

Bank Market Power and Corporate Stock Price Crash Risk: Borrowers' Manipulation Incentives

Shengfeng Li

Sheffield University Management School,
University of Sheffield, Shengfeng.Li@sheffield.ac.uk

Liang Han

Surrey International Institute, Dongbei University of Finance and Economics; Faculty of Arts and Social Sciences, University of Surrey, L.Han@Surrey.ac.uk

Biao Mi

Henley Business School, University of Reading, Biao.Mi@Henley.ac.uk

ABSTRACT

Using syndicated loan data to match borrowers and lenders, we document a positive and robust effect of lenders' bank market power on the 2-year-ahead corporate stock price crash risk. Our further analyses reveal that powerful banks tend to issue loans with more financial covenants, after controlling for bank, firm and loan-level characteristics. Firms borrowing from these powerful banks exhibit greater information opacity and engage more in real activities manipulation. These findings support the manipulation incentive channel, evidencing that borrowers have stronger incentives to manipulate financial information and conceal bad news when lenders have greater market power and rely more on hard information for monitoring. Our results challenge the common perception that powerful banks are more effective at screening, monitoring, and controlling borrowers. The impact of bank market power on corporate stock price crash risk can be mitigated by issuing loans with shorter maturities, to borrowers in the same geographical area, and by structuring loan syndicates with higher lender concentration, which are often associated with more frequent soft monitoring activities. Overall, our findings enhance the understanding of the role of creditors and loan contracts in determining corporate stock price crash risk and the stability of non-financial sectors.

Keywords: Bank market power, bank competition, monitor, stock price crash risk, information asymmetry, syndicated loans

JEL classification: D82; G12; G21; L11

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Abstract

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1 Introduction

Prior studies have extensively debated the relationship between banking market structure and economic stability (e.g., Allen and Gale, 2004; Beck et al., 2006, 2013; Schaeck et al., 2009; Huber, 2021; Jiang et al., 2022). One strand of research argues that banks in less competitive markets are more profitable, prioritize charter value protection, and exhibit greater risk aversion, thereby enhancing the stability of the banking system (e.g., Keeley, 1990; Beck et al., 2006; Jiang et al., 2022). In contrast, another strand posits that banks in less competitive markets possess greater market power and are “too big to fail”, which incentivizes them to take on more risks, jeopardizing financial system stability (e.g., Huber, 2021; Mishkin, 1999; Schaeck et al., 2009). This debate is crucial for investors and regulators seeking to understand the impact of banking market on the real economy, especially given that financial institutions’ excessive risk-taking can lead to a financial crisis. As the debate progressed, the US banking sector has substantially consolidated, with the top 5 banks’ market share rising from under 15% in the 1990s to over 45%. Policymakers constantly strive to design sound banking systems that balance economic efficiency with enhanced stability. To date, these debates have relied heavily on evidence from the banking sector, while evidence from non-financial sectors remains underdeveloped. Our study contributes to this discussion by investigating the impact of bank market power on corporate borrowers’ stock price crash risk. We aim to enrich the existing literature on the relationship between banking market structure and economic stability by providing valuable insights from non-financial sectors.

Corporate stock price crash risk has garnered substantial attention from academics and policymakers since the dot-com bubble and the 2008 financial crisis. This risk reflects the extent to which a firm’s stock return distribution is negatively skewed (Chen et al., 2001), often stemming from businesses’ tendency to hoard bad news (Jin and Myers, 2006; Kothari et al., 2009). Recent

studies have identified various firm-level determinants of stock price crash risk, including financial reporting and disclosure practices (e.g., DeFond, et al., 2015; Kim et al., 2016b; Chen et al., 2017), managerial characteristics and incentives (e.g., Kim et al., 2011b; Kim et al., 2016a; Al Mamum et al., 2020), stock return and trading volume patterns (e.g., Chen et al., 2001; Chang et al., 2017), and corporate governance mechanisms (e.g., Andreou et al., 2016; Xu et al., 2014). Although prior research has explored how dedicated institutional investors (An and Zhang, 2013) and corporate board reforms (Hu et al., 2020) can reduce managers' bad news hoarding and risk-taking, little is known about how creditors' characteristics influence firms' stock price crash risk. We collect market data and empirically examine this crucial question.

We use syndicated loan data from Thomson-Reuters' Loan Pricing Corporation Dealscan database to identify borrowers and lenders for each syndicated loan facility. We then collect stock price and financial report data for firms from *CRSP/Compustat* and bank data from the Federal Deposit Insurance Corporation (FDIC). We employ three metrics to measure stock price crash risk: negative conditional skewness (*NCSKEW*), down-to-up volatility (*DUVOL*) of stock returns, and a stock price crash dummy (*CRASHD*), as established in the literature (e.g., Kim et al., 2011a, 2011b). We use the Lerner index of the lead arranger and a weighted Lerner index to assess banks' market power, as adopted by Beck et al. (2013) and Delis et al. (2017).

We find a positive and statistically significant effect of the lead bank's market power on corporate stock price crash risk in the second year after loan origination. Specifically, a one-standard-deviation increase in the *Bank_Lerner* index (0.19 units) is associated with a 0.043-unit increase in *NCSKEW*. This result suggests that strong bank market power leads to borrowers hoarding bad news, which increases stock price crash risk and undermines economic stability. It challenges the conventional belief that powerful banks, equipped with more soft information,

better screen borrowers and use their market power to impose effective covenant restrictions for monitoring and control. Our results are robust across various settings, including alternative measures of stock price crash risk, controlling for the lagged crash risk, using alternative estimation methods, controlling for additional bank- and loan-level variables including changes in bank market power during the two years following loan origination. Furthermore, we use the staggered removal of state-level banking expansion restrictions and the state-average bank Lerner index as instrumental variables to address endogeneity concerns; we also use the k-nearest neighbor matching and the Mahalanobis distance algorithm to construct a quasi-experiment to test our hypothesis; we use the Heckman selection model to remove concerns that firms may self-select into syndicated loan financing. Our finding remains robust.

We delve deeper into the mechanism through which bank market power impacts corporate stock price crash risk, focusing on the manipulation incentive channel. This channel suggests that powerful banks, relying on hard information to monitor borrowers, incentivize borrowers to manipulate their financial information, particularly earnings. We conduct three tests to investigate this relationship: First, from the lender's perspective, we examine and confirm that powerful banks include more financial covenants in their loan contracts. This effect remains robust after controlling for borrower-, lender-, and loan-level characteristics. Second, we investigate the relationship between the number of financial covenants in a loan contract and corporate stock price crash risk. Given our baseline results suggesting that powerful banks do not provide adequate monitoring, we anticipate that firms under stricter hard monitoring, i.e., those with more covenant restrictions, are more likely to manipulate information and conceal bad news to meet those criteria, ultimately leading to stock price crashes. We find a positive effect of covenant intensity on corporate stock price crash risk, supporting this conjecture. Third, we examine the impact of bank

market power on borrowers' financial reporting opacity and real activities manipulation. The literature has established that earnings management and opaque financial reports contribute to the accumulation of bad news, leading to stock price crashes (e.g., Hutton et al., 2009; Chen et al., 2017). Following this logic, we find that, after receiving loans, firms borrowing from powerful banks exhibit greater financial reporting opacity and engage more in real activities manipulation, which rise in the two years after loan origination. These manipulation activities can create information asymmetries between managers and investors, leading to the hoarding of bad news from outsiders and, ultimately, stock price crashes. These three tests, examining the mechanism from the perspectives of lenders, loans and borrowers, respectively, provide strong support for the manipulation incentive channel. Finally, we test and rule out two alternative channels (i.e., the capital supply channel and the profitability and creditworthiness channel) as potential explanations for the link between bank market power and corporate stock price crash risk. Overall, our findings support the manipulation incentive channel, where strong bank market power and the associated hard monitoring motivate firms to manipulate information and hoard bad news, leading to increased stock price crashes.

Next, we explore whether features that facilitate bank monitoring reduce the detrimental effect of bank market power on corporate stock price crash risk. The literature has established that shorter loan maturities (Gustafson et al., 2021) and closer distances between borrowers and lenders (DeYoung et al., 2008) are associated with more frequent borrower-lender interactions, which enhance monitoring and reduce information asymmetries. Therefore, we expect a weaker effect of bank market power on corporate stock price crash risk when syndicated loans have shorter maturities and when banks grant loans to borrowers from their home states. Our results support this conjecture, indicating that short-term and local lending, often associated with more frequent

soft monitoring activities, complements the hard monitoring by powerful banks and helps detect hoarded bad news. Furthermore, we examine whether the effect of bank market power on corporate stock price crash risk is weaker for loans with a concentrated syndicate structure. The literature has shown that a concentrated syndicate structure reduces moral hazard and motivates lead arrangers to be more active in monitoring borrowers (e.g., Sufi, 2007; Chen, 2014; Gustafson et al., 2021). Following this logic, we anticipate a weaker effect of bank market power on corporate stock price crash risk for loans with a more concentrated syndicate structure (i.e., fewer lenders, a greater share held by the lead bank, and a higher lender concentration). Our results support this prediction, indicating that a concentrated syndicate structure and active monitoring can alleviate the detrimental effect of strong bank market power on corporate stock price crash risk.

This paper contributes to the literature in four important ways. First, it advances our understanding of the impact of banking market structure on economic stability by providing crucial evidence from non-financial sectors. Prior studies have debated the relationship between banking market competition and financial system stability, but the evidence remains mixed (Allen and Gale, 2004; Beck et al., 2013; Jiang et al., 2022), with the competition-stability view suggesting a favorable effect, while the competition-fragility view arguing for an unfavorable effect. Recent studies examining the non-financial sector find that the banking market deregulation encourages bank mergers and argue that it equips banks with stronger monitoring efficiency, which improves borrowers' financial reporting quality (Mi et al., 2024) and reduces their stock price crash risk (Dang et al., 2022).¹ However, notably, the proportion of syndicated loan borrowers crossing state

¹ To be more specific on the differences, Dang et al. (2022) show that firms' stock price crash risk decrease after U.S. intrastate branch reforms, but interstate deregulation does not have a significant impact, reasoning that intrastate reforms increase bank consolidations, making acquiring banks more powerful and efficient in monitoring local borrowers. Wu (2023) presents an opposing view, showing that increased city-level bank competition in China reduces stock price crash risk for firms, although the mechanism remains unexplored. In another study, Jiang et al. (2020) report that firms' stock return volatility decreases after interstate banking deregulations, reasoning that a competitive banking market increases the supply of capital, enabling firms to cope with negative financial shocks. Our research is

borders has risen from 34% in 1992 to 84% in 2019, casting doubts on prior studies examining the impact of state-level banking deregulations on local public corporations. Using syndicated loan data to identify specific lending relationships and relax the assumption in prior studies that public corporations borrow solely from local banks, we provide evidence opposite to the extant literature and show that firms borrowing from powerful banks are more inclined to hide bad news, lending support to the competition stability view. Overall, by directly matching borrowers and lenders, our research offers a new explanation for the phenomenon and enhances our understanding of the true relationship between bank market power and economic stability.

Second, this paper enriches the study of corporate stock price crash risk by examining the impact of creditors. Stock price crash risk literature has primarily focused on firm-level fundamentals, such as financial reporting and disclosure (e.g., DeFond, et al., 2015; Kim et al., 2016b; Chen et al., 2017) and the internal governance mechanism and AI (e.g., Andreou et al., 2016; Xu et al., 2014), while the impact of external monitors remains underexplored. Our research addresses this gap by investigating a crucial external determinant of stock price crash risk: lenders. Challenging the common perception that powerful banks have superior monitoring capabilities (e.g., Petersen and Rajan, 1995; Dass and Massa, 2011), we show that lenders' strong market power can incentivize borrowers to manipulate information and hoard bad news, ultimately leading to a higher incidence of stock price crashes. Additionally, unlike prior studies that typically focus on the immediate effect of internal governance on reducing crash risk, we demonstrate a 2-year-ahead impact of lenders' market power on borrowers' stock price crash risk. Our results indicate that it takes an average of 2 years after loan origination for accumulated bad news to reach a tipping

different from Dang et al. (2022) by looking at matched borrower-lender data and diverges from Jiang et al. (2020) by examining the third moment (i.e., skewness) of stock returns and comparing down and up volatility, rather than the second moment (i.e., variance).

point and finally be revealed. We encourage researchers and practitioners to pay attention to stock price crashes in a longer term, as the absence of an immediate increase in crash risk does not guarantee the absence of risk for investors in the subsequent years.

Third, our results shed new light on the relative efficacy of hard and soft monitoring approaches. Existing research suggests that large and powerful banks tend to use hard information (e.g., financial ratios and loan covenants) to screen and monitor borrowers (e.g., Stein, 2002; Cole et al., 2004), whereas banks with limited market power are inclined to gather soft information through more frequent interactions (e.g., Gustafson et al., 2021). Building on these insights, our results, showing that firms borrowing from powerful banks have stronger incentives to manipulate information and are more likely to experience stock price crashes, would imply that reliance on hard information alone creates incentives and opportunities for borrowers to manipulate financial information, leading to stock price crashes and jeopardizing shareholders' wealth. Conversely, soft monitoring, which involves more frequent and direct interactions, serves as a valuable complement in detecting hoarded bad news and preventing stock price crashes. To further support this finding, we demonstrate that the detrimental effect of strong bank market power is greater if the lead bank has a larger size but can be mitigated by banks issuing loans with short maturities, lending to local borrowers, and using a concentrated syndicate structure, where lead arrangers usually engage in more active interactions and soft monitoring activities.

Fourth, our findings advance the understanding of how syndicated loan financing impacts corporate performance. While existing research has explored the influence of corporate characteristics on the structure and terms of syndicated loans (e.g., Graham et al., 2008; Kim and Song, 2011; Lin et al., 2012; Chen, 2014), little is known of how syndicated loans impact corporate performance. Beyond existing evidence that big and powerful banks issue loans to poorly

performing firms, which boosts their performance (i.e., Delis et al., 2017) and market value (Biswas et al., 2017), our results show adverse economic consequences of borrowing from powerful banks (i.e., crash risk). We also demonstrate that various aspects of syndicated loans, including lead bank market power, loan size, maturity, syndicate structure, financial covenants and performance pricing provisions determine borrowers' manipulation incentives and associated risks for investors.

The remainder of the paper is organized as follows. Section 2 reviews relevant literature and develops our hypotheses. Section 3 describes the variables and data. Section 4 presents our empirical results, and Section 5 concludes the paper.

2 Literature Review and Hypothesis Development

This section reviews the existing debate on the relationship between bank market power and economic stability, followed by a review of the literature on corporate stock price crash risk and the development of our hypotheses.

2.1 Bank Market Power and Economic Stability

The relationship between bank market power and economic stability has been extensively studied, with two main perspectives emerging. One branch of literature, known as the “competition-fragility view”, argues that competition in the banking sector leads to instability, while a concentrated banking market, where banks possess significant market power, enhances stability. Specifically, Keeley (1990) develops a model demonstrating that banks in a competitive market are under strong pressure and have to invest in risky projects, making the banking system more fragile. Conversely, banks in less competitive markets enjoy higher profitability and prioritize protecting their charter value, leading them to avoid risky investments and contributing to financial

system stability. A series of studies provide empirical evidence supporting the competition-fragility view. For example, using data from 69 countries, Beck et al. (2006) show that banks in less competitive markets are better equipped to handle negative economic shocks, reducing the likelihood of a banking crisis. Using household bankruptcy data, Dick and Lehnert (2010) document a positive impact of U.S. banking deregulation on personal bankruptcy rates at the state level, suggesting a detrimental impact of bank competition on economic stability. By constructing measures of the competitive pressure faced by individual banks, Jiang et al. (2022) demonstrate that increased bank competition reduces banks' profits, pricing power, and charter values, leading to more risk-taking and fragility.

The other branch of literature challenges the competition-fragility view, advocating the "competition-stability view", which argues that a banking system dominated by a small group of powerful banks is detrimental to economic stability. For example, Mishkin (1999) posits that banks in less competitive markets take more risks because they are "too big to fail". These large and powerful banks are aware that the government is likely to bail them out to prevent bankruptcy, leading them to pursue highly risky investment projects. Boyd and Nicolo (2005) offer an alternative explanation, suggesting that when banks use their strong market power to charge higher loan prices, borrowers are incentivized to undertake riskier projects, thereby increasing the banks' risk exposure. This excessive risk-taking and inadequate monitoring result in a fragile financial system, as evidenced by the 2008 financial crisis. Using the H-statistics to measure bank competition at the country level, Schaeck et al. (2009) provide empirical evidence that a more competitive banking system is less prone to financial crises, whereas bank concentration correlates with a higher probability of a systematic crisis. Examining bank reforms in postwar Germany,

Huber (2021) finds that enlarged banks did not experience improved profitability or efficiency; but rather, their credits became riskier.

Although a few studies have investigated how banking market structure impacts the stability of non-financial sectors, the debate between the competition-fragility view and the competition-stability view persists. For example, Dass and Massa (2011) find that stronger lending relationships fostered by less competitive banking markets enhance banks' monitoring efficiency and improve borrowers' corporate governance, supporting the competition-fragility view. In contrast, Jiang et al. (2020) demonstrate that firms' stock return volatility decreases after interstate banking deregulation, arguing that competitive banking markets increase the supply of capital that helps firms cope with negative financial shocks, supporting the competition-stability view. By examining the effect of bank market power on corporate stock price crash risk and study identified lending relationships, our study offers new insights into this ongoing debate, providing crucial evidence from a fresh perspective.

2.2 Stock Price Crash Risk

A stock price crash refers to a negative extreme value in a firm's stock returns (Chen et al., 2001; Jin and Myers, 2006). The literature recognizes that the sudden release of stockpiled bad news is the primary driver of stock price crashes (Kothari et al., 2009). Managers, often motivated by personal interests, tend to promptly disclose good news while delaying the release of bad news (Chen et al., 2001; Kothari et al., 2009). This behavior creates severe information asymmetries, leaving investors unable to adjust their investment portfolios or liquidate assets in a timely manner. When bad news accumulates and reaches a critical threshold, where managers can no longer conceal it or resolve the underlying business issue before disclosure, the stockpiled information is released all at once (Kothari et al., 2009). At this tipping point, shareholders react by rapidly selling

their stocks, triggering a sudden collapse in the stock price, which is reflected in the negative conditional skewness of the firm's stock return distribution (Chen et al., 2001). Subsequent studies have validated this mechanism and shown that firms with greater informational opacity are susceptible to stock price crashes (e.g., Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2016b). Qualitative evidence also supports this theory. For instance, Graham et al. (2005) surveyed top managers and found that they indeed delay the release of bad news to buy time for studying the negative information and potentially improving the situation before mandatory disclosure. The literature remains inconclusive about the impact of bank market power on corporate stock price crash risk, because information theory and manipulation incentive theory offer competing predictions regarding this relationship.

2.3 Hypothesis Development

2.3.1 Bank Market Power, Information, and Corporate Stock Price Crash Risk

As financial intermediaries, banks have an information advantage and the capability to monitor borrowers (Freixas and Rochet, 2008). Petersen and Rajan (1995) suggest that banks in less competitive banking markets possess greater market power, which enables them to screen and monitor borrowers more effectively. Moreover, banks in these markets develop long-term lending relationships with borrowers, facilitating the acquisition of private information. These enduring relationships also allow powerful banks to develop expertise in specific areas, further enhancing their monitoring efficiency. Additionally, the literature has noted that powerful banks have strong bargaining power, which they use to negotiate and impose accounting-based contract terms with borrowers (Rajan, 1992; Dou, 2020). These contract terms, along with the private information acquired, provide banks with greater control over borrowers and to monitor and intervene more effectively when potential issues arise. Conversely, maintaining close lending relationships and

imposing restrictive covenants are more challenging in competitive banking markets, where borrowers have a broader range of options to switch to alternative lenders (Boot and Thakor, 2002). Consequently, banks in such markets face greater difficulty in collecting private information and effectively monitoring borrowers.

The information theory predicts a negative effect of bank market power on corporate stock price crash risk. Since stock price crash risk is driven by the information asymmetries between managers and investors, we expect that banks with strong market power use their extensive networks, lending relationships, bargaining power and resources to collect information and enforce strict contract terms to monitor borrowers. The strong lending relationships and lenders' motivation to acquire private information mitigate information asymmetries, reduce borrowers' bad news hoarding, and decrease the amount of negative information hidden from outsiders, thereby lowering corporate stock price crash risk. Conversely, in competitive banking markets where banks have limited market power and struggle to maintain lending relationships or impose restrictive covenants, the free-riding problem in information collection discourages lead arrangers from gathering soft information and effectively monitoring borrowers (Marquez, 2002), leading to greater information asymmetries and the failure to detect concealed bad news. Therefore, we develop our first hypothesis:

H1a: Bank market power is negatively correlated with corporate stock price crash risk.

2.3.2 Bank Market Power, Manipulation Incentive, and Corporate Stock Price Crash Risk

Prior studies have found that banks in less competitive banking markets with substantial market power rely more heavily on standard quantitative criteria to screen and monitor borrowers. Specifically, Stein (2002) develops a model to investigate the optimal organizational form for allocating capital to investment projects, finding that hard information, such as financial ratios,

can be effectively transmitted within large organizations to allocate capital to the best investment projects. This model suits large and powerful banks, especially after consolidations. Conversely, small banks use qualitative information generated through loan officers' personal interactions with borrowers, enabling them to develop superior knowledge about borrowers and allocate capital efficiently. Empirically, Cole et al. (2004) analyze small business surveys and find that large banks are more likely to extend credits to borrowers who use their financial statements to demonstrate sound financial conditions. Lian (2018) examines syndicated loans and shows that banks in concentrated markets tend to issue loans with more covenants, providing evidence for the hard monitoring practices of powerful banks.

As a consequence of this hard monitoring, firms borrowing from powerful banks have incentives to manipulate their financial information to secure funding and meet loan covenant requirements. Evidence of firms' manipulation activities around raising external finance has been documented as firms' smooth earnings before issuing equity (e.g., Teoh et al., 1998; Cohen and Zarowin, 2010) and debt (Liu et al., 2010). Firms that have received loans also face pressure from the capital market, which influences their accounting choices and leads to manipulation to avoid covenant violations (Dechow et al., 2010). Fan et al. (2019) investigate private loans and observe that firms with EBITDA-related financial covenants are more likely to misclassify core expenses as special items, especially when they are close to violating debt covenants. These studies suggest that firms receiving loans with strict covenant restrictions may manipulate their accounting numbers to meet covenant requirements and avoid consequences such as increased interest rates, early repayment demands, shifting control rights to lenders, or having to close the credit line.

The manipulation incentive theory predicts a positive effect of bank market power on corporate stock price crash risk. Firms borrowing from powerful banks and subject to stringent

hard monitoring have a strong incentive to manipulate their financial reports and conceal negative information from outsiders in an attempt to signal their credibility. Moreover, powerful banks that rely heavily on hard information for monitoring conduct fewer site visits and interact less with borrowers (Cole et al., 2004), which result in less soft information being collected, reducing the ability to detect concealed bad news, leaving more room for borrowers to manipulate and increasing the potential for a stock price crash. Conversely, less powerful banks rely on borrowers' soft information and engage in more soft monitoring activities (Gustafson et al., 2021), which facilitates better information collection and helps them uncover concealed bad news. Therefore, we propose our second hypothesis:

H1b: *Bank market power is positively correlated with corporate stock price crash risk.*

3 Variable Definitions and Data Collection

3.1 Stock Price Crash Risk Measures

Following the literature (e.g., Chen et al., 2001; Kim et al., 2011b; Xu et al., 2014; Callen and Fang, 2015; Al Mamum et al., 2020), we employ three variables to capture a firm's stock price crash risk: *NCSKEW*, *DUVOL*, and *CRASHD*. The first measure, *NCSKEW*, is the negative conditional skewness of a firm's weekly stock return distribution. We follow the literature (e.g., Dimson, 1979; Kim et al., 2011a, 2011b) and estimate firm-specific weekly stock returns using the following equation:

$$r_{i,\tau} = \alpha_i + \beta_{1i}r_{m,\tau-2} + \beta_{2i}r_{m,\tau-1} + \beta_{3i}r_{m,\tau} + \beta_{4i}r_{m,\tau+1} + \beta_{5i}r_{m,\tau+2} + \varepsilon_{i,\tau} \quad (1)$$

where $r_{i,\tau}$ represents the stock return of firm i in week τ . $r_{m,\tau}$ is the return of a CRSP value-weighted portfolio, serving as the market weekly return. One- and two-week leads and lags of the market return control for the impact of nonsynchronous trading. Firm i 's specific weekly return,

denoted as $W_{i,\tau}$, is calculated as the natural log of one plus the regression residual in Equation (1): $W_{i,\tau} = \ln(1 + \varepsilon_{i,\tau})$. The value of *NCSKEW* for firm i at year t is calculated as the negative of the third moment of firm-specific weekly returns $W_{i,\tau}$ for each year, scaled by the standard deviation of $W_{i,\tau}$ to the power of three. The derivation of *NCSKEW* is specified in Eq. (2) below and n denotes the number of weeks in the fiscal year:

$$NCSKEW_{i,t} = - \left[n(n-1)^{\frac{3}{2}} \sum W_{i,\tau}^3 \right] / \left[(n-1)(n-2) (\sum W_{i,\tau}^2)^{3/2} \right] \quad (2).$$

The second measure, *DUVOL*, is the down-to-up volatility. We separate the weeks of each year and for each firm into down-weeks and up-weeks. Down-weeks (up-weeks) are those weeks with firm-specific returns $W_{i,\tau}$ below (above) their annual mean value. We then calculate the standard deviation for the two subgroups of returns separately. *DUVOL* for firm i at year t is measured as the natural log of the ratio of the standard deviation of down-weeks to the standard deviation of up-weeks:

$$DUVOL_{i,t} = \ln \{ ((n_u - 1) \sum_{Down} W_{j,\tau}^2) / ((n_d - 1) \sum_{UP} W_{j,\tau}^2) \} \quad (3).$$

Compared to *NCSKEW*, *DUVOL* does not use the third moment and is therefore less susceptible to the influence of extreme values of stock returns (Chen et al., 2001).

The third measure, *CRASHD*, is a dummy variable for stock price crash. It equals 1 if the specific weekly return, $W_{i,\tau}$, in any week of the calendar year is at least 3.09 standard deviations below the firm's annual mean value, and 0 otherwise (Hutton et al., 2009). For all three measures, a higher value indicates more negatively skewed stock returns and a greater propensity for crashes.

3.2 Bank Market Power Measure

We measure individual bank market power using the Lerner index (*Bank_Lerner*), following the established literature (e.g., Beck et al., 2013; Delis et al., 2017)². The Lerner index, also known as the profit-cost margin, is calculated using the formula, $Lerner\ index = (P - MC)/P$, where P is the price of bank output and MC is the marginal cost of production. The marginal cost is estimated using parametric techniques and a standard translog cost function, as described by Delis et al. (2017). We use the Lerner ratio of the lead bank in syndicated loans because the lead bank bears primary responsibility for monitoring (Lin et al., 2012; Gustafson et al., 2021)³. Our results remain robust when using the weighted average Lerner index of lenders within the loan cluster and when applying alternative cost function variants to calculate the Lerner index. These results are not reported for brevity but are available upon request.

3.3 Data Collection and Descriptive Statistics

We construct a dataset by using syndicated loan data to link banks as lenders and *Compustat* firms as borrowers of each loan facility. We gather syndicated loan data from the Thomson Reuters Loan Pricing Corporation Dealscan database. The sample period is from 1992 to 2020, encompassing approximately 29,000 syndicated loan facilities⁴. We then match each loan facility with relevant bank and firm characteristics, using bank data from the Federal Deposit Insurance Corporation (FDIC) database, corporate stock price data from the *CRSP*, and financial report data from *Compustat*. Aligned with the literature on stock price crash risk (e.g., Chen et al., 2001; Kim et al., 2011a, 2011b; Al Mamum et al., 2020), we exclude borrowers (firms) in financial (SIC Codes

² A few studies use structural measures of banking market competition (e.g., the HHI and CRk) at the state or country levels. While these proxies are useful in calculating the level of competition for the local market, they do not suit our study, because borrowers could borrow across their state borders (a mean value of 55.5% in our sample). Therefore, these proxies are not accurate measures of the lenders' market power, and we decide not to use them in this study.

³ There are 8% of loan facilities having more than one lead arranger. In this case, we use the Lerner of the lead arranger with the largest share. We also test and find that having multiple lead arrangers do not influence our baseline relationship. These results are not tabulated for the sake of brevity.

⁴ Our findings remain robust when excluding major crisis periods (i.e., 2001, 2007-2008, and 2020), during which stock price crashes were especially frequent. These results are not tabulated for the sake of brevity.

6000-6999) and utility (4900-4949) sectors, as well as firm-year observations with fewer than 26 active weeks or with year-end stock prices below \$1.⁵ This final selection leaves us with approximately 25,000 loan facilities with identified values for both stock price crash risk and the lead bank's Lerner index. The number of observations used in the regression analysis is slightly lower due to the availability of information required to calculate control variables.

[Insert Table 1 here]

Table 1 reports the descriptive statistics, with variables winsorized at the 1% and 99% levels. *NCSKEW* has a mean value of 0.072 and a standard deviation of 0.869. *DUVOL* has a mean value of 0.024 and a standard deviation of 0.363. Despite differences in their constructions, untabulated results show that *NCSKEW* and *DUVOL* have a correlation coefficient of 0.910, indicating that these two variables have significant commonalities: the skewness of stock return distribution. *CRASHD* has a mean value of 0.209, indicating that 20.9% of the observations experienced a stock price crash. *Bank_Lerner* has a mean value of 0.320, suggesting that, on average, profits constitute 32% of bank output. These figures are economically close to those reported in prior studies on stock price crash risk (e.g., Kim et al., 2011b; 2016a) and bank market power (e.g., Wang et al., 2020).

4 Empirical Results

4.1 The Effect of Bank Market Power on Corporate Stock Price Crash Risk

We investigate the impact of bank market power on corporate stock price crash risk. Unlike prior studies that typically examine the immediate effect of an attribute on stock price crash risk, we analyze the effect of bank market power over a five-year period, from loan origination to 4 years

⁵ Our findings are robust to relaxing these restrictions and including borrower-year observations with fewer than 26 active weeks or with year-end stock prices below \$1. These results are not tabulated for the sake of brevity.

down the line. This approach allows us to determine whether there is an effect and, if so, how long it takes for the bad news to accumulate and eventually emerge. We employ the same set of control variables commonly used in the stock price crash risk literature (e.g., Kim et al., 2011a; 2016a).

The results, presented in Table 2 and illustrated in Fig. 1, show a positive effect of bank market power on two-year-ahead corporate stock price crash risk. Specifically, we find no relationship between bank market power and corporate stock price crash risk at the time of loan origination ($n=0$). The coefficients of $Bank_Lerner_{i,t}$ in columns (1) and (6) of Table 2 are negative and statistically insignificant. One year later ($n=1$), the sign flips but remains statistically insignificant, as shown in columns (2) and (7). We calculate and test the change in the coefficient of $Bank_Lerner_{i,t}$ and our results in columns (2) and (7) suggest an increase in the effect from year t to year $t+1$. In the second year after loan origination ($n=2$), the positive effect becomes economically larger and statistically significant. According to column (3), a one-standard-deviation increase in $Bank_Lerner_{i,t}$ (0.19 units) is associated with an increase in $NCSKEW_{i,t+2}$ by 0.043 units. The increase in the coefficient of $Bank_Lerner_{i,t}$ from 0.035 in year $t+1$ to 0.224 in year $t+2$ ($t=352.32$) is substantial. The positive relationship is robust to using $DUVOL$ and $CRASHD$ to measure stock price crash risk, as reported in columns (8) and (13) of Table 2.⁶ In the third year after loan origination ($n=3$), the positive effect diminishes. Specifically, the relationship remains statistically significant in the $CRASHD$ equation (column 14) but is insignificant in the $NCSKEW$ (column 4) and $DUVOL$ (column 9) equations. Furthermore, the effect becomes statistically insignificant in the fourth year ($n=4$), as shown in columns (5), (10) and (15).⁷

⁶ One may question whether this 2-year-ahead effect is driven by the firm's subsequent borrowings. To address this concern, we use a dummy variable and set its value equal to 1 if the firm has other borrowings, including new facilities, over the 5 years from year $t-2$ to year $t+2$. We test and find that multiple borrowing does not influence the observed relationship between bank market power and 2-year-ahead corporate stock price crash risk. These results are reported in Table A1 of the Online Appendix.

⁷ One may question whether there was an increasing trend in crash risk before loan origination, so strong bank market power reduces crash risk from year $t+3$ onward. We test this conjecture and find that bank Lerner ratio does not

The positive effect of bank market power on 2-year-ahead corporate stock price crash risk supports our *Hypothesis H1b*, indicating that strong bank market power increases managers' tendency to hoard bad news. These results suggest that the manipulation incentive theory provides a more convincing explanation than the information theory in predicting the effect of bank market power on corporate stock price crash risk. We observe a substantial increase in crash risk in the second year after loan issuance, with weaker effects in the first and third years, indicating that it takes an average of 2 years after loan origination for bad news to accumulate, reach a tipping point, and finally emerge.⁸ In terms of the timing, if firms' earnings manipulation persists until the first year after issuing securities (Cohen and Zarowin, 2010; Liu et al., 2010), then a stock price crash in the second year after loan origination is plausible and may indicate that it is the hoarded bad news in the earning smoothing period that breaks out and leads to a stock price crash. Overall, our results demonstrate that strong bank market power is detrimental to the stability of non-financial sectors. Conversely, a competitive banking market, where lenders have limited market power, could reduce corporate stock price crash risk and enhance economic stability.

[Insert Fig. 1 here]

[Insert Table 2 here]

We incorporate lagged crash risk variables to account for potential autoregressive conditional skewness in stock returns (Harvey and Siddique, 1999). We find that the positive relationship between bank market power and two-year-ahead corporate stock price crash risk remains

determine corporate stock price crash risk before loan origination and that there wasn't an increasing trend, which remove the concern. These results are not reported to save space but are available from the authors upon request.

⁸ We acknowledge that our crash-risk data depend on calendar-year timing, and thus we do not claim that crashes always occur exactly 24 months after loan issuance. For example, if a loan is issued in December of year t and the crash occurs in January of year $t+2$, the interval is 13 months. In contrast, a loan issued in January of year t that crashes in December of year $t+2$ spans is 35 months. Although our variables do not explicitly model this variation, they nevertheless reveal a significant rise in crashes during the second fiscal year. The main implication is that these crashes tend to materialize later than one year after loan issuance (i.e., year $t+1$), rather than sooner or within.

statistically significant and economically meaningful. Moreover, we control for crash risk at year t when the loan was issued to address the concern that the observed positive relationship stems from risky firms attracting banks seeking a higher risk premium. We find that the positive effect of bank market power on two-year-ahead corporate stock price crash risk holds for controlling for crash risk at loan origination, implying that high bank market power is associated with an increase in crash risk for borrowers after loan origination. These results are reported in Table A2 of the Online Appendix.

One might question whether our results are specific to financially constrained firms or those heavily reliant on bank financing – borrowers potentially more susceptible to lender influence. Others might expect the effect of bank market power on borrowers' crash risk to be more pronounced among firms that depend more on external finance. To examine these possibilities, we test whether and how our baseline result varies with borrowers' external finance dependence. Specifically, we follow Dang et al. (2022) and define external finance dependence as $(\text{capital expenditures} + \text{R\&D expenses} + \text{M\&A expenses} - \text{operating income before depreciation and amortization}) / (\text{capital expenditures} + \text{R\&D expenses} + \text{M\&A expenses})$. We measure financial constraints using the size-age index (Hadlock and Pierce, 2010). Based on these measures, we construct two dummy variables equal to 1 if a borrower's external finance dependence (or financial constraints) exceeds its industry-year average, and 0 otherwise. Interacting these dummies with *Bank_Lerner* in our baseline model yields insignificant coefficients, suggesting that the relationship between bank market power and corporate stock price crash risk holds across the full sample, regardless of borrowers' financial dependence or constraints. These results are presented in Table A3 of the Online Appendix.

4.2 Robustness Checks and Addressing Endogeneity Concerns

The time-varying nature of the effect significantly alleviates many endogeneity concerns. Specifically, if an unobservable factor simultaneously influences bank market power and corporate stock price crash risk, resulting in a positive relationship, this relationship should normally persist, especially at loan origination ($n=0$). However, we do not observe such persistence or a significant relationship at loan origination, indicating a low likelihood of an unobservable factor simultaneously influence both variables. To further address potential endogeneity inherent in this research context and rigorously verify the robustness of our findings, we conduct a series of tests.

We employ alternative estimation methods to check the robustness of our findings. First, we cluster standard errors at the firm and year levels to address potential within-firm and within-year correlations in error terms, following Cameron and Miller (2015). Second, we incorporate industry $\times$ year fixed effects to control for shocks to an individual industry each year. Third, we cluster standard errors at the bank-year level to address potential errors correlated within each bank-year cluster. The results in Table 3 show that the coefficients of $Bank_Lerner_{i,t}$ remain positive and statistically significant in the *NCSKEW* and *DUVOL* equations. The correlation between $Bank_Lerner_{i,t}$ and $CRASHD_{i,t+2}$ weakens slightly, with t -values ranging from 1.63 to 1.94, but this does not contradict our main finding of a positive relationship. Overall, these results indicate that the positive relationship between bank market power and corporate stock price crash risk is robust to using these alternative estimation methods.

[Insert Table 3 here]

Next, we test whether our finding is robust to controlling for bank- and loan-level variables. Specifically, we control for bank characteristics, such as bank size, Tier 1 capital ratio, and lead bank reputation, as well as loan characteristics, including the cost of loans, facility amount, maturity, number of lenders, loan purpose, performance pricing, and whether the loan is

collateralized. The results in columns (1)-(3) of Table 4 show that the effect of bank market power on corporate stock price crash risk remains positive and statistically significant after controlling for variables at the bank and loan facility levels. For example, in column (1), the coefficient of $Bank_Lerner_{i,t}$ is 0.275, indicating that a one-standard-deviation increase in $Bank_Lerner_{i,t}$ is associated with a 0.052-unit increase in $NCSKEW_{i,t+2}$. Beyond the effect of bank market power, we find a negative coefficient of $Facility_Amount_{i,t}$, suggesting that firms granted larger loans are less likely to experience a crash. This implies that banks devote greater attention to monitoring larger loans. *Performance pricing dummy* $_{i,t}$ has a positive coefficient, indicating that firms with performance-based loan pricing are more likely to hoard bad news to meet relevant requirements and reduce their borrowing costs. In columns (4)-(6), we incorporate $\Delta Bank_Lerner_{i,t \sim t+2}$ to control for the change in bank market power over the two years after loan origination. We find that $\Delta Bank_Lerner_{i,t \sim t+2}$ is not significantly correlated with stock price crash risk, suggesting that the observed positive effect of bank market power on two-year-ahead corporate stock price crash risk is independent of changes in bank market power after loan origination. It appears that the bank's market power at the point of offering the loan determines stock price crash risk. In columns (7)-(9), we further control for fixed-effects at the bank level. Although $Bank_Lerner$ is a bit weaker in predicting $NCSKEW$ and $DUVOL$, the effect on $CRASHD$ becomes stronger. Overall, the results in Table 4 demonstrate that our main finding, the positive relationship between bank market power and corporate stock price crash risk, is robust to controlling for bank- and facility-level variables.

[Insert Table 4 here]

We employ an instrumental variable (IV) approach to deal with potential endogeneity concerns that bank market power and borrowers' stock price crash risk are influenced by an omitted variable. The first IV we use is the branching restrictiveness index, following Rice and

Strahan (2010). The authors highlight that the relaxation of geographical restrictions on bank expansion allowed states to erect barriers to branch expansion, which were not removed until 2006. The loosening of such banking expansion restrictions is an exogenous shock to the market power of local banks; therefore, we use this staggered change in banking restrictions at the state level. For an alternative IV, we use bank size as the weighting factor to calculate the average Lerner ratio for banks headquartered in each state and year. We then use this weighted Lerner ratio as the IV for a single bank's market power. The rationale behind using the state-average bank Lerner as the IV is that, due to the gradual removal of cross-state branching restrictions, banks headquartered in the same state tend to face the same regulatory environment, which influences the degree of bank market power. Therefore, the average bank Lerner ratio can be a good predictor of an individual bank's Lerner, while reflecting state-level bank regulatory policies and being arguably exogenous to corporate managers' bad news hoarding and stock price crashes. We also empirically test the validity of our IVs.

The results in Table 5 demonstrate that the effect of bank market power on corporate stock price crash risk is robust to using an IV to address endogeneity concerns and test the relationship. In column (1) of Panel A, the coefficient of $Bank_Lerner_{i,t}$ is 1.727 ($t = 2.64$), indicating that a one-standard-deviation increase in $Bank_Lerner_{i,t}$ is associated with an increase in $NCSKEW_{i,t+2}$ by 0.33 units. The effect is robust when we use $DUVOL$ to measure crash risk in column (2). Although the effect is a bit weaker in column (3) where we use $CRASHD$ to measure crash risk ($t = 1.49$), it does not argue against our main finding of a positive relationship. The result of a positive relationship is robust when we use the state-average Lerner index as the IV in columns (4)-(6). Panel B of Table 5 reports the first-stage results and shows that both instruments have a strong first stage in statistical tests. The test results of first-stage partial R^2 and F-statistics suggest that

these IVs are relevant in explaining *Bank_Lerner* and do not have a weak instrument problem. We examine whether the IV is exogenous by testing whether it is correlated with the regression residual of our baseline model. The test p-values varying between 0.082 and 0.464 show that these IVs are not correlated with the regression residual of our baseline model and suggest that they satisfy the exclusion restriction.

One may question the validity of using the state-average Lerner as the IV, as there could be attributes influencing the state-average Lerner and corporate stock price crash risk simultaneously, making the IV endogenous. Despite our diagnostic test showing exogeneity, we further reduce the endogeneity concern by restricting our sample to observations where firms borrow across their state borders. The rationale is that, while unobservable local business factors might simultaneously influence banks and corporations in the state, it is less likely for this local factor to influence borrowers across state borders and systematically affect every paired cross-state borrowing relationships. Therefore, focusing on cross-state borrowing helps further alleviate endogeneity concerns. Columns (7)-(9) of Panel A report the results of these tests, showing that the relationship between bank market power and corporate stock price crash risk holds.

[Insert Table 5 here]

While the IV approach we employed can address the endogeneity concern that a common factor may drive both bank market power and borrowers' stock price crash risk, it does not rule out the potential selection problem that powerful banks may select or attract firms with certain characteristics, and these characteristics could coincidentally drive stock price crash risk. We conduct tests to address this concern. First, we test whether borrowers' stock price crash risk reversely attracts powerful banks, which leads to an empirical relationship between bank market power and corporate stock price crash risk. Our results, tabulated in Table A4 of the Online

Appendix, show little evidence that stock price crash risk significantly determines *Bank_Lerner* at loan origination, which removes the concern of self-selection bias and reverse causality. Interestingly, our results show that borrowers' past stock price performance (*DTURNOVER*, *SIGMA* and *RET*), size and leverage ratio determine *Bank_Lerner*, indicating that powerful banks indeed select firms with certain characteristics, although stock price crash risk is not on that list. Therefore, we use a matched sample to further reduce the endogeneity concern due to the potential selection problem.

Specifically, we use the k-nearest neighbor and the Mahalanobis distance matching algorithm to construct a quasi-experiment to test the treatment effect of borrowing from a powerful bank. We refer treatment to the firms that borrow from a bank with its Lerner ratio higher than the annual median value plus 0.1, which gives us around 20% of observations. We then construct a group of control firms from the remaining 80% of observations by finding the “statistical twins”. We use the firm-level control variables to match the observations, and we require the matched observation from the same industry-year pool. We use the 5 nearest neighbors for balancing the bias-variance trade-off. We use this constructed sample as a quasi-experiment to test our hypothesis.

The results in Table 6 continue to show a positive relationship between bank market power and corporate stock price crash risk. For example, according to column (1) of Panel A, the 2-year-forward *NCSKEW* is greater for the treated firms by 0.069, and this positive relationship is statistically significant at the 1% level. Panel B reports the mean values of firm characteristics for the treated and control firms, respectively. The standardized mean differences are below 0.1 while the variance ratios are within the range of (0.5, 2), particularly for the variables that determine *Bank_Lerner* (i.e., *DTURNOVER*, *SIGMA*, *RET*, *SIZE* and *LEV*). These results show that the

treated and control groups are comparable and that the constructed sample has successfully mimicked a randomized experiment.

[Insert Table 6 here]

One may question the identification and interpretation of the relationship between bank market power and corporate stock price crash risk: Is it the banks' strong market power or their size and complex structure that led to the increase in borrowers' stock price crash risk? While hierarchical banks may adopt rigid borrower screening criteria, using the Lerner index as the primary measure does not establish a direct connection between market power and bank size, the latter often serving as an indicator of organizational complexity. To address this crucial question, we delve deeper into the underlying relationship by exploring the effects of *Bank_Lerner* and *Bank_Size*, as well as their interactions, on borrowers' stock price crash risk. To simplify interpretation, we create a dummy variable, *Large_Bank*, which equals 1 if the lender's total assets exceed the annual median value across all banks, and 0 otherwise.

The results in Table 7 show that the baseline relationship is driven by lenders' market power rather than their size. For example, in column (1), we find a positive relationship between *Bank_Lerner_{i,t}* and *NCSKEW_{i,t+2}* (0.17, $t = 1.87$), while the effect of *Large_Bank_{i,t}* is negative (-0.068, $t = -2.13$). This result suggests that large banks may leverage their professionalism, expertise, and robust internal control to reduce borrowers' bad news hoarding and stock price crashes. The interaction term *Bank_Lerner_{i,t} × Large_Bank_{i,t}* has a positive sign, indicating that bank size amplifies the impact of market power. To elaborate, firms borrowing from powerful banks of larger size are more incentivized to hoard bad news, while the expertise of large banks in monitoring and mitigating borrowers' risks is undermined by their strong market power. To further verify this explanation, we interact *Bank_Lerner* with an alternative dummy variable,

Bank_reputation, which equals 1 if the lead bank is ranked in the top 10 based on loan arrangement volume over the past three years. Consistent with the results of bank size, *Bank_Reputation* has a negative effect on stock price crash risk, and its interaction with *Bank_Lerner* has a positive effect, supporting our conjecture.

[Insert Table 7 here]

Finally, we employ a Heckman selection model to mitigate concerns that firms with specific characteristics may select syndicated loan financing over alternative sources, introducing selection bias. The first-stage equation models the probability of firm participation in syndicated loan financing. We use the number of syndicated loan facilities utilized by firms in the same industry (3-digit SIC) over the previous two years ($t-1$ and $t-2$) as an instrument, because it captures peer learning effect. We also validate by tests showing no significant correlation with stock price crash risk, which plausibly satisfies the exclusion restriction. The second-stage equation estimates the effect of bank market power on corporate stock price crash risk, controlling for the inverse Mills ratio derived from the first stage. Our results reported in Table A5 of the online Appendix indicate that our baseline findings remain robust when accounting for firms' selection into syndicated loan financing.

4.3 Bank Market Power and Corporate Stock Price Crash Risk: the Mechanism

Building on the previous sections' finding of a positive and robust effect of bank market power on corporate stock price crash risk, this section delves deeper into the mechanism driving this relationship, i.e., the manipulation incentive channel. Given that firms' bad news hoarding is the primary cause for stock price crashes (e.g., Kothari et al., 2009), it is plausible to hypothesize that high bank market power motivates firms to manipulate their financial information and hoard bad news. Specifically, as powerful banks rely on financial ratios and loan covenants to screen and

monitor borrowers, firms subject to this stringent hard monitoring may manipulate their earnings and operations to temporarily meet loan covenant requirements, thereby avoiding the transfer of control rights to creditors in the event of a covenant violation. Under this manipulation incentive framework, we expect, from the lender's perspective, that powerful banks are more inclined to use hard monitoring, as evidenced by the imposition of a larger number of financial covenants in loan contracts. From the loan's perspective, we expect that a larger number of financial covenants is associated with higher stock price crash risk for borrowers. From the borrower's perspective, we expect that firms borrowing from powerful banks engage in more manipulation activities. We proceed to verify the manipulation incentive channel from these three distinct perspectives:

We first test the effect of lenders' bank market power on covenant intensity. Since our *Hypothesis H1b* is based on prior findings that powerful banks tend to use hard information to screen and monitor borrowers (e.g., Stein, 2002; Cole et al., 2004; Lian, 2018), we expect *a positive relationship between bank market power and loan covenant intensity*. We regress the number of loan covenants on the Lerner index, controlling for bank-, loan- and firm-level characteristics.

The results in Table 8 support our conjecture that powerful banks issue loans with a larger number of financial covenants. A one-standard-deviation increase in *Bank_Lerner* is associated with an increase in the number of financial covenants by 0.08 units (column 1), indicating that powerful banks indeed rely on hard monitoring and impose more covenant restrictions in loan contracts. This effect is statistically significant and remains robust to controlling for bank and loan characteristics in column (2) and further controlling for borrower characteristics in columns (3) and (4). In column (5), we use a negative binomial regression, instead of a linear model, to address potential bias due to *Financial_Covenants* using count data, and the results are similar to those

from a linear regression model (column 4), showing that the effect of bank market power on covenant intensity is robust.

[Insert Table 8 here]

We then study the effect of loan covenant intensity on borrowers' stock price crash risk. Given that lenders' reliance on hard information can create opportunities for borrowers to manipulate their financial information and hoard bad news, we expect *a positive relationship between hard monitoring (i.e., number of financial covenants) and borrowers' stock price crash risk*. In addition to the number of financial covenants, we use *abnormal covenants* as an alternative measure. Since banks may impose more financial covenants to constrain riskier borrowers, the raw number of covenants could reflect borrower characteristics or the bank's strategy to restrict risky borrowers (Graham et al., 2008). To isolate this effect, we regress the number of financial covenants on a list of firm, bank, and loan characteristics, which are determinants of loan syndicate structure according to Chen (2014). These variables include firms' stock returns, return volatility, firm size, market-to-book ratio, leverage, tangibility, profitability, bank size, Tier 1 capital ratio, bank reputation, loan size, loan maturity, cost of the loan, number of lenders, loan purpose, performance pricing, collateral and fixed-effects at the borrower's industry, year and bank levels. We then use the regression residual as abnormal covenants, which represents the portion of covenant intensity not explained by borrower characteristics and lender risk preference. Therefore, this measure arguably offers a cleaner picture of how bank market power shapes loan contract design.

The results in Table 9 show that corporate stock price crash risk is positively correlated with covenant intensity. According to column (1), a one-standard-deviation increase in *Financial_Covenants_{i,t}* (i.e., 1.322 items) is associated with an increase in *NCSKEW_{i,t+2}* by 0.016 units, after controlling for other variables. This effect is robust when using *DUVOL* and *CRASHD*

to measure crash risk in columns (2) and (3), and when using *Abnormal_Covenants_{i,t}* as an alternative measure in columns (4)-(6). These results support our conjecture that covenant intensity is positively correlated with corporate stock price crash risk, implying that the hard monitoring practices of powerful banks stimulate borrowers' incentives to manipulate financial information, leading them to hide bad news to meet financial covenant requirements, thereby increasing stock price crash risk.

[Insert Table 9 here]

Next, we examine whether firms engage more in manipulation when bank market power is greater. The literature on stock price crash risk has established that informationally opaque firms hide more bad news from external stakeholders, increasing their stock price crash risk (e.g., Hutton et al., 2009; Kim et al., 2016b). To verify the manipulation incentive channel from the borrower's perspective, we expect that *firms borrowing from powerful banks exhibit a greater degree of earnings manipulation*, leading to higher stock price crash risk. Our first measure is the financial reporting opacity indicator (*Opaque*), defined as the three-year moving sum of the absolute value of discretionary accruals, following Hutton et al. (2009), to capture the degree of information opacity. Discretionary accruals are estimated using the modified Jones model, following Dechow et al. (1995). Hutton et al. (2009) argue that accruals management obscures information about firms' fundamentals and enables managers to hide bad news from external stakeholders. Therefore, the estimated opacity serves as an indicator of information asymmetry, as firms with consistently large discretionary accruals are more likely to engage in earnings management. We then investigate firms' real activities manipulation, another crucial way of manipulating earnings information (Cohen and Zarowin, 2010), which can lead to stock price crashes (Francis et al., 2016). We use real earnings management indicators, *RM_1* and *RM_2*, following Cohen and

Zarowin (2010). *RM_1* captures the extent to which firms cut discretionary expenses and increase abnormal production costs, while *RM_2* captures the extent to which firms engage in sales manipulation and cut discretionary expenses to boost reported earnings. Given that our baseline results show a two-year lagged increase in crash risk, we calculate the average of real earnings management for each individual firm in the two years following loan origination and then test the effect of lenders' bank market power on borrowers' real activities manipulation.

The results in Panel A of Table 10 show that bank market power exacerbates borrowers' information manipulation. Column (1) displays a positive effect of bank market power on firms' financial reporting opacity. A one-standard-deviation increase in *Bank_Lerner_{i,t}* is associated with an increase in *Opaque_{i,t+2}* by 0.01 units, controlling for bank- and loan-level variables. In column (2), we control for the degree of opacity at loan origination to evaluate changes in opaqueness and find that the impact of bank market power remains positive and statistically significant. These results demonstrate that firms borrowing from more powerful banks exhibit a higher degree of financial reporting opacity. The results in columns (3) and (5) show a positive effect of bank market power on real earnings manipulation, indicating that firms borrowing from powerful banks engage more in real activities manipulation. This finding is robust to controlling for the real earnings manipulation at loan origination, as reported in columns (4) and (6). Overall, our results support the conjecture that strong bank market power incentivizes borrowers to engage more in manipulation activities, leading to higher stock price crash risk.

[Insert Table 10 here]

Given that our baseline result shows bank market power affects corporate stock price crash risk with a 2-year lag, this implies borrowers' earnings manipulation likely peaks in the two years after loan origination. To test this conjecture and further clarify crash timing, we investigate

whether bank market power correlates with subsequent earnings manipulation (i.e., years $t+3$ and $t+4$). As shown in Panel B of Table 10, controlling for earnings manipulation in year $t+2$, which accounts for the sum (or average) of earnings manipulation since loan origination, *Bank_Lerner* exhibits no significant relationship with earnings manipulation beyond $t+2$. This indicates that borrowers' earnings manipulation indeed rises by year $t+2$ and does not further intensify. This finding offers a clear explanation for why crashes materialize specifically in the second-year post-origination.

We then test two alternative explanations for the positive relationship between bank market power and corporate stock price crash risk. One potential mechanism underlying this relationship is the capital supply channel. Specifically, Jiang et al. (2020) find that U.S. banking deregulations led to improved access to external finance for firms, allowing them to tackle financial difficulties and reduce volatilities in their earnings and stock returns. Under this framework, we expect that banks with strong market power limit the availability of external finance, making it harder for borrowers to mitigate the impact of negative shocks before releasing bad news, thereby increasing the likelihood of stock price crashes. To examine whether bank market power influences corporate stock price crash risk through this capital supply channel, we test whether firm investments are more sensitive to cash flows when bank market power is greater. Jiang et al. (2020) show that U.S. firms' investment-cash flow sensitivity decreases after banking deregulations, suggesting that firms gaining better access to external finance rely less on internal cash flows but use the increased supply of capital to deal with negative shocks and reduce performance volatility. Following this logic, we conjecture that, if bank market power influences stock price crash risk through the capital supply channel, we should observe *greater investment-cash flow sensitivity when bank market power is stronger*. We employ the investment-cash flow sensitivity model from Jiang et al. (2020),

where cash flow (CF) is defined as (*operating cash flows / total assets*), and investment (INV) is defined as (*capital expenditures / total assets*). We also employ an alternative definition of investments ($INVR$), as (*capital expenditures + M&A expenses + R&D expenses – sale of property, plant, and equipment + investment to maintain existing assets in place*) / *total assets*, following Richardson (2006) and Li et al. (2021). We interact $Bank_Lerner$ with the cash flow variable (CF). A positive coefficient of the interaction term, $CF_{i,t+1} \times Bank_Lerner_{i,t}$, would indicate that firms rely more on internal cash flows when bank market power is greater, and vice versa.

However, our results in Panel A of Table 11 do not support the capital supply channel. The coefficient of $CF_{i,t+1} \times Bank_Lerner_{i,t}$ in column (1) is statistically insignificant, indicating no impact of bank market power on the cash flow sensitivity of firm investments. This result is robust to controlling for bank- and loan-level variables in column (2). In columns (3) and (4), we use the second definition of investments ($INVR$). The coefficient of the interaction term, $CF_{i,t+1} \times Bank_Lerner_{i,t}$, is negative and statistically significant, indicating that cash flow sensitivity is weaker when bank market power is greater. This result contradicts our prediction for the capital supply channel but aligns with prior evidence that EU firms face less financial constraint when their local banking market is more concentrated (Ratti et al., 2008).

The second alternative explanation for our baseline result is that stronger market power could reduce the availability of funds or increase the cost of capital, leading to lower firm profitability and, consequently, triggering a stock price crash. If bank market power influences borrowers through this channel, one would expect a decrease in firm profitability and creditworthiness in the second-year post-origination. Therefore, we examine the effects of bank market power on two-year-ahead profitability (i.e., ROA and ROE) and creditworthiness (i.e., using Altman Z -score).

Our results in Panel B of Table 11 do not support this conjecture. Specifically, *Bank_Lerner* is not significantly correlated with borrowers' *ROA* (column 1), *ROE* (column 2) or *Z-score* (column 3), indicating that strong bank market power at loan origination does not influence two-year-ahead corporate profitability and creditworthiness.⁹ This result indicates that the relationship between bank market power and corporate stock price crash risk is unlikely driven by banks influencing firms' profitability or creditworthiness. Overall, our results in Tables 11 rule out the capital supply channel and the profitability and creditworthiness channel, suggesting that the impact of bank market power on corporate stock price crash risk operates through the manipulation incentive channel.

[Insert Table 11 here]

4.4 Heterogeneous Effects of Bank Market Power

4.4.1 Syndicated Loan Maturity and Cross-state Lending

We investigate the features that facilitate bank monitoring and likely mitigate the effect of bank market power on corporate stock price crash risk. The first feature is loan maturity. The literature on corporate debt maturity has established that short-term debt facilitates monitoring because the cost of rolling over short-term debt and the refinancing risk prevent firms from engaging in high-risk activities (Demirguc-Kunt and Maksimovic, 1999; Ben-Nasr et al., 2015). Additionally, refinancing involves frequent and direct contact, allowing banks to evaluate borrowers' operations and associated risks. Therefore, we predict *the detrimental effect of bank market power on corporate stock price crash risk to be weaker for loans with shorter maturity*. We use the natural logarithm of loan maturity to interact with the coefficient of *Bank_Lerner_{i,t}* in determining

⁹ Our results do not argue against Delis et al. (2017). Note that we are testing the 2-year-ahead effect, because our results show that crashes take place in year $t+2$. We did not report the 1-year ahead effect, but we indeed observed a positive effect of *Bank_Lerner* on *ROA* at year $t+1$, which is consistent with Delis et al. (2017).

corporate stock price crash risk. The second feature is the distance between lenders and borrowers. The literature has established that a longer distance between borrower and lender hinders information collection and makes monitoring more difficult (DeYoung et al., 2008). Therefore, we expect *a longer distance to make it harder for banks to detect hoarded bad news, thereby amplifying the impact of bank market power on corporate stock price crash risk*. We use a dummy variable, *Across_State*, to capture loans where firms borrow across state borders to test this effect.

The results in Table 12 demonstrate that features facilitating monitoring reduce the impact of bank market power on corporate stock price crash risk. Specifically, in column (1), $Bank_Lerner_{i,t} \times Ln_Maturity_{i,t}$ has a positive coefficient (0.88, $t = 1.69$), indicating that bank market power has a stronger impact on corporate stock price crash risk for loans with longer maturities. Economically, for a one-standard-deviation increase in loan maturity (22.44 months) from its mean value (47.87 months), the effect of *Bank_Lerner* on *NCSKEW* increases from 0.197 to 0.231. Conversely, the impact is smaller for shorter loan maturities.¹⁰ This finding is robust to using *DUVOL* and *CRASHD* to measure stock price crash risk, as reported in columns (2) and (3). Columns (4)-(6) show that firms borrowing across states are more sensitive to the impact of bank market power. For example, according to column (4), the effect of *Bank_Lerner* on *NCSKEW* is 0.113 for firms borrowing within their states but increases to 0.396 for firms borrowing across state borders. These results imply that shorter maturities and closer proximity between borrowers and lenders encourage soft monitoring and information collection, preventing borrowers from manipulating their accounting numbers, thereby reducing the detrimental effect of strong bank market power.

[Insert Table 12 here]

4.4.2 Loan Syndicate Structure

¹⁰ The increase in 2-year-ahead crash risk and the moderating role of loan maturity are robust to removing the 4,018 loan facilities that mature in year $t+1$. The effects are insignificant for the loans that have matured in year $t+1$.

We examine whether the impact of lenders' market power on borrowers' stock price crash risk is moderated by the structure of syndicated loans. The literature exploring determinants of loan syndicate structure suggests that more concentrated loans are associated with increased soft monitoring activities and enhanced monitoring efficiency, thereby resolving moral hazard problems in the loan sales market. For example, Sufi (2007) shows that lead banks retain a larger proportion of the loan and conduct more intensive investigation and monitoring when borrowers are financially opaque. Chen (2014) suggests that having fewer lenders and the lead arranger retaining a larger proportion of the loan reduce the free-riding problem and improve banks' monitoring efficiency, thereby suppressing borrowers' risk-taking. Gustafson et al. (2021) observe that lenders with a greater lead share have stronger incentives and conduct more frequent soft monitoring activities, such as site visits and third-party appraisals. Motivated by these studies, we expect that *the detrimental effect of bank market power on corporate stock price crash risk is weaker when the loan has a more concentrated syndicate structure*. We use three measures of lender concentration: The first measure is the logarithm of the number of lenders in the lending cluster. The second measure is the share of the loan retained by the lead bank. The third indicator is the lender concentration ratio, calculated using the Herfindahl-Hirschman Index (HHI), i.e., the sum of squared shares held by each lender in the cluster.

The results in Table 13 show that bank market power has a smaller impact on corporate stock price crash risk when the syndicate structure is more concentrated. For example, in column (2), $Bank_Lerner_{i,t} \times Number_of_Lenders_{i,t}$ has a positive sign (0.032, $t = 2.23$), indicating that bank market power has a greater impact on corporate stock price crash risk for loans with more lenders. Conversely, the detrimental effect is smaller for loans with fewer lenders. In column (5), $Bank_Lerner_{i,t} \times Lead_Share_{i,t}$ has a negative coefficient (-0.145, $t = -2.37$), suggesting that bank

market power has a smaller impact if the lead bank retains a larger proportion of the loan. Similarly, in column (8), $Bank_Lerner_{i,t} \times Lender_Concentration_{i,t}$ has a negative coefficient (-0.156, $t = -3.02$), showing that bank market power has a smaller impact if lenders are more concentrated. Overall, these results support our prediction that a concentrated syndicate structure improves monitoring efficiency and alleviates the detrimental effect of bank market power on corporate stock price crash risk. Our findings imply that loans with a concentrated syndicate structure and the associated soft monitoring complement the hard monitoring of powerful banks, effectively mitigating borrowers' bad news hoarding and reducing their stock price crash risk.

[Insert Table 13 here]

5 Conclusion

Using matched data of syndicated loan borrowers and lenders, this paper documents a positive and robust effect of lenders' bank market power on two-year-ahead corporate stock price crash risk. It suggests that when lenders wield greater market power, borrowers are more inclined to conceal negative information, consequently increasing the likelihood of stock prices crashes. Our results challenge the common perception that powerful banks are more effective at screening, monitoring, and controlling borrowers. We conduct further analyses to validate the manipulation incentive channel: From the lender's perspective, we observe that powerful banks enforce more financial covenants in their loan contracts, demonstrating their reliance on hard information to monitor borrowers. From the loan's standpoint, we find that borrowers with a larger number of financial covenants face higher stock price crash risk, implying that these covenants incentivize manipulation and bad news hoarding by borrowers. Examining borrowers' behaviors, we demonstrate that firms borrowing from powerful banks have more opaque financial reports and

engage more in real activities manipulation after loan origination, revealing that great bank market power amplifies managers' manipulation incentives and exacerbates the degree of information asymmetries. In the ongoing debate regarding the relationship between banking market structure and economic stability, our findings align with the competition-stability view by offering novel and crucial evidence from non-financial sectors. We also examine heterogeneous features and discover that the detrimental impact of bank market power on corporate stock price crash risk can be mitigated through several measures, such as issuing loans with short maturity, lending to borrowers within their home state, and structuring syndicated loans with a concentrated composition.

Our findings carry significant implications for both investors and regulators. First, we show that firms borrowing from powerful banks exhibit tendencies to conceal bad news, leading to heightened uncertainty and potential wealth destruction for shareholders. Therefore, our results recommend that a competitive banking market, where banks have limited market power but engage more in soft monitoring activities, can discourage managers' manipulation incentives, reduce information asymmetries, and bolster stability in non-financial sectors. Second, we demonstrate that lenders' soft monitoring, for instance, through shorter loan maturity, closer proximity between borrowers and lenders, and a concentrated syndicate structure, complement hard monitoring and alleviate the detrimental effect of strong bank market power on borrowers' stock price crash risk. Overall, our findings contribute to a deeper understanding of lending relationships and propose a new dimension (i.e., creditors and loan contracts) for mitigating borrowers' stock price crash risk and enhance economic stability.

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Appendix 1 Definitions of Variables

Variables	Definitions
<u><i>Variables for the crash risk</i></u>	
NCSKEW	Negative conditional skewness of a firm's weekly stock return distribution, we follow Chen et al. (2001). The model is presented in Section 3.1.
DUVOL	Down-to-up volatility of stock return, we follow Chen et al. (2001). The model is presented in Section 3.1.
CRASHD	A dummy variable equalling 1 for crash and 0 otherwise, following Kim et al. (2011a, 2011b). The measure is explained in Section 3.1.
<u><i>Firm-level variables</i></u>	
DTURNOVER	Detrended average monthly stock turnover, we follow Kim et al. (2011a, 2011b).
SIGMA	Standard deviation of firm-specific weekly returns, we follow Kim et al. (2011a, 2011b).
RET	Arithmetic average of firm-specific weekly returns, we follow Kim et al. (2011a, 2011b).
SIZE	Log value of the market value of equity, we follow Kim et al. (2011a, 2011b).
MB	Market value of equity divided by book value of equity, we follow Kim et al. (2011a, 2011b).
LEV	Long-term debt over total assets, we follow Kim et al. (2011a, 2011b).
ROA	Income before extraordinary items divided by lagged total assets, we follow Kim et al. (2011a, 2011b).
ROE	We use net income divided by total equity.
Z-score	We use Altman Z-score to measure the borrower's creditworthiness.
Opaque	The three-year moving sum of absolute discretionary accruals, we follow Hutton et al. (2009).
RM_1	We follow Cohen and Zarowin (2010) and use the sum of discretionary expenses management and abnormal production cost to measure real earnings management.
RM_2	We follow Cohen and Zarowin (2010) and use the sum of abnormal cash flows and abnormal discretionary expenses, both multiplied by negative one, to measure real earnings management.
Sales_Growth	The growth in sales dividend by one year lagged sales, we follow Hazarika et al. (2012).
INV	Capital expenditures divided by total assets, we follow Jiang et al. (2020).
INVR	(Capital expenditures + M&A expenses + R&D expenses – Sale of property, plant, and equipment, and investments) / total assets, we follow Richardson (2006).
CF	Operating cash flows divided by total assets, we follow Jiang et al. (2020).
<u><i>Bank- and loan-level variables</i></u>	
Bank_Lerner	We follow Delis et al. (2017) and use the Lerner index to measure lead bank's market power.
Bank_Size	The logarithm of book value of total assets of the lead bank, we follow Delis et al. (2017).
Tier_One	The tier one capital ratio of the lead bank, we follow Delis et al. (2017).
Bank_Reputation	A dummy variable equalling 1 for the banks ranked in the top-10 based on the amount of loans they provided in the past three years and 0 otherwise, we follow Chen (2014).
State-average Lerner	The (size) weighted average Lerner of banks in the lead bank's headquarter state.
Cost_of_Loan	The all in drawn spread, which is the base points of interest rates over the LIBOR plus annual fees.
Financial_Covenants	The number of financial covenants of the loan facility, we follow Delis et al. (2017).
Non_Financial_Covenants	The number of non-financial covenants of the loan facility.
Facility_Amount	The logarithm of the size of the loan facility, we follow Delis et al. (2017).
Maturity	The maturity of the loan in months, we follow Delis et al. (2017).
Across_State	A dummy variable equalling 1 for the loan where firms borrow across their state borders, and 0 otherwise.
Number_of_Lenders	The logarithm of the number of lenders in the lending cluster, we follow Chen (2014).
Performance_Pricing	A dummy variable equalling 1 for the loan with performance pricing and 0 otherwise, we follow Delis et al. (2017).
Secured	A dummy variable equalling 1 if the loan is secured with collateral and 0 otherwise, we follow Delis et al. (2017).
Loan_Purpose	Purpose of the loan, e.g., refinancing, working capital, and acquisition, we follow Chen (2014).
Lead_Share	Lead bank's share in the syndicated loan, we follow Chen (2014).
Lender_Concentration	The Herfindahl-Hirschman Index (sum of squared share) of lenders in the lending cluster, we follow Chen (2014).

Table 1 Descriptive Statistics

Variable	N	Mean	Median	Std.Dev	p. 5	p. 95
<u><i>Variables for the crash risk</i></u>						
NCSKEW	29,494	0.072	0.050	0.869	-1.347	1.614
DUVOL	29,494	0.024	0.017	0.363	-0.579	0.639
CRASHD	29,550	0.209	0.000	0.407	0.000	1.000
<u><i>Firm-level variables</i></u>						
DTURNOVER	29,161	0.003	0.000	0.056	-0.064	0.072
SIGMA	29,497	0.054	0.049	0.025	0.022	0.103
RET	29,499	-0.002	-0.002	0.008	-0.016	0.010
SIZE	29,437	7.087	7.119	2.095	3.529	10.627
MB	29,426	2.910	2.080	5.447	0.313	10.027
LEV	29,472	0.297	0.270	0.215	0.000	0.700
ROA	29,480	0.018	0.038	0.130	-0.163	0.138
ROE	26,225	0.048	0.101	0.876	-0.661	0.559
Z-score	24,547	3.131	2.953	3.863	-1.552	8.633
Opaque	23,150	0.223	0.178	0.179	0.042	0.551
RM_1	21,390	-0.019	-0.027	0.429	-0.706	0.693
RM_2	23,869	-0.008	-0.009	0.257	-0.425	0.415
Sales_Growth	28,548	0.106	0.060	0.334	-0.253	0.550
INV	28,392	0.063	0.039	0.075	0.007	0.203
INVR	28,392	0.132	0.080	0.163	0.013	0.418
CF	28,546	0.081	0.086	0.117	-0.091	0.227
<u><i>Bank- and loan-level variables</i></u>						
Bank_Lerner	25,394	0.320	0.371	0.190	-0.033	0.572
Bank_Size	26,309	19.22	19.62	2.00	15.25	21.45
Tier_One	26,309	0.073	0.067	0.020	0.055	0.106
Bank_Reputation	29,550	0.459	0.000	0.498	0.000	1.000
State-average Lerner	25,777	0.311	0.362	0.147	0.042	0.478
Cost_of_Loan	23,411	190.0	175.0	119.4	25.00	405.0
Financial_Covenants	26,310	1.135	1.000	1.322	0.000	4.000
Non_Financial_Covenants	26,310	1.703	0.000	2.234	0.000	6.000
Facility_Amount	29,550	18.72	18.98	1.83	15.28	21.42
Maturity	27,892	47.89	60.00	22.44	12.00	84.00
Across_State	26,310	0.555	1.000	0.497	0.000	1.000
Number_of_Lenders	29,550	1.582	1.792	1.046	0.000	3.135
Performance_Pricing	29,550	0.356	0.000	0.479	0.000	1.000
Secured	29,550	0.496	0.000	0.500	0.000	1.000
Lead_Share	25,343	0.488	0.376	0.302	0.096	1.000
Lender_Concentration	29,550	0.380	0.219	0.334	0.061	1.000

This table presents the descriptive statistics. Stock price data are collected from *CRSP*. Firm financial report data are collected from *Compustat*. The sample includes *Compustat* U.S. firms, except for those in financial (SIC Codes 6000-6999) and utility (4900-4949) sectors. Syndicated loan data are collected from Loan Pricing Corporation Dealscan. Bank data are collected from the Federal Deposit Insurance Corporation (FDIC). The sample period is from 1992 to 2020. The data are winsorized at the 1% and 99% levels. Definitions of the variables are summarized in APPENDIX 1.

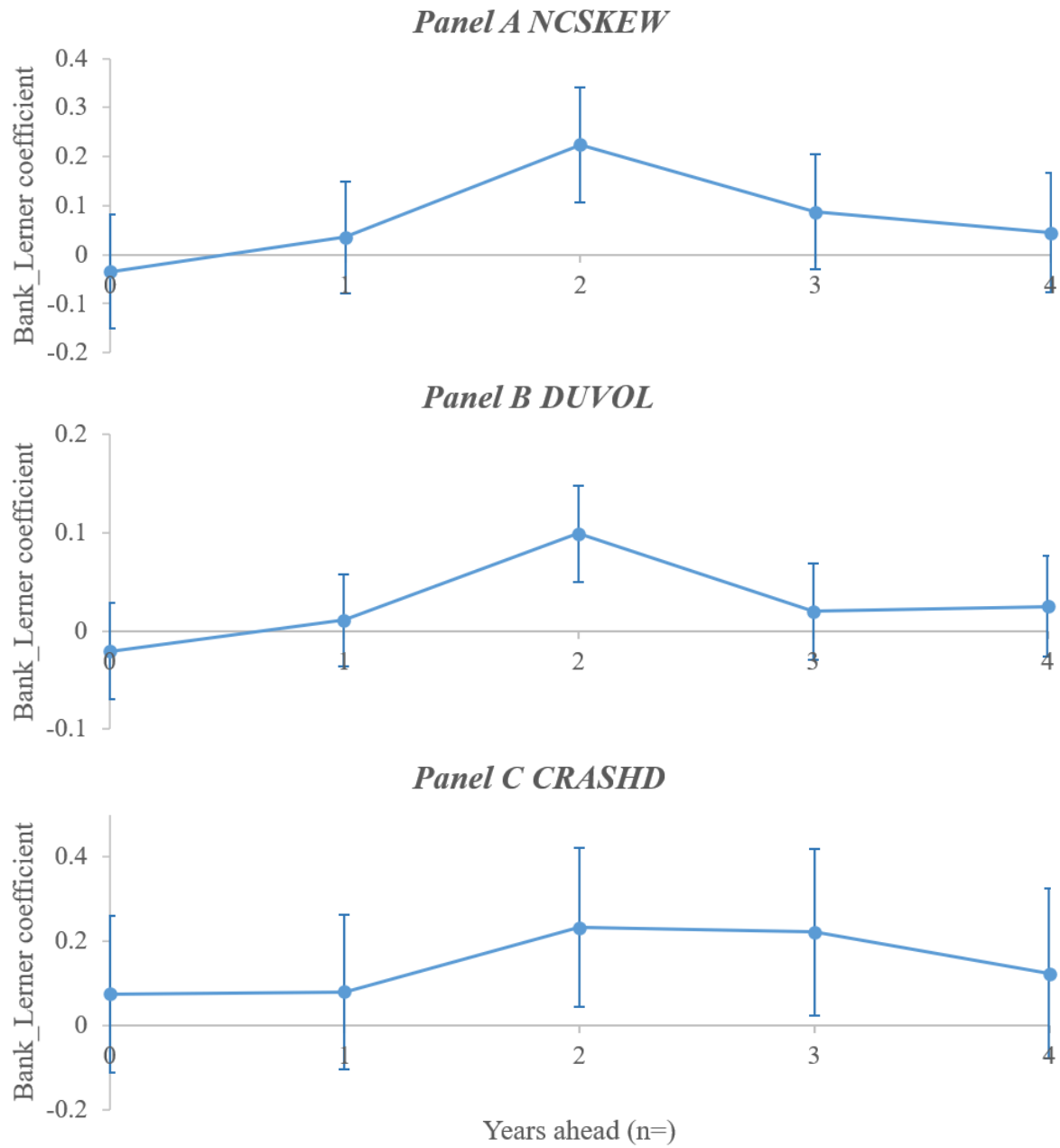


Fig. 1. displays the regression coefficient of Bank_Lerner in determining stock price crash risk. The error bar shows the 95% confidence interval.

Table 2 Bank Market Power and Corporate Stock Price Crash Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent variables	NCSKEW _{i,t+n}					DUVOL _{i,t+n}					CRASHD _{i,t+n}				
Years ahead (n=)	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Bank_Lerner _{i,t}	-0.035 (-0.59)	0.035 (0.60)	0.224*** (3.74)	0.087 (1.46)	0.045 (0.72)	-0.021 (-0.84)	0.011 (0.46)	0.099*** (3.98)	0.020 (0.80)	0.025 (0.95)	0.074 (0.78)	0.079 (0.84)	0.232** (2.41)	0.221** (2.18)	0.123 (1.19)
DTURNOVER _{i,t+n-1}	-0.188* (-1.88)	0.198* (1.93)	0.042 (0.45)	0.200** (2.04)	0.259** (2.40)	-0.100** (-2.24)	0.069 (1.50)	0.029 (0.71)	0.080* (1.84)	0.103** (2.09)	0.330* (1.71)	0.366* (1.89)	0.666*** (3.35)	0.267 (1.33)	0.308*** (1.39)
SIGMA _{i,t+n-1}	1.482*** (4.39)	1.585*** (4.65)	1.032*** (3.12)	0.014 (0.04)	0.212 (0.61)	0.428*** (2.90)	0.365** (2.46)	0.135 (0.94)	-0.124 (-0.84)	-0.054 (-0.35)	-5.031*** (-8.12)	-5.023*** (-8.05)	-6.399*** (-10.13)	-7.928*** (-12.06)	-7.377*** (-10.67)
RET _{i,t+n-1}	4.439*** (6.55)	5.772*** (8.85)	5.977*** (8.97)	6.709*** (10.04)	8.425*** (12.09)	2.114*** (6.94)	2.422*** (8.21)	2.740*** (9.05)	3.459*** (11.59)	3.875*** (12.31)	1.388 (1.04)	3.432*** (2.64)	5.230*** (3.88)	6.843*** (4.88)	7.464*** (5.18)
SIZE _{i,t+n-1}	0.058*** (15.08)	0.036*** (9.27)	0.043*** (11.55)	0.041*** (10.52)	0.043*** (10.69)	0.023*** (14.26)	0.013*** (7.81)	0.016*** (10.19)	0.017*** (10.42)	0.018 (10.40)	0.006 (1.00)	0.011* (1.70)	0.003 (0.42)	0.014** (2.08)	0.004 (0.63)
MB _{i,t+n-1}	0.002* (1.76)	-0.003** (-2.19)	-0.002** (-2.12)	0.001 (0.61)	-0.001 (-1.11)	0.001* (1.83)	-0.001 (-1.58)	-0.001* (-1.81)	0.000 (0.62)	-0.000 (-0.02)	0.002 (0.89)	-0.002 (-1.04)	-0.001 (-0.31)	0.002 (1.25)	-0.006*** (-2.72)
LEV _{i,t+n-1}	-0.144*** (-4.71)	-0.049* (-1.66)	-0.102*** (-3.59)	-0.083*** (-2.81)	-0.113*** (-3.61)	-0.055*** (-4.21)	-0.012 (-0.96)	-0.032*** (-2.65)	-0.017 (-1.35)	-0.053*** (-3.95)	-0.168*** (-3.21)	0.012 (0.24)	-0.155*** (-3.00)	-0.090 (-1.64)	-0.150*** (-2.64)
ROA _{i,t+n-1}	0.057 (1.46)	0.160*** (3.62)	0.118*** (3.24)	-0.027 (-0.63)	-0.013 (-0.34)	0.024 (1.30)	0.100*** (4.87)	0.058*** (3.21)	0.008 (0.40)	0.015 (0.80)	0.757*** (6.68)	0.654*** (5.27)	0.617*** (5.27)	0.410*** (3.50)	0.575*** (4.45)
Intercept	-0.505*** (-5.33)	-0.315*** (-3.28)	-0.391*** (-3.79)	-0.364*** (-4.00)	-0.479*** (-5.23)	-0.234*** (-5.84)	-0.095** (-2.22)	-0.148*** (-3.22)	-0.185*** (-4.48)	-0.202*** (-4.62)	-0.671*** (-3.71)	-1.096*** (-5.71)	-0.552*** (-3.13)	-0.787*** (-4.19)	-0.992*** (-4.62)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in Coefficient of Bank_Lerner		0.070*** (132.14)	0.189*** (352.32)	-0.137*** (-245.90)	-0.042*** (-70.52)		0.032*** (145.27)	0.088*** (397.44)	-0.079*** (-339.63)	0.005*** (19.97)		0.005*** (5.88)	0.153*** (177.21)	-0.011*** (-11.92)	-0.098*** (-98.26)
Observations	24,687	24,645	23,962	22,098	20,134	24,685	24,645	23,962	22,097	20,134	24,694	24,643	23,979	22,116	20,153
R ²	4.80%	3.41%	4.06%	4.95%	5.61%	5.68%	4.18%	4.97%	6.43%	7.03%	5.60%	5.55%	5.68%	6.65%	6.12%

This table presents the results of testing the effect of bank market power on corporate stock price crash risk. We test the effect from year t ($n=0$), when the syndicated loan is issued, till 4 years later, respectively. We also calculate the change in the coefficient of $Bank_Lerner_{i,t}$ from year $t+n-1$ to year $t+n$, and test the difference. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 3 Bank Market Power and Corporate Stock Price Crash Risk: Alternative Estimation Methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Estimation methods	Two-way clustered standard errors			Industry × year fixed effects			Bank-year clustered standard errors		
Bank_Lerner _{i,t}	0.224** (2.20)	0.099** (2.33)	0.232* (1.87)	0.204** (2.56)	0.093*** (2.91)	0.050 (1.63)	0.317*** (3.32)	0.105*** (2.72)	0.237* (1.94)
DTURNOVER _{i,t+1}	0.042 (0.24)	0.029 (0.36)	0.666** (2.22)	-0.040 (-0.20)	0.005 (0.06)	0.142* (1.72)	0.055 (0.32)	0.029 (0.40)	0.540** (1.97)
SIGMA _{i,t+1}	1.032 (1.38)	0.135 (0.38)	-6.399*** (-5.92)	0.974 (1.27)	0.132 (0.37)	-1.542*** (-7.17)	4.384*** (8.71)	2.326*** (9.79)	-3.007*** (-4.12)
RET _{i,t+1}	5.977*** (3.47)	2.740*** (3.28)	5.230** (2.27)	5.842*** (3.41)	2.718*** (3.35)	1.115* (1.83)	8.403*** (6.92)	2.994*** (5.71)	13.02*** (7.02)
SIZE _{i,t+1}	0.043*** (4.52)	0.016*** (3.39)	0.003 (0.18)	0.038*** (4.55)	0.015*** (3.45)	0.001 (0.12)	0.034*** (5.17)	0.007** (2.43)	0.026*** (2.85)
MB _{i,t+1}	-0.002 (-1.21)	-0.001 (-0.96)	-0.001 (-0.14)	-0.002 (-1.14)	-0.001 (-0.98)	-0.001 (-0.21)	-0.001 (-0.79)	-0.000 (-0.54)	-0.003 (-1.03)
LEV _{i,t+1}	-0.102** (-2.44)	-0.032 (-1.63)	-0.155 (-1.57)	-0.092** (-2.69)	-0.033** (-2.15)	-0.041* (-1.72)	-0.115** (-2.40)	-0.025 (-1.34)	-0.192*** (-2.68)
ROA _{i,t+1}	0.118 (1.32)	0.058 (1.38)	0.617*** (2.83)	0.071 (1.00)	0.037 (1.18)	0.079** (2.58)	0.010 (0.15)	-0.017 (-0.58)	1.017*** (6.59)
Intercept	-0.391* (-1.98)	-0.148* (-1.84)	-0.552* (-1.73)	-0.272*** (-3.02)	-0.103*** (-2.35)	0.284*** (8.87)	-0.235 (-1.39)	-0.112* (-1.67)	-0.786*** (-2.89)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,962	23,962	23,979	23,890	23,890	23,910	23,734	23,734	23,732
R ²	4.06%	4.97%	5.68%	18.37%	20.12%	17.07%	3.84%	5.56%	5.33%

This table presents the results of using alternative estimation methods to test the effect of bank market power on corporate stock price crash risk. Columns (1)-(3) use firm-year two-way clustered standard errors following Thompson (2011). Columns (4)-(6) control for fixed effects at the industry × year level. Columns (7)-(9) cluster standard errors at the lead bank-year level. Definitions of the variables are summarized in APPENDIX 1. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 4 Bank Market Power and Corporate Stock Price Crash Risk: Controlling for Bank and Facility Level Variables

Dependent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	0.275*** (3.32)	0.089*** (2.79)	0.186* (1.81)	0.258*** (2.88)	0.079** (2.28)	0.165 (1.61)	0.287*** (2.68)	0.083** (2.04)	0.153** (2.21)
ΔBank_Lerner _{i,t~t+2}				-0.109 (-0.96)	-0.057 (-1.29)	-0.112 (-0.74)	0.016 (0.12)	-0.018 (-0.34)	0.058 (0.94)
DTURNOVER _{i,t+1}	0.033 (0.29)	0.027 (0.55)	0.483** (2.40)	0.014 (0.12)	0.019 (0.38)	0.430** (2.08)	0.016 (0.12)	0.034 (0.62)	0.145** (2.31)
SIGMA _{i,t+1}	4.072*** (10.06)	2.186*** (12.97)	-3.012*** (-4.73)	4.179*** (9.91)	2.222*** (12.73)	-2.800*** (-4.26)	4.221*** (8.81)	2.243*** (11.45)	-0.686*** (-3.11)
RET _{i,t+1}	7.238*** (8.76)	2.580*** (7.25)	12.38*** (8.86)	7.043*** (8.10)	2.401*** (6.46)	13.36*** (9.23)	5.497*** (5.65)	1.742*** (4.21)	3.342*** (7.46)
SIZE _{i,t+1}	0.050*** (7.46)	0.014*** (5.25)	0.037*** (4.00)	0.051*** (7.40)	0.014*** (5.22)	0.037*** (3.95)	0.052*** (6.59)	0.014*** (4.49)	0.014*** (4.30)
MB _{i,t+1}	-0.002 (-1.46)	-0.001 (-1.29)	-0.003 (-1.58)	-0.002 (-1.35)	-0.001 (-1.33)	-0.003 (-1.44)	-0.004** (-2.55)	-0.002*** (-2.92)	-0.001 (-1.33)
LEV _{i,t+1}	-0.160*** (-3.99)	-0.045*** (-2.80)	-0.224*** (-3.80)	-0.157*** (-3.76)	-0.049*** (-2.94)	-0.190*** (-3.14)	-0.171*** (-3.73)	-0.051*** (-2.83)	-0.072*** (-3.61)
ROA _{i,t+1}	0.014 (0.35)	-0.015 (-0.71)	1.020*** (7.70)	0.034 (0.79)	-0.007 (-0.35)	1.013*** (7.45)	0.073 (1.36)	0.019 (0.78)	0.181*** (7.18)
Bank_Size _{i,t}	0.003 (0.39)	0.002 (0.62)	0.088 (0.79)	-0.002 (-0.21)	-0.000 (-0.11)	0.006 (0.53)	0.010 (0.32)	0.005 (0.39)	0.004 (0.29)
Tier_One _{i,t}	0.631 (0.97)	0.242 (0.94)	2.047** (2.27)	0.571 (0.79)	0.207 (0.73)	2.254** (2.30)	1.467 (1.29)	0.671 (1.51)	0.515 (1.02)
Bank_Reputation _{i,t}	-0.018 (-0.98)	-0.009 (-1.30)	-0.038 (-1.59)	-0.022 (-1.18)	-0.011 (-1.49)	-0.049** (-2.02)	-0.005 (-0.21)	0.002 (0.21)	-0.008 (-0.72)
Cost_of_Loan _{i,t}	0.000 (1.04)	0.000 (1.06)	-0.001*** (-2.65)	0.000 (0.92)	0.000 (1.11)	-0.001*** (-2.94)	-0.000 (-0.21)	0.000 (-0.01)	-0.001*** (-2.09)
Facility_Amount _{i,t}	-0.012 (-1.52)	-0.006* (-1.76)	-0.028** (-2.54)	-0.013 (-1.53)	-0.006* (-1.77)	-0.029*** (-2.58)	-0.006 (-0.59)	-0.003 (-0.73)	-0.010** (-2.58)
Maturity _{i,t}	0.032** (2.49)	0.009* (1.88)	0.067*** (3.78)	0.033** (2.47)	0.009* (1.82)	0.068*** (3.70)	0.033 (1.34)	0.012 (1.22)	0.030*** (2.82)
Number_of_Lenders _{i,t}	-0.007 (-0.69)	-0.003 (-0.76)	0.008 (0.54)	-0.007 (-0.62)	-0.003 (-0.63)	0.004 (0.28)	-0.008 (-0.60)	-0.003 (-0.52)	0.002 (0.45)
Performance pricing dummy _{i,t}	0.074*** (4.38)	0.026*** (4.02)	0.074*** (2.99)	0.073*** (4.15)	0.025*** (3.74)	0.072*** (3.05)	0.064*** (3.29)	0.022*** (2.93)	0.022*** (2.71)
Secured dummy _{i,t}	0.021 (1.15)	0.015** (2.11)	0.008 (0.33)	0.027 (1.44)	0.015** (2.12)	0.019 (0.77)	0.037* (1.85)	0.019** (2.43)	0.004 (0.52)
Intercept	-0.192 (-0.88)	-0.011 (-1.19)	-0.699** (-2.14)	-0.151 (-0.65)	-0.070 (-0.75)	-0.750** (-2.19)	-0.723 (-1.06)	-0.32 (-1.19)	0.154 (0.50)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Loan purpose dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank effects	No	No	No	No	No	No	Yes	Yes	Yes
Observations	20,550	20,550	20,524	19,366	19,366	19,336	16,392	16,392	16,392
R ²	4.30%	6.17%	6.10%	4.13%	5.85%	5.99%	5.28%	7.29%	8.15%

This table presents the results of testing the effect of bank market power on corporate stock price crash risk and controlling for a series of bank- and loan-level variables. Definitions of the variables are summarized in APPENDIX 1. Columns (4)-(9) control for the change in Lerner index after loan origination ($\Delta Bank_Lerner_{i,t-t+2}$). Columns (7)-(9) control for bank-fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 5 Bank Market Power and Corporate Stock Price Crash Risk: An Instrumental Variable Approach

Panel A Second-stage regression									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
IVs	RS index			State-average Lerner			State-average Lerner		
Predicted Bank_Lerner _{i,t}	1.727*** (2.64)	0.710*** (2.67)	0.417 (1.49)	0.407*** (3.60)	0.192*** (4.13)	0.150*** (2.85)	0.422*** (2.97)	0.232*** (4.08)	0.104 (1.62)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank- and Loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,339	13,339	13,339	22,312	22,312	22,331	13,113	13,113	13,119
R ²	4.05%	4.92%	6.56%	4.50%	5.41%	5.88%	5.02%	6.21%	6.36%
Testing exogeneity (p-value)	0.107	0.082	0.373	0.427	0.375	0.464	0.776	0.694	0.159
Panel B First-stage Regression									
	(1)	(2)	(3)						
Dependent variable	Bank_Lerner _{i,t}								
IVs	State-average Lerner								
IV	RS index	State-average Lerner	State-average Lerner						
	-0.012*** (-15.41)	0.985*** (80.20)	1.101*** (77.64)						
DTURNOVER _{i,t}	0.006 (0.46)	-0.005 (-0.48)	-0.022* (-1.67)						
SIGMA _{i,t}	-0.069 (-1.46)	-0.004 (-0.13)	0.101** (2.32)						
RET _{i,t}	0.064 (0.69)	0.050 (0.69)	-0.125 (-1.28)						
SIZE _{i,t}	-0.001* (-1.83)	-0.001*** (-2.71)	0.001 (1.26)						
MB _{i,t}	0.001* (1.66)	0.001 (0.69)	0.001 (0.89)						
LEV _{i,t}	-0.011*** (-2.61)	-0.005* (-1.75)	-0.005 (-1.27)						
ROA _{i,t}	0.019*** (2.91)	0.020*** (3.94)	0.022*** (3.29)						
Bank_Size _{i,t}	0.016*** (15.38)	0.009*** (11.01)	0.002* (1.87)						
Tier_One _{i,t}	1.529*** (16.23)	0.951*** (14.00)	0.572*** (6.36)						
Bank_Reputation _{i,t}	-0.019*** (-8.20)	-0.028*** (-24.04)	-0.019*** (-13.83)						

Cost_of_Loan _{i,t}	-0.001 (-1.05)	-0.001** (-2.56)	-0.001 (-0.75)
Facility_Amount _{i,t}	-0.003*** (-3.16)	-0.002*** (-3.83)	-0.004*** (-5.06)
Maturity _{i,t}	0.003** (2.16)	0.002* (1.83)	0.001 (1.28)
Number_of_Lenders _{i,t}	-0.005*** (-4.78)	-0.004*** (-4.46)	-0.001 (-1.24)
Performance pricing dummy _{i,t}	0.001 (0.47)	-0.001 (-1.10)	-0.004*** (-2.77)
Secured dummy _{i,t}	-0.002 (-1.21)	-0.003** (-2.15)	-0.003* (-1.95)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	13,339	22,385	13,119
R ²	57.23%	84.76%	88.13%
First-stage partial R ²	1.92%	33.71%	41.37%
First-stage F-stats	237.63	6,434.84	6,034.36
First-stage F-stats (p-value)	0.00	0.00	0.00

This table presents the results of using instrumental variables (IVs) to test the effect of bank market power on corporate stock price crash risk. In columns (1)-(3) of Panel A, we use an exogenous policy change, the staggered banking market deregulation following Rice and Strahan (2010), as the IV. The sample period is from 1992 to 2006. In columns (4)-(9), we use the weighted average Lerner index of banks in the lead bank's state as an alternative IV. In columns (7)-(9), we examine the observations where firms borrow from a lead bank outside of their state border to further reduce endogeneity concerns. We check the exogeneity of the instrument by testing the relationship between the instrument and the regression residual in our baseline model. The null hypothesis is that there is no relationship between the instrument and the regression error, and a p-value greater than 0.05 indicates that the instrument is exogenous. Panel B reports the first-stage regressions, respectively. The first-stage partial R² statistic measures the correlation between *Bank_Lerner* and the instrument. We report the first-stage F-statistics and the p-value. The null hypothesis is that the instrument is unrelated to the endogenous regressor. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 6 Bank Market Power and Corporate Stock Price Crash Risk: Using a Matched Sample

Panel A Testing the Treatment Effects				
Dependent Variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	
Treatment _{i,t}	0.069*** (2.71)	0.024** (2.39)	0.044** (2.18)	
Firm Control Variables	Yes	Yes	Yes	
Industry Effects	Yes	Yes	Yes	
Year Effects	Yes	Yes	Yes	
Loan Purpose dummy	Yes	Yes	Yes	
Observations	10,156	10,156	10,156	
Panel B Differences in Firm Characteristics of Treatment and Control				
	Treated	Control	Std.Dif	Ratio
DTURNOVER	-0.001	0.002	-0.024	1.613
SIGMA	0.052	0.050	0.096	1.117
RET	0.000	0.000	0.000	1.204
SIZE	7.152	7.360	-0.100	1.105
MB	3.049	2.917	0.026	1.848
LEV	0.275	0.276	-0.006	1.132
ROA	0.032	0.036	-0.031	1.535

This table presents the results of using a matched sample to test the effect of bank market power on corporate stock price crash risk. Treatment refers to the firms that borrow from a bank with its Lerner ratio higher than the annual median value plus 0.1, which gives around 20% of the total observations. We then select from the remaining firms to construct a control group. We use the k-nearest neighbor (k=5) and the Mahalanobis distance matching to construct a sample, and we request the matched sample firms are from the same industry-year of each treated observation. Panel A reports the regression results testing the effect of the treatment on corporate stock price crash risk. Panel B reports the mean values of key firm characteristics for the treated and control firms, separately, with the standardized mean difference (Std.Dif) smaller than 0.1 and the variance ratio (Ratio) between 0.5 and 2.0 indicating a good balance. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 7 Bank Market Power and Corporate Stock Price Crash Risk: Bank Size and Reputation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	0.170*	0.050	0.002	0.179**	0.057*	0.036
	(1.87)	(1.43)	(0.01)	(2.03)	(1.68)	(0.32)
Bank_Lerner _{i,t} × Large_Bank _{i,t}	0.193**	0.069**	0.359***			
	(2.38)	(2.22)	(3.40)			
Large_Bank _{i,t}	-0.068**	-0.027***	-0.106***			
	(-2.13)	(-2.22)	(-2.63)			
Bank_Lerner _{i,t} × Bank_Reputation _{i,t}				0.214***	0.070**	0.323***
				(2.69)	(2.28)	(3.11)
Bank_Reputation _{i,t}				-0.077**	-0.028**	-0.127***
				(-2.54)	(-2.44)	(-3.42)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,551	20,551	20,525	20,551	20,551	20,525
R-squared	4.32%	6.17%	6.13%	4.33%	6.17%	6.13%

This table presents the results of testing the moderating effect of bank size (and reputation) on the relationship between bank market power and corporate stock price crash risk. Definitions of the variables are summarized in APPENDIX 1. *Large_Bank* is a dummy variable equalling 1 if its size (total assets) is greater than the annual median value; *Bank_Reputation* is a dummy variable equalling 1 if the lead bank is among the top 10 syndicated loan arrangers, and 0 otherwise. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 8 Bank Market Power and Financial Covenants

	(1)	(2)	(3)	(4)	(5)
Bank_Lerner _{i,t}	0.419*** (5.56)	0.230*** (3.62)	0.180*** (2.79)	0.189* (1.86)	0.106* (1.82)
Bank_Size _{i,t}		-0.025*** (-3.50)	-0.017** (-2.24)	-0.111*** (-3.71)	-0.022*** (-3.63)
Tier_One _{i,t}		-1.911*** (-3.49)	-1.617*** (-2.85)	-1.128 (-1.16)	-2.361*** (-5.13)
Bank_Reputation _{i,t}		-0.105*** (-7.34)	-0.101*** (-6.93)	-0.145*** (-7.33)	-0.124*** (-9.35)
Non_Financial_Covenants _{i,t}		0.271*** (68.09)	0.266*** (65.48)	0.269*** (63.20)	0.170*** (57.69)
Facility_Amount _{i,t}		-0.090*** (-16.46)	-0.049*** (-7.68)	-0.040*** (-5.47)	-0.091*** (-16.93)
Maturity _{i,t}		0.048*** (4.79)	0.035*** (3.39)	0.039*** (3.76)	0.020* (1.90)
Number_of_lenders _{i,t}		0.006 (0.72)	0.028*** (3.19)	0.051*** (4.86)	0.029*** (3.85)
Performance pricing dummy _{i,t}		0.511*** (30.60)	0.501*** (29.48)	0.453*** (24.29)	0.466*** (33.38)
Secured dummy _{i,t}		0.189*** (13.04)	0.160** (10.48)	0.120*** (7.22)	0.152*** (10.42)
DTURNOVER _{i,t-1}			-0.103 (-0.77)	-0.190 (-1.34)	-0.05 (-0.05)
SIGMA _{i,t-1}			0.580 (1.43)	0.708 (1.56)	0.786** (2.38)
RET _{i,t-1}			2.116** (2.26)	1.897* (1.85)	2.593*** (3.64)
SIZE _{i,t-1}			-0.068*** (-12.22)	-0.064*** (-10.15)	-0.076*** (-14.25)
MB _{i,t-1}			-0.001 (-0.47)	0.001 (0.32)	-0.001 (-0.014)
LEV _{i,t-1}			-0.189*** (-5.27)	-0.142*** (-3.64)	-0.209*** (-6.86)
ROA _{i,t-1}			0.288*** (5.23)	0.281*** (4.04)	0.214*** (3.75)
Intercept	-0.090 (-0.79)	1.734*** (9.32)	1.228*** (6.39)	4.367*** (6.99)	-2.571*** (-6.54)
Industry effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Loan purpose dummy	Yes	Yes	Yes	Yes	Yes
Bank effects	No	No	No	Yes	Yes
Observations	25,068	23,618	22,385	18,740	18,740
R ²	24.55%	55.21%	55.49%	57.30%	22.74%

This table presents the results of testing the effect of bank market power on the number of financial covenants in the loan. Columns (1)-(4) use linear regression model. Column (5) uses the negative binominal regression. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 9 Syndicated Loan Covenants and Corporate Stock Price Crash Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Financial_Covenants _{i,t}	0.012** (2.06)	0.004* (1.73)	0.038*** (3.84)			
Abnormal_Covenants _{i,t}				0.016** (2.56)	0.006** (2.42)	0.037*** (3.32)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank- and loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,854	27,854	27,870	18,750	18,750	18,732
R ²	4.05%	4.88%	5.98%	4.74%	5.78%	6.76%

This table presents the results of testing the effect of syndicated loan covenants on stock price crash risk. Columns (1)-(3) use the number of covenants in the loan contract. Columns (4)-(6) use estimated abnormal covenants. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 10 Bank Market Power and Corporate Information Opaqueness

Panel A Bank Market Power and Corporate Information Opaqueness: From Year t to Year t+2						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Opaque _{i,t+2}		Avg_RM_1 _{i,t+2}		Avg_RM_2 _{i,t+2}	
Bank_Lerner _{i,t}	0.052*** (4.41)	0.035*** (3.43)	0.090*** (3.05)	0.041*** (3.58)	0.042** (2.54)	0.019** (2.39)
Opaque _{i,t}		0.537*** (50.60)				
RM_1 _{i,t}				0.849*** (145.84)		
RM_2 _{i,t}						0.786*** (115.57)
SIZE _{i,t+1}	-0.013*** (-10.25)	-0.005*** (-5.07)	-0.040*** (-15.82)	-0.001 (-1.15)	-0.026*** (-18.33)	-0.002*** (-3.06)
MB _{i,t+1}	0.001** (2.46)	0.000 (1.05)	-0.008*** (-11.53)	-0.001*** (-4.43)	-0.004*** (-11.45)	-0.002*** (-8.49)
LEV _{i,t+1}	-0.021*** (-2.81)	-0.007 (-0.99)	-0.013 (-0.75)	0.027*** (3.66)	0.014 (1.49)	0.007 (1.34)
ROA _{i,t+1}	-0.176*** (-10.82)	-0.105*** (-7.40)	0.106*** (3.24)	0.007 (0.37)	-0.171*** (-9.79)	-0.158*** (-11.02)
Sales_Growth _{i,t+1}	0.077*** (10.06)	0.036*** (4.64)				
Age _{i,t+1}			0.001*** (7.36)	0.001*** (4.61)	0.001*** (4.70)	0.001*** (5.16)
Intercept	0.529*** (14.60)	0.183*** (5.83)	-0.340*** (-3.85)	-0.187*** (-4.55)	-0.246*** (-5.09)	-0.142*** (-4.80)
Bank- and loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,036	16,268	17,976	16,235	20,086	18,143
R ²	22.72%	48.57%	31.43%	88.90%	31.91%	82.83%
Panel B Bank Market Power and Corporate Information Opaqueness: After Year t+2						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	Opaque _{i,t+3}	Opaque _{i,t+4}	Avg_RM_1 _{i,t+3}	Avg_RM_1 _{i,t+4}	Avg_RM_2 _{i,t+3}	Avg_RM_2 _{i,t+4}
Bank_Lerner _{i,t}	0.012 (1.14)	0.002 (0.22)	0.012 (1.18)	-0.025** (-2.45)	0.010 (1.27)	-0.006 (-0.75)
Opaque _{i,t+2}	0.524*** (45.69)	0.577*** (48.90)				
RM_1 _{i,t+2}			0.880*** (168.49)	0.899*** (172.08)		
RM_2 _{i,t+2}					0.827*** (151.38)	0.835*** (140.58)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank- and loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,652	14,480	15,958	15,616	17,736	16,835
R-squared	48.76%	52.14%	90.54%	91.21%	85.50%	85.70%

This table presents the results of testing the effect of bank market power on corporate information opacity. Panel A presents the main results. $Opaque_{i,t+2}$ is the 3-year moving sum of the absolute value of discretionary accruals, from year t to year $t+2$, following Hutton et al. (2009), where discretionary accruals are estimated by using the modified Jones model. $Avg_RM_1_{i,t+2}$ and $Avg_RM_2_{i,t+2}$ are measures of real earnings management, and we calculate the average (mean) for the 2 years after loan origination. Panel B investigates the timing issue and tests whether $Bank_Lerner$ influences information opacity after year $t+2$, controlling for the level of information opacity at year $t+2$. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 11 Testing Alternative Explanations

Panel A Testing the Capital Supply Channel				
	(1)	(2)	(3)	(4)
Dependent variables	INV _{i,t+2}		INVR _{i,t+2}	
CF _{i,t+1}	0.102*** (7.39)	0.103*** (7.55)	0.150*** (4.72)	0.164*** (5.31)
CF _{i,t+1} × Bank_Lerner _{i,t}	-0.027 (-0.66)	-0.019 (-0.45)	-0.215** (-2.59)	-0.182** (-2.27)
Bank_Lerner _{i,t}	0.015*** (2.67)	0.008 (1.37)	0.060*** (4.31)	0.044*** (3.16)
MB _{i,t+1}	0.001*** (7.12)	0.001*** (7.96)	0.003*** (10.77)	0.003*** (11.91)
Intercept	0.073*** (12.74)	0.133*** (10.43)	0.084*** (7.67)	0.487*** (15.59)
Bank- and loan-level variables	No	Yes	No	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	22,802	21,237	22,802	21,244
R ²	37.22%	38.54%	11.91%	14.70%
Panel B Testing the Profitability and Creditworthiness Channel				
	(1)	(2)	(3)	
Dependent variables	ROA _{i,t+2}	ROE _{i,t+2}	Z-score _{i,t+2}	
Bank_Lerner _{i,t}	-0.001 (-0.07)	-0.013 (-0.23)	0.013 (0.10)	
DTURNOVER _{i,t+1}	-0.049** (-2.10)	0.121 (0.79)	0.305 (0.79)	
SIGMA _{i,t+1}	-0.701*** (-11.46)	-2.067*** (-5.05)	-11.968*** (-11.08)	
RET _{i,t+1}	2.216*** (13.84)	5.933*** (5.96)	26.52*** (11.71)	
SIZE _{i,t+1}	0.002*** (3.72)	0.012*** (3.04)	-0.074*** (-8.21)	
MB _{i,t+1}	0.001*** (2.63)	0.018*** (6.65)	0.012*** (4.02)	
LEV _{i,t+1}	0.011** (2.15)	0.032 (0.79)	-0.507*** (-5.02)	
ROA _{i,t+1}	0.376*** (14.50)			
ROE _{i,t+1}		0.044** (2.20)		
Z-score _{i,t+1}			0.853*** (86.82)	
Intercept	0.034** (2.11)	-0.047 (-0.67)	1.908*** (10.22)	
Industry effects	Yes	Yes	Yes	
Year effects	Yes	Yes	Yes	
Observations	23,685	26,673	22,128	
R-squared	29.81%	4.72%	77.96%	

This table presents the results of testing two alternative explanations (i.e., the capital supply channel and the profitability and creditworthiness channel). Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 12 Bank Market Power and Corporate Stock Price Crash Risk: Effects of Loan Maturity and Cross-state Lending

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	-0.143 (-0.72)	-0.046 (-0.56)	-0.303 (-0.95)	0.113 (1.26)	0.030 (0.86)	-0.099 (-0.85)
Bank_Lerner _{i,t} × Ln_Maturity _{i,t}	0.088* (1.69)	0.036* (1.70)	0.142* (1.73)			
Ln_Maturity _{i,t}	-0.025 (-1.17)	-0.008 (-0.93)	-0.026 (-0.80)			
Bank_Lerner _{i,t} × Across_State _{i,t}				0.283*** (3.50)	0.100*** (3.21)	0.409*** (3.94)
Across_State _{i,t}				-0.131*** (-3.83)	-0.046*** (-3.56)	-0.172*** (-4.10)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank- and loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,313	22,313	22,267	23,734	23,734	23,715
R ²	4.60%	5.52%	6.11%	4.39%	6.16%	5.81%

This table presents the results of testing the effects of syndicated loan maturity and cross-border lending on the relationship between bank market power and corporate stock price crash risk. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table 13 Bank Market Power and Corporate Stock Price Crash Risk: Effects of Loan Syndicate Structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	0.089 (1.04)	0.031 (0.87)	-0.110 (-0.76)	0.279*** (2.85)	0.139*** (3.41)	0.305** (2.00)	0.283*** (3.65)	0.138*** (4.31)	0.323*** (2.65)
Bank_Lerner _{i,t} × Number_of_Lenders _{i,t}	0.052 (1.54)	0.031** (2.23)	0.160*** (2.85)						
Number_of_Lenders _{i,t}	-0.016 (-1.04)	-0.013** (-2.11)	-0.046* (-1.93)						
Bank_Lerner _{i,t} × Lead_Share _{i,t}				-0.280* (-1.92)	-0.145** (-2.37)	-0.356 (-1.45)			
Lead_Share _{i,t}				0.052 (0.71)	0.040 (1.34)	-0.011 (-0.09)			
Bank_Lerner _{i,t} × Lender_Concentration _{i,t}							-0.312** (-2.54)	-0.156*** (-3.02)	-0.484** (-2.32)
Lender_Concentration _{i,t}							0.139** (2.02)	0.075*** (2.58)	0.068 (0.58)
Firm control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank- and loan-level variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,313	22,313	22,267	19,311	19,311	19,288	22,313	22,313	22,267
R ²	4.60%	5.53%	6.14%	4.78%	5.76%	6.23%	4.61%	5.55%	6.14%

This table presents the results of testing the effects of loan syndicate structure on the relationship between bank market power and corporate stock price crash risk. Columns (1)-(3) test the effect of the number of lenders in the loan cluster. Columns (4)-(6) test the effect of the share of the lead bank in the loan amount. Columns (7)-(9) test the effect of lender concentration. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Online Appendix

This online appendix contains additional estimates that are mentioned and described in the manuscript but were not reported there to save space.

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Table A1 Firms borrowing more than once during the 5-year period

	(1)	(2)	(3)
Dependent variables	NCSKEWi,t+2	DUVOLi,t+2	CRASHDi,t+2
Bank_Lerner _{i,t}	0.326*** (3.32)	0.095** (2.52)	0.253** (1.98)
Bank_Lerner _{i,t} × Multiple_borrowing _{i,t}	-0.016 (-0.18)	0.009 (0.28)	-0.025 (-0.22)
Multiple_borrowing _{i,t}	0.065* (1.89)	0.019 (1.51)	0.004 (0.09)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	23,736	23,736	23,734
R-squared	3.89%	5.61%	5.34%

This table presents the results of testing the moderating effect of multiple borrowing on the effect of bank market power on corporate stock price crash risk. *Multiple_borrowing_{i,t}* is an indicator, with value equal to 1 if the borrowing firm has other syndicated loan borrowings (including new facilities) within the 5-year period, from year $t-2$ to year $t+2$, and 0 otherwise. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table A2 Bank Market Power and Corporate Stock Price Crash Risk: Controlling for Dynamics of Crash Risk

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	0.220*** (3.69)	0.098*** (3.93)	0.233** (2.42)	0.183*** (2.99)	0.080*** (3.14)	0.251** (2.55)
Crash Risk _{i,t+1}	0.051*** (5.81)	0.049*** (5.39)	0.193*** (8.62)	0.051*** (5.72)	0.049*** (5.31)	0.187*** (8.18)
Crash Risk _{i,t}				-0.027*** (-3.88)	-0.025*** (-3.78)	0.061*** (2.62)
DTURNOVER _{i,t+1}	0.024 (0.26)	0.021 (0.52)	0.646*** (3.22)	0.139 (1.35)	0.055 (1.18)	1.025*** (4.74)
SIGMA _{i,t+1}	1.055*** (3.19)	0.184 (1.27)	-6.486*** (-10.18)	1.013*** (2.95)	0.170 (1.13)	-6.567*** (-9.96)
RET _{i,t+1}	9.337*** (11.37)	4.358*** (10.67)	7.180*** (5.24)	9.187*** (10.74)	4.340*** (10.21)	6.550*** (4.64)
SIZE _{i,t+1}	0.042*** (11.14)	0.016*** (9.97)	0.001 (0.13)	0.043*** (11.10)	0.016*** (9.94)	0.000 (0.05)
MB _{i,t+1}	-0.002* (-1.94)	-0.001* (-1.70)	-0.000 (-0.17)	-0.003** (-2.35)	-0.001** (-1.99)	-0.001 (-0.27)
LEV _{i,t+1}	-0.099*** (-3.47)	-0.031** (-2.57)	-0.156*** (-3.00)	-0.099*** (-3.29)	-0.034*** (-2.65)	-0.119** (-2.20)
ROAi,t+1	0.105*** (2.89)	0.052*** (2.91)	0.591*** (5.01)	0.115*** (2.94)	0.062*** (3.32)	0.625*** (4.97)
Intercept	-0.380*** (-3.69)	-0.146*** (-3.18)	-0.571*** (-3.26)	-0.384*** (-3.54)	-0.153*** (-3.15)	-0.618*** (-3.39)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,960	23,960	23,979	22,916	22,905	22,967
R ²	4.22%	5.09%	5.97%	4.28%	5.14%	6.03%

This table presents the results of testing the effect of bank market power on corporate stock price crash risk after controlling for the autoregressive conditional skewness in stock returns. *Crash Risk_{i,t+1}* is the one-year forward crash risk. *Crash Risk_{i,t}* is the crash risk at the loan origination. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table A3 External Finance Dependence and Financial Constraints

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}	NCSKEW _{i,t+2}	DUVOL _{i,t+2}	CRASHD _{i,t+2}
Bank_Lerner _{i,t}	0.299*** (3.76)	0.089*** (2.91)	0.229*** (2.33)	0.323*** (4.17)	0.107*** (3.61)	0.259*** (2.72)
Bank_Lerner _{i,t} × Financial_dependence _{i,t}	0.031 (0.41)	0.035 (1.20)	0.020 (0.20)			
Financial_dependence _{i,t}	0.027 (0.92)	0.007 (0.65)	0.033 (0.88)			
Bank_Lerner _{i,t} × Financial_constraints _{i,t}				-0.034 (-0.43)	-0.014 (-0.44)	-0.115 (-1.05)
Financial_constraints _{i,t}				0.046 (1.44)	0.021* (1.70)	0.084** (2.07)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,526	23,526	23,524	23,734	23,734	23,732
R ²	3.85%	5.62%	5.26%	3.87%	5.61%	5.36%

This table presents the results of testing the effect of external finance dependence and financial constraints on corporate stock price crash risk. *Financial_dependence_{i,t+1}* is a dummy variable equaling 1 for the firms dependent more on external finance (the top 50% of the industry year group), where external finance is calculated as *(Capital expenditures + R&D expenditures + Acquisition - Operating Income Before Depreciation and Amortization) / (Capital expenditures + R&D expenditures + Acquisition)*, following Dang et al. (2022). *Financial_constraints_{i,t}* is a dummy variable equaling 1 for the firms in the top 50% of the industry year group, where we measure financial constraints using the size-age index (Hadlock and Pierce, 2010). In our sample, 36.6% of borrowers are classified as financial dependence and 28.3% of borrowers are classified as financially constrained. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table A4 Testing the Effect of Firm Characteristics on Bank Market Power

	(1)	(2)	(3)
Dependent variables	Bank_Lerner _{i,t}		
NCSKEW _{i,t-1}	0.001 (0.97)		
DUVOL _{i,t-1}		0.002 (1.01)	
CRASHD _{i,t-1}			0.002 (1.35)
DTURNOVER _{i,t-1}	0.024* (1.71)	0.023* (1.70)	0.024* (1.75)
SIGMA _{i,t-1}	0.070* (1.75)	0.070* (1.75)	0.070* (1.77)
RET _{i,t-1}	0.277*** (2.75)	0.304*** (2.67)	0.248*** (2.78)
SIZE _{i,t-1}	-0.006*** (-14.10)	-0.006*** (-14.13)	-0.007*** (-14.22)
MB _{i,t-1}	-0.000 (-0.03)	-0.000 (-0.03)	-0.000 (-0.00)
LEV _{i,t-1}	-0.014*** (-3.25)	-0.014*** (-3.26)	-0.014*** (-3.28)
ROA _{i,t-1}	0.007 (0.85)	0.007 (0.84)	0.007 (0.83)
ROE _{i,t-1}	-0.009 (-0.88)	-0.009 (-0.88)	-0.009 (-0.88)
Z-score _{i,t-1}	0.001 (1.61)	0.001 (1.62)	0.001 (1.56)
Intercept	0.483*** (41.45)	0.483*** (41.48)	0.483*** (41.49)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	21,538	21,538	21,538
R-squared	75.38%	75.38%	75.38%

This table presents the results of testing the effect of firm characteristics on bank market power (what kind of firms attract banks with strong market power). Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.

Table A5 Bank Market Power and Corporate Stock Price Crash Risk: Using the Heckman Selection Model

	(1) First-stage Participate _{i,t}	(2) NCSKEW _{i,t+2}	(3) Second-stage DUVOL _{i,t+2}	(4) CRASHD _{i,t+2}
Lerner _{i,t}		0.317*** (4.66)	0.106*** (3.99)	0.079*** (2.72)
Industry_use _{i,t}	0.003** (151.45)			
IMR _{i,t}		-0.015 (-1.02)	-0.004 (-0.69)	-0.004 (-0.66)
DTURNOVER _{i,t}	0.063 (0.58)	0.071 (0.55)	0.038 (0.75)	0.157*** (2.87)
SIGMA _{i,t}	-3.156*** (-9.21)	4.397*** (10.88)	2.341*** (14.80)	-0.897*** (-5.17)
RET _{i,t}	-5.731*** (-7.29)	8.283*** (9.34)	2.962*** (8.53)	3.363*** (8.83)
SIZE _{i,t}	0.086*** (22.45)	0.033*** (7.22)	0.007*** (3.67)	0.008*** (4.33)
MB _{i,t}	-0.005*** (-4.20)	-0.001 (-0.98)	-0.001 (-0.71)	-0.001 (-0.73)
LEV _{i,t}	0.908*** (28.40)	-0.113*** (-3.15)	-0.024* (-1.68)	-0.070*** (-4.59)
ROA _{i,t}	0.526*** (10.67)	0.017 (0.29)	-0.014 (-0.60)	0.167*** (6.73)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	103,673	103,676	103,676	103,676
Pseudo R ²	51.45%			

This table presents the results of testing the effect of bank market power on corporate stock price crash risk using the Heckman Selection Model. The first-stage regression studies the determinants of the decision to participate in syndicated loan financing. *Industry_use* denotes the number of syndicated loan facilities used by firms in the same industry (3-digit SIC) over the previous two years (*t-1* and *t-2*). *IMR* denotes the Inverse Mills Ratio, derived from the first-stage equation. Definitions of the variables are summarized in APPENDIX 1. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote significant differences at 1%, 5% and 10% levels, respectively.