Herfindahl–Hirschman Index (HHI) for two important reasons. First, HHI relies on two dimensions of input, namely the number of lenders and their respective shares in the syndicate. However, only 23% of loans in DealScan have nonmissing lender shares and hence lender-share HHI would have missing value for more than three quarters of loans. Second, we mathematically show that the variation in the number of lenders accounts for the majority of the variation in HHI in the context of loan syndicate concentration.<sup>2</sup> Intuitively, HHI captures a loan syndicate’s deviations from 1) the ‘fully competitive’ state with infinite

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<sup>1</sup>We develop a simple theoretical framework in Online Appendix OA.1 to illustrate the potential negative relation between loan quality and syndicate concentration as reflected in the number of participant lenders in a loan syndicate, based on which we measure syndicate concentration.

<sup>2</sup>We discuss the mathematical decomposition of HHI in Online Appendix OA.2.

number of lenders and 2) the state where all lenders have equal loan share. We show that when HHI is small, the deviation from the ‘fully competitive’ state explains the majority of the variation in HHI. Further, we find that HHI based on DealScan data with nonmissing lender shares is generally small, as most of the lender shares are similar. Therefore, in the context of measuring loan syndicate concentration, the reciprocal of the number of lenders is an excellent alternative to HHI, allowing a much larger sample coverage at low cost.

Our measure of bank-level syndicate concentration is then the loan-size-weighted-average of the loan-level syndicate concentration, the reciprocal of the number of lenders in the syndicate, based on all newly originated syndicated loans that a bank participates in over the past twelve months. The measure is constructed based on the syndicate concentration data from all DealScan loans for each bank-quarter. We then study the following unexplored research questions: (i) Can bank-level syndicate concentration predict future bank risks? (ii) If so, does the predictive power of bank syndicate concentration come from loans joined by the bank, loans lead-arranged by the bank, or both? (iii) Does a build up of aggregate syndicate concentration within the financial system foreshadow future financial-sector risks and real-sector economic activity?

Our empirical evidence shows that bank-level syndicate concentration is a powerful predictor for future bank risks. Higher values of bank syndicate concentration predict, for at least three years ahead, increasing bank risks (i.e., greater loan loss provisions, higher idiosyncratic return volatility, higher default probability, and greater frequency of lawsuits involving the bank as a defendant) and lower bank profitability (i.e., lower return on equity (ROE) and return on assets (ROA)). For example, banks in the top decile of the syndicate concentration measure, relative to those in the bottom decile, have on average a 0.189-percentage-point higher quarterly loan loss provisions (scaled by total loans) or additional expected loan losses of over \$138 million per year, a 3.6-percentage-point higher default probability (31% of the sample mean), and a 8.1-percentage-point higher idiosyncratic stock return volatility (60% of the sample mean), for three years ahead. Similarly, an increase in

the decile rank of bank-level syndicate concentration from the bottom rank to the top rank predicts, for three years ahead, a 2.691 (0.234)-percentage-point lower ROE (ROA), which is around 40% (37%) of the sample mean ROE (ROA).

We further decompose our measure of bank-level syndicate concentration into two distinct measures based on syndicated loans joined and loans lead-arranged by the bank, respectively. We conjecture that syndicate concentration of the loans joined by the bank may be a stronger risk predictor than syndicate concentration of the loans lead-arranged by the bank. This is because banks prefer to join syndicated loans with better perceived quality and thus higher number of participant lenders (as we show in the theoretical framework in the Online Appendix), but they also have the incentive to retain large loan shares for the loans that they lead-arrange themselves to signal better loan quality (Leland and Pyle, 1977; Ivashina, 2009). Consistent with this conjecture, we find that the risk predictive power of bank-level syndicate concentration derives mainly from syndicated loans joined by the bank but not from syndicated loans lead-arranged by the bank.

Moreover, we find that the predictive power of bank-level syndicate concentration is particularly strong for opaque and/or complex banks, likely because it is more difficult for such banks to timely manage the risks arising from syndicate concentration given their high opacity and/or complexity. Our findings are robust to controlling for various time-varying bank characteristics, lending specializations, year-quarter fixed effects and/or bank fixed effects. Further, we find that higher bank-level syndicate concentration is related to lower contemporaneous bank valuation (i.e., lower market-to-book equity ratio and Tobin's Q). For example, an increase in the decile rank of bank-level syndicate concentration from the bottom rank to the top rank is related to a 26-percentage-point reduction in the market-to-book equity ratio (around 15% of the sample mean).

Next, we exploit a quasi-natural experiment to further validate the syndicate concentration measure as an early-warning bank risk measure. We closely examine the reputational shocks to banks when they failed the Federal Reserve's forward-looking stress tests. Using

stacked-cohort difference-in-differences (DiD) and dynamic DiD regressions, we find that banks that publicly failed the Federal Reserve’s Comprehensive Capital Analysis and Review (CCAR) stress tests, relative to control banks that passed the stress tests, subsequently exhibited a significant reduction in bank-level syndicate concentration. Given that banks that fail the forward-looking stress tests are required to improve their risk management practices,<sup>3</sup> the finding of a reduction in bank-level syndicate concentration after failing a forward-looking stress test further validates the bank-level syndicate concentration measure as an early-warning bank risk measure. Moreover, consistent with the earlier finding that the risk predictive power of bank-level syndicate concentration comes mainly from loans joined by the bank, we find that the reduction in bank-level syndicate concentration after a stress test failure derives only from the loans participated, but not from the loans lead-arranged, by the failure bank.

Moving to the aggregate level, we find that when more banks start to lend in smaller syndicates with fewer participants, a resulting higher aggregate syndicate concentration in the financial system is closely related to greater future financial-sector risks and real-sector economic activity slowdowns. Higher levels of aggregate syndicate concentration in the financial system critically foreshadow greater aggregate financial-sector risks as captured by the financial-sector catastrophic risk (CATFIN) measure of [Allen, Bali, and Tang \(2012\)](#) and aggregate loan loss provision growth. Moreover, we find that higher aggregate syndicate concentration is associated with decreased credit supply as measured by the excess bond premium ([Gilchrist and Zakrajšek, 2012](#)) and future real-sector economic slowdowns as measured by the growth in both economic inputs and outputs such as private-sector investment, business activity, total factor productivity, industrial production, and gross domestic product.

Our study contributes to several strands of literature. First, it contributes to the literature on syndicated lending (e.g. [Simons, 1993](#); [Sufi, 2007](#); [Ivashina, 2009](#)) by shedding

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<sup>3</sup>See, e.g., <https://www.federalreserve.gov/newsevents/speech/quarles20190709a.htm>.



new light on the relationship between syndicate structure and future bank risks. [Simons \(1993\)](#) suggests that the incentive for loan portfolio diversification drives lending syndication. [Sufi \(2007\)](#) shows that the lead bank forms a more concentrated syndicate and retains a larger loan share when the borrower is more information-intensive and requires more careful due diligence and monitoring. [Ivashina \(2009\)](#) further shows that syndicate structure and lead lender share are an equilibrium outcome driven by both the need for loan portfolio diversification and the information asymmetry between the lead lender and other lenders and that greater lead lender share can signal the safety of the loan to other participants in the syndicate. Our study extends this literature by documenting how bank-level syndicate concentration can affect future bank risks. Our findings reveal that bank-level syndicate concentration is informative and relates to future bank risks for at least three years ahead, and there are real economic implications from having highly concentrated syndicates in the syndicated lending market. To the best of our knowledge, these findings are new in the literature.

Second, the study also contributes to the literature on financial instability and its real economic consequences (e.g. [Bernanke, 1983](#); [Diamond and Dybvig, 1983](#); [Calomiris and Mason, 2003](#); [Ivashina and Scharfstein, 2010a](#); [Allen et al., 2012](#); [Jermann and Quadrini, 2012](#); [Acharya, Pedersen, Philippon, and Richardson, 2017](#)). We add to the literature by devising a new early-warning indicator for both increasing bank risks at the micro level and to rapid deteriorations in financial-sector risks and economic activity slowdowns at the macro level. Third, the study extends the prior literature on bank risk taking (e.g. [Keeley, 1990](#); [Saunders, Strock, and Travlos, 1990](#); [Boyd and De Nicoló, 2005](#); [Laeven and Levine, 2009](#)). The literature suggests that bank competition, ownership and regulations all affect banks' risk-taking incentives. The study fills a void in the literature by relating bank-level syndicate concentration to future bank risks and profitability. We also show that there are clear valuation implications for banks when they are frequently involved in tightly held syndicated loans.

There are clear policy implications from the findings of the study as well. The findings suggest that bank-level syndicate concentration can be used as an informative, early-warning bank risk measure. Moreover, higher syndication concentration at the aggregate level indicates that serious risks may be presented for the financial sector and the real economy. Thus, in order to better control financial-sector risks and maintain financial stability, regulators need to be particularly vigilant on the levels of syndicate concentration of individual banks and the financial sector as a whole.

The rest of the paper is structured as follows. Section 2 develops our main hypotheses. Section 3 discusses our sample and construction of variables. Section 4 reports the predictive ability of bank-level syndicate concentration on future bank risks. Section 5 discusses the heterogeneity in the predictive ability of bank-level syndicate concentration for bank risks. Section 6 explores the impact of stress test failures on bank-level syndicate concentration. Section 7 discusses the implications of aggregate syndicate concentration for future financial-sector risks and real-sector economic activities. Finally, Section 8 concludes. The Appendix provides the detailed definitions of the variables used in this study and additional empirical results.

## 2. Hypothesis Development

In a typical syndicated loan structure, multiple banks and/or institutional lenders participate to contractually co-lend in a bank loan to a specific borrower firm, with a lead bank (arranger) tasked with conducting the ex-ante due diligence in screening the borrower and ex-post monitoring of the borrower. As the lead bank establishes a relationship with the borrower firm, collects relevant information from the borrower, negotiates the lending terms with the borrower, originates the lending deal, and markets the loan to participating banks and institutional investors, such a risk-sharing arrangement crucially functions on the perceived quality and reputation of the lead bank and the trust of other participant lenders

(e.g. [Holmstrom and Milgrom, 1987](#); [Dennis and Mullineaux, 2000](#); [Pichler and Wilhelm, 2001](#); [Gopalan et al., 2011](#)). If the syndicated loan subsequently underperforms (or enters into default), it will hurt the perceived quality and reputation of the lead bank, thereby decreasing the future syndicating ability of the lead bank in the syndicated lending market.

For example, [Gopalan et al. \(2011\)](#) find that following borrower bankruptcies, which indicates low loan quality, lead banks are observed to assume higher loan share allocations and work with fewer loan participants in future syndicated loans arranged. These lead banks also become more likely to lend alone in the future. That is, if other lenders have greater concerns on the perceived quality of the loans originated by a bank, fewer lenders will participate in these loans, leading to fewer participants and greater syndicate concentration.

Thus, given that banks have the incentive to diversify their lending portfolios through syndication (e.g. [Simons, 1993](#); [Ivashina, 2009](#)), a lower participant number in a syndicated loan should on average indicate lower perceived loan quality and greater perceived credit risk. Given the rational expectation of syndicated lending market participants, we conjecture that if a bank on average participates in syndicated loans with higher syndicate concentration (i.e., fewer loan participants), the bank should have lower average loan quality and greater average credit risk in its lending portfolio. We develop a simple theoretical framework in the Online Appendix [OA.1](#), which conjectures a potential positive relation between the expected number of lenders in the lending syndicate and loan quality. Based on this conjecture, we construct a measure of bank syndicate concentration, which is the value-weighted-average of the reciprocal of the syndicate size of all newly originated syndicated loans that the bank participates in over the recent period.

We hypothesize that, all else equal, higher values of the syndicate concentration measure for a bank should be related to greater levels of future bank risks, lower future bank profitability and thus lower concurrent bank valuation. We use a battery of bank risk proxies including banks' loan loss provisions, idiosyncratic stock return volatility, default probability, and the frequency of getting involved in lawsuits as a defendant. To proxy for bank

profitability, we use return on equity and return on assets. Consistent with the literature, we further use the market-to-book equity ratio and Tobin’s Q to proxy for bank valuation (charter value).

**Hypothesis 1.** *Banks with higher levels of syndicate concentration within their syndicated loan portfolios have greater future bank risks, lower future bank profitability and thus lower concurrent bank valuation.*

However, Hypothesis 1 is not clear cut, and the relationship may instead be in the opposite direction. Due to their information-intensive relations with the borrower firms, lead banks have the incentive to syndicate bad or risky loans (adverse selection) and reduce their costly monitoring effort after loan origination (moral hazard) with the view that they can partly offload the risk to the rest of the lending syndicate. The theory of [Leland and Pyle \(1977\)](#) implies that an important way to alleviate such information asymmetry problems is for the lead bank to retain a large share of the loan on its balance sheet to signal high loan quality to participant lenders and ensure enough ‘skin in the game’ to provide an ex-post monitoring incentive.<sup>4</sup>

Consistent with this theoretical stance, using the lead bank’s diversification demand shift as an instrument for the lead share of the loan, [Ivashina \(2009\)](#) shows that greater (instrumented) lead share results in a significantly lower loan spread demanded by participant lenders, consistent with the lower credit risk borne. Since lead share and number of participants are well known to be highly negatively correlated ([Ivashina, 2009](#); [Ivashina and Scharfstein, 2010b](#)),<sup>5</sup> a higher value of the syndicate concentration measure across a bank’s syndicated lending portfolio (i.e., lower average participant number and higher average lead share) may thus indicate better loan quality and lower credit risk, which in turn can be

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<sup>4</sup>Although a lead bank may sell its share of a loan in the secondary market after loan initiation, [Blickle, Fleckenstein, Hillenbrand, and Saunders \(2020\)](#) show that the loans sold by the lead bank tend to have significantly lower credit risk than those kept on the lead bank’s lending book. Thus, the signal of retaining a large loan share is a credible one. However, [Giannetti and Meisenzahl \(2021\)](#) show that regulations and capital constraints may force banks to sell deteriorating loans.

<sup>5</sup>For example, [Ivashina \(2009\)](#) reports a correlation between lead share and participant number of -0.70.

associated with lower future bank risks, higher future bank profitability and thus higher concurrent bank valuation.

In this study, we will rigorously investigate the empirical relations between the bank-level syndicate concentration measure and bank risks, bank profitability and bank valuation, respectively. We show that the bank-level syndicate concentration measure is a strong early-warning predictor of bank risks, particularly when the bank's operations are opaque or complex. We further decompose the bank-level syndicate concentration measure into two distinct measures based on syndicated loans joined and loans lead-arranged by the bank, respectively. Although banks may prefer to join syndicated loans with better perceived quality and thus higher number of participant lenders, they also have the incentive to retain large shares for the loans that they lead-arrange to signal better quality of these loans (Leland and Pyle, 1977; Ivashina, 2009). Thus, we conjecture that syndicate concentration of the loans joined by the bank may be a stronger risk predictor than syndicate concentration of the loans lead-arranged by the bank.

**Hypothesis 2.** *The positive predictive power of the bank-level syndicate concentration measure on future bank risks mainly derives from the loans joined by the bank rather than from the loans lead-arranged by the bank.*

To further validate the bank-level syndicate concentration measure as an early-warning bank risk measure, we also use banks failing the Federal Reserve's forward-looking Comprehensive Capital Analysis and Review (CCAR) stress tests as quasi-natural experiments and conduct difference-in-differences (DiD) analysis to examine the changes in the syndicate concentration measure for failure banks relative to control banks after the stress-test-failure shocks.<sup>6</sup> We conjecture that banks that failed a forward-looking stress test should exhibit a significant reduction in bank-level syndicate concentration relative to control banks subsequently, and the effect should be driven mainly by the new loans joined, and not by the new

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<sup>6</sup>Failing a CCAR stress test leads to significant reputational damage and constraints on a bank's capital distribution plan. Failure banks will be required to improve risk management practices, raise new equity capital and/or change their distribution plans.

loans lead-arranged, by the failure banks.

After establishing the bank-level syndicate concentration measure as a strong early-warning bank risk predictor, we further study the predictive power of syndicate concentration at the aggregate level on future financial-sector risks, future economy-wide private-sector investment growth, and future economy-wide economic activities. If the bank-level syndicate concentration measure is a good early-warning bank risk predictor, we conjecture that higher aggregate syndicate concentration in the economy will indicate lower aggregate lending quality and higher aggregate credit risk, which should be translated into greater future financial-sector risks, lower private-sector investment growth, and thus slower economic activities.

**Hypothesis 3.** *Greater economy-wide syndicate concentration is related to higher future financial-sector risks and future economic activity slowdowns.*

### 3. Sample and Variable Construction

#### 3.1. Measuring syndicate concentration

We propose a simple measure of syndicate concentration entirely based on syndicate size. At the loan level, the syndicate concentration of a loan  $k$ ,  $s_k$ , is the reciprocal of syndicate size measured by the number of lenders:

$$s_k = \frac{1}{\# \text{ lenders}} \quad (1)$$

where  $s_k = 1$  means that the loan involves a single lender, and  $s_k$  becomes smaller and closer to 0 with more lenders. A higher  $s_k$  implies a more concentrated syndicate in terms of the number of lenders.

A major advantage of the syndicate concentration measure  $s_k$  is that it does not rely on the distribution of lender shares within the syndicate. The severe drawback in relying on

lender shares is that the data on lender shares is not consistently reported. For example, in the period from 1990 to 2020, DealScan recorded a total of 171,036 loan tranches originated within the U.S., of which only 38,840 or 23% have non-missing lender shares data. Thus, a syndicate concentration measure based on lender shares would inevitably miss over three quarters of loans. Furthermore, in the context of loan syndicate concentration, our measure requires only the number of lenders to compute as opposed to the alternative more established concentration measures, e.g., the Herfindahl–Hirschman Index (HHI), which takes into account both the number of lenders and the distribution of lender shares. We provide a detailed explanation in the Online Appendix [OA.2](#), which shows that the variation in the number of lenders accounts for the majority of the variation in HHI in the context of loan syndicate concentration. We briefly discuss the intuition as follows.

Mathematically, we can conceptualize HHI as the sum of the loan syndicate’s deviations from 1) all lenders having the same share in the syndicate, and from 2) a ‘fully competitive’ environment with infinite number of lenders in the syndicate. The former is the effect of the inequality in the distribution of lender shares and the latter is the effect of the number of lenders. We can show that when HHI is small, the number of lenders contributes the most to the level of concentration rather than the distribution of lender shares.<sup>7</sup> Empirically, we find that most lenders have similar shares and hence the syndicate’s HHI is small. Based on the 38,840 loans with nonmissing lender shares data, 90% of the syndicates have a HHI below 0.5 (excluding syndicates with a sole lender, in which case the HHI is 1, same as our concentration measure), of which 95% of lending syndicates have a HHI below 0.36. In this case, with reference to Figure [A1](#) in the Online Appendix [OA.2](#), we can see that the number of lenders is the most important driving factor of HHI. Therefore, our measure based entirely on the number of lenders not only captures the actual concentration of loan syndicates, but also ensures a large sample coverage when the availability of lender shares data is known to be sporadic.<sup>8</sup>

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<sup>7</sup>See Appendix [OA.2](#) for a detailed discussion.

<sup>8</sup>Nevertheless, for robustness, we calculate a version of syndicate concentration using lender shares when-

We define  $SC_{i,t}$  as the syndicate concentration of a bank  $i$  at time  $t$ , measured by:

$$SC_{i,t} = \sum_{k=1}^n s_k \times w_{k,t} \quad (2)$$

where  $n$  is the number of newly syndicated loans that bank  $i$  participates in the past 12 months as at time  $t$ , and  $w_{k,t}$  is the dollar weight of loan  $k$  in these  $n$  new loans. It is effectively a loan-size-weighted-average of the reciprocal of syndicate size (number of lenders) in new syndicated loans involving a given bank.<sup>9</sup> A bank with a larger  $SC$  is involved more frequently in loans made by syndicates of smaller sizes. In an extreme case where a bank behaves like a ‘lone wolf’ and lends alone during the past 12 months, its syndicate concentration score  $SC$  is 1. To an extent,  $SC$  is an opposite measure of the activeness of loan diversification and risk sharing at the bank level. We measure bank syndicate concentration at the quarterly interval to match the frequency of bank characteristics available from FR Y-9C. Lastly, to mitigate the concern of measurement error, we compute the quarterly decile rank of banks’ syndicate concentration  $SC$  and use it in our empirical analyses.

At the aggregate level, we measure syndicate concentration at the monthly interval because we no longer require quarterly bank characteristics and a monthly frequency generates more observations for our subsequent time-series analyses. The aggregate syndicate concentration at time  $t$ ,  $SC_t$ , is measured by:

$$SC_t = \sum_{k=1}^N s_k \times w_{k,t} \quad (3)$$

where  $N$  is the number of newly syndicated loans by all banks in the past 6 months as at time  $t$ , and  $w_{k,t}$  is the dollar weight of loan  $k$  in these  $N$  new loans. We shorten the rolling window from 12 months to 6 months to allow more rapid changes in the aggregate syndicate

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ever available (to replace the reciprocal of the number of lenders), and find qualitatively similar results for all our following analyses.

<sup>9</sup>We find qualitatively similar results if we use an alternative sampling period length such as 24 months or 36 months instead.



concentration.

### *3.2. Sample construction and descriptive statistics*

Our cross-sectional analysis of the predictive power of bank-level syndicate concentration uses a sample of U.S. bank holding companies' (BHC, or bank hereafter) lending data and financial characteristics from 1990 to 2020. Specifically, we collect all syndicated loans by U.S. banks from the Refinitiv LPC DealScan database, bank characteristics from Form FR Y-9C (consolidated financial statements for bank holding companies), and stock market data from the Center for Research in Security Prices (CRSP). For bank characteristics, we consider bank size, equity capital ratio, market-to-book ratio, the size and growth rate of the loan portfolio, the allowance for loan losses, as well as bank liquidity. We merge bank characteristics and market data using the CRSP-FRB link table provided by the Federal Reserve Bank of New York.<sup>10</sup> Data on syndicated loans from DealScan are matched to bank characteristics based on the lenders' parent company using hand-matched bank name concordance files aggregated at the BHC level.<sup>11</sup>

**[Insert Table 1 about here]**

Table 1 reports the summary statistics for the main variables used in our cross-sectional and aggregate-level analyses. Definitions of the variables and data sources are provided in Table A1 in the Appendix. We winsorize all continuous variables in the cross-sectional analysis by year-quarter at the 1<sup>st</sup> and 99<sup>th</sup> percentiles. Figure 1 plots the quarterly decile ranks of syndicate concentration for the top-five (bottom-five) banks with the highest (lowest) average syndicate concentration in our sample. Specifically, we require banks to have at least 40 quarterly observations, or 10 years of data, to be included in the plot. In addition to the time series, we use the grayscale of shaded horizontal bars to further indicate the frequency of

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<sup>10</sup>The link table is available at [https://www.newyorkfed.org/research/banking\\_research/datasets.html](https://www.newyorkfed.org/research/banking_research/datasets.html).

<sup>11</sup>The hand-matching is carried out by two groups of research assistants independently and then carefully cross-checked by the authors for matching quality and consistency.

the bank scoring a certain rank of syndicate concentration, with darker color indicating higher frequency. We find that bank-level syndicate concentration rank is somewhat persistent over time, although significant changes over time in syndicate concentration rank can and do occur. We further report the transition matrix of syndicate concentration ranks for all sample banks in our sample period in Table A2 in the Appendix. A bank’s syndicate concentration rank has an average probability of staying unchanged in the next quarter at about 53%, and there is about 85% chance that it remains within +/-1 rank in the next quarter.

**[Insert Figure 1 about here]**

To study the predictive power of syndicate concentration at the aggregate level, we further collect a variety of metrics for financial-sector risks and U.S. macroeconomic indicators. Specifically, we use the monthly CATFIN measure introduced by Allen et al. (2012) as our primary measure for financial-sector risk. For macroeconomic indicators, we collect the data on gross private domestic investment (GPDI), gross domestic product (GDP), industrial production (INDP), and the Chicago Fed National Activity Index (CFNAI) from the FRED database by the Federal Reserve Bank of St. Louis. We also collect the Aruoba-Diebold-Scotti Business Conditions Index (ADS) from the Federal Reserve Bank of Philadelphia, and the U.S. recession indicator from the National Bureau of Economic Research (NBER). We use the estimated total factor productivity (TFP) measure by John Fernald from the Federal Reserve Bank of San Francisco.<sup>12</sup> We generate monthly values for GPDI, GDP, INDP and TFP (which are available at quarterly frequency) through linear interpolation. We then compute the monthly growth rates of these variables. We use the month-end values for ADS (since it is available at the daily frequency).

**[Insert Figure 2 about here]**

Figure 2 plots the aggregate syndicate concentration and the financial-sector risk mea-

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<sup>12</sup>The data of quarterly TFP and utilization-adjusted TFP is available at <https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/>.

sured by CATFIN over time. Given that syndicate size is typically related to loan size (i.e., larger loans tend to have larger syndicate size), we also plot the time series of the aggregate syndicate concentration orthogonal to loan issuance, measured by the residuals from regressing the aggregate syndicate concentration from Equation 3 on the total dollar amount of loans issued. The figure shows that the aggregate syndicate concentration seems to lead CATFIN, especially in the years before the 2008 Global Financial Crisis, indicating some potential predictive power.

In our predictive regression models for financial-sector risks and real-sector economic activity, we control for a large set of macroeconomic and financial variables as in Allen et al. (2012), including *Default spread*, defined as the difference between the BAA-rated and AAA-rated corporate bonds; *Term spread*, defined as the difference between the ten-year T-bond and three-month T-bill yields; *Relative short-term interest rate*, defined as the difference between three-month T-bill rate and its twelve-month backward-moving average; *Financial sector return*, defined as the value-weighted average excess returns of all financial firms<sup>13</sup>; *Financial sector volatility*, defined as the realized monthly volatility of excess stock returns of all financial firms; *Financial sector skewness*, defined as the realized monthly skewness of excess stock returns of all financial firms; *Financial sector average beta*, defined as the average market beta of all financial firms estimated from monthly stock returns over the past five years; *Market return*, defined as the monthly excess return on the CRSP value-weighted index; *Market volatility*, defined as the realized monthly volatility of excess returns of the aggregate stock market portfolio; *Correlation in financial sector*, defined as the average correlation between excess returns on individual financial firms and excess returns on the financial market index with a rolling window of 24 months; *Average financial firm size*, defined as the natural logarithm of the average market capitalization of firms in the financial sector; and *Aggregated financial sector leverage*, defined as the ratio of total liabilities to total assets of the entire financial sector. Additionally, we include *Syndicated loan issuance*

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<sup>13</sup>Financial firms are identified if their two-digit SIC code is between 60 and 67.

measured by the natural logarithm of the monthly total dollar amount of loans originated, as well as *Credit tightening* measured by the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium sized firms, collected from the Federal Reserve Bank of St. Louis (Ivashina and Scharfstein, 2010b).

## 4. Predictive Ability of Bank-level Syndicate Concentration on Future Bank Risks and Bank Profitability

### 4.1. Predicting bank-specific risks

We estimate the following  $h$ -quarter-ahead predictive regressions of  $SC$  on alternative bank risk proxies after controlling for a set of bank-level control variables:

$$Risk_{i,t+h} = \beta Rank SC_{i,t} + \gamma X_{i,t} + \theta_t + \varepsilon_{i,t+h} \quad (4)$$

where  $Risk_{i,t+h}$  is one of the bank-level risk measures for bank  $i$  at time  $t + h$ ,  $Rank SC_{i,t}$  is the quarterly decile rank of the syndicate concentration measure of bank  $i$  at time  $t$ ,  $X_{i,t}$  is a vector of bank-level control variables, and  $\theta_t$  is the year-quarter fixed effects. We do not control for bank fixed effects because our focus is on the cross-sectional risk predictive power of bank-level syndicate concentration.<sup>14</sup> For bank-level control variables, we include the natural logarithm of the book value of total assets, equity capital ratio, returns on assets, market-to-book equity ratio, size of loan portfolio, growth rate of loan portfolio, loan loss allowance, quarterly buy-and-hold stock return, and liquidity ratio. However, in all analyses, we also estimate the predictive regression models where we include only the year-quarter fixed effects but not the bank-level control variables.

The first bank risk measure we examine is the loan loss provisions scaled by total loans.

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<sup>14</sup>Nevertheless, we also estimate the risk predictive regressions with bank fixed effects and report the results in Table A4 in the Appendix. The results remain qualitatively unchanged.

Loan loss provisions represent an allowance set aside for uncollected loans and loan payments. Rising loan loss provisions not only imply an expected loan loss but also signal higher bank credit risk. Panel A of Table 2 shows that in the predictive regressions without bank-level control variables, the coefficient estimates of the decile rank of bank-level syndicate concentration are all positive and mostly significant at the 1% level. After controlling for a variety of bank-level factors, the coefficient estimates of Rank  $SC_{i,t}$  remain positive and statistically significant at the 1% level across all the 12 predictive regressions. This finding suggests that bank-level syndicate concentration significantly and positively predicts bank loan loss provisions in the cross-section for at least 12 quarters ahead. Specifically, an increase from the bottom decile rank of  $SC$  to the top rank predicts, for three years ahead, a 0.189-percentage-point ( $0.021 \times 9$ ) higher quarterly loan loss provisions (scaled by total loans), which is around 59% of the sample mean loan loss provisions of 0.322. Moreover, given the sample average ratio of total loans to total assets of 0.592 and the average bank size of 17.248 (natural logarithm of total assets in thousands), it implies an additional expected loan loss of over \$138 million per year ( $e^{17.248} \times 0.592 \times 0.189\% \times 4$ ).

**[Insert Table 2 about here]**

The second bank risk measure we examine is the default probability estimated from the Merton (1974) model. Given that greater bank-level syndicate concentration positively predicts higher bank credit risk as proxied by loan loss provisions, it is natural to expect that a bank's default probability increases in its syndicate concentration. Panel B of Table 2 shows that the coefficient estimates of the decile rank of bank-level syndicate concentration are indeed all positive and statistically significant at least at the 5% level for at least 12 quarters ahead, without and without bank-level controls, which confirms that greater bank-level syndicate concentration predicts higher bank default probability. An increase from the bottom decile rank of  $SC$  to the top rank predicts, for three years ahead, a 3.6-percentage-point ( $0.004 \times 9$ ) higher default probability, which is around 31% of the sample mean default

probability of 0.116. Further, Nagel and Purnanandam (2020) propose a modified default probability measure for banks taking into account the special nature of bank assets (e.g., concave payoffs due to risky debt claims). Table A3 in the Appendix shows that syndicate concentration continues to significantly and positively predict the modified default probability using the Nagel and Purnanandam (2020) model.<sup>15</sup>

The third bank risk measure we examine is the idiosyncratic volatility of bank stock returns, measured by the natural logarithm of the standard deviation of the residuals from the Fama-French three-factor model estimated for each year-quarter.<sup>16</sup> If a bank is frequently involved in more concentrated syndicated loans, we expect the bank to have more idiosyncratic risk due to the lack of risk sharing, as reflected in higher idiosyncratic stock return volatility. Panel C of Table 2 shows that the coefficient estimates of the decile rank of bank-level syndicate concentration are all positive and statistically significant at the 1% level in the predictive regressions without bank-level controls, and remains positive and mostly significant for different forecast horizons in the regressions with bank-level controls, confirming that syndicate concentration positively predicts bank-level idiosyncratic volatility. An increase from the bottom decile rank of *SC* to the top decile rank predicts, for three years ahead, a 8.1-percentage-point ( $0.009 \times 9$ ) higher idiosyncratic stock return volatility, which is around 60% of the sample mean idiosyncratic volatility of 0.134.

The fourth bank risk measure we examine relates to the litigation risk faced by the bank, measured by the natural logarithm of one plus the number of lawsuits where the bank is the defendant in the quarter. We collect from Audit Analytics the lawsuit data on civil litigation cases filed in federal district courts since 2000. We match this litigation data to the banks in our sample based on CIK. Panel D of Table 2 shows that the coefficient estimates of the decile rank of bank-level syndicate concentration are positive in all predictive regressions and

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<sup>15</sup>We thank the authors for making available their data on bank default probabilities using the Merton model and their modified model at <https://voices.uchicago.edu/stefannagel/code-and-data/>.

<sup>16</sup>We require at least 45 days of available stock return data per quarter when estimating the idiosyncratic volatility. If a bank has multiple securities traded on exchanges, we use the average idiosyncratic volatility across these securities for the bank.

statistically significant mostly at the 1% level in the predictive regressions with bank-level controls, suggesting that greater syndicate concentration predicts higher bank litigation risk for at least 12 quarters ahead. Although we cannot directly associate the concentration of syndicated loans with specific legal cases, the positive predictability of bank-level syndicate concentration on the frequency of future lawsuits involving the bank as a defendant still indicates the potential build up of future riskiness when the bank has limited risk-sharing opportunities.

#### 4.2. *Predicting bank profitability*

We next investigate the predictive ability of bank-level syndicate concentration on future bank profitability. Since banks with higher bank-level syndication concentration have higher bank-specific risks such as higher expected loan losses, we expect such banks to have lower future profitability. Thus, we reestimate the predictive regression models as in Equation 4 by replacing the bank risk measures with two bank profitability measures, ROE and ROA. The results are reported in Table 3.

[Insert Table 3 about here]

Consistent with our expectation, we find that the coefficient estimates on bank-level syndicate concentration are negative in all predictive regressions and are statistically significant at the 5% level from 6 quarters to 12 quarters ahead for both the ROE and ROA predictive regressions. This finding confirms that higher bank-level syndicate concentration predicts lower future bank profitability for at least 12 quarters ahead. An increase from the bottom decile rank of  $SC$  to the top decile rank predicts, for three years ahead, a 2.691-percentage-point ( $0.299 \times 9$ ) lower ROE, which is around 40% of the sample mean ROE of 6.756%, as well as a 0.234-percentage-point ( $0.026 \times 9$ ) lower ROA, which is around 37% of the sample mean ROA of 0.628%.

Thus, our empirical results clearly show that banks with higher syndicate concentration

within their syndicated loan portfolio have greater future bank risks and lower future bank profitability, lending support to Hypothesis 1.

### 4.3. *Loans arranged vs. loans joined*

As discussed earlier, given that lead banks have the incentive to retain large loan shares (resulting in a greater syndicate concentration) in order to signal good loan quality, we conjecture that the positive risk predictive power of bank-level syndicate concentration should derive primarily from syndicated loans joined by the bank rather than loans lead-arranged. To validate this conjecture, we decompose the measure of bank-level syndicate concentration into two distinct measures. Specifically, we classify loans as loans lead-arranged by a bank if the bank’s ‘Primary Role’ in the DealScan database is one of ‘Arranges’, ‘Co-arranger’, ‘Co-lead arranger’, ‘Lead arranger’, ‘Mandated Lead arranger’, ‘Mandated arranger’, or ‘Sole lender’, or if the lender’s name is listed in the ‘Lead Arranger’ column. The rest of the syndicated loans are classified as loans joined by the bank. We then construct the two bank-level syndicate concentration measures based on the loans lead-arranged by the bank and those joined by the bank and reestimate the baseline predictive regressions using the decile ranks of these two measures. The results are reported in Table 4.

**[Insert Table 4 about here]**

As expected, we find that the predictive power of bank syndicate concentration on future bank risks and future bank profitability derives mainly from the loans joined by the bank and not from the loans lead-arranged.<sup>17</sup> This finding supports Hypothesis 2.

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<sup>17</sup>Note that the loans with a sole lender do not drive our results. Single lender loans are included in the loans lead-arranged by the bank when we calculate the bank-level syndicate concentration measure based on loans lead-arranged. In untabulated results, we exclude all single-lender loans from the sample and our results remain qualitatively unchanged.



#### 4.4. *Robustness*

We next conduct a battery of robustness checks to validate the predictive power of bank-level syndicate concentration on future bank risks and bank profitability. First, as shown in Table A5 in the Appendix, we find that the results remain qualitatively unchanged if standard errors are instead double-clustered at both the bank and year-quarter levels.

Second, we additionally include two bank specialization measures in the baseline predictive regressions. The first one captures a bank's specialization in the syndicated loan market by summing the total value of syndicated loans it participates in over the past 12 months, divided by the size of the total loans on its balance sheet. A higher value indicates that the bank is a more specialized lender in the syndicated loan market. The second measure, capturing a bank's industry specialization, is the HHI index based on the borrowers' two-digit SIC codes and loan amounts of the syndicated loans the bank participates in over the past 12 months. A higher value indicates that the bank is specialized in lending to certain industries. Both bank specialization measures may correlate with a bank's syndicate concentration. Table A6 in the Appendix shows that our results remain qualitatively unchanged after controlling for these two different dimensions of the bank's specialization in its lending activities.

Third, we additionally control for the weighted-average loan spread of the bank's syndicated loan portfolio, measured by the weighted-average all-in-drawn spread (in percentage points and weighted by dollar loan amount) of all syndicated loans the bank participates in over the past 12 months. Table A7 in the Appendix shows that our results again remain qualitatively unchanged after controlling for the weighted-average loan spread, which implies that the predictive ability of bank-level syndicate concentration on future bank risks and bank profitability is beyond the credit-quality signal from the bank's weighted-average loan spread.

Fourth, we further control for the bank's reputation measured by the total amount of syndicated loans lead-arranged by the bank divided by the total amount of all newly-originated

syndicated loans in the market over the past 12 months. A higher value indicates that the bank holds a larger share in the syndicated loan market and thus is more likely to be a reputable bank. Table A8 in the Appendix shows that our results remain qualitatively unchanged even after controlling for bank reputation. This alleviates the concern that less reputable banks may have higher risks and lower profitability, who are also less likely to be invited to join loan syndicates and thus have higher bank-level syndicate concentration. The results also suggest that the predictive power of bank-level syndicate concentration on future bank risks and profitability goes beyond bank reputation.

Fifth, given that at the end of any quarter, we use the loans a bank participates in over the past 12 months to measure its bank-level syndicate concentration, there can be a concern that the overlapping nature of our sample can bias the results. To alleviate this concern, we further construct a non-overlapping sample for the predictive regressions. Specifically, we sample observations annually at the quarter ends of Q1, Q2, Q3 and Q4 respectively, and then use these four samples for the predictive regressions on one-year-ahead bank risks and bank profitability. That is, we use all Q1 observations to estimate Equation 4 with  $h = 4$ . We then similarly use all Q2 observations to run the predictive regressions with  $h = 4$ , and so on. Since our bank-level syndicate concentration measure is based on loans participated over the past 4 quarters, this sampling method ensures all the four samples used for the one-year-ahead predictive regressions are non-overlapping samples. Table A9 in the Appendix shows that the results using the four non-overlapping samples are again qualitatively similar to our main results.

#### 4.5. *Effect on bank valuation*

Given that bank-level syndicate concentration positively predicts bank risks and negatively predicts bank profitability, one would expect it to negatively predict bank's stock market performance. In untabulated results, however, we find that bank-level syndicate concentration does not predict banks' stock market performance measured by quarterly

buy-and-hold returns. A possible explanation is that the stock market recognizes the effects of banks often lending alone or joining concentrated syndicates on future bank risks and profitability and reflect the effects into concurrent bank stock prices . Thus, we conjecture that a bank with greater bank-level syndicate concentration should have lower concurrent bank valuation.

[Insert Table 5 about here]

We examine this conjecture by regressing concurrent bank market-to-book equity ratio (MTB) on the decile rank of bank-level syndicate concentration. Further, we progressively include bank-level control variables used in the earlier predictive regressions. As shown in Panel A of Table 5, we find that the coefficient estimates of the syndicate concentration decile rank are all negative and statistically significant. An increase from the bottom decile rank of  $SC$  to the top decile rank is associated with a 0.261 ( $0.029 \times 9$ ) reduction in the market-to-book ratio, which is about 15% of the sample mean market-to-book ratio of 1.779. Moreover, using Tobin's Q as an alternative market valuation measure, we find qualitatively similar results in Panel B of Table 5. The results suggest that the stock market has priced in bank-level syndicate concentration. These results are consistent with Hypothesis 1.

## 5. Cross-sectional Analyses

In this section, we explore the predictive ability of bank-level syndicate concentration for future bank risks and profitability conditional on bank opacity and complexity. We conjecture that the predictive ability of bank-level syndicate concentration may be stronger for more opaque and/or complex banks because such banks may not be able to timely manage the risks arising from syndicate concentration due to their high opacity and/or complexity.

### 5.1. Bank opacity

We measure bank opacity by aggregating three separate proxies. The first proxy is the discretionary loan loss provisions following [Jiang, Levine, and Lin \(2016\)](#), defined as the natural logarithm of the absolute value of the residuals from estimating the following model:<sup>18</sup>

$$\begin{aligned}
 LLP_{i,j,t} = & \alpha_1 \Delta NPA_{i,j,t+1} + \alpha_2 \Delta NPA_{i,j,t} + \alpha_3 \Delta NPA_{i,j,t-1} + \alpha_4 Size_{i,j,t-1} \\
 & + \alpha_5 \Delta Loan_{i,j,t} + \delta_{j,t} + \varepsilon_{i,j,t}
 \end{aligned} \tag{5}$$

where  $LLP_{i,j,t}$  is the loan loss provisions scaled by lagged total loans for bank  $i$  in state  $j$  at quarter  $t$ ,  $\Delta NPA_{i,j,t}$  is the change in the non-performing assets for bank  $i$  in state  $j$  from quarter  $t-1$  to  $t$  scaled by lagged total loans,  $Size_{i,j,t-1}$  is the natural logarithm of the bank's total assets in  $t-1$ ,  $\Delta Loan_{i,j,t}$  is the change in total loans for bank  $i$  from  $t-1$  to  $t$ , and  $\delta_{j,t}$  is the state-quarter fixed effect. Lead and lag of  $\Delta NPA_{i,j,t}$  are included because banks might use forward-looking and historical information on non-performing assets in setting their provisions for loan losses.

Following the prior literature (e.g., [Flannery, Kwan, and Nimalendran, 2004](#)), the second and third proxies for bank opacity are banks' analysts' forecast error and forecast dispersion. Specifically, analysts' forecast error is the absolute value of the difference between actual earnings per share and the mean analyst forecast, divided by the stock price. Analysts' forecast dispersion is the standard deviation of analysts' earnings forecasts divided by the stock price.

We then aggregate the three standalone proxies for bank opacity by first dividing the decile rank (from 0 to 9) of each proxy by 9 and then taking the mean of the resulting ratios. This aggregation method allows us to combine proxies of different scales and yields a continuous measure for bank opacity ranging from 0 to 1, with a higher value indicating

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<sup>18</sup>We drop the three state characteristics, including the Case-Shiller Real Estate Index, the change in gross state product, and the change in the state's unemployment rate, and replace the state fixed effects with the state-quarter fixed effects  $\delta_{j,t}$  to absorb all state-level, time-varying factors.

greater opacity. To investigate the risk predictive power of bank-level syndicate concentration conditional on the degree of bank opacity, we estimate the following regression specification similar to Equation 4 by adding the bank opacity measure at time  $t$  and its interaction term with the decile rank of bank-level syndicate concentration:

$$Risk_{i,t+h} = \beta_1 Rank\ SC_{i,t} + \beta_2 Opacity_{i,t} + \beta_3 Rank\ SC_{i,t} \times Opacity_{i,t} + \gamma X_{i,t} + \theta_t + \varepsilon_{i,t+h} \quad (6)$$

The results are reported in Panel A of Table 6. We find that the coefficient estimates of the interaction term between bank-level syndicate concentration and bank opacity are all positive and are mostly significant for the bank risk measures, which suggests a stronger risk predictive power of bank-level syndicate concentration for the banks that are more opaque. For loan loss provisions and default probability, the coefficient estimates on the interaction term are generally larger in size with higher statistical significance in shorter predictive horizons. For idiosyncratic risk and litigation risk, the coefficient estimates on the interaction term are generally larger in size and more significant in longer predictive horizons. Panel B of Table 6 further shows that the coefficient estimates of the interaction term between bank-level syndicate concentration and bank opacity are negative for both bank profitability measures, again suggesting a stronger predictive ability of bank-level syndicate concentration for lower bank profitability in more opaque banks. For both the ROE and ROA regressions, the coefficient estimates on the interaction term are larger in size and more significant in shorter predictive horizons (i.e., six quarters ahead or less).

[Insert Table 6 about here]

## 5.2. Bank complexity

We capture bank complexity using a simple measure based on the number of non-missing items reported in FR Y-9C. Complex banks arguably have more items to report and thus

the ratio of the number of non-missing items to the number of total items in FR Y-9C provides an intuitive and parsimonious measure of a bank’s complexity. This measure is similar to the measure proposed by [Chen, Miao, and Shevlin \(2015\)](#), which is the ratio of the number of non-missing items to the number of total items in Compustat. [Chen et al. \(2015\)](#) use it to capture the ‘disclosure fineness’ of industrial firms as it reflects the level of disaggregation of accounting data in annual reports. In the context of banking, we argue that this measure captures more of the complexity of a bank’s business. As at February 2022, Compustat has 948 distinct line items for firms’ annual reports, while FR Y-9C has over 2,300 line items. Apart from the standard balance-sheet items, banks are required to report in great detail about their off-balance-sheet activities including, for example, the unused loan commitments, standby letters of credit, revolving underwriting facilities, and credit derivatives, among other things. A missing item naturally implies that the reporting bank does not have such business. Hence, the more non-missing items reported by a bank, the more complex the bank’s business activities typically are.

Given that the number of non-missing items reported in FR Y-9C may be positively correlated with bank size, we perform an orthogonalization of bank complexity to bank size by regressing the complexity ratio on bank size. We then use the residual from this regression as our bank complexity measure (*Complexity*).<sup>19</sup> We then estimate the following regression specification to investigate the risk predictive ability of bank-level syndicate concentration conditional on bank complexity:

$$\begin{aligned}
 Risk_{i,t+h} = & \beta_1 Rank\ SC_{i,t} + \beta_2 Complexity_{i,t} + \beta_3 Rank\ SC_{i,t} \times Complexity_{i,t} \\
 & + \gamma X_{i,t} + \theta_t + \varepsilon_{i,t+h}
 \end{aligned}
 \tag{7}$$

Panel A of [Table 7](#) shows that the coefficient estimates of the interaction term between the decile rank of bank-level syndicate concentration and bank complexity are positive and

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<sup>19</sup>Our (untabulated) results remain qualitatively unchanged when we use the plain bank complexity ratio without orthogonalization instead.

mostly significant for predicting future bank risks except for litigation risk. The results suggest a stronger risk predictive power of bank-level syndicate concentration particularly for more complex banks. For loan loss provisions and default probability, the coefficient estimates on the interaction term are again larger and more significant in longer predictive horizons. For idiosyncratic volatility, the coefficient estimates on the interaction term are largest in around two-year-ahead predictive horizons. The coefficient estimates on the interaction term are statistically insignificant in the litigation risk predictive regressions. Panel B of Table 7 further shows that the coefficient estimates on the interaction term between bank-level syndicate concentration and complexity are negative for both bank profitability measures, ROE and ROA, with the interaction effect being more significant in longer predictive horizons. These findings suggest a stronger negative predictive ability of bank-level syndicate concentration on future bank profitability in more complex banks.

[Insert Table 7 about here]

## 6. Stress Test Failures and Bank-level Syndicate Concentration

In this section, we examine the impact of banks failing the supervisory stress tests on their syndicate concentration. In the wake of the Global Financial Crisis, the supervisory bank stress tests, which started with the Supervisory Capital Assessment Program (SCAP) in 2009, were introduced by the Federal Reserve as a forward-looking supervisory tool to ensure that banks have enough capital to survive adverse economic shocks. Most of the tested bank holding companies failed the 2009 SCAP test. From 2011, the Federal Reserve began conducting the annual Comprehensive Capital Analysis and Review (CCAR) stress test to determine the capital adequacy of large bank holding companies. Banks that failed a stress test are required to improve risk management, raise new capital, and/or change their

capital distribution plans. Thus, a stress test failure is a bad public signal and significantly damages the bank’s reputation. An overview of the participating banks and the outcomes of the stress tests across different rounds are shown in Table [A10](#) in the Appendix.

The earlier sections show that bank-level syndicate concentration serves as an early-warning bank risk measure and increases future bank risks. Given the exogenous negative shock to a bank when it failed a supervisory stress test and the mandate to enhance risk management, we expect the failure bank would take actions to decrease its bank-level syndicate concentration (e.g., by participating in syndicated loans with larger syndicate size). We thus perform a stacked difference-in-differences (DiD) estimation using stress test failure as the treatment to investigate the effect of failing a stress test on bank-level syndicate concentration.

Specifically, we use only the CCAR tests from 2012 through 2019 in our stacked DiD analyses. This is because most of the tested banks failed in the SCAP test in 2009 and the result of the CCAR test in 2011 has not been publicly disclosed. Thus, our sample consists of all banks that have ever participated in a CCAR test from 2012 to 2019. We construct a subsample (cohort) for each round of the CCAR tests. We classify banks that failed (passed) the focal round of CCAR as the treated (control) banks. If a bank failed multiple rounds of CCAR, we only consider the first stress test failure of the bank and remove the bank from the subsamples of subsequent test rounds. Since a bank may have permanently changed its lending behaviour after a stress test failure, considering subsequent stress test failures of the bank may bias our estimation results. For each cohort, we use an event window surrounding each CCAR test round from two years before to two years after the year of the focal test round. We then stack all the cohorts together and estimate a standard DiD regression specification as follows:

$$SC_{i,c,t} = \beta_1 Treat_{i,c} + \beta_2 Post_{c,t} + \beta_3 Treat_{i,c} \times Post_{c,t} + \gamma X_{i,c,t-1} + \lambda_i + \theta_t + \varepsilon_{i,c,t} \quad (8)$$



where  $SC_{i,c,t}$  is our bank-level syndicate concentration measure for bank  $i$  in cohort  $c$  at year  $t$ ,  $Treat_{i,c}$  is an indicator variable that equals 1 if bank  $i$  in cohort  $c$  is a treatment bank and equals 0 otherwise,  $Post_{c,t}$  is an indicator variable that equals 1 if year  $t$  in cohort  $c$  is after the focal test year and equals 0 otherwise (excluding the focal test year),  $X_{i,c,t-1}$  is a vector of lagged bank-level control variables,  $\lambda_i$  is the bank fixed effects, and  $\theta_t$  is year fixed effects.

For robustness, we also estimate a similar regression specification where we replace bank fixed effects with the more conservative cohort-bank fixed effects and year fixed effects with cohort-year fixed effects as follows:

$$SC_{i,c,t} = \beta Treat_{i,c} \times Post_{c,t} + \gamma X_{i,c,t-1} + \omega_{i,c} + \gamma_{c,t} + \varepsilon_{i,c,t} \quad (9)$$

The  $Treat_{i,c}$  and  $Post_{c,t}$  indicators are absorbed by the cohort-bank fixed effects  $\omega_{i,c}$  and cohort-year fixed effects  $\gamma_{c,t}$ , respectively. When estimating the above two DiD regression specifications, we cluster standard errors at the bank level or at both the bank and year levels. The results are reported in Panel A of Table 8.

Columns (1) and (2) of Panel A in Table 8 report the estimation results for Equation 8. Specifically, the specification in column (1) clusters standard errors at the bank level and that in column (2) clusters standard errors at both the bank and year levels. Columns (3) and (4) report the results of estimating Equation 9, where the specification in column (3) clusters standard errors at the bank level and that in column (4) clusters standard errors at both the bank and year levels. We find that the coefficient estimates of the DiD term,  $Treat \times Post$ , are negative across all the regression specifications, significant at the 5% level in three out of the four specifications, and significant at the 10% level in the remaining one. These findings confirm that banks indeed take actions to decrease bank-level syndicate concentration after their stress test failures via participating in loans with larger syndicate size.

[Insert Table 8 about here]

Moreover, we employ a dynamic DiD regression framework to examine whether the treatment effect of stress test failures on bank-level syndicate concentration is driven by potential nonparallel syndication trends between the treatment and control banks prior to the release of a stress test outcome. Specifically, we include the focal stress test year in the sample and use the following dynamic DiD regression specification to identify the exact timing of the treatment effect:

$$\begin{aligned}
SC_{i,c,t} = & \beta_1 Treat_{i,c} \times d_{-1,c,t} + \beta_2 Treat_{i,c} \times d_{0,c,t} + \beta_3 Treat_{i,c} \times d_{1,c,t} \\
& + \beta_4 Treat_{i,c} \times d_{2,c,t} + \beta_5 d_{-1,c,t} + \beta_6 d_{0,c,t} \\
& + \beta_7 d_{1,c,t} + \beta_8 d_{2,c,t} + \beta_9 Treat_{i,c} \\
& + \lambda_i + \theta_t + \varepsilon_{i,c,t}
\end{aligned} \tag{10}$$

where we replace the single  $Post_{c,t}$  indicator in Equation 8 with year-specific indicators  $d_{j,c,t}$  ( $j \in \{-1, 0, 1, 2\}$ ). Specifically,  $d_{j,c,t}$  equals 1 if year  $t$  is the  $j$ th year after the event year in cohort  $c$  and equals 0 otherwise. For robustness, we also estimate the following dynamic DiD regression specification with the cohort-bank and cohort-year fixed effects:

$$\begin{aligned}
SC_{i,c,t} = & \beta_1 Treat_{i,c} \times d_{-1,c,t} + \beta_2 Treat_{i,c} \times d_{0,c,t} + \beta_3 Treat_{i,c} \times d_{1,c,t} \\
& + \beta_4 Treat_{i,c} \times d_{2,c,t} + \omega_{i,c} + \gamma_{c,t} + \varepsilon_{i,c,t}
\end{aligned} \tag{11}$$

In the dynamic DiD regression framework, the referencing year in each cohort is the second year before the focus stress test year. As such, the regression specification enables us to identify the timing of the onset of the treatment effect. If the reduction in bank-level syndicate concentration is indeed caused by bank stress test failures, we should expect no difference-in-differences between the treatment and control banks prior to the release of the stress test outcome, which implies a statistically insignificant  $\beta_1$ . Further, the DiD estimate for the focal stress test year,  $\beta_2$ , may also be statistically insignificant because banks may not immediately respond to the release of stress test outcomes. Therefore, any reduction in

bank-level syndicate concentration due to stress test failures should be captured by negative and significant post-event DiD estimates,  $\beta_3$  and  $\beta_4$ .

Panel B of Table 8 reports the dynamic DiD estimation results. We find that across all regression specifications, the coefficient estimates of  $\beta_1$  and  $\beta_0$  are statistically insignificant, which confirms the parallel-trend assumption that treatment and control banks have parallel syndicate concentration trends prior to stress test failures. Importantly, the negative and significant treatment effect of stress test failures on bank-level syndicate concentration is observed only for the years after the release of the stress test outcomes. Taken together, these findings suggest that stress test failures may causally prompt failure banks to reduce their bank-level syndicate concentration through participating in loans with larger syndicate size. Given that stress tests are a forward-looking supervisory tool and failure banks are mandated to improve their risk management, these findings further validate the bank-level syndicate concentration measure as a suitable early-warning measure for bank risks.

Lastly, in Panel C of Table 8, we examine the impact of stress test failures on bank-level syndicate concentration measures estimated on loans lead-arranged and loans joined, respectively. Since our earlier results in Section 4.3 show that the predictive power of bank-level syndicate concentration for future bank risks comes mainly from the loans joined by the bank and not from the loans lead-arranged, we expect to observe a significant treatment effect of stress test failures on bank-level significant concentration only for the loans joined and not for the loans lead-arranged by the bank. For brevity, we present the DiD estimation results with the cohort-bank and cohort-year fixed effects under different standard error clustering structures, using each of the two bank-level syndicate concentration measures. Consistent with our expectation, we find that the reduction in bank-level syndicate concentration comes entirely from the loans joined by the failure banks and not from the loans lead-arranged. This finding again assures the validity of the bank-level syndicate concentration measure.

## 7. Predictive Power of Aggregate Syndicate Concentration on Financial-sector Risks and Real Economic Activities

We now turn to investigate the predictive power of aggregate syndicate concentration on future financial-sector risks and real economic activities (i.e., Hypothesis 3). Specifically, at the end of each month, we aggregate the loan-level syndicate concentration (Equation 1) of all the loans originated in the past 6 months weighted by the loan amount. We use the monthly frequency because we no longer require the availability of quarterly bank-level control variables, which also yields more observations for our time-series predictive regression analyses. We shorten the rolling window from 12 months to 6 months to capture the dynamic changes in aggregate syndicate concentration across the syndicated lending market.<sup>20</sup>

Similar to Allen et al. (2012), we estimate the following  $h$ -month-ahead predictive regression specification of financial-sector risk measures on aggregate syndicate concentration with control for a large set of macroeconomic and financial variables as well as one-month to twelve-month lags of the predictand:

$$Risk_{t+h} = \alpha + \beta_0 SC_t + \beta X_t + \sum_{i=1}^{12} \lambda_i Risk_{t-i+1} + \varepsilon_{t+h} \quad (12)$$

where  $Risk_{i,t+h}$  is one of the financial-sector risk measures at time  $t+h$  with  $h$  ranging from 1 to 6,  $SC_t$  is the market-wide aggregate syndicate concentration measure at time  $t$  (Equation 3),  $X_t$  is the vector of control variables at time  $t$ . Specifically, we control for the same set of macroeconomic and financial variables as in Allen et al. (2012), including default spread, term spread, relative short-term interest rate, financial sector return, financial sector skewness, financial sector average beta, market return, market volatility, the correlation in financial sector, the average financial firm size, and the aggregate financial sector leverage.

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<sup>20</sup>Our results remain qualitatively unchanged if we use a 12-month rolling window instead.

Additionally, we control for total syndicate loan issuance and credit tightening (Ivashina and Scharfstein, 2010b).

Further, we delay the start of our sample period by 12 months because we include the twelve lags of the predictand in the regression. Thus, the sample period for our time-series predictive regression analyses is now from January 1991 to March 2020. We estimate Equation 12 using ordinary least squares regressions with Newey and West (1987) standard errors, where the number of lags  $q$  is set by the formula:  $q = \text{floor} \left( 4 \times \left( \frac{T-h}{100} \right)^{\frac{2}{9}} \right)$ , where  $T = 349$  is the number of months between January 1991 and March 2020, and  $h$  is predictive horizon in Equation 12).

### 7.1. Predicting financial-sector risks

We use two measures to capture the risks in the financial sector. Following Allen et al. (2012), the first measure we use is *CATFIN*, which is the average of three different value-at-risk (VaR) measures (see Allen et al., 2012, for details). This measure reflects the aggregate catastrophic risk in the financial sector. The results on the predictive ability of aggregate syndicate concentration on future *CATFIN* are reported in Panel A of Table 9. We find that the coefficient estimates of aggregate syndicate concentration, *AggregateSC*, are positive for all predictive horizons and statistically significant for the one-month, two-month, and three-month horizons. Hence, the aggregate syndicate concentration measure positively predicts short-term future catastrophic risk in the financial sector.

**[Insert Table 9 about here]**

The second financial-sector risk measure, *LLPgrowth*, is the growth rate of the mean ratio of bank loan loss provisions (LLP) to loan size. Specifically, we first compute the ratio of loan loss provisions to loan size for each bank-quarter. We then use linear interpolation to compute the monthly average from the quarterly average ratio at the aggregate level.<sup>21</sup> We

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<sup>21</sup>Note that we use the incremental loan loss provisions per quarter, instead of the year-to-date (YTD)

use the ratio instead of the sum of loan loss provisions (in dollars) because banks may join or leave our sample during the sample period and dollar loan loss provisions are heavily affected by the size of individual bank’s loan portfolio. As such, *LLPgrowth* measures the growth rate of the newly created provisions for credit losses on a monthly basis.<sup>22</sup> The results on the predictive ability of aggregate syndicate concentration on future *LLPgrowth* are reported in Panel B of Table 9. We find that *AggregateSC* significantly and positively predicts the growth of loan loss provisions for up to 4 months in the future. In untabulated results, we find that it also positively predicts the ratio of monthly aggregate loan loss provisions (i.e., the addition to loan loss provisions) to loan size for at least 6 months ahead.

As a robustness check, we further include the investor sentiment measure in Baker and Wurgler (2006) as an additional control variable and reestimate Equation 12,<sup>23</sup> because Ivashina and Scharfstein (2010b) suggest that the time-series variation in the number of syndicate loan participants may be driven by investor sentiment. In Panel C of Table 9, we show that the positive predictive power of aggregate syndicate concentration on both *CATFIN* and *LLPgrowth* remains qualitatively unchanged, if not stronger, after controlling for investor sentiment.

Overall, the results in this section lends empirical support to Hypothesis 3 and suggest that the aggregate syndicate concentration measure can reliably foreshadow the build ups of financial-sector risks.

## 7.2. Predicting future real economic activities

Given that aggregate syndicate concentration has predictive power for future catastrophic risk and loan losses in the financial sector, we next examine whether it can also predict future

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loan loss provisions as reported in Y-9C. The incremental loan loss provisions per quarter is the difference between the YTD values in the current quarter and in the past quarter, except for the first quarter in a year. We winsorize the bank-quarter ratios of loan loss provisions to loan size at the 1st and 99th percentiles before computing the average.

<sup>22</sup>Our (untabulated) results remain qualitatively unchanged if we use the mean ratio of loan loss provisions to loan size, instead of its growth rate.

<sup>23</sup>We thank the authors for making the data on investor sentiment publicly available at <http://people.stern.nyu.edu/jwurgler/>.

real economic activities.

We start by investigating the predictive ability of aggregate syndicate concentration on the credit supply conditions as measured by excess bond premium as in [Gilchrist and Zakrajšek \(2012\)](#).<sup>24</sup> Specifically, we estimate Equation 12 with monthly excess bond premium as the predictand, controlling for the same macroeconomic and financial variables and investor sentiment, as well as one-month to twelve-month lags of excess bond premium. Table 10 shows that aggregate syndicate concentration significantly and positively predicts higher future excess bond premium in the next two months, which implies worsening credit supply conditions. Thus, greater values of aggregate syndicate concentration not only are informative about higher future financial sector risks but also are associated with worsening credit supply conditions.

**[Insert Table 10 about here]**

Next, We use a variety of measures to examine whether aggregate syndicate concentration predicts future macroeconomic activity slowdowns. The first measure we use is the growth rate of gross private domestic investment (*GPDI*), which captures the total private-sector investment made domestically. We use a linear interpolation to generate monthly *GPDI* from the quarterly data and then compute its monthly growth rate. We reestimate Equation 12 using the growth rate of GDP (*GDPIgrowth*) as the predictand, controlling for the same set of macroeconomic and financial variables as well as 12 lags of *GPDIgrowth*. The results are reported in Panel A of Table 11. We find that, as expected, aggregate syndicate concentration significantly and negatively predicts *GPDIgrowth* for at least 6 months in the future. Hence, an increase in aggregate syndicate concentration (and the associated increase in financial-sector risks and worsening credit supply conditions) may hinder future domestic investment growth.

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<sup>24</sup>The excess bond premium data is publicly available at <https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/recession-risk-and-the-excess-bond-premium-20160408.html>.

[Insert Table 11 about here]

We next turn to a set of macroeconomic variables reflecting the state of macroeconomic conditions, including the growth rates of total factor productivity ( $TFPgrowth$ ), gross domestic product ( $GDPgrowth$ ), and industrial production ( $INDPgrowth$ ). Panel A of Table 11 shows that aggregate syndicated concentration also significantly and negatively predicts all these real economic measures. Taken together, we find that higher aggregate syndicate concentration not only curbs future aggregate investment growth, but also reduces future growth in economic outputs and productivity.

We next use the Chicago Fed National Activity Index (CFNAI) and the Aruoba-Diebold-Scotti Business Conditions Index (ADS index) compiled by the Federal Reserve Bank of Philadelphia as the predictands. CFNAI is a monthly index that is designed to reflect overall economic activity and related inflationary pressure. Similarly, the ADS index is designed to track real business conditions at daily and weekly frequencies (Allen et al., 2012). As shown in Panel A of Table 11, We continue to find some negative predictive ability of aggregate syndicate concentration on future CFNAI and ADS index, consistent with the other macroeconomic measures and our expectations. To capture economic downturns, we use a recession indicator that equals 1 if the U.S. economy is in recession as marked by the National Bureau of Economic Research (NBER) and equals 0 otherwise. We also document some evidence that aggregate syndicate concentration positively predicts the likelihood of an upcoming economic recession.

In Panel B of Table 11, we further include the two financial-sector risk measures,  $CATFIN$  and  $LLPgrowth$ , as control variables and predictors. Allen et al. (2012) show that the financial-sector risk measure,  $CATFIN$ , positively predicts future economic downturns. By controlling for  $CATFIN$  and  $LLPgrowth$  in the predictive regression models, we test for the incremental predictive power of aggregate syndicate concentration beyond these financial-sector risk measures. We find that, after controlling for the financial-sector risk measures, aggregate syndicate concentration still predicts the economic slowdowns in domestic invest-



ment, gross domestic product, total factor productivity, business activities, and a higher likelihood of recession, albeit its predictive power gets slightly weaker.

Lastly, Panel C of Table 11 reports the results from a robustness check where we additionally control for investor sentiment. We find that, except for the recession indicator, the predictive power of aggregate syndicate concentration for all other macroeconomic conditions remains qualitatively unchanged, if not stronger. This finding confirms that aggregate syndicate concentration can serve as an early-warning indicator for the slowdowns in real economic activities.

In summary, the empirical results in this section suggest that greater aggregate syndicate concentration foreshadows greater future financial-sector risks, lower future private-sector investment growth, and thus slower future economic activities, lending support to Hypothesis 3.

## 8. Conclusion

In this paper, we use comprehensive syndicated bank lending data spanning three decades from 1990 to 2020 to examine how a bank's involvement in syndicated lending as gleaned from its bank-level syndicate concentration, is related to future bank risks, future profitability and concurrent valuation. We show that bank-level syndicate concentration, captured as the loan-size-weighted-average of the inverse of syndicate size on all newly originated syndicated loans that a bank participates in over the recent period, serves as a reliable early-warning bank risk measure and can predict future bank risks and profitability for at least three years ahead. The loans that the bank chooses to participate in with other syndicate members and not the loans that it lead-arranges, give rise to the predictive ability of bank-level syndicate concentration. Moreover, aggregate syndicate concentration within the financial system reliably foreshadows future financial-sector risks and real-sector economic activities.

Our findings suggest that bank-level syndicate concentration can serve as an informative,

early-warning bank risk measure for depositors, investors and other stakeholders. Furthermore, higher syndication concentration at the aggregate level indicates significant risks for the financial sector and predicts real economic activity slowdowns. Thus, in order to better maintain financial stability, regulators need to be vigilant on the levels of syndicate concentration of individual banks and the financial sector as a whole. Preemptive monitoring by bank supervisors may be warranted in the syndicated lending market when syndicate concentration is high.

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Fig. 1. Banks with Highest and Lowest Syndicate Concentration

Figure 1 plots the quarterly decile rank of syndicate concentration for top-five banks with the highest (blue) and lowest (red) syndicate concentration from 1990 to 2020. Specifically, we require banks to have at least 40 observations (i.e., 10 years of data) to be included in the plot. The top-five (bottom-five) banks with the highest (lowest) syndicate concentration are identified based on the average rank of bank-level syndicate concentration. The grayscale of the shaded horizontal bars indicates the frequency of the bank scoring a certain syndicate concentration rank.



Fig. 2. **Aggregate Syndicate Concentration and Financial Sector Risk**

Figure 2 plots the aggregate syndicate concentration from January 1991 to March 2020, as well as the financial sector risk measured by CATFIN as in [Allen et al. \(2012\)](#). Specifically, to mitigate the effect of loan size on syndicate concentration, we regress the aggregate syndicate concentration on the total dollar amount of loans issued and use the residuals as the measure of aggregate syndicate concentration orthogonal to loan issuance. For the ease of comparison, all time series are the 6-month moving average, standardized using the sample mean and standard deviation.

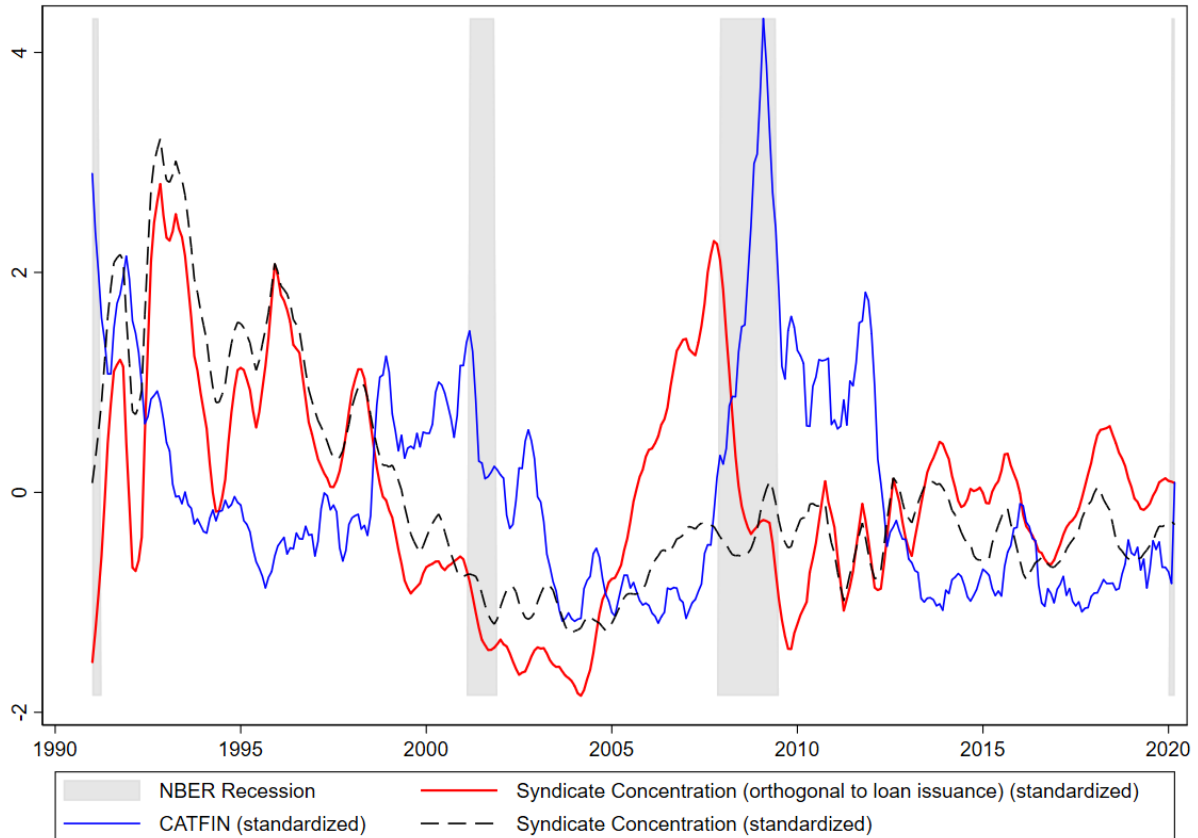


Table 1: **Summary Statistics**

Table 1 presents the summary statistics. The sample period is from January 1990 to March 2020. Definitions of the variables are provided in Table A1 in the Appendix. All continuous variables in the cross-sectional analysis are winsorized by year-quarter at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

	Observations	Mean	Std. Deviation	10 <sup>th</sup> Percentile	Median	90 <sup>th</sup> Percentile
<b><i>Cross-sectional variables</i></b>						
<i>SC</i>	3001	0.166	0.200	0.052	0.098	0.333
Rank <i>SC</i>	3001	5.247	2.826	1.000	5.000	9.000
Loan loss provision	3001	0.322	0.557	0.006	0.168	0.700
Default probability	2549	0.116	0.158	0.015	0.061	0.266
ln(IVOL)	2997	0.134	0.494	-0.423	0.050	0.801
#Lawsuits	3001	0.175	0.758	0.000	0.000	1.000
ln(#Lawsuits+1)	3001	0.094	0.297	0.000	0.000	0.693
ROE	3001	6.756	9.013	2.013	6.549	14.129
ROA	3001	0.628	0.807	0.212	0.632	1.259
Size	3001	17.248	1.798	15.097	17.063	19.709
Equity capital	3001	0.098	0.025	0.071	0.097	0.130
MTB	3001	1.779	0.906	0.849	1.598	2.893
Loan size	3001	0.592	0.170	0.371	0.633	0.762
Loan growth	3001	2.941	10.622	-1.614	1.540	6.628
Loan loss allowance	3001	0.895	0.462	0.420	0.852	1.455
Stock return	3001	0.029	0.158	-0.133	0.030	0.185
Liquidity	3001	0.222	0.132	0.095	0.187	0.409
<b><i>Aggregate-level variables</i></b>						
Aggregate <i>SC</i>	349	0.194	0.055	0.139	0.177	0.280
CATFIN	349	0.250	0.119	0.135	0.223	0.398
LLP growth	349	0.004	0.105	-0.097	-0.004	0.089
GPDI growth	349	0.004	0.010	-0.005	0.004	0.015
TFP growth	349	0.001	0.002	-0.002	0.001	0.003
GDP growth	349	0.004	0.003	0.001	0.004	0.006
INDP growth	349	0.001	0.007	-0.005	0.002	0.008
CFNAI	349	-0.069	0.535	-0.580	0.010	0.430
ADS Index	349	-0.208	1.488	-0.715	-0.051	0.476
Recession	349	0.089	0.285	0.000	0.000	0.000
Syndicated loan issuance	349	13.492	0.608	12.583	13.648	14.061
Credit tightening	349	0.034	0.211	-0.181	-0.032	0.372
Default spread	349	0.948	0.389	0.632	0.874	1.320
Term spread	349	1.752	1.145	0.169	1.850	3.348
Relative short-term interest rate	349	-0.101	0.715	-1.165	-0.012	0.784
Financial sector return	349	0.013	0.054	-0.051	0.019	0.069
Financial sector volatility	349	4.950	2.133	2.638	4.848	7.340
Financial sector skewness	349	4.345	5.974	0.620	2.362	10.137
Financial sector average beta	349	0.721	0.294	0.477	0.738	0.858
Market return	349	0.004	0.041	-0.050	0.009	0.054
Market volatility	349	0.044	0.029	0.022	0.037	0.073
Correlation in financial sector	349	0.256	0.083	0.138	0.254	0.375
Average financial firm size	349	14.665	0.742	13.389	14.760	15.634
Aggregated financial sector leverage	349	0.608	0.110	0.472	0.619	0.743

Table 2: **Predicting Bank-Specific Risks**

Table 2 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A. Dependent variable (t+h): Loan loss provision**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.019**	0.019**	0.020**	0.022**	0.022***	0.022***	0.023***	0.025***	0.025***	0.024***	0.025***	0.025***
	(2.380)	(2.360)	(2.396)	(2.601)	(2.705)	(2.847)	(2.981)	(3.219)	(3.179)	(3.076)	(2.984)	(3.031)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.521	0.530	0.535	0.539	0.543	0.552	0.563	0.566	0.564	0.561	0.556	0.556
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.017***	0.017***	0.017***	0.018***	0.018***	0.018***	0.019***	0.021***	0.021***	0.021***	0.021***	0.021***
	(4.048)	(3.535)	(3.181)	(3.171)	(3.064)	(3.214)	(3.270)	(3.460)	(3.606)	(3.583)	(3.572)	(3.624)
Size	0.038***	0.042***	0.048***	0.054***	0.060***	0.063***	0.067***	0.072***	0.074***	0.072***	0.071***	0.070***
	(4.733)	(5.023)	(5.723)	(6.377)	(6.862)	(7.142)	(7.243)	(7.173)	(7.146)	(6.949)	(6.436)	(6.216)
Equity capital	-0.094	-0.258	-0.218	0.087	-0.057	-0.157	-0.079	0.523	1.033	1.282	1.785	2.042
	(-0.139)	(-0.398)	(-0.338)	(0.129)	(-0.089)	(-0.245)	(-0.120)	(0.746)	(1.244)	(1.171)	(1.308)	(1.389)
ROA	-0.066	-0.042	-0.047	-0.062	-0.070***	-0.105***	-0.132***	-0.159***	-0.109***	-0.068***	-0.019	0.002
	(-1.410)	(-1.053)	(-1.309)	(-1.495)	(-5.011)	(-3.765)	(-3.483)	(-4.004)	(-3.129)	(-2.762)	(-1.526)	(0.214)
MTB	-0.032	-0.036*	-0.034*	-0.034*	-0.035*	-0.023	-0.015	-0.006	-0.014	-0.018	-0.026	-0.028
	(-1.632)	(-1.908)	(-1.825)	(-1.735)	(-1.789)	(-1.080)	(-0.656)	(-0.253)	(-0.595)	(-0.801)	(-1.230)	(-1.340)
Loan size	-0.374***	-0.266*	-0.115	0.024	0.188	0.298*	0.391**	0.426**	0.429**	0.397**	0.365*	0.345
	(-2.877)	(-1.991)	(-0.857)	(0.170)	(1.161)	(1.699)	(2.190)	(2.414)	(2.422)	(2.086)	(1.726)	(1.558)
Loan growth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001***	-0.000	-0.000	-0.000	-0.001***	-0.001*	-0.000
	(-0.900)	(-1.610)	(-1.202)	(-1.131)	(-1.220)	(-3.548)	(-1.321)	(-0.318)	(-0.669)	(-3.686)	(-1.835)	(-0.603)
Loan loss allowance	0.430***	0.359***	0.263***	0.169***	0.075*	0.025	-0.025	-0.058	-0.081*	-0.086*	-0.089*	-0.096**
	(7.563)	(6.500)	(5.066)	(3.706)	(1.687)	(0.511)	(-0.531)	(-1.275)	(-1.765)	(-1.888)	(-1.891)	(-2.077)
Stock return	0.064	-0.110	-0.190**	-0.121	-0.066	-0.304***	-0.174***	-0.207***	-0.101	-0.212**	-0.138*	-0.070
	(0.870)	(-0.850)	(-2.010)	(-1.282)	(-1.257)	(-5.156)	(-2.975)	(-4.609)	(-1.553)	(-2.211)	(-2.001)	(-1.444)
Liquidity	-0.189	-0.231	-0.269*	-0.302*	-0.300*	-0.296*	-0.285*	-0.275*	-0.284*	-0.338**	-0.356**	-0.378**
	(-1.401)	(-1.666)	(-1.942)	(-2.005)	(-1.950)	(-1.865)	(-1.820)	(-1.770)	(-1.798)	(-2.038)	(-2.033)	(-2.081)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.642	0.632	0.625	0.622	0.622	0.643	0.661	0.672	0.645	0.633	0.622	0.620



Table 2: Continued

## Panel B. Dependent variable (t+h): Default probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	0.006*** (3.336)	0.006*** (3.569)	0.006*** (3.493)	0.006*** (3.517)	0.006*** (3.680)	0.007*** (3.738)	0.007*** (3.959)	0.007*** (3.940)	0.007*** (4.004)	0.007*** (3.932)	0.007*** (3.572)	0.006*** (3.176)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2298	2229	2198	2159	2120	2080	2041	2003	1966	1928
Adjusted $R^2$	0.673	0.683	0.690	0.701	0.707	0.708	0.709	0.709	0.711	0.707	0.700	0.691
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	0.003** (2.155)	0.003** (2.504)	0.003** (2.594)	0.004*** (2.920)	0.004*** (3.148)	0.005*** (3.335)	0.005*** (3.672)	0.005*** (3.626)	0.005*** (3.673)	0.005*** (3.545)	0.004*** (3.079)	0.004** (2.569)
Size	-0.001 (-0.310)	0.001 (0.183)	0.002 (0.580)	0.003 (0.881)	0.004 (0.989)	0.005 (1.225)	0.006 (1.365)	0.006 (1.409)	0.007 (1.533)	0.007 (1.658)	0.008* (1.762)	0.008* (1.719)
Equity capital	-0.305 (-1.224)	-0.253 (-1.038)	-0.175 (-0.724)	-0.119 (-0.466)	-0.173 (-0.667)	-0.205 (-0.752)	-0.251 (-0.860)	-0.274 (-0.908)	-0.258 (-0.874)	-0.253 (-0.837)	-0.291 (-0.916)	-0.345 (-1.038)
ROA	-0.024 (-1.471)	-0.023 (-1.441)	-0.021 (-1.385)	-0.020 (-1.432)	-0.021 (-1.560)	-0.021 (-1.672)	-0.018 (-1.633)	-0.015 (-1.585)	-0.011 (-1.354)	-0.009 (-1.163)	-0.007 (-1.163)	-0.007 (-1.148)
MTB	-0.017* (-1.957)	-0.017* (-1.991)	-0.016** (-2.093)	-0.013* (-1.852)	-0.011 (-1.536)	-0.010 (-1.582)	-0.012* (-1.782)	-0.011* (-1.708)	-0.012* (-1.755)	-0.012* (-1.741)	-0.013* (-1.732)	-0.013* (-1.757)
Loan size	-0.191*** (-3.341)	-0.174*** (-3.064)	-0.158*** (-2.727)	-0.141** (-2.408)	-0.114** (-2.019)	-0.081 (-1.404)	-0.054 (-0.892)	-0.035 (-0.558)	-0.018 (-0.273)	-0.002 (-0.031)	0.018 (0.248)	0.035 (0.487)
Loan growth	-0.000 (-0.688)	0.000 (0.234)	0.000 (0.160)	-0.000 (-0.025)	0.000 (0.744)	-0.000 (-1.001)	-0.000 (-0.971)	-0.000 (-0.298)	-0.000 (-0.545)	-0.000 (-0.546)	0.000 (0.170)	-0.000 (-0.413)
Loan loss allowance	0.091*** (5.544)	0.080*** (5.424)	0.066*** (5.199)	0.053*** (4.876)	0.038*** (4.146)	0.022** (2.595)	0.011 (1.267)	0.002 (0.239)	-0.007 (-0.888)	-0.018* (-1.944)	-0.028*** (-2.862)	-0.035*** (-3.380)
Stock return	-0.012 (-0.610)	-0.035 (-1.566)	-0.026 (-0.911)	-0.055** (-2.070)	-0.084*** (-4.370)	-0.056** (-2.476)	-0.039* (-1.911)	-0.066*** (-2.841)	-0.058*** (-3.372)	-0.036** (-2.354)	-0.036** (-2.142)	-0.033** (-2.085)
Liquidity	-0.154*** (-3.660)	-0.151*** (-3.614)	-0.158*** (-3.690)	-0.162*** (-3.710)	-0.166*** (-3.885)	-0.166*** (-3.895)	-0.158*** (-3.697)	-0.159*** (-3.591)	-0.161*** (-3.473)	-0.169*** (-3.472)	-0.173*** (-3.370)	-0.174*** (-3.277)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2298	2229	2198	2159	2120	2080	2041	2003	1966	1928
Adjusted $R^2$	0.759	0.762	0.757	0.761	0.761	0.754	0.748	0.745	0.743	0.737	0.732	0.724

Table 2: Continued

## Panel C. Dependent variable (t+h): ln(IVOL)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	0.021*** (3.405)	0.019*** (3.226)	0.019*** (3.315)	0.020*** (3.326)	0.021*** (3.391)	0.022*** (3.406)	0.022*** (3.493)	0.022*** (3.505)	0.023*** (3.869)	0.022*** (3.797)	0.019*** (3.329)	0.018*** (3.210)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2793	2716	2686	2645	2603	2558	2517	2478	2442	2402
Adjusted <i>R</i> <sup>2</sup>	0.609	0.613	0.624	0.631	0.632	0.633	0.637	0.642	0.647	0.649	0.649	0.656
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	0.008 (1.426)	0.007 (1.221)	0.008 (1.551)	0.010* (1.879)	0.011** (2.060)	0.012** (2.255)	0.013** (2.461)	0.013** (2.500)	0.014*** (2.971)	0.013*** (2.930)	0.010** (2.354)	0.009** (2.063)
Size	-0.083*** (-7.256)	-0.080*** (-7.047)	-0.075*** (-6.816)	-0.072*** (-6.607)	-0.070*** (-6.421)	-0.067*** (-6.105)	-0.063*** (-5.630)	-0.060*** (-5.237)	-0.057*** (-5.097)	-0.056*** (-4.949)	-0.054*** (-4.816)	-0.052*** (-4.568)
Equity capital	0.030 (0.047)	0.139 (0.215)	0.425 (0.657)	0.403 (0.593)	0.269 (0.384)	0.212 (0.290)	0.098 (0.131)	0.145 (0.193)	0.182 (0.246)	-0.041 (-0.055)	-0.280 (-0.374)	-0.428 (-0.555)
ROA	-0.039 (-1.352)	-0.041 (-1.381)	-0.035 (-1.377)	-0.034 (-1.300)	-0.038 (-1.497)	-0.038 (-1.462)	-0.032 (-1.435)	-0.032 (-1.536)	-0.032 (-1.597)	-0.028 (-1.636)	-0.025 (-1.571)	-0.022 (-1.520)
MTB	-0.038 (-1.649)	-0.035 (-1.643)	-0.031 (-1.495)	-0.029 (-1.385)	-0.026 (-1.275)	-0.021 (-1.061)	-0.021 (-1.048)	-0.017 (-0.837)	-0.014 (-0.679)	-0.019 (-0.906)	-0.023 (-1.123)	-0.028 (-1.320)
Loan size	-0.759*** (-4.707)	-0.726*** (-4.593)	-0.691*** (-4.384)	-0.632*** (-3.979)	-0.591*** (-3.620)	-0.544*** (-3.278)	-0.484*** (-2.820)	-0.463** (-2.631)	-0.426** (-2.387)	-0.367* (-1.989)	-0.278 (-1.479)	-0.198 (-0.985)
Loan growth	0.001 (0.993)	0.001 (1.210)	0.001 (1.108)	0.001 (1.288)	0.001** (2.162)	0.001 (1.621)	0.001 (1.351)	0.001* (1.710)	0.001 (1.324)	0.001* (1.841)	0.001** (2.186)	0.000 (0.218)
Loan loss allowance	0.199*** (3.574)	0.167*** (3.055)	0.150*** (2.845)	0.128** (2.527)	0.107** (2.213)	0.089* (1.996)	0.067 (1.599)	0.054 (1.291)	0.030 (0.758)	0.009 (0.230)	-0.013 (-0.311)	-0.040 (-1.031)
Stock return	-0.126*** (-2.895)	-0.095** (-2.157)	-0.124** (-2.452)	-0.027 (-0.391)	-0.052 (-0.745)	-0.099** (-2.171)	-0.084 (-1.645)	-0.112** (-2.115)	0.019 (0.395)	-0.026 (-0.651)	0.015 (0.356)	0.021 (0.508)
Liquidity	-0.460** (-2.522)	-0.502*** (-2.933)	-0.479*** (-2.804)	-0.451** (-2.666)	-0.459** (-2.668)	-0.441** (-2.487)	-0.407** (-2.218)	-0.406** (-2.146)	-0.429** (-2.283)	-0.426** (-2.212)	-0.390** (-2.219)	-0.375** (-2.189)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2793	2716	2686	2645	2603	2558	2517	2478	2442	2402
Adjusted <i>R</i> <sup>2</sup>	0.681	0.680	0.683	0.685	0.683	0.680	0.678	0.679	0.682	0.683	0.683	0.689

Table 2: Continued

Panel D. Dependent variable (t+h):  $\ln(\#\text{Lawsuits} + 1)$ 

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.005	0.006	0.007	0.006	0.007	0.008	0.007	0.006	0.006	0.008	0.008	0.009
	(0.666)	(0.737)	(0.773)	(0.765)	(0.820)	(0.882)	(0.773)	(0.678)	(0.726)	(0.904)	(0.927)	(0.988)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.052	0.050	0.049	0.046	0.046	0.050	0.048	0.048	0.047	0.047	0.048	0.048
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.020***	0.020**	0.020***	0.019***	0.019***	0.020***	0.019***	0.018***	0.018***	0.020***	0.020***	0.019***
	(2.684)	(2.664)	(2.699)	(2.766)	(2.806)	(2.804)	(2.758)	(2.690)	(2.809)	(3.149)	(3.063)	(3.312)
Size	0.075***	0.075***	0.074***	0.074***	0.076***	0.078***	0.079***	0.079***	0.081***	0.082***	0.083***	0.083***
	(5.129)	(5.135)	(5.277)	(5.304)	(5.084)	(5.019)	(5.065)	(4.917)	(4.851)	(4.989)	(4.945)	(4.962)
Equity capital	0.000	0.011	0.051	-0.097	-0.064	-0.023	-0.086	0.056	0.156	0.129	0.032	-0.024
	(0.001)	(0.029)	(0.131)	(-0.246)	(-0.169)	(-0.060)	(-0.223)	(0.153)	(0.434)	(0.346)	(0.082)	(-0.055)
ROA	0.002	0.007	0.005	0.002	-0.003	0.002	0.003	0.005	0.007	0.001	-0.002	0.002
	(0.199)	(1.234)	(0.816)	(0.319)	(-0.472)	(0.364)	(0.431)	(0.637)	(0.814)	(0.121)	(-0.262)	(0.271)
MTB	-0.014	-0.011	-0.010	-0.007	-0.006	-0.003	-0.004	-0.000	-0.000	-0.001	-0.001	0.001
	(-1.320)	(-1.095)	(-0.955)	(-0.603)	(-0.508)	(-0.276)	(-0.287)	(-0.027)	(-0.031)	(-0.060)	(-0.041)	(0.071)
Loan size	-0.349**	-0.357**	-0.346**	-0.342**	-0.339**	-0.340**	-0.331**	-0.352**	-0.353**	-0.331**	-0.319**	-0.296*
	(-2.327)	(-2.335)	(-2.234)	(-2.125)	(-2.128)	(-2.203)	(-2.186)	(-2.295)	(-2.276)	(-2.124)	(-2.092)	(-1.921)
Loan growth	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	0.001*	-0.000	-0.000	-0.001**	0.000	-0.000
	(-0.174)	(-0.861)	(-0.773)	(-0.546)	(-0.436)	(-1.078)	(1.873)	(-0.976)	(-0.222)	(-2.354)	(0.410)	(-0.622)
Loan loss allowance	0.008	0.004	-0.005	-0.007	-0.006	-0.013	-0.013	-0.011	-0.014	-0.018	-0.021	-0.032
	(0.306)	(0.142)	(-0.195)	(-0.240)	(-0.184)	(-0.420)	(-0.418)	(-0.324)	(-0.460)	(-0.557)	(-0.654)	(-1.071)
Stock return	0.009	-0.019	-0.044	-0.067	0.049	-0.011	-0.014	-0.071	0.131**	0.023	-0.049	0.056
	(0.245)	(-0.519)	(-1.223)	(-1.574)	(1.043)	(-0.259)	(-0.437)	(-1.549)	(2.336)	(0.649)	(-1.062)	(1.207)
Liquidity	-0.235**	-0.263**	-0.282**	-0.319**	-0.317**	-0.341***	-0.342***	-0.371***	-0.367***	-0.336***	-0.330***	-0.350***
	(-2.342)	(-2.428)	(-2.603)	(-2.591)	(-2.629)	(-2.875)	(-2.801)	(-3.054)	(-2.931)	(-2.715)	(-2.952)	(-2.884)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.301	0.300	0.298	0.295	0.294	0.299	0.300	0.299	0.300	0.299	0.301	0.297

Table 3: Predicting Bank Profitability

Table 3 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Dependent variable (t+h): ROE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	-0.256** (-2.067)	-0.262** (-2.162)	-0.282** (-2.131)	-0.320** (-2.185)	-0.334** (-2.157)	-0.383** (-2.172)	-0.386** (-2.071)	-0.416** (-2.056)	-0.453** (-2.064)	-0.464** (-2.013)	-0.483* (-1.997)	-0.480** (-2.021)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.248	0.241	0.230	0.222	0.223	0.226	0.224	0.221	0.222	0.221	0.219	0.214
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.001 (0.021)	-0.017 (-0.392)	-0.047 (-1.030)	-0.084* (-1.747)	-0.105** (-2.222)	-0.154** (-2.676)	-0.163** (-2.406)	-0.186** (-2.401)	-0.240** (-2.402)	-0.262** (-2.281)	-0.298** (-2.176)	-0.299** (-2.153)
Size	0.124** (2.404)	0.238* (1.694)	0.289 (1.264)	0.291 (1.058)	0.250 (0.927)	0.213 (0.832)	0.193 (0.788)	0.160 (0.671)	0.158 (0.638)	0.160 (0.611)	0.174 (0.611)	0.198 (0.644)
Equity capital	-66.760*** (-5.686)	-83.350*** (-3.094)	-103.954** (-2.372)	-118.588** (-2.314)	-117.917** (-2.251)	-113.200** (-2.315)	-103.068** (-2.321)	-99.739** (-2.383)	-92.822** (-2.366)	-86.263** (-2.397)	-79.112** (-2.451)	-73.634** (-2.531)
ROA	7.977*** (13.658)	4.811*** (20.087)	2.085*** (3.665)	0.774 (1.132)	0.692* (1.988)	0.901*** (3.849)	1.166*** (5.590)	1.479*** (5.553)	0.959*** (5.384)	0.619*** (2.973)	0.358 (1.153)	0.360 (0.827)
MTB	0.651*** (3.656)	1.172*** (4.626)	1.507*** (5.364)	1.624*** (4.734)	1.574*** (4.257)	1.472*** (4.275)	1.399*** (4.368)	1.269*** (4.190)	1.250*** (3.593)	1.199*** (3.206)	1.193*** (2.993)	1.144*** (2.893)
Loan size	0.622 (0.598)	3.229 (1.086)	5.242 (1.032)	6.146 (1.021)	5.273 (0.887)	4.456 (0.807)	3.256 (0.635)	2.232 (0.458)	1.274 (0.276)	0.770 (0.172)	0.193 (0.043)	-0.110 (-0.024)
Loan growth	0.006 (0.929)	0.013 (1.564)	0.028** (2.301)	0.030* (1.806)	0.027 (1.415)	0.000 (0.031)	0.001 (0.112)	-0.024 (-1.404)	-0.014 (-1.073)	-0.012 (-0.882)	0.007 (1.169)	0.007 (0.806)
Loan loss allowance	0.049 (0.116)	-0.338 (-0.418)	-0.243 (-0.214)	0.036 (0.029)	0.591 (0.514)	0.865 (0.824)	1.190 (1.199)	1.400 (1.414)	1.730* (1.844)	1.941** (2.160)	2.198** (2.533)	2.256** (2.485)
Stock return	0.265 (0.157)	5.949 (1.068)	4.744 (1.528)	2.767** (2.664)	1.035 (1.031)	2.588** (2.210)	1.787** (2.228)	2.780* (1.900)	1.179 (1.389)	0.341 (0.499)	0.028 (0.040)	-0.055 (-0.066)
Liquidity	1.136 (1.220)	3.153 (1.451)	5.353 (1.417)	6.732 (1.469)	6.767 (1.551)	6.319 (1.594)	5.740 (1.617)	4.824 (1.529)	4.467 (1.477)	4.583 (1.478)	4.543 (1.390)	4.791 (1.430)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.654	0.430	0.334	0.318	0.314	0.312	0.301	0.298	0.284	0.273	0.263	0.253

Table 3: Continued

## Panel B. Dependent variable (t+h): ROA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	-0.018*	-0.018**	-0.020*	-0.023**	-0.024**	-0.028**	-0.029*	-0.032*	-0.035*	-0.035*	-0.037*	-0.037*
	(-1.843)	(-2.009)	(-2.005)	(-2.097)	(-2.071)	(-2.103)	(-2.005)	(-1.972)	(-1.972)	(-1.898)	(-1.889)	(-1.908)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted <i>R</i> <sup>2</sup>	0.233	0.228	0.215	0.210	0.210	0.213	0.213	0.212	0.213	0.210	0.209	0.206
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank <i>SC</i>	-0.000	-0.002	-0.004	-0.007	-0.008*	-0.013**	-0.013**	-0.016**	-0.021**	-0.022**	-0.026**	-0.026**
	(-0.023)	(-0.456)	(-0.891)	(-1.485)	(-1.762)	(-2.304)	(-2.202)	(-2.187)	(-2.256)	(-2.142)	(-2.096)	(-2.072)
Size	0.009	0.019	0.024	0.023	0.018	0.014	0.012	0.008	0.007	0.007	0.007	0.009
	(1.247)	(1.165)	(0.964)	(0.782)	(0.648)	(0.517)	(0.465)	(0.320)	(0.269)	(0.256)	(0.249)	(0.288)
Equity capital	-1.191	-2.858	-4.862	-6.391	-6.392	-6.182	-5.597	-5.472	-4.894	-4.388	-4.065	-3.696
	(-0.887)	(-1.014)	(-1.120)	(-1.279)	(-1.249)	(-1.272)	(-1.247)	(-1.283)	(-1.195)	(-1.129)	(-1.128)	(-1.106)
ROA	0.717***	0.431***	0.203***	0.088	0.075*	0.092***	0.120***	0.153***	0.099***	0.065**	0.043	0.046
	(22.784)	(20.106)	(3.200)	(1.149)	(1.818)	(3.239)	(4.550)	(4.406)	(4.248)	(2.671)	(1.276)	(0.975)
MTB	0.064***	0.110***	0.141***	0.157***	0.155***	0.145***	0.138***	0.123***	0.123***	0.120***	0.118***	0.112***
	(4.635)	(4.068)	(4.342)	(3.964)	(3.664)	(3.589)	(3.673)	(3.460)	(3.194)	(2.996)	(2.837)	(2.745)
Loan size	0.118	0.356	0.520	0.597	0.508	0.434	0.342	0.246	0.145	0.096	0.049	0.016
	(0.801)	(1.064)	(1.018)	(0.997)	(0.866)	(0.788)	(0.661)	(0.500)	(0.304)	(0.204)	(0.103)	(0.034)
Loan growth	0.000	0.001	0.003**	0.004**	0.002	0.001	0.000	-0.002	-0.001	-0.000	0.001*	0.002*
	(0.904)	(1.673)	(2.661)	(2.164)	(1.389)	(0.466)	(0.371)	(-1.042)	(-0.697)	(-0.365)	(1.953)	(1.683)
Loan loss allowance	0.011	-0.022	0.001	0.033	0.088	0.118	0.149	0.175*	0.212**	0.235***	0.256***	0.265***
	(0.269)	(-0.275)	(0.006)	(0.282)	(0.837)	(1.234)	(1.663)	(1.965)	(2.519)	(2.882)	(3.260)	(3.338)
Stock return	0.037	0.503	0.379	0.224**	0.149*	0.262**	0.192**	0.296**	0.117	0.029	0.017	0.019
	(0.191)	(0.998)	(1.319)	(2.355)	(1.846)	(2.266)	(2.256)	(2.125)	(1.460)	(0.471)	(0.289)	(0.249)
Liquidity	0.156**	0.348	0.554	0.667	0.668	0.629*	0.588*	0.508*	0.475*	0.486	0.465	0.488
	(2.054)	(1.635)	(1.586)	(1.574)	(1.666)	(1.728)	(1.787)	(1.769)	(1.686)	(1.663)	(1.495)	(1.526)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted <i>R</i> <sup>2</sup>	0.630	0.390	0.287	0.268	0.264	0.266	0.263	0.265	0.251	0.241	0.236	0.230

Table 4: **Syndicate Concentration of Loans Arranged vs Loans Joined**

Table 4 reestimates the baseline models (Table 2 and 3) by replacing the bank-level *SC* rank with 1) *SC* based on loans lead-arranged by the bank and 2) *SC* based on loans joined by the bank (excluding lead-arranged ones). For simplicity, we report only the coefficients of the two syndicate concentration measures. Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed *t*-statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<i>Panel A: Bank-specific risks</i>												
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank <i>SC</i> loans arranged	-0.004 (-1.007)	-0.002 (-0.524)	-0.001 (-0.228)	-0.000 (-0.020)	0.002 (0.545)	0.002 (0.379)	0.002 (0.401)	0.001 (0.328)	0.001 (0.222)	-0.000 (-0.063)	0.001 (0.161)	-0.000 (-0.051)
Rank <i>SC</i> loans joined	0.015*** (4.211)	0.016*** (4.368)	0.016*** (3.749)	0.017*** (3.538)	0.018*** (3.549)	0.019*** (3.663)	0.019*** (3.639)	0.020*** (3.514)	0.021*** (3.519)	0.019*** (3.441)	0.018*** (3.412)	0.017*** (3.343)
<b>Dependent variable (t+h): Default probability</b>												
Rank <i>SC</i> loans arranged	-0.003** (-2.180)	-0.003** (-2.316)	-0.003** (-2.190)	-0.002* (-1.855)	-0.002 (-1.667)	-0.002 (-1.559)	-0.002 (-1.412)	-0.002 (-1.292)	-0.002 (-1.199)	-0.002 (-1.102)	-0.002 (-1.213)	-0.002 (-1.357)
Rank <i>SC</i> loans joined	0.003** (2.049)	0.003*** (2.953)	0.003*** (3.232)	0.004*** (3.507)	0.004*** (3.960)	0.005*** (4.085)	0.005*** (4.255)	0.005*** (4.081)	0.005*** (3.822)	0.004*** (3.324)	0.004*** (2.905)	0.004** (2.552)
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank <i>SC</i> loans arranged	0.001 (0.182)	0.002 (0.387)	0.002 (0.426)	0.003 (0.705)	0.003 (0.643)	0.003 (0.711)	0.003 (0.581)	0.002 (0.534)	0.004 (0.807)	0.003 (0.653)	0.003 (0.553)	0.004 (0.693)
Rank <i>SC</i> loans joined	0.009* (1.699)	0.009* (1.908)	0.010** (2.043)	0.011** (2.368)	0.010** (2.177)	0.011** (2.502)	0.015*** (3.374)	0.014*** (3.314)	0.016*** (3.880)	0.014*** (3.383)	0.009** (2.269)	0.011** (2.647)
<b>Dependent variable (t+h): ln(#Lawsuits+1)</b>												
Rank <i>SC</i> loans arranged	-0.003 (-0.854)	-0.004 (-1.237)	-0.004 (-1.341)	-0.005 (-1.318)	-0.006 (-1.594)	-0.007* (-1.732)	-0.007** (-2.288)	-0.008* (-2.009)	-0.009** (-2.119)	-0.011** (-2.150)	-0.009* (-1.900)	-0.008* (-1.986)
Rank <i>SC</i> loans joined	0.009* (1.925)	0.009** (2.007)	0.010** (2.510)	0.010*** (2.787)	0.010** (2.507)	0.010** (2.101)	0.010* (1.885)	0.009* (1.733)	0.009* (1.798)	0.010* (1.956)	0.010** (2.258)	0.010** (2.414)
<i>Panel B: Bank profitability</i>												
<b>Dependent variable (t+h): ROE</b>												
Rank <i>SC</i> loans arranged	-0.043 (-1.278)	-0.067 (-0.984)	-0.093 (-1.043)	-0.080 (-0.868)	-0.080 (-0.857)	-0.075 (-0.766)	-0.068 (-0.636)	-0.059 (-0.595)	-0.064 (-0.577)	-0.067 (-0.513)	-0.077 (-0.535)	-0.086 (-0.574)
Rank <i>SC</i> loans joined	-0.022 (-0.883)	-0.061 (-1.557)	-0.103** (-2.587)	-0.106** (-2.252)	-0.133*** (-3.100)	-0.193*** (-3.124)	-0.203*** (-2.721)	-0.240** (-2.465)	-0.264** (-2.567)	-0.267** (-2.461)	-0.281** (-2.350)	-0.268** (-2.315)
<b>Dependent variable (t+h): ROA</b>												
Rank <i>SC</i> loans arranged	-0.003 (-0.967)	-0.004 (-0.695)	-0.006 (-0.768)	-0.005 (-0.570)	-0.004 (-0.535)	-0.004 (-0.465)	-0.002 (-0.259)	-0.002 (-0.192)	-0.002 (-0.218)	-0.003 (-0.215)	-0.004 (-0.269)	-0.004 (-0.315)
Rank <i>SC</i> loans joined	-0.003* (-1.735)	-0.006* (-1.904)	-0.010** (-2.392)	-0.009* (-1.824)	-0.012** (-2.602)	-0.019*** (-2.806)	-0.018** (-2.587)	-0.023** (-2.248)	-0.025** (-2.439)	-0.025** (-2.322)	-0.025** (-2.226)	-0.024** (-2.149)

Table 5: **Impact of Syndicate Concentration on Bank Valuation**

Table 5 explores the relation between bank-level syndicate concentration and concurrent bank valuation measured by the market-to-book ratio and Tobin's Q. In all specifications, we use a contemporaneous model and add bank-level control variables progressively. We restrict to the sample where all control variables are available for the consistency of sample size. Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A: Dependent variable: MTB**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank $SC$	-0.043**	-0.050**	-0.046**	-0.042**	-0.038**	-0.038**	-0.029*
	(-2.182)	(-2.522)	(-2.439)	(-2.343)	(-2.150)	(-2.157)	(-1.744)
Size		-0.046	-0.055	-0.058*	-0.045	-0.043	-0.016
		(-1.455)	(-1.573)	(-1.798)	(-1.253)	(-1.199)	(-0.441)
Equity capital			-6.240**	-6.865**	-6.588**	-6.621**	-6.555**
			(-2.023)	(-2.237)	(-2.137)	(-2.150)	(-2.073)
ROA				0.202	0.186	0.186	0.175
				(1.393)	(1.330)	(1.385)	(1.347)
Loan size					0.256	0.292	0.944
					(0.487)	(0.554)	(1.519)
Loan growth					0.001	0.000	0.001
					(0.658)	(0.338)	(0.551)
Loan loss allowance					-0.342**	-0.360**	-0.324**
					(-2.130)	(-2.201)	(-2.050)
Stock return						0.980***	0.971***
						(6.862)	(6.988)
Liquidity							1.358
							(1.572)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3001	3001	3001	3001	3001	3001	3001
Adjusted $R^2$	0.404	0.411	0.432	0.456	0.470	0.484	0.499

**Panel B: Dependent variable: Tobin's Q**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank $SC$	-0.003*	-0.004**	-0.004**	-0.004**	-0.003**	-0.003**	-0.002
	(-1.788)	(-2.529)	(-2.418)	(-2.311)	(-2.102)	(-2.112)	(-1.453)
Control(s) as in Panel A	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3001	3001	3001	3001	3001	3001	3001
Adjusted $R^2$	0.315	0.335	0.335	0.372	0.380	0.394	0.422

Table 6: **Heterogeneity Test: Bank Opacity**

Table 6 presents the  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration interacting with bank opacity. In all specifications, we include the bank-level syndicate concentration (Rank SC), opacity, and control variables measured at time  $t$ . For brevity, we report only the coefficient estimates of the interaction terms. Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<i>Panel A: Bank-Specific Risks</i>												
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC \times$ Opacity	0.066*** (3.567)	0.064*** (3.219)	0.060*** (2.854)	0.065*** (3.234)	0.059*** (3.141)	0.049*** (2.794)	0.044*** (2.898)	0.034** (2.028)	0.033** (2.236)	0.023 (1.558)	0.026 (1.493)	0.026 (1.511)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2877	2808	2758	2683	2654	2615	2576	2532	2493	2457	2423	2385
Adjusted $R^2$	0.649	0.637	0.629	0.627	0.626	0.646	0.663	0.674	0.646	0.633	0.623	0.621
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC \times$ Opacity	0.021*** (4.397)	0.021*** (4.315)	0.020*** (3.746)	0.020*** (3.442)	0.020*** (3.518)	0.021*** (3.433)	0.022*** (3.543)	0.019*** (3.523)	0.018*** (3.612)	0.016*** (3.222)	0.017*** (3.415)	0.014** (2.682)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2422	2337	2265	2195	2162	2122	2084	2043	2004	1967	1930	1892
Adjusted $R^2$	0.777	0.780	0.775	0.778	0.778	0.771	0.763	0.759	0.756	0.749	0.743	0.736
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC \times$ Opacity	0.019 (1.527)	0.024* (1.831)	0.024* (1.724)	0.031** (2.167)	0.029** (2.075)	0.036** (2.416)	0.040*** (2.716)	0.038** (2.535)	0.036** (2.341)	0.042** (2.617)	0.040** (2.416)	0.037** (2.134)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2877	2808	2757	2680	2649	2608	2567	2521	2480	2442	2406	2366
Adjusted $R^2$	0.706	0.699	0.701	0.700	0.696	0.690	0.686	0.688	0.689	0.689	0.688	0.695
<b>Dependent variable (t+h): ln(#Lawsuits+1)</b>												
Rank $SC \times$ Opacity	0.014 (0.904)	0.019 (1.231)	0.018 (1.202)	0.017 (1.237)	0.024 (1.543)	0.025* (1.692)	0.020 (1.344)	0.018 (1.314)	0.031* (1.934)	0.038** (2.259)	0.033* (1.898)	0.025 (1.374)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2877	2808	2758	2683	2654	2615	2576	2532	2493	2457	2423	2385
Adjusted $R^2$	0.303	0.303	0.300	0.297	0.297	0.302	0.302	0.301	0.304	0.306	0.306	0.300



Table 6: Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<i>Panel B: Bank profitability</i>												
<b>Dependent variable (t+h): ROE</b>												
Rank $SC \times$ Opacity	-0.131 (-1.116)	-0.372** (-2.466)	-0.528** (-2.553)	-0.687*** (-3.185)	-0.528** (-2.461)	-0.544*** (-3.064)	-0.164 (-0.726)	-0.132 (-0.467)	-0.042 (-0.105)	-0.150 (-0.485)	-0.078 (-0.257)	-0.110 (-0.370)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2877	2808	2758	2683	2654	2615	2576	2532	2493	2457	2423	2385
Adjusted $R^2$	0.652	0.429	0.336	0.322	0.317	0.315	0.302	0.299	0.284	0.273	0.264	0.254
<b>Dependent variable (t+h): ROA</b>												
Rank $SC \times$ Opacity	-0.022* (-1.853)	-0.045*** (-2.978)	-0.059*** (-2.895)	-0.075*** (-3.462)	-0.065*** (-3.125)	-0.064*** (-3.436)	-0.027 (-1.205)	-0.015 (-0.527)	-0.011 (-0.291)	-0.019 (-0.649)	-0.011 (-0.366)	-0.001 (-0.036)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2877	2808	2758	2683	2654	2615	2576	2532	2493	2457	2423	2385
Adjusted $R^2$	0.629	0.391	0.292	0.275	0.270	0.272	0.267	0.268	0.254	0.244	0.239	0.232

Table 7: **Heterogeneity Test: Bank Complexity**

Table 7 presents the  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration interacting with bank complexity. In all specifications, we include the bank-level syndicate concentration (Rank SC), complexity, and control variables measured at time  $t$ . For brevity, we report only the coefficient estimates of the interaction terms. Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<i>Panel A: Bank-specific risks</i>												
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank SC × Complexity	-0.001 (-0.022)	0.128* (1.856)	0.127* (1.827)	0.211** (2.387)	0.185** (2.267)	0.285*** (3.426)	0.339*** (4.123)	0.378*** (3.814)	0.353*** (3.546)	0.417*** (3.929)	0.447*** (4.113)	0.445*** (4.043)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.645	0.635	0.627	0.625	0.624	0.646	0.666	0.678	0.650	0.640	0.629	0.627
<b>Dependent variable (t+h): Default probability</b>												
Rank SC × Complexity	0.022 (1.062)	0.031 (1.469)	0.049** (2.367)	0.066*** (2.754)	0.072*** (2.826)	0.087*** (3.355)	0.096*** (3.435)	0.113*** (3.505)	0.111*** (3.423)	0.125*** (3.506)	0.125*** (3.245)	0.126*** (2.895)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2298	2229	2198	2159	2120	2080	2041	2003	1966	1928
Adjusted $R^2$	0.759	0.763	0.759	0.763	0.764	0.759	0.753	0.752	0.750	0.746	0.740	0.732
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank SC × Complexity	0.051 (0.797)	0.128* (1.883)	0.118* (1.776)	0.143* (1.904)	0.136* (1.698)	0.193** (2.195)	0.205** (2.344)	0.241** (2.662)	0.183** (2.131)	0.199** (2.081)	0.128 (1.396)	0.196* (1.947)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2793	2716	2686	2645	2603	2558	2517	2478	2442	2402
Adjusted $R^2$	0.681	0.681	0.683	0.686	0.684	0.682	0.680	0.683	0.684	0.686	0.685	0.691
<b>Dependent variable (t+h): ln(#Lawsuits+1)</b>												
Rank SC × Complexity	-0.036 (-0.700)	-0.034 (-0.509)	-0.014 (-0.235)	-0.001 (-0.015)	0.011 (0.222)	0.013 (0.191)	-0.023 (-0.392)	-0.006 (-0.138)	0.027 (0.445)	0.025 (0.402)	0.068 (0.965)	0.047 (0.655)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.303	0.301	0.300	0.299	0.300	0.305	0.305	0.307	0.310	0.308	0.308	0.305

Table 7: **Continued**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<i>Panel B: Bank profitability</i>												
<b>Dependent variable (t+h): ROE</b>												
Rank $SC \times$ Complexity	-0.251 (-0.612)	-1.078 (-0.947)	-2.194 (-1.065)	-4.249 (-1.456)	-4.485 (-1.365)	-6.487* (-1.703)	-6.902 (-1.654)	-7.579* (-1.774)	-7.873* (-1.731)	-8.651* (-1.774)	-9.149* (-1.971)	-9.164** (-2.450)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.654	0.430	0.334	0.320	0.317	0.318	0.307	0.305	0.292	0.283	0.275	0.265
<b>Dependent variable (t+h): ROA</b>												
Rank $SC \times$ Complexity	-0.023 (-0.554)	-0.069 (-0.736)	-0.194 (-1.098)	-0.381 (-1.511)	-0.440 (-1.474)	-0.581* (-1.727)	-0.660* (-1.754)	-0.709* (-1.876)	-0.777* (-1.885)	-0.795* (-1.818)	-0.852** (-2.125)	-0.840** (-2.577)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.629	0.390	0.288	0.270	0.267	0.271	0.270	0.273	0.261	0.251	0.248	0.242

Table 8: **Impact of Stress Test Failure on Syndicate Concentration**

Table 8 examines the impact of stress test failure on bank-level syndicate concentration as measured at each year's end. The difference-in-differences (DiD) estimations are conducted using the CCAR test results from 2012 to 2019, where the sample consists of all banks that have ever participated in any of the CCAR tests. The treatment events are the banks' first CCAR test failures. In each cohort, Treat equals 1 for the bank that failed the CCAR test and equals 0 for banks that have never or not yet failed any CCAR test by that year, with a five-year event window from two years before the failure of the treated bank until two years afterwards. Further, Post equals 1 (0) for all years after (before) the treatment year in each cohort, and time indicators  $d_j$  equals 1 for the year that is  $j$  year(s) relative to the treatment year. Standard errors are clustered at the bank level or at both the bank and year levels. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<b>Panel A. Standard DiD</b>				
	(1)	(2)	(3)	(4)
Treat $\times$ Post	-0.047** (-2.358)	-0.047* (-2.084)	-0.055** (-2.498)	-0.055** (-2.432)
Treat	0.011 (0.991)	0.011 (0.890)		
Post	0.001 (0.912)	0.001 (0.669)		
<i>Lagged bank controls</i>				
Size	0.033 (0.408)	0.033 (0.445)	0.006 (0.070)	0.006 (0.084)
Equity capital	1.687 (1.420)	1.687 (1.475)	1.355 (1.155)	1.355 (1.203)
ROA	-0.057 (-1.106)	-0.057 (-1.013)	-0.066 (-1.212)	-0.066 (-1.232)
MTB	0.064 (1.376)	0.064 (1.287)	0.057 (1.206)	0.057 (1.189)
Loan size	0.079 (0.597)	0.079 (0.828)	0.053 (0.360)	0.053 (0.390)
Loan growth	0.002*** (4.665)	0.002** (3.103)	0.002*** (4.878)	0.002*** (3.562)
Loan loss allowances	-0.000 (-0.013)	-0.000 (-0.010)	-0.012 (-0.505)	-0.012 (-0.438)
Quarterly return	-0.000 (-1.540)	-0.000 (-0.744)	-0.000 (-0.592)	-0.000 (-0.489)
Liquidity	0.015 (0.299)	0.015 (0.304)	-0.019 (-0.360)	-0.019 (-0.406)
Bank Fixed Effect	Yes	Yes	No	No
Year Fixed Effect	Yes	Yes	No	No
Cohort-Bank Fixed Effect	No	No	Yes	Yes
Cohort-Year Fixed Effect	No	No	Yes	Yes
Standard Error Clustering	Bank	Bank & Year	Bank	Bank & Year
Observations	635	635	631	631
Adjusted $R^2$	0.671	0.671	0.567	0.567

Table 8: **Continued**

<b>Panel B. Dynamic DiD</b>				
	(1)	(2)	(3)	(4)
Treat $\times d_{-1}$	-0.026 (-0.905)	-0.026 (-0.725)	-0.028 (-0.896)	-0.028 (-0.696)
Treat $\times d_0$	0.005 (0.398)	0.005 (0.166)	0.004 (0.298)	0.004 (0.147)
Treat $\times d_1$	-0.075*** (-3.579)	-0.075*** (-5.048)	-0.082*** (-4.240)	-0.082*** (-5.008)
Treat $\times d_2$	-0.052*** (-3.505)	-0.052** (-2.463)	-0.061*** (-4.022)	-0.061** (-3.405)
Lagged Bank Controls	Yes	Yes	Yes	Yes
Treatment and Post Dummies	Yes	Yes	No	No
Bank Fixed Effect	Yes	Yes	No	No
Year Fixed Effect	Yes	Yes	No	No
Cohort-Bank Fixed Effect	No	No	Yes	Yes
Cohort-Year Fixed Effect	No	No	Yes	Yes
Standard Error Clustering	Bank	Bank & Year	Bank	Bank & Year
Observations	835	835	831	831
Adjusted $R^2$	0.681	0.681	0.608	0.608

<b>Panel C. Standard DiD: <i>SC</i> based on loans arranged and loans joined</b>				
	(1)	(2)	(3)	(4)
	Loans arranged	Loans arranged	Loans joined	Loans joined
Treat $\times$ Post	0.139 (1.604)	0.139 (1.323)	-0.042** (-2.315)	-0.042** (-2.772)
Size	0.412 (1.157)	0.412 (1.252)	0.027 (0.671)	0.027 (0.664)
Equity capital	4.761 (1.099)	4.761 (1.540)	0.204 (0.397)	0.204 (0.445)
ROA	0.021 (0.163)	0.021 (0.137)	-0.021 (-1.256)	-0.021 (-1.261)
MTB	-0.097 (-0.433)	-0.097 (-0.468)	0.009 (0.583)	0.009 (0.574)
Loan size	0.444 (0.552)	0.444 (0.622)	-0.064 (-0.850)	-0.064 (-1.029)
Loan growth	-0.005 (-1.712)	-0.005 (-1.756)	0.002*** (4.261)	0.002*** (3.705)
Loan loss allowances	-0.278 (-1.411)	-0.278 (-1.432)	0.016 (1.199)	0.016 (1.124)
Quarterly return	0.001 (0.425)	0.001 (0.450)	0.000 (0.073)	0.000 (0.072)
Liquidity	-0.156 (-0.728)	-0.156 (-0.721)	-0.029 (-0.701)	-0.029 (-0.756)
Bank Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Cohort-Bank Fixed Effect	Bank	Bank & Year	Bank	Bank & Year
Cohort-Year Fixed Effect	564	564	631	631
Standard Error Clustering	0.471	0.471	0.577	0.577

Table 9: **Aggregated Syndicate Concentration and Financial Sector Risks**

Table 9 examines the predictive power of monthly aggregate syndicate concentration for financial sector risks from January 1991 to March 2020 (time  $t$ ). In all specifications, we control for aggregate syndicated loan issuance, credit tightening, all control variables in Allen et al. (2012) and 12 lags of the dependent variable. For brevity, we omit the coefficient estimates of the 12 lags of the dependent variable in Panel A and B. In Panel C, we further include investor sentiment as in Baker and Wurgler (2006) as a control variable and omit the coefficient estimates of the other control variables. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are the Newey-West  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A: Dependent variable (t+h): CATFIN**

	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
Aggregate $SC$	0.397** (2.464)	0.362* (1.816)	0.407** (2.044)	0.308 (1.370)	0.287 (1.160)	0.299 (1.252)
Syndicated loan issuance	0.027 (1.457)	0.054** (2.104)	0.069** (2.389)	0.070** (2.149)	0.083** (2.284)	0.087** (2.284)
Credit tightening	0.097 (1.443)	0.085 (0.943)	0.125 (1.233)	0.098 (0.873)	0.107 (0.912)	0.101 (0.939)
Default spread	-0.024 (-1.237)	-0.045* (-1.713)	-0.069** (-2.084)	-0.079** (-2.112)	-0.075** (-2.072)	-0.057* (-1.677)
Term spread	0.002 (0.376)	0.008 (0.949)	0.010 (1.044)	0.008 (0.726)	0.004 (0.385)	-0.001 (-0.051)
Relative short-term interest rate	0.000 (0.028)	-0.016 (-1.299)	-0.017 (-1.249)	-0.026* (-1.701)	-0.033** (-2.088)	-0.042** (-2.288)
Financial sector return	-0.223 (-1.444)	0.236 (1.140)	0.177 (0.961)	-0.115 (-0.470)	0.114 (0.520)	0.051 (0.287)
Financial sector volatility	-0.002 (-0.264)	0.012 (1.326)	0.009 (0.864)	0.013 (1.134)	0.007 (0.709)	0.004 (0.414)
Financial sector skewness	-0.001* (-1.767)	-0.001 (-1.538)	-0.002** (-2.196)	-0.000 (-0.003)	0.000 (0.190)	-0.002* (-1.791)
Financial sector average beta	-0.017* (-1.677)	-0.011 (-1.245)	0.002 (0.154)	-0.005 (-0.575)	-0.016 (-1.404)	-0.015 (-1.474)
Market return	-0.067 (-0.308)	-0.315 (-1.196)	-0.339 (-1.356)	-0.059 (-0.188)	-0.290 (-0.995)	0.098 (0.441)
Market volatility	0.108 (0.290)	-0.379 (-0.937)	-0.512 (-0.941)	-0.624 (-1.149)	-1.226** (-2.589)	-1.334** (-2.569)
Correlation in financial sector	0.111 (1.077)	0.179 (1.200)	0.209 (1.322)	0.147 (0.879)	0.201 (1.194)	0.213 (1.284)
Average financial firm size	0.001 (0.075)	0.011 (0.495)	0.001 (0.046)	0.006 (0.250)	-0.011 (-0.459)	-0.019 (-0.689)
Aggregated financial sector leverage	0.012 (0.312)	0.027 (0.708)	0.009 (0.268)	-0.008 (-0.191)	0.034 (0.969)	0.009 (0.223)
12 lags of the dependent	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349	349	349	349	349	349
Adjusted $R^2$	0.570	0.488	0.458	0.411	0.419	0.423

Table 9: **Continued****Panel B: Dependent variable (t+h): LLP growth**

	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
Aggregate $SC$	0.341** (2.206)	0.446*** (2.933)	0.503*** (2.851)	0.411* (1.924)	0.332 (1.617)	0.250 (1.187)
Syndicated loan issuance	0.017 (0.966)	0.032 (1.226)	0.031 (0.991)	0.023 (0.600)	0.007 (0.154)	0.014 (0.297)
Credit tightening	0.042 (1.038)	0.060 (1.234)	0.050 (0.785)	0.046 (0.553)	0.015 (0.151)	-0.002 (-0.015)
Default spread	-0.022 (-1.295)	-0.017 (-0.928)	-0.007 (-0.296)	0.025 (0.847)	0.037 (1.269)	0.052 (1.381)
Term spread	-0.011 (-1.480)	-0.017 (-1.599)	-0.020 (-1.575)	-0.019 (-1.327)	-0.023 (-1.418)	-0.027 (-1.590)
Relative short-term interest rate	-0.012 (-1.078)	-0.018 (-0.939)	-0.019 (-0.811)	-0.013 (-0.547)	-0.013 (-0.557)	-0.016 (-0.740)
Financial sector return	-0.032 (-0.309)	0.108 (0.873)	0.139 (0.889)	-0.045 (-0.299)	-0.107 (-0.559)	-0.091 (-0.614)
Financial sector volatility	-0.004 (-0.865)	-0.008 (-1.262)	-0.004 (-0.633)	0.005 (0.612)	0.010 (0.897)	0.012 (0.990)
Financial sector skewness	-0.001 (-0.759)	0.001 (0.615)	0.002 (0.747)	0.001 (0.776)	-0.001 (-0.565)	-0.001 (-0.656)
Financial sector average beta	0.007 (1.244)	0.005 (0.517)	0.002 (0.179)	-0.001 (-0.067)	-0.006 (-0.370)	-0.007 (-0.398)
Market return	0.057 (0.408)	-0.170 (-1.049)	-0.210 (-0.971)	-0.106 (-0.546)	0.046 (0.231)	0.054 (0.286)
Market volatility	0.604*** (2.953)	0.531 (1.601)	0.225 (0.614)	-0.878 (-1.644)	-0.809** (-2.039)	-1.085* (-1.965)
Correlation in financial sector	0.073 (0.690)	0.010 (0.098)	-0.068 (-0.645)	-0.147 (-1.419)	-0.215* (-1.817)	-0.218* (-1.805)
Average financial firm size	0.012 (0.568)	0.006 (0.290)	0.021 (0.813)	0.042 (1.147)	0.058 (1.193)	0.052 (0.981)
Aggregated financial sector leverage	0.130*** (2.914)	0.009 (0.381)	-0.015 (-0.499)	0.081* (1.963)	0.010 (0.307)	-0.008 (-0.309)
12 lags of the dependent	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349	349	349	349	349	349
Adjusted $R^2$	0.367	0.165	0.098	0.101	0.080	0.103

Table 9: **Continued****Panel C: Controlling for investor sentiment**

	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
<b>Dependent variable (t+h): CATFIN</b>						
Aggregate <i>SC</i>	0.359**	0.351*	0.396**	0.363	0.347	0.387
	(2.368)	(1.776)	(2.028)	(1.628)	(1.379)	(1.559)
Investor sentiment	-0.010	-0.028	-0.041**	-0.057**	-0.063***	-0.050**
	(-0.691)	(-1.477)	(-2.005)	(-2.417)	(-2.700)	(-2.368)
All controls in Panel A & B	Yes	Yes	Yes	Yes	Yes	Yes
Observations	334	334	334	334	334	334
Adjusted $R^2$	0.614	0.537	0.505	0.464	0.469	0.466
<b>Dependent variable (t+h): LLP growth</b>						
Aggregate <i>SC</i>	0.221**	0.415***	0.557***	0.540***	0.454**	0.358**
	(2.589)	(3.001)	(3.252)	(2.813)	(2.530)	(2.029)
Investor sentiment	-0.004	-0.009	-0.006	0.001	0.003	0.004
	(-0.545)	(-0.719)	(-0.436)	(0.069)	(0.171)	(0.280)
All controls in Panel A & B	Yes	Yes	Yes	Yes	Yes	Yes
Observations	334	334	334	334	334	334
Adjusted $R^2$	0.590	0.340	0.189	0.181	0.155	0.127



Table 10: **Aggregated Syndicate Concentration and Credit Supply**

Table 10 examines the predictive power of monthly aggregate syndicate concentration for credit supply conditions measured by excess bond premium as in Gilchrist and Zakrajšek (2012) from January 1991 to March 2020 (time  $t$ ). In all specifications, we control for investor sentiment, aggregate syndicated loan issuance, credit tightening, all control variables in Allen et al. (2012) and 12 lags of the dependent variable. For brevity, we omit the coefficient estimates of the 12 lags of the dependent variable. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are the Newey-West  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<b>Dependent variable (t+h): Excess bond premium</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
Aggregate $SC$	1.021** (2.426)	1.133* (1.783)	1.214 (1.498)	1.352 (1.440)	1.396 (1.295)	1.295 (1.104)
Investor sentiment	-0.012 (-0.307)	-0.009 (-0.166)	-0.023 (-0.305)	-0.021 (-0.227)	-0.024 (-0.201)	-0.009 (-0.075)
Syndicated loan issuance	0.059 (0.906)	0.090 (0.753)	0.124 (0.751)	0.110 (0.618)	0.121 (0.620)	0.192 (0.886)
Credit tightening	0.804*** (3.412)	1.461*** (2.792)	2.008*** (2.874)	2.532*** (2.892)	2.901*** (3.140)	3.063*** (3.352)
Default spread	-0.061 (-0.698)	-0.081 (-0.636)	-0.165 (-0.978)	-0.160 (-0.820)	-0.217 (-0.904)	-0.240 (-0.887)
Term spread	0.060*** (2.777)	0.095** (2.279)	0.133** (2.287)	0.151** (2.215)	0.167** (2.257)	0.172** (2.268)
Relative short-term interest rate	0.050* (1.904)	0.080 (1.577)	0.076 (1.363)	0.086 (1.265)	0.065 (0.860)	0.012 (0.115)
Financial sector return	0.996* (1.737)	0.404 (0.587)	1.196 (1.300)	0.419 (0.465)	0.158 (0.138)	0.191 (0.178)
Financial sector volatility	0.029 (1.382)	0.047* (1.747)	0.084** (1.970)	0.078* (1.734)	0.102* (1.936)	0.111** (2.268)
Financial sector skewness	-0.002 (-0.762)	-0.005* (-1.674)	-0.008* (-1.813)	-0.008* (-1.757)	-0.009 (-1.600)	-0.009 (-1.520)
Financial sector average beta	-0.006 (-0.234)	0.008 (0.280)	0.041 (0.883)	0.017 (0.278)	0.003 (0.052)	-0.000 (-0.006)
Market return	-2.558*** (-3.043)	-1.696* (-1.962)	-2.805** (-2.258)	-1.814* (-1.892)	-1.690 (-1.291)	-1.505 (-1.394)
Market volatility	1.364 (1.297)	-0.794 (-0.543)	-1.800 (-0.717)	-2.717 (-0.999)	-3.225 (-1.080)	-5.082 (-1.640)
Correlation in financial sector	-0.184 (-0.784)	-0.251 (-0.607)	-0.319 (-0.609)	-0.433 (-0.763)	-0.545 (-0.873)	-0.391 (-0.614)
Average financial firm size	0.118** (2.237)	0.173** (2.154)	0.271** (2.564)	0.300** (2.557)	0.375*** (2.879)	0.365** (2.503)
Aggregated financial sector leverage	-0.037 (-0.374)	-0.108 (-0.814)	-0.032 (-0.312)	-0.044 (-0.383)	-0.103 (-0.829)	-0.039 (-0.336)
12 lags of the dependent	Yes	Yes	Yes	Yes	Yes	Yes
Observations	334	334	334	334	334	334
Adjusted $R^2$	0.900	0.817	0.751	0.695	0.630	0.579

Table 11: **Implications for Real Economy**

Table 11 examines the predictive power of monthly aggregate syndicate concentration for a variety of real economic activity measures from January 1991 to March 2020 (time  $t$ ). In all specifications, we control for aggregate syndicated loan issuance, credit tightening, all control variables in Allen et al. (2012) and 12 lags of the dependent variable as in Table 9. For brevity, we report only the coefficient estimates of aggregate syndicate concentration in Panel A. In Panel B, we additionally include the two financial sector risk measures, CATFIN and LLP growth, as additional control variables. In Panel C, we further include investor sentiment as in Baker and Wurgler (2006) as a control variable. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are Newey-West  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

<b>Panel A: Without controlling for CATFIN and LLP growth</b>						
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
<b>Dependent variable (t+h): GPDI growth</b>						
Aggregate $SC$	-0.023** (-2.074)	-0.045** (-2.577)	-0.085*** (-3.280)	-0.089*** (-3.345)	-0.082*** (-2.961)	-0.058** (-2.012)
<b>Dependent variable (t+h): TFP growth</b>						
Aggregate $SC$	-0.009** (-2.404)	-0.017*** (-3.024)	-0.021*** (-2.994)	-0.020*** (-2.756)	-0.014* (-1.899)	-0.009 (-1.307)
<b>Dependent variable (t+h): GDP growth</b>						
Aggregate $SC$	-0.007*** (-2.750)	-0.011** (-2.140)	-0.025*** (-3.641)	-0.023*** (-3.266)	-0.024*** (-2.960)	-0.011* (-1.718)
<b>Dependent variable (t+h): INDP growth</b>						
Aggregate $SC$	-0.011 (-0.885)	-0.022 (-1.499)	-0.029* (-1.945)	-0.039** (-2.436)	-0.012 (-0.791)	-0.002 (-0.115)
<b>Dependent variable (t+h): CFNAI</b>						
Aggregate $SC$	0.089 (0.058)	-3.760* (-1.861)	-3.782** (-2.495)	-4.513*** (-3.140)	-1.164 (-0.728)	-0.705 (-0.423)
<b>Dependent variable (t+h): ADS Index</b>						
Aggregate $SC$	-3.388 (-1.463)	-5.172* (-1.682)	-5.111** (-2.037)	-2.345 (-1.092)	0.645 (0.210)	0.417 (0.168)
<b>Dependent variable (t+h): Recession</b>						
Aggregate $SC$	0.363* (1.738)	0.678* (1.913)	0.785 (1.631)	0.937 (1.601)	0.846 (1.348)	0.778 (1.184)

Table 11: **Continued****Panel B: Controlling for CATFIN and LLP growth**

	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
<b>Dependent variable (t+h): GDI growth</b>						
Aggregate <i>SC</i>	-0.019*	-0.037**	-0.078***	-0.088***	-0.090***	-0.066**
	(-1.765)	(-2.259)	(-3.119)	(-3.318)	(-3.153)	(-2.314)
CATFIN	0.007	0.004	-0.002	-0.010	-0.012	-0.020
	(1.226)	(0.552)	(-0.179)	(-1.016)	(-0.967)	(-1.448)
LLP growth	-0.014***	-0.038***	-0.037***	-0.016*	0.033**	0.027**
	(-3.478)	(-5.031)	(-3.857)	(-1.849)	(2.249)	(2.012)
<b>Dependent variable (t+h): TFP growth</b>						
Aggregate <i>SC</i>	-0.009**	-0.016***	-0.020***	-0.019**	-0.014*	-0.010
	(-2.385)	(-2.879)	(-2.670)	(-2.532)	(-1.888)	(-1.468)
CATFIN	0.001	0.003	0.003	0.001	-0.002	-0.002
	(0.537)	(1.008)	(0.904)	(0.229)	(-0.792)	(-0.787)
LLP growth	-0.001	-0.003*	-0.008**	-0.006*	-0.002	0.008**
	(-1.209)	(-1.913)	(-2.347)	(-1.876)	(-0.863)	(2.425)
<b>Dependent variable (t+h): GDP growth</b>						
Aggregate <i>SC</i>	-0.006**	-0.008	-0.023***	-0.023***	-0.027***	-0.015**
	(-2.343)	(-1.626)	(-3.150)	(-3.158)	(-3.431)	(-2.262)
CATFIN	0.002	0.002	0.000	-0.005	-0.008***	-0.010**
	(0.843)	(0.634)	(0.038)	(-1.647)	(-2.699)	(-2.403)
LLP growth	-0.006***	-0.018***	-0.017***	-0.006	0.018**	0.014***
	(-2.708)	(-3.287)	(-2.982)	(-1.410)	(2.575)	(2.632)
<b>Dependent variable (t+h): INDP growth</b>						
Aggregate <i>SC</i>	-0.004	-0.007	-0.015	-0.048***	-0.028*	-0.011
	(-0.327)	(-0.571)	(-1.020)	(-2.591)	(-1.706)	(-0.706)
CATFIN	0.016	0.009	-0.011	-0.010	-0.020*	-0.012
	(1.479)	(1.145)	(-1.299)	(-1.425)	(-1.858)	(-1.443)
LLP growth	-0.010*	-0.037***	-0.047**	0.019	0.032*	0.018
	(-1.879)	(-2.690)	(-1.993)	(1.604)	(1.816)	(1.544)
<b>Dependent variable (t+h): CFNAI</b>						
Aggregate <i>SC</i>	0.793	-2.472*	-2.412	-5.658***	-2.469*	-1.483
	(0.474)	(-1.750)	(-1.588)	(-3.157)	(-1.823)	(-0.971)
CATFIN	1.756	0.613	-0.921	-1.316*	-2.058**	-1.654**
	(1.553)	(0.592)	(-0.986)	(-1.877)	(-2.292)	(-2.512)
LLP growth	-1.043**	-4.139**	-5.750*	3.016*	2.956*	1.397*
	(-2.262)	(-2.333)	(-1.839)	(1.883)	(1.891)	(1.752)
<b>Dependent variable (t+h): ADS Index</b>						
Aggregate <i>SC</i>	-1.413	-0.716	-3.839*	-4.497**	-1.366	-0.467
	(-1.017)	(-0.297)	(-1.829)	(-1.997)	(-0.545)	(-0.193)
CATFIN	1.626	1.879	0.389	-1.959**	-2.601*	-1.182
	(1.235)	(1.233)	(0.265)	(-2.082)	(-1.817)	(-1.187)
LLP growth	-4.646**	-11.725**	-3.450**	4.930*	4.070*	1.760
	(-2.431)	(-2.433)	(-2.234)	(1.742)	(1.845)	(1.341)
<b>Dependent variable (t+h): Recession</b>						
Aggregate <i>SC</i>	0.248	0.578	0.789	1.066*	0.968	0.880
	(1.139)	(1.604)	(1.645)	(1.825)	(1.563)	(1.356)
CATFIN	-0.085	-0.024	0.323**	0.534**	0.609**	0.535**
	(-0.939)	(-0.128)	(2.099)	(2.385)	(2.591)	(2.071)
LLP growth	0.421**	0.416**	0.296*	-0.046	0.052	0.069
	(2.424)	(2.373)	(1.854)	(-0.264)	(0.266)	(0.383)

Table 11: Continued

## Panel C: Controlling for investor sentiment in addition to CATFIN and LLP growth

	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=2	h=3	h=4	h=5	h=6
<b>Dependent variable (t+h): GPDI growth</b>						
Aggregate <i>SC</i>	-0.022*	-0.045***	-0.077***	-0.085***	-0.081***	-0.066**
	(-1.795)	(-2.626)	(-3.518)	(-3.579)	(-3.059)	(-2.283)
Investor sentiment	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(-1.164)	(-0.792)	(-0.458)	(-0.261)	(-0.413)	(-0.714)
<b>Dependent variable (t+h): TFP growth</b>						
Aggregate <i>SC</i>	-0.010***	-0.018***	-0.023***	-0.021***	-0.015**	-0.009
	(-2.925)	(-3.631)	(-3.714)	(-3.108)	(-2.136)	(-1.337)
Investor sentiment	-0.000	-0.001*	-0.001	-0.000	-0.000	-0.001
	(-1.369)	(-1.855)	(-1.296)	(-0.897)	(-0.752)	(-1.066)
<b>Dependent variable (t+h): GDP growth</b>						
Aggregate <i>SC</i>	-0.009***	-0.015***	-0.023***	-0.021***	-0.020***	-0.014***
	(-3.625)	(-3.975)	(-4.559)	(-4.015)	(-3.540)	(-2.603)
Investor sentiment	-0.000*	-0.000	-0.000	-0.001	-0.001	-0.001
	(-1.825)	(-1.238)	(-1.065)	(-1.021)	(-1.132)	(-1.425)
<b>Dependent variable (t+h): INDP growth</b>						
Aggregate <i>SC</i>	-0.011	-0.011	-0.022**	-0.032***	-0.019	-0.014
	(-1.025)	(-1.230)	(-2.277)	(-2.866)	(-1.646)	(-1.042)
Investor sentiment	-0.002**	-0.001	0.001	-0.000	0.000	0.001
	(-2.126)	(-0.611)	(0.580)	(-0.467)	(0.413)	(0.783)
<b>Dependent variable (t+h): CFNAI</b>						
Aggregate <i>SC</i>	-2.018***	-1.725***	-2.413***	-3.742***	-2.418***	-2.304**
	(-2.905)	(-2.857)	(-3.619)	(-4.136)	(-2.604)	(-2.168)
Investor sentiment	-0.078*	-0.020	0.013	-0.010	0.019	0.061
	(-1.854)	(-0.382)	(0.213)	(-0.118)	(0.218)	(0.557)
<b>Dependent variable (t+h): ADS Index</b>						
Aggregate <i>SC</i>	-0.982**	-2.092**	-3.143***	-3.029***	-2.041	-1.423
	(-2.076)	(-2.487)	(-3.148)	(-2.600)	(-1.575)	(-0.948)
Investor sentiment	-0.036	-0.012	0.011	0.032	0.072	0.073
	(-0.827)	(-0.137)	(0.101)	(0.245)	(0.499)	(0.445)
<b>Dependent variable (t+h): Recession</b>						
Aggregate <i>SC</i>	0.319	0.516	0.680	0.883	0.844	0.810
	(1.581)	(1.536)	(1.537)	(1.598)	(1.391)	(1.246)
Investor sentiment	0.056*	0.066	0.055	0.048	0.036	0.005
	(1.821)	(1.267)	(0.933)	(0.713)	(0.477)	(0.062)

# Appendix

Table A1: Variable Definition

Variable	Definition	Source
<b><i>Bank-level variables</i></b>		
<i>SC</i>	Bank-level syndicate concentration, measured as the average of 1/# lenders of the syndicated loans a bank participates over the past 12 months, weighted by the dollar loan size.	DealScan
Loan loss provision	The percentage ratio of loan loss provision (BHCK4230) to total loans (BHCK2122).	FR Y-9C
Default probability	The probability of default estimated using the <a href="#">Merton (1974)</a> model.	<a href="#">Nagel and Purnanandam (2020)</a>
ln(IVOL)	Idiosyncratic volatility of bank stock returns, measured as the natural logarithm of the standard deviation of the residuals from the Fama-French three-factor model estimated for each year-quarter.	CRSP, Kenneth R. French Data Library
#Lawsuits	The quarterly number of new civil litigation cases filed in federal district court (excl. New Mexico) where the bank is the defendant.	Audit Analytics
Size	The natural logarithm of total assets (BHCK2170).	FR Y-9C
Equity capital	Total equity capital (BHCK3210) normalized by total assets (BHCK2170).	FR Y-9C
ROE	Net income (BHCK4340) normalized by total equity capital (BHCK3210) times 100.	FR Y-9C
ROA	Net income (BHCK4340) normalized by total assets (BHCK2170) times 100.	FR Y-9C
MTB	The ratio of a bank's market capitalization to its book value of total equity.	FR Y-9C, CRSP
Loan size	Total loans (BHCK2122) normalized by total assets (BHCK2170).	FR Y-9C
Loan growth	The percentage growth rate of total loans (BHCK2122).	FR Y-9C
Loan loss allowance	Allowance for loan and lease losses (BHCK3123) normalized by total assets (BHCK2170).	FR Y-9C
Stock return	The quarterly buy-and-hold stock return.	CRSP
Liquidity	The ratio of cash (BHCK0010) and short-term securities (BHCK1773) to total assets (BHCK2170).	FR Y-9C
NPA	The nonperforming assets, sum of total loans, leasing financing receivables and debt securities and other assets, 90 days past due (BHCK5525) and nonaccrual (BHCK5526).	FR Y-9C
Opacity	The average rank of three bank opacity measures, including the discretionary loan loss provision (the natural logarithm of the absolute value of residuals from Equation 5), analysts' forecast error and forecast dispersion. The 0 to 9 indexed decile rank of each measure is divided by 9 to range from 0 to 1. Specifically, analysts' forecast error is measured by the mean absolute difference between analysts' forecast and actual earnings normalized by stock price. Analysts' forecast error is measured by the standard deviation of analysts' forecasts normalized by stock price.	FR Y-9C, I/B/E/S, CRSP
Complexity	The ratio of the number of non-missing items to the total number of items in FR Y-9C in each year-quarter.	FR Y-9C
Specialization in syndicated loan	The total dollar amount of the syndicated loans a bank participates over the past 12 months normalized by the total loans (BHCK2122).	DealScan, FR Y-9C
Specialization in industry	The borrower's industry concentration of a bank's syndicated loan portfolio over the past 12 months, measured by the HHI index based on the borrowers' 2-digit SIC codes and the loan amounts.	DealScan
Loan spread	The all-in-drawn spread, weighted by dollar loan amount, of syndicated loans a bank participates over the past 12 months.	DealScan
Reputation	The total amount of syndicated loans lead-arranged by a bank divided by the total amount of all syndicated loans in the past 12 months.	DealScan

Table A1: Continued

Variable	Definition	Source
<i>Aggregate-level variables</i>		
Aggregate <i>SC</i>	Aggregate-level syndicate concentration, measured as the average of $1/\#\text{lenders}$ of all syndicated loans originated over the past 6 months, weighted by the dollar loan size.	DealScan
Excess bond premium	The (option-adjusted) excess bond premium (in percentage points) extracted from GZ credit spread.	Gilchrist and Zakrajšek (2012)
CATFIN	Catastrophic risk in the financial sector by Allen et al. (2012).	Allen et al. (2012)
LLP growth	The growth rate of the mean ratio of bank loan loss provision to loan size.	FR Y9-C
GPDI growth	The growth rate of the gross private domestic investment	FRED database
GDP growth	The growth rate of the gross domestic product	FRED database
INDP growth	The growth rate of the industrial production index	FRED database
TFP growth	The growth rate of the total factor productivity	FRB San Francisco
CFNAI	The Chicago Fed National Activity Index	FRED database
ADS Index	The Aruoba-Diebold-Scotti Business Conditions Index (ADS)	FRB Philadelphia
Recession	An indicator variable that takes the value of one, and zero otherwise, if U.S. economy is in recession.	NBER
Syndicated loan issuance	The total issuance of syndicated loans measured by the natural logarithm of the monthly total dollar amount of loans originated	DealScan
Credit tightening	Credit tightening, measured by the net percentage of domestic respondents tightening standard for commercial and industrial loans to large and medium sized firms (DRTSCILM).	FRED database
Default spread	The default spread, defined as the difference between the BAA-rated and AAA-rated corporate bonds (DBAA-AAA).	FRED database
Term spread	The term spread, defined as the difference between the ten-year T-bond and three-month T-bill yields (DGS10-DTB3).	FRED database
Relative short-term interest rate	The relative short-term interest rate, defined as the difference between three-month T-bill rate (DTB3) and its twelve-month backward-moving average.	FRED database
Financial sector return	The value-weighted average excess returns of all financial firms (with two-digit SIC code between 60 and 67).	CRSP
Financial sector volatility	The realized monthly volatility of excess returns of all financial firms, defined as the square root of the sum of squared daily returns in a month.	CRSP
Financial sector skewness	The realized monthly skewness of excess returns of all financial firms.	CRSP
Financial sector average beta	The average market beta of all financial firms estimated from monthly returns over the past five years.	CRSP
Market return	The monthly excess return on the CRSP value-weighted index.	CRSP
Market volatility	The realized monthly volatility of excess returns of the aggregate stock market portfolio, defined as the square root of the sum of squared daily returns in a month.	CRSP
Correlation in financial sector	The average correlation between excess returns on individual financial firms and excess returns on the financial market index with a rolling window of 24 months, updated on a monthly basis.	CRSP
Average financial firm size	The natural logarithm of the average market capitalization of firms in the financial sector	CRSP
Aggregate financial sector leverage	The aggregate leverage in the financial sector defined as the ratio of total liabilities to total assets of the entire financial sector	Compustat

Table A2: **Transition Matrix for Syndicate Concentration**

Table A2 shows the transition matrix for bank-quarter rank of syndicate concentration from January 1990 to March 2020. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in the table are the percentage probabilities of a bank's syndicate concentration rank changes from one to the other in the next year.

Rank	1	2	3	4	5	6	7	8	9	10	Total
1	77.20	13.73	2.85	1.55	0.78	0.78	0.52	0.52	0.78	1.30	100.00
2	16.57	52.03	20.64	4.94	2.03	2.03	0.58	0.29	0.87	0.00	100.00
3	2.39	18.83	48.81	21.49	4.51	1.33	1.59	0.80	0.27	0.00	100.00
4	1.12	6.74	19.94	39.89	21.35	7.02	1.40	1.97	0.56	0.00	100.00
5	1.65	1.10	4.95	20.88	43.68	20.88	4.95	1.65	0.00	0.27	100.00
6	1.08	0.81	3.23	5.93	21.29	45.55	17.79	2.70	1.08	0.54	100.00
7	0.00	1.54	0.92	1.85	3.69	19.69	49.54	17.54	4.62	0.62	100.00
8	1.25	1.25	0.62	0.93	1.25	4.67	17.45	48.29	22.43	1.87	100.00
9	1.10	0.82	0.55	0.27	1.10	1.37	3.02	19.51	60.16	12.09	100.00
10	0.54	0.54	1.08	0.54	1.08	1.08	1.08	3.23	23.12	67.74	100.00
Total	11.40	10.22	11.08	10.46	10.70	10.93	9.69	9.37	10.67	5.48	100.00

Table A3: Predicting Modified Default Probability

Table A3 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable (t+h): Modified default probability												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
Rank $SC$	0.002*	0.002*	0.002*	0.002**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003*	0.002
	(1.787)	(1.870)	(1.852)	(2.032)	(2.306)	(2.376)	(2.577)	(2.536)	(2.390)	(2.272)	(1.702)	(1.343)
Size	-0.002	-0.001	0.001	0.003	0.003	0.005	0.006	0.006	0.008*	0.008*	0.009**	0.009**
	(-0.766)	(-0.196)	(0.365)	(0.790)	(0.947)	(1.230)	(1.422)	(1.556)	(1.761)	(1.906)	(2.034)	(2.047)
Equity capital	-1.388***	-1.239***	-1.095***	-0.960***	-0.950***	-0.902***	-0.871***	-0.818***	-0.750**	-0.695**	-0.683**	-0.712**
	(-4.724)	(-4.491)	(-4.193)	(-3.693)	(-3.594)	(-3.276)	(-2.981)	(-2.770)	(-2.577)	(-2.325)	(-2.172)	(-2.143)
ROA	-0.021	-0.021	-0.020	-0.019	-0.019*	-0.017*	-0.014	-0.012	-0.010	-0.008	-0.007	-0.007
	(-1.580)	(-1.575)	(-1.537)	(-1.595)	(-1.707)	(-1.692)	(-1.565)	(-1.452)	(-1.304)	(-1.213)	(-1.154)	(-1.083)
MTB	-0.059***	-0.056***	-0.054***	-0.050***	-0.047***	-0.046***	-0.045***	-0.042***	-0.041***	-0.040***	-0.039***	-0.038***
	(-4.762)	(-4.833)	(-5.092)	(-5.112)	(-5.062)	(-5.118)	(-5.003)	(-4.891)	(-4.926)	(-4.793)	(-4.670)	(-4.582)
Loan size	-0.126**	-0.118**	-0.105**	-0.099*	-0.081	-0.060	-0.044	-0.033	-0.019	-0.013	0.001	0.014
	(-2.462)	(-2.325)	(-2.058)	(-1.895)	(-1.575)	(-1.154)	(-0.807)	(-0.597)	(-0.328)	(-0.215)	(0.014)	(0.239)
Loan growth	0.000	0.000	-0.000	-0.000	-0.000	-0.000**	-0.000**	-0.000**	-0.000**	-0.000***	-0.000*	-0.000***
	(0.612)	(0.159)	(-1.036)	(-0.667)	(-0.467)	(-2.394)	(-2.340)	(-2.092)	(-2.184)	(-2.844)	(-1.780)	(-2.812)
Loan loss allowance	0.055***	0.045***	0.032**	0.023*	0.012	-0.001	-0.010	-0.018	-0.026**	-0.033***	-0.038***	-0.043***
	(3.718)	(3.281)	(2.578)	(1.950)	(0.994)	(-0.094)	(-0.903)	(-1.566)	(-2.314)	(-2.852)	(-3.330)	(-3.693)
Stock return	-0.038**	-0.025	-0.021	-0.039**	-0.053***	-0.018	-0.021	-0.042**	-0.032**	-0.019	-0.017	-0.014
	(-2.365)	(-1.425)	(-1.002)	(-2.669)	(-3.778)	(-1.105)	(-1.467)	(-2.601)	(-2.521)	(-1.545)	(-1.422)	(-1.270)
Liquidity	-0.107**	-0.112***	-0.121***	-0.127***	-0.131***	-0.135***	-0.134***	-0.139***	-0.140***	-0.150***	-0.151***	-0.153***
	(-2.655)	(-2.807)	(-2.927)	(-3.018)	(-3.167)	(-3.315)	(-3.244)	(-3.329)	(-3.260)	(-3.351)	(-3.419)	(-3.481)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2298	2229	2198	2159	2120	2080	2041	2003	1966	1928
Adjusted $R^2$	0.756	0.747	0.739	0.736	0.725	0.710	0.696	0.689	0.686	0.679	0.671	0.662



Table A4: Predicting Bank Risks and Profitability with Bank Fixed Effect

Table A4 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC$	0.014*** (3.347)	0.015** (2.529)	0.015** (2.107)	0.018** (2.632)	0.019*** (2.821)	0.020*** (3.394)	0.021*** (4.249)	0.025*** (5.019)	0.024*** (4.672)	0.021*** (3.974)	0.019*** (4.020)	0.017*** (4.316)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2791	2718	2691	2652	2611	2568	2530	2490	2459	2420
Adjusted $R^2$	0.683	0.673	0.664	0.661	0.661	0.684	0.705	0.714	0.684	0.671	0.661	0.659
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC$	0.003** (2.205)	0.004*** (2.834)	0.005*** (3.053)	0.005*** (3.523)	0.006*** (3.646)	0.007*** (3.627)	0.007*** (3.906)	0.007*** (3.880)	0.007*** (3.938)	0.006*** (3.834)	0.005*** (3.304)	0.004** (2.598)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2295	2228	2198	2158	2119	2078	2039	2000	1966	1927
Adjusted $R^2$	0.818	0.818	0.811	0.812	0.811	0.805	0.799	0.797	0.795	0.792	0.789	0.786
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC$	0.004 (0.905)	0.003 (0.697)	0.006 (1.583)	0.008** (2.046)	0.009* (1.954)	0.010** (2.114)	0.012** (2.588)	0.013*** (3.261)	0.016*** (4.805)	0.014*** (4.674)	0.010*** (3.876)	0.011*** (3.794)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2790	2715	2686	2645	2602	2557	2517	2475	2442	2401
Adjusted $R^2$	0.748	0.745	0.746	0.747	0.746	0.744	0.741	0.742	0.744	0.747	0.746	0.753
<b>Dependent variable (t+h): ln(#lawsuits+1)</b>												
Rank $SC$	0.013* (1.770)	0.013 (1.661)	0.012 (1.602)	0.010 (1.468)	0.010 (1.487)	0.011 (1.486)	0.008 (1.236)	0.006 (0.960)	0.006 (0.992)	0.008 (1.515)	0.008 (1.436)	0.007 (1.539)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2791	2718	2691	2652	2611	2568	2530	2490	2459	2420
Adjusted $R^2$	0.362	0.361	0.359	0.358	0.360	0.367	0.372	0.373	0.376	0.375	0.378	0.375
<b>Dependent variable (t+h): ROE</b>												
Rank $SC$	0.019 (0.466)	0.030 (0.376)	0.016 (0.183)	-0.019 (-0.227)	-0.050 (-0.749)	-0.118* (-1.850)	-0.108 (-1.580)	-0.146* (-1.940)	-0.207** (-2.084)	-0.212* (-1.758)	-0.234* (-1.683)	-0.211 (-1.679)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2791	2718	2691	2652	2611	2568	2530	2490	2459	2420
Adjusted $R^2$	0.651	0.433	0.354	0.351	0.347	0.343	0.330	0.325	0.316	0.310	0.306	0.298
<b>Dependent variable (t+h): ROA</b>												
Rank $SC$	0.001 (0.276)	0.001 (0.176)	0.000 (0.006)	-0.003 (-0.389)	-0.006 (-0.794)	-0.013** (-2.278)	-0.012** (-2.250)	-0.017** (-2.593)	-0.022** (-2.570)	-0.022** (-2.103)	-0.025** (-2.024)	-0.023** (-2.061)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effect and Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2791	2718	2691	2652	2611	2568	2530	2490	2459	2420
Adjusted $R^2$	0.629	0.403	0.323	0.320	0.316	0.315	0.308	0.308	0.299	0.293	0.291	0.286

Table A5: Predicting Bank Risks and Profitability with Double-clustered Standard Error Clustering

Table A5 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are double clustered at both the bank and year-quarter levels. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC$	0.017*** (3.741)	0.017*** (3.295)	0.017*** (2.968)	0.018*** (2.934)	0.018*** (2.870)	0.018*** (2.941)	0.019*** (2.866)	0.021*** (2.948)	0.021*** (2.913)	0.021*** (2.926)	0.021*** (3.001)	0.021*** (3.057)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.642	0.632	0.625	0.622	0.622	0.643	0.661	0.672	0.645	0.633	0.622	0.620
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC$	0.003** (2.274)	0.003** (2.608)	0.003** (2.658)	0.004*** (2.948)	0.004*** (3.120)	0.005*** (3.171)	0.005*** (3.370)	0.005*** (3.273)	0.005*** (3.346)	0.005*** (3.273)	0.004*** (2.956)	0.004** (2.606)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2454	2371	2298	2229	2198	2159	2120	2080	2041	2003	1966	1928
Adjusted $R^2$	0.759	0.762	0.757	0.761	0.761	0.754	0.748	0.745	0.743	0.737	0.732	0.724
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC$	0.008 (1.486)	0.007 (1.265)	0.008 (1.619)	0.010* (1.955)	0.011** (2.149)	0.012** (2.312)	0.013** (2.544)	0.013** (2.585)	0.014*** (3.066)	0.013*** (3.043)	0.010** (2.457)	0.009** (2.163)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2793	2716	2686	2645	2603	2558	2517	2478	2442	2402
Adjusted $R^2$	0.681	0.680	0.683	0.685	0.683	0.680	0.678	0.679	0.682	0.683	0.683	0.689
<b>Dependent variable (t+h): ln(#lawsuits+1)</b>												
Rank $SC$	0.020*** (2.748)	0.020*** (2.720)	0.020*** (2.739)	0.019*** (2.788)	0.019*** (2.823)	0.020*** (2.841)	0.019*** (2.783)	0.018*** (2.736)	0.018*** (2.856)	0.020*** (3.211)	0.020*** (3.141)	0.019*** (3.380)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.301	0.300	0.298	0.295	0.294	0.299	0.300	0.299	0.300	0.299	0.301	0.297
<b>Dependent variable (t+h): ROE</b>												
Rank $SC$	0.001 (0.018)	-0.017 (-0.387)	-0.047 (-1.028)	-0.084* (-1.710)	-0.105** (-2.082)	-0.154** (-2.426)	-0.163** (-2.260)	-0.186** (-2.254)	-0.240** (-2.304)	-0.262** (-2.297)	-0.298** (-2.167)	-0.299** (-2.141)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.654	0.430	0.334	0.318	0.314	0.312	0.301	0.298	0.284	0.273	0.263	0.253
<b>Dependent variable (t+h): ROA</b>												
Rank $SC$	-0.000 (-0.020)	-0.002 (-0.463)	-0.004 (-0.900)	-0.007 (-1.460)	-0.008* (-1.697)	-0.013** (-2.143)	-0.013** (-2.102)	-0.016** (-2.091)	-0.021** (-2.178)	-0.022** (-2.174)	-0.026** (-2.096)	-0.026** (-2.075)
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2914	2845	2794	2719	2691	2652	2612	2569	2530	2493	2459	2421
Adjusted $R^2$	0.630	0.390	0.287	0.268	0.264	0.266	0.263	0.265	0.251	0.241	0.236	0.230

Table A6: Predicting Bank Risks and Profitability Controlling for Bank Lending Specialization

Table A6 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration, similar to Table 2. We additionally control for bank specialization in syndicated loan and industry. For brevity, we report only the coefficient estimates of bank-level syndicate concentration and two bank lending specialization measures. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC$	0.015*** (3.225)	0.015*** (2.895)	0.015** (2.642)	0.017*** (2.943)	0.018*** (3.134)	0.019*** (3.424)	0.020*** (3.576)	0.022*** (3.776)	0.022*** (3.831)	0.021*** (3.737)	0.021*** (3.646)	0.021*** (3.803)
Specialization in syndicated loan	0.371 (0.469)	0.262 (0.333)	0.232 (0.297)	0.553 (0.743)	0.535 (0.693)	0.399 (0.499)	0.448 (0.522)	0.508 (0.555)	0.438 (0.516)	-0.167 (-0.186)	-0.912 (-0.851)	-1.334 (-1.084)
Specialization in industry	0.075 (1.445)	0.072 (1.366)	0.055 (1.004)	0.030 (0.582)	0.003 (0.056)	-0.008 (-0.195)	-0.031 (-0.792)	-0.026 (-0.586)	-0.011 (-0.237)	-0.004 (-0.082)	-0.016 (-0.324)	-0.013 (-0.265)
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC$	0.002 (1.291)	0.002* (1.774)	0.003** (2.007)	0.003** (2.538)	0.004*** (2.989)	0.004*** (3.171)	0.005*** (3.496)	0.005*** (3.540)	0.005*** (3.619)	0.005*** (3.394)	0.004*** (2.906)	0.004** (2.373)
Specialization in syndicated loan	0.444 (0.933)	0.331 (0.800)	0.220 (0.620)	0.085 (0.281)	0.017 (0.058)	0.011 (0.036)	0.052 (0.166)	-0.044 (-0.148)	-0.137 (-0.485)	-0.218 (-0.809)	-0.322 (-1.267)	-0.398 (-1.547)
Specialization in industry	0.033** (2.260)	0.027* (1.793)	0.021 (1.446)	0.013 (0.879)	0.009 (0.649)	0.010 (0.667)	0.011 (0.704)	0.010 (0.666)	0.007 (0.407)	0.003 (0.186)	0.001 (0.034)	0.002 (0.123)
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC$	0.008 (1.362)	0.007 (1.209)	0.008 (1.584)	0.010* (1.995)	0.011** (2.090)	0.012** (2.320)	0.014** (2.541)	0.014** (2.600)	0.015*** (3.119)	0.014*** (3.132)	0.011** (2.450)	0.009* (1.986)
Specialization in syndicated loan	4.775*** (3.765)	4.361*** (3.560)	4.116*** (3.522)	3.844*** (3.479)	3.441*** (3.201)	2.839** (2.559)	2.539** (2.391)	2.384** (2.393)	2.327** (2.317)	1.657 (1.597)	1.437 (1.284)	1.308 (1.104)
Specialization in industry	0.068 (1.607)	0.054 (1.184)	0.042 (0.952)	0.027 (0.606)	0.028 (0.681)	0.019 (0.464)	0.007 (0.144)	0.004 (0.091)	0.006 (0.116)	-0.002 (-0.047)	0.001 (0.027)	0.019 (0.384)
<b>Dependent variable (t+h): ln(#lawsuits+1)</b>												
Rank $SC$	0.015*** (3.549)	0.015*** (3.260)	0.014*** (3.326)	0.014*** (3.503)	0.013*** (3.673)	0.015*** (3.724)	0.014*** (3.355)	0.013*** (3.126)	0.013*** (3.300)	0.014*** (3.966)	0.014*** (3.947)	0.014*** (4.105)
Specialization in syndicated loan	2.029** (2.050)	2.123** (2.164)	2.103** (2.270)	1.912** (2.050)	1.990* (2.008)	1.895* (1.897)	1.705* (1.817)	1.515 (1.588)	1.670* (1.786)	1.843* (1.994)	1.953** (2.090)	1.944** (2.204)
Specialization in industry	0.157* (1.984)	0.172** (2.264)	0.173** (2.352)	0.168** (2.242)	0.176** (2.161)	0.178** (2.177)	0.154** (2.298)	0.167** (2.527)	0.171*** (2.830)	0.181*** (2.820)	0.190** (2.683)	0.181*** (2.779)
<b>Dependent variable (t+h): ROE</b>												
Rank $SC$	-0.000 (-0.004)	-0.005 (-0.098)	-0.040 (-0.878)	-0.073 (-1.567)	-0.110** (-2.374)	-0.168*** (-2.724)	-0.182** (-2.307)	-0.209** (-2.287)	-0.266** (-2.229)	-0.291** (-2.098)	-0.336** (-2.039)	-0.340** (-2.062)
Specialization in syndicated loan	-5.312 (-0.709)	7.633 (0.396)	24.121 (0.851)	34.497 (1.060)	37.848 (1.164)	39.349 (1.166)	36.535 (1.076)	31.625 (0.945)	26.497 (0.814)	26.083 (0.831)	30.037 (0.950)	35.331 (1.069)
Specialization in industry	-0.042 (-0.178)	-0.241 (-0.564)	0.097 (0.155)	0.114 (0.157)	0.596 (0.808)	0.858 (1.004)	0.975 (0.968)	1.027 (0.969)	1.047 (0.865)	1.129 (0.901)	1.431 (1.056)	1.623 (1.168)
<b>Dependent variable (t+h): ROA</b>												
Rank $SC$	0.000 (0.090)	-0.000 (-0.048)	-0.003 (-0.503)	-0.005 (-0.968)	-0.008 (-1.538)	-0.013** (-2.251)	-0.014** (-2.036)	-0.017** (-2.071)	-0.022** (-2.067)	-0.024* (-1.930)	-0.028* (-1.938)	-0.028* (-1.961)
Specialization in syndicated loan	0.711 (0.767)	1.868 (0.903)	3.252 (1.152)	4.087 (1.317)	4.717 (1.561)	4.925 (1.593)	4.695 (1.532)	4.183 (1.393)	3.909 (1.329)	3.849 (1.347)	4.267 (1.462)	4.719 (1.549)
Specialization in industry	0.000 (0.018)	-0.023 (-0.472)	-0.002 (-0.034)	-0.007 (-0.088)	0.039 (0.569)	0.068 (0.929)	0.073 (0.885)	0.085 (0.924)	0.085 (0.796)	0.089 (0.815)	0.122 (1.029)	0.142 (1.162)

Table A7: Predicting Bank Risks and Profitability Controlling for Loan Pricing

Table A7 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration, similar to Table 2. We additionally control for the all-in-drawn spread (in percentage points) weighted by dollar loan amount of syndicate loans the bank participates in over the past 12 months. For brevity, we report only the coefficient estimates of the bank-level syndicate concentration and loan spread. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC$	0.017***	0.016***	0.016**	0.018***	0.018***	0.019***	0.020***	0.022***	0.022***	0.021***	0.020***	0.019***
	(3.592)	(2.942)	(2.613)	(2.763)	(2.690)	(3.002)	(3.238)	(3.543)	(3.643)	(3.534)	(3.237)	(3.226)
Loan spread	0.003	0.005	0.008	0.013	0.018	0.010	-0.003	-0.011	-0.004	0.001	0.013	0.024
	(0.234)	(0.292)	(0.425)	(0.726)	(0.978)	(0.619)	(-0.191)	(-0.880)	(-0.291)	(0.069)	(0.682)	(1.386)
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC$	0.002	0.003*	0.003**	0.003**	0.004**	0.004***	0.005***	0.005***	0.005***	0.005***	0.004***	0.004**
	(1.506)	(1.930)	(2.046)	(2.363)	(2.628)	(3.011)	(3.454)	(3.501)	(3.350)	(3.240)	(2.764)	(2.245)
Loan spread	0.005	0.005	0.006	0.007	0.004	0.002	0.000	0.001	0.003	0.004	0.007	0.008
	(1.132)	(1.122)	(1.271)	(1.182)	(0.775)	(0.410)	(0.068)	(0.205)	(0.686)	(0.862)	(1.230)	(1.481)
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC$	0.006	0.004	0.006	0.008	0.009	0.010*	0.013**	0.013**	0.014***	0.013***	0.010**	0.009**
	(0.981)	(0.703)	(1.168)	(1.591)	(1.649)	(1.898)	(2.325)	(2.595)	(3.038)	(3.037)	(2.469)	(2.195)
Loan spread	0.038**	0.042***	0.036**	0.032*	0.033*	0.024	0.014	0.009	0.010	0.016	0.018	0.016
	(2.624)	(2.799)	(2.453)	(1.904)	(1.936)	(1.317)	(0.764)	(0.533)	(0.673)	(1.146)	(1.214)	(1.000)
<b>Dependent variable (t+h): ln(#lawsuits+1)</b>												
Rank $SC$	0.019**	0.018**	0.017**	0.017***	0.018***	0.019***	0.018***	0.016***	0.016***	0.018***	0.017***	0.018***
	(2.655)	(2.593)	(2.629)	(2.841)	(2.839)	(2.820)	(2.962)	(2.981)	(3.067)	(3.534)	(3.563)	(3.296)
Loan spread	0.017**	0.016*	0.020**	0.016	0.015	0.018	0.014	0.018	0.018	0.021	0.020	0.015
	(2.333)	(1.865)	(2.050)	(1.478)	(1.297)	(1.186)	(0.908)	(1.122)	(1.122)	(1.150)	(1.056)	(0.886)
<b>Dependent variable (t+h): ROE</b>												
Rank $SC$	0.004	-0.011	-0.022	-0.051	-0.083	-0.138**	-0.130**	-0.165***	-0.209***	-0.235**	-0.272**	-0.249**
	(0.116)	(-0.231)	(-0.411)	(-0.904)	(-1.648)	(-2.601)	(-2.450)	(-2.935)	(-2.937)	(-2.664)	(-2.461)	(-2.588)
Loan spread	-0.029	-0.114	-0.337	-0.509*	-0.347	-0.305	-0.500	-0.392	-0.533	-0.535	-0.545	-0.800
	(-0.404)	(-1.039)	(-1.580)	(-1.706)	(-1.105)	(-0.878)	(-0.942)	(-0.769)	(-0.846)	(-0.866)	(-0.819)	(-0.860)
<b>Dependent variable (t+h): ROA</b>												
Rank $SC$	-0.000	-0.002	-0.003	-0.006	-0.008	-0.013**	-0.011**	-0.015**	-0.018**	-0.021**	-0.024**	-0.021**
	(-0.033)	(-0.401)	(-0.499)	(-0.974)	(-1.496)	(-2.337)	(-2.039)	(-2.479)	(-2.495)	(-2.359)	(-2.281)	(-2.346)
Loan spread	0.001	-0.005	-0.022	-0.036	-0.019	-0.015	-0.039	-0.029	-0.044	-0.041	-0.047	-0.072
	(0.266)	(-0.452)	(-1.132)	(-1.405)	(-0.735)	(-0.538)	(-0.849)	(-0.709)	(-0.808)	(-0.783)	(-0.781)	(-0.874)

Table A8: Predicting Bank Risks and Profitability Controlling for Bank Reputation

Table A8 presents the baseline  $h$ -quarter-ahead prediction results of bank-level quarterly syndicate concentration, similar to Table 2. We additionally control for bank reputation measured by the total amount of syndicated loans lead-arranged by the bank divided by the total amount of all syndicated loans in the past 12 months. For brevity, we report only the coefficient estimates of the bank-level syndicate concentration and bank reputation. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9	h=10	h=11	h=12
<b>Dependent variable (t+h): Loan loss provision</b>												
Rank $SC$	0.016***	0.016***	0.016***	0.017***	0.016***	0.017***	0.017***	0.018***	0.019***	0.018***	0.018***	0.018***
	(3.674)	(3.191)	(2.819)	(2.863)	(2.722)	(2.821)	(2.867)	(3.021)	(3.092)	(3.012)	(3.014)	(3.113)
Reputation	1.025	1.150	1.395*	1.288	1.422*	1.740**	1.966**	1.990**	2.013**	2.101**	2.229**	2.249**
	(1.257)	(1.413)	(1.744)	(1.669)	(1.757)	(2.062)	(2.359)	(2.316)	(2.088)	(2.054)	(2.126)	(2.075)
<b>Dependent variable (t+h): Default probability</b>												
Rank $SC$	0.004***	0.004***	0.004***	0.005***	0.005***	0.005***	0.006***	0.006***	0.006***	0.006***	0.005***	0.005***
	(2.697)	(3.165)	(3.295)	(3.567)	(3.649)	(3.852)	(4.240)	(4.243)	(4.402)	(4.343)	(3.881)	(3.225)
Reputation	-0.810***	-0.868***	-0.890***	-0.889***	-0.852***	-0.866***	-0.909***	-0.877***	-0.878**	-0.887**	-0.875**	-0.823**
	(-2.699)	(-2.891)	(-2.957)	(-2.924)	(-2.791)	(-2.865)	(-2.994)	(-2.829)	(-2.678)	(-2.599)	(-2.442)	(-2.154)
<b>Dependent variable (t+h): ln(IVOL)</b>												
Rank $SC$	0.011*	0.009*	0.011**	0.012**	0.013**	0.015**	0.016***	0.016***	0.017***	0.016***	0.013***	0.012***
	(1.828)	(1.679)	(2.021)	(2.357)	(2.491)	(2.645)	(2.903)	(3.105)	(3.617)	(3.572)	(3.105)	(2.801)
Reputation	-2.197***	-2.262***	-2.343***	-2.448***	-2.509***	-2.695***	-2.886***	-2.973***	-3.114***	-2.987***	-2.672***	-2.565***
	(-3.340)	(-3.269)	(-3.386)	(-3.493)	(-3.549)	(-3.862)	(-4.265)	(-4.497)	(-4.715)	(-4.374)	(-3.836)	(-3.373)
<b>Dependent variable (t+h): ln(#lawsuits+1)</b>												
Rank $SC$	0.019*	0.019*	0.019*	0.018*	0.018*	0.019*	0.018*	0.017*	0.017*	0.019**	0.019**	0.018**
	(1.930)	(1.888)	(1.880)	(1.893)	(1.928)	(1.937)	(1.838)	(1.754)	(1.807)	(2.054)	(2.024)	(2.111)
Reputation	0.960	1.149	1.222	1.141	0.996	0.937	0.997	1.047	1.028	0.988	0.894	1.116
	(0.395)	(0.469)	(0.507)	(0.478)	(0.395)	(0.356)	(0.370)	(0.382)	(0.366)	(0.356)	(0.321)	(0.407)
<b>Dependent variable (t+h): ROE</b>												
Rank $SC$	0.011	-0.007	-0.040	-0.081	-0.104**	-0.156***	-0.166**	-0.188**	-0.243**	-0.267**	-0.305**	-0.308**
	(0.350)	(-0.147)	(-0.809)	(-1.606)	(-2.179)	(-2.731)	(-2.492)	(-2.482)	(-2.489)	(-2.377)	(-2.254)	(-2.235)
Reputation	-10.650***	-9.761	-6.554	-2.528	-0.542	2.671	3.324	1.733	2.640	5.155	6.934	8.319
	(-2.857)	(-1.097)	(-0.550)	(-0.186)	(-0.041)	(0.211)	(0.280)	(0.153)	(0.216)	(0.425)	(0.563)	(0.660)
<b>Dependent variable (t+h): ROA</b>												
Rank $SC$	0.000	-0.002	-0.004	-0.008	-0.009*	-0.014**	-0.014**	-0.017**	-0.022**	-0.023**	-0.027**	-0.027**
	(0.024)	(-0.396)	(-0.851)	(-1.504)	(-1.841)	(-2.431)	(-2.368)	(-2.336)	(-2.397)	(-2.282)	(-2.199)	(-2.180)
Reputation	-0.126	-0.091	0.105	0.421	0.536	0.808	0.824	0.719	0.771	0.915	0.954	1.032
	(-0.245)	(-0.087)	(0.077)	(0.272)	(0.344)	(0.532)	(0.571)	(0.515)	(0.513)	(0.614)	(0.621)	(0.656)

Table A9: **Predicting Bank Risks and Profitability with Non-overlapping Sampling**

Table A9 presents the 4-quarter-ahead prediction results of bank-level syndicate concentration using non-overlapping sampling where observations are sampled annually (at various quarter ends) since the bank-level syndicate concentration is computed based on loans in the past 4 quarters. This is equivalent to a one-year-ahead prediction with annual observations to mitigate the biases in long-horizon predictive regressions. In all specifications, the bank-level syndicate concentration and control variables are measured at time  $t$ . Standard errors are clustered at the bank level. Definitions of the variables are provided in Table A1 in the Appendix. Numbers in parentheses are two-tailed  $t$ -statistics. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	t=Q1	t=Q2	t=Q3	t=Q4
<b>Dependent variable (t+4): Loan loss provision</b>				
Rank $SC$	0.008*** (3.000)	0.012* (1.770)	0.018** (2.540)	0.032*** (3.605)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	675	681	688	675
Adjusted $R^2$	0.452	0.586	0.631	0.645
<b>Dependent variable (t+4): Default probability</b>				
Rank $SC$	0.004*** (3.150)	0.004*** (2.778)	0.003** (2.381)	0.003** (2.534)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	550	559	564	556
Adjusted $R^2$	0.761	0.746	0.780	0.758
<b>Dependent variable (t+4): ln(IVOL)</b>				
Rank $SC$	0.012* (1.880)	0.012** (2.069)	0.009 (1.480)	0.006 (1.150)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	675	681	687	673
Adjusted $R^2$	0.688	0.672	0.697	0.678
<b>Dependent variable (t+4): ln(#lawsuits+1)</b>				
Rank $SC$	0.018** (2.532)	0.016** (2.576)	0.021*** (3.257)	0.020** (2.194)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	675	681	688	675
Adjusted $R^2$	0.267	0.310	0.327	0.263
<b>Dependent variable (t+4): ROE</b>				
Rank $SC$	-0.030 (-1.233)	-0.135** (-2.343)	-0.052 (-0.830)	-0.096 (-1.164)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	675	681	688	675
Adjusted $R^2$	0.158	0.192	0.234	0.354
<b>Dependent variable (t+4): ROA</b>				
Rank $SC$	-0.003 (-1.174)	-0.012** (-2.118)	-0.004 (-0.597)	-0.008 (-0.957)
Bank Controls	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	675	681	688	675
Adjusted $R^2$	0.098	0.135	0.159	0.273

Table A10: Overview of Stress Test Outcomes, 2009-2019

Table A10 provides an overview of the participating bank holding companies and outcomes of the stress tests across different rounds. "1" indicates that the bank's capital plan received an objection or conditional non-objection and "0" indicates otherwise. Shaded cells indicate banks that are not eligible to participate in a focal round of stress test. Note that Deutsche Bank launched its US intermediate holding company, DB USA Corporation, on July 1, 2016, under which most of its US-based operations were consolidated. MUFG Americas Holdings Corporation was formerly UnionBanCal Corporation before 2014. In February 2019, the Federal Reserve announced that certain banks with total consolidated assets between \$100 billion and \$250 billion would not be subject to the company-run and supervisory stress testing requirements nor the requirement to submit a capital plan during the 2019 cycle.

Bank	RSSD ID	SCAP 2009	CCAR 2012	CCAR 2013	CCAR 2014	CCAR 2015	CCAR 2016	CCAR 2017	CCAR 2018	CCAR 2019
Ally Financial Inc.	1562859	1	1	1	0	0	0	0	0	
American Express Company	1275216	0	0	0	0	0	0	0	0	
Bank of America Corporation	1073757	1	0	0	0	1	0	0	0	0
BancWest Corporation	1025608						0	0		
Barclays US LLC	5006575								0	0
BB&T Corporation	1074156	0	0	1	0	0	0	0	0	
BBVA Compass Bancshares, Inc.	1078529				0	0	0	0	0	
BMO Financial Corp.	1245415				0	0	0	0	0	
BNP Paribas USA, Inc.	1575569								0	
Capital One Financial Corporation	2277860	0	0	0	0	0	0	1	0	0
CIT Group Inc.	1036967							0		
Citigroup Inc.	1951350	1	1	0	1	0	0	0	0	0
Credit Suisse Holdings (USA), Inc.	1574834									1
Comerica Incorporated	1199844				0	0	0	0	0	
Deutsche Bank Trust Corporation	1032473					1	1	0		
DB USA Corporation	2816906								1	0
Discover Financial Services	3846375				0	0	0	0	0	
Fifth Third Bancorp	1070345	1	0	0	0	0	0	0	0	
HSBC North America Holdings Inc.	3232316				1	0	0	0	0	0
Huntington Bancshares Incorporated	1068191				0	0	0	0	0	
JPMorgan Chase & Co.	1039502	0	0	1	0	0	0	0	0	0
Keycorp	1068025	1	0	0	0	0	0	0	0	
M&T Bank Corporation	1037003				0	0	0	0	0	
MetLife, Inc.	2945824	0	1							
Morgan Stanley	2162966	1	0	0	0	0	1	0	1	0
MUFG Americas Holdings Corporation	1378434				0	0	0	0	0	
Northern Trust Corporation	1199611				0	0	0	0	0	0
RBC USA Holdco Corporation	3226762								0	
RBS Citizens Financial Group, Inc.	1132449				1	0	0	0	0	
Regions Financial Corporation	3242838	1	0	0	0	0	0	0	0	
Santander Holdings USA, Inc.	3981856				1	1	1	0	0	
State Street Corporation	1111435	0	0	0	0	0	0	0	1	0
SunTrust Banks, Inc.	1131787	1	1	0	0	0	0	0	0	
TD Group US Holdings LLC	3606542						0	0	0	0
The Bank of New York Mellon Corporation	3587146	0	0	0	0	0	0	0	0	0
The Goldman Sachs Group, Inc.	2380443	0	0	1	0	0	0	0	1	0
The PNC Financial Services Group, Inc.	1069778	1	0	0	0	0	0	0	0	0
U.S. Bancorp	1119794	0	0	0	0	0	0	0	0	0
UBS Americas Holding LLC	4846998									0
Wells Fargo & Company	1120754	1	0	0	0	0	0	0	0	0
Zions Bancorporation	1027004				1	0	0	0	0	

# Online Appendix

## OA.1. A Simple Model of Loan Syndicate Size and Loan Quality

In this Online Appendix, we develop a simple theoretical framework to illustrate the negative relation between syndicate concentration and loan quality. Consider a bank loan arranged by a lead lender and marketed to  $N$  potential participant (non-lead) lenders. Since the non-lead lenders do not directly engage with the borrower and do not conduct due diligence themselves, the quality of the bank loan  $q \sim N(\bar{q}, \sigma_q^2)$  is unknown to the non-lead lenders.  $\bar{q}$  is the non-lead lenders' unconditional expectation of the loan quality and  $\sigma_q^2$  is their ex-ante uncertainty about the loan quality. We can think of the loan quality  $q$  as the risk-adjusted return from the loan per unit of lending capital.

When deciding on whether to join the loan syndicate, non-lead lenders do not directly observe the realized loan quality  $q$  but can observe a noisy signal,  $s$ , about the loan quality. This noisy quality signal  $s$  may be interpreted as the reputation and track record of the lead arranger, as well as the loan information distributed by the lead arranger (e.g., tear sheet, prospectus), among other things. Without loss of generality, we assume the noisy signal  $s$  is positively correlated with  $q$  as  $s = q + \varepsilon$ , with  $\varepsilon \sim N(0, \sigma_\varepsilon^2)$  being the independent random noise in the signal. Therefore, even though more reputable lead arrangers with stronger track record tend to have better screening skills and hence syndicate better loans, the signal does not perfectly reveal the quality of the loan to the potential non-lead lenders .

Each of the  $N$  potential non-lead lenders has a cost  $c$  per unit of lending capital, which is uniformly distributed in  $[\underline{c}, \bar{c}]$ . A non-lead lender will join the loan syndicate if and only if the expected profit from the loan per unit of lending capital is greater than 0, i.e.,  $E(q|s) - c > 0$ . We then have

$$\begin{aligned} E(q|s) &= E(q) + \frac{\text{cov}(q, s)}{\text{var}(s)} (s - E(s)) \\ &= \bar{q} + \frac{\sigma_q^2}{\sigma_q^2 + \sigma_\varepsilon^2} (s - \bar{q}) \end{aligned} \tag{OA.1.1}$$



Denote  $a \equiv \frac{\sigma_\varepsilon^2 \bar{q}}{\sigma_q^2 + \sigma_\varepsilon^2}$  and  $b \equiv \frac{\sigma_q^2}{\sigma_q^2 + \sigma_\varepsilon^2}$ . We thus have  $E(q|s) = a + bs$ . That is, the perceived loan quality is an increasing function of the observed signal (e.g., the lead bank's reputation and lending record as well as the disclosed loan-related information).

Since a participant with cost  $c$  per unit of lending capital will only join the syndicate when  $E(q|s) - c > 0$ , the expected number of actual non-lead lenders joining the syndicate  $E(n|s)$  will be

$$E(n|s) = N \times \frac{E(q|s) - \underline{c}}{\bar{c} - \underline{c}} = \frac{Nb}{\bar{c} - \underline{c}} s + \frac{N(a - \underline{c})}{\bar{c} - \underline{c}} \quad (\text{OA.1.2})$$

Clearly, Equation (OA.1.2) shows that the expected syndicate size is increasing in the perceived loan quality  $E(q|s)$  and hence increasing in the quality signal  $s$ . Of course, when  $E(q|s) > \bar{c}$ , all the potential non-lead lenders will join the syndicate; when  $E(q|s) < \underline{c}$ , none of the potential non-lead lenders will join. Given the rational expectation of the non-lead lenders, the average number of lenders in the loan syndicate will thus be a good indicator of the loan quality and credit risk (i.e., higher participant number and lower syndicate concentration indicate better loan quality).

## OA.2. Decomposing Herfindahl–Hirschman (HHI) Index

In this Online Appendix, we illustrate a simple decomposition of the Herfindahl–Hirschman Index following [de Gioia \(2017\)](#).

Herfindahl–Hirschman (HHI) Index is a well-known market concentration measure defined as the sum of squared market shares of all firms in a market:

$$H = \sum_{i=1}^n \left( \frac{x_i}{\sum x} \right)^2 \in \left[ \frac{1}{n}, 1 \right] \quad (\text{OA.2.3})$$

where  $x_i$  is the size of firm  $i$ , and  $n$  is the number of firms.

Since HHI is jointly determined by the distribution (variance) of firm sizes and the number of firms, we can conceptualize HHI as the sum of the actual market state's deviations from 1) all firms having the same size, and from 2) a fully competitive environment with infinite number of firms in the market. We now try to decompose HHI into two components that respectively measure such two contributing factors.

Suppose there are  $n$  firms sized  $x_1, x_2, \dots, x_n$  in a market, thus we can describe the market using a  $\mathbb{R}_+^n$  vector  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ .

The first hypothetical state is where all firms' sizes are equal, i.e.,  $\mathbf{x} = \bar{\mathbf{x}} \equiv (\bar{x}, \bar{x}, \dots, \bar{x})$ , where  $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$  is the average firm size. We can denote by  $d(\mathbf{x}, \bar{\mathbf{x}})$  the Euclidean distance between  $\mathbf{x}$  and  $\bar{\mathbf{x}}$ :

$$d(\mathbf{x}, \bar{\mathbf{x}}) = \sqrt{\sum_{i=1}^n x_i^2 - n\bar{x}^2} \quad (\text{OA.2.4})$$

The second hypothetical state is where there are infinite number of firms in the market. But for the ease of discussion, we assume there is only one firm in the market whose size is the sum of all firms in the first hypothetical state (i.e.  $n\bar{x}$ ). We know that this market is in the most concentrated state,  $\mathbf{x}^*$ , because of the monopoly. In other words, its distance to the market state in the first hypothetical state is the largest.

$$\max_x d(\mathbf{x}, \bar{\mathbf{x}}) = d(\mathbf{x}^*, \bar{\mathbf{x}}) = \sqrt{(\sum x_i - \bar{x})^2 + (n-1)(0 - \bar{x})^2} = \sqrt{(n-1)n\bar{x}^2} \quad (\text{OA.2.5})$$

As a result, the distance of any market state  $\mathbf{x}$  to the first hypothetical state,  $\bar{\mathbf{x}}$ , should range between 0 to  $d(\mathbf{x}^*, \bar{\mathbf{x}})$ . Thus we can derive a relative index of concentration (when  $n > 1$ ) as  $\tau$ , with a higher value of  $\tau$  implying a market state  $\mathbf{x}$  closer to the most concentrated state  $\mathbf{x}^*$ :

$$\tau = \frac{d(\mathbf{x}, \bar{\mathbf{x}})}{d(\mathbf{x}^*, \bar{\mathbf{x}})} \in [0, 1] \quad (\text{OA.2.6})$$

Now, given that  $H = \sum_{i=1}^n \left(\frac{x_i}{n\bar{x}}\right)^2$ , we can get:

$$\tau = \sqrt{\frac{n}{n-1} \left(H - \frac{1}{n}\right)} = \sqrt{\frac{nH-1}{n-1}}$$

When we observe a market state  $\mathbf{x} = (x_1, x_2, \dots, x_n)$  at a given time, the total market size is fixed and thus  $\tau$  is only varying with the distance between the observed actual market state and state  $\bar{\mathbf{x}}$  where all firms have the same size. This implies that  $\tau$  could be a measure of the first determinant of market concentration, i.e. the size distribution (variance) of firms.

Further,  $\tau$  represents a sequence of functions whose limit is  $\sqrt{H}$  as  $n \rightarrow +\infty$ , when the market is in a fully competitive environment. Thus, given a  $H'$  from the knowledge of  $n'$  and  $\mathbf{x}'$ , we know there is one and only one matching  $\tau'$  and its limit of  $\sqrt{H'}$  in the fully competitive environment.

We can therefore decompose  $H$  into two components,  $E_i = \tau^2$ , and  $E_n = H - \tau^2$ :

$$H = E_i + E_n \quad (\text{OA.2.7})$$

where  $E_i = \tau^2 < H$  measures the effect of the size distribution of firms on concentration,

and  $E_n$  measures the effect of the number of firms on concentration.<sup>25</sup>

Figure A1 visualizes the decomposition of HHI, without loss of generality, assuming 5 firms in the market.

[Insert Figure A1 near here]

$E_n$  is effectively the horizontal difference between the two curves, i.e. the ‘distance’ between the actual market state and the fully competitive market with infinite number of firms. As such, another finding from the figure is that with higher market concentration measured by  $H$ , the relative importance of  $E_n$  and  $E_i$  is changing:

- When  $H$  is small, most of the concentration is resulted from  $E_n$ , which means the number of firms has a greater impact on market concentration..
- When  $H$  is larger, on the other hand,  $E_i$  contributes more to  $H$ , which means the firm size inequality plays a bigger role in market concentration.

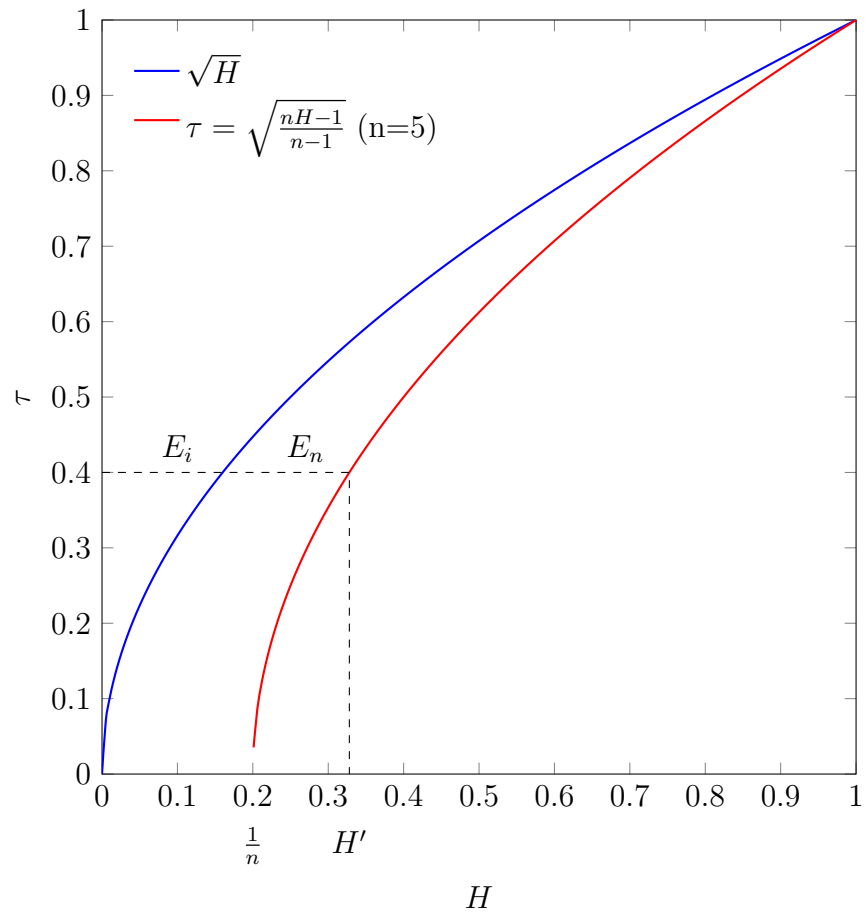
## References

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<sup>25</sup>For comparison, the normalized HHI =  $\frac{H-1/n}{1-1/n} \in [0, 1]$  is nothing but  $E_i = \tau^2$ , which reflects the market concentration due to the inequality of firm sizes.

Fig. A1. An Example Decomposition of HHI



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