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# Bank Market Power and Corporate Stock Price Crash Risk: Borrowers' Manipulation Incentives[1]

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**Abstract**

Using syndicated loan data to match borrowers and lenders, we document a positive and robust effect of bank market power on the two-year-ahead corporate stock price crash risk. Further analysis reveals that powerful banks tend to issue loans with more financial covenants, after controlling for bank-, firm-, and loan-level characteristics. Firms borrowing from powerful banks engage more in real activities manipulation. These findings support the manipulation-incentive channel, providing evidence that borrowers have stronger incentives to manipulate financial information and conceal bad news when lenders possess 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 is stronger for firms with greater demand for external finance and a higher likelihood of covenant violation. Banks can, however, mitigate the adverse effect by lending to geographically closer borrowers and by structuring loan syndicates with higher lender concentration, which are often associated with more frequent soft-monitoring activities. Overall, these findings enhance our understanding of the role of creditors and loan contracts in shaping corporate stock price crash risk and the stability of non-financial sectors.

**Keywords**: Bank market power; Bank competition; Stock price crash risk; Bank monitoring; Earnings management; Information asymmetry; Covenants

**JEL classification**: D82; G12; G14; G21; G32

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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 the 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 banking sector has become substantially more consolidated, with the top five banks' market share in the U.S. rising from under 15% in the 1990s to over 40% after 2008. 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 limited. 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.

Bank market power can influence corporate stock price crash risk via two competing channels. The monitoring-enhancement channel predicts that greater market power strengthens banks' monitoring and control capabilities and reduces borrowers' stock price crash risk, while the manipulation-incentive channel predicts that firms borrowing from powerful banks may have

stronger incentives to manipulate financial information and therefore have greater crash risk. To test these predictions, we obtain U.S. syndicated loan data from the Thomson Reuters Loan Pricing Corporation (Dealscan) database to identify borrowers and lenders for each syndicated loan facility. We then collect firm-level stock price and financial statement data 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*), following the established literature (e.g., Kim et al., 2011a, 2011b). We use the Lerner index of the lead arranger to assess bank market power, following Beck et al. (2013) and Delis et al. (2017).

Our baseline results reveal a positive and statistically significant effect of lenders' market power on borrowers' stock price crash risk in the second year after loan origination. Specifically, a one-standard-deviation increase in *Bank_Lerner* (0.19 units) is associated with a 1.16-percentage-point increase in the probability of a crash. This result suggests that greater bank market power leads borrowers to hoard bad news, thereby increasing stock price crash risk and undermining economic stability. This finding challenges the conventional belief that powerful banks, equipped with superior soft information and stronger bargaining power, are more effective at screening borrowers and using their market power to impose covenant restrictions for monitoring and control.

To validate the main findings, we perform an extensive battery of robustness checks and address potential endogeneity concerns. Our results are robust to alternative measures of crash risk and bank market power, controlling for lagged crash risk, alternative estimation methods, additional bank- and loan-level controls including changes in bank market power during the two years following loan origination, and the inclusion of macroeconomic variables. To address

endogeneity, we first employ instrumental variable (IV) estimation, using the staggered removal of state-level banking expansion restrictions as the instrument. We also perform tests for reverse causality and find that stock price crash risk does not determine bank market power. We use alternative model specifications, implementing an event-study design to estimate the effect of borrowing from a powerful bank and using a Cox proportional hazards model to test the hazard of a crash. Our primary findings remain robust across these approaches.

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 screen and monitor borrowers can incentivize borrowers to manipulate their financial information, particularly earnings, and hoard bad news, leading to increased stock price crashes. We use financial covenant intensity and earnings manipulation to test the mechanism from two perspectives. From the lender's perspective, we conjecture that powerful banks would impose more financial covenants in their loan contracts. From the borrower's perspective, we conjecture that firms borrowing from powerful banks and facing stringent hard monitoring tend to manipulate information and conceal bad news to meet those covenant requirements, ultimately leading to stock price crashes. We conduct mediation analysis, and the results suggest that financial covenant intensity and real activities manipulation mediate the relationship between bank market power and corporate stock price crash risk, supporting our conjectures and 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.

Next, we explore heterogeneity in our baseline effect. In line with our manipulation-incentive explanation, we find that the effect is stronger for firms with greater demand for external finance and facing stricter covenant restrictions, indicating that firms facing greater pressure are more sensitive to the effect of bank market power. Conversely, features that facilitate bank monitoring attenuate the detrimental effect of bank market power on corporate stock price crash risk (i.e., closer physical proximity and more concentrated syndicate structure). These findings are in line with the literature showing that shorter distances between borrowers and lenders (DeYoung et al., 2008) and a concentrated syndicate structure (e.g., Sufi, 2007; Chen, 2014; Gustafson et al., 2021) are associated with more frequent borrower-lender interactions, which enhance monitoring and reduce information asymmetries. These results imply that soft and active monitoring alleviates 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 the understanding of how banking market structure affects economic stability by providing crucial evidence from non-financial sectors. While prior studies have debated the relationship between banking market competition and financial system stability, the evidence remains mixed (e.g., Allen and Gale, 2004; Boyd and De Nicoló, 2005; Beck et al., 2013; Jiang et al., 2022). The competition-stability view suggests a favorable effect, whereas the competition-fragility view argues for an unfavorable effect. Recent studies examining the non-financial sector have shown that banking market deregulation encourages bank mergers, equipping banks with superior monitoring capabilities that improves borrowers' financial reporting quality (Mi et al., 2024) and reduces their stock price crash risk (Dang et al., 2022). However, the proportion of syndicated loan borrowers crossing state borders rose from 34% in 1992 to 84% in 2019, casting doubt on studies that rely solely on state-level deregulations to proxy for local credit conditions. By using syndicated loan

data to identify specific lending relationships, we relax the assumption that public corporations borrow primarily from local banks. Our findings contrast with recent literature, showing that firms borrowing from powerful banks are more inclined to hide bad news, offering a new perspective that supports the competition-stability view. Overall, by directly matching borrowers and lenders and testing borrowers' manipulation incentives, our findings offer a new explanation for the phenomenon and clarify the relationship between bank market power and economic instability.

Second, this paper enriches the literature on corporate stock price crash risk by examining the role of creditors. Stock price crash risk, often stemming from a firm's tendency to hoard bad news (Jin and Myers, 2006; Kothari et al., 2009), has garnered substantial academic and policy attention since the dot-com bubble and the 2008 financial crisis. Extant 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; Liu et al., 2024), 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; Cai et al., 2026; Xu et al., 2014). However, while prior research has shown that dedicated institutional investors (An and Zhang, 2013) and board reforms (Hu et al., 2020) can reduce managers' bad news hoarding and risk-taking, the influence of creditor characteristics on corporate bad news hoarding and stock price crash risk remains underexplored. We fill this gap by investigating the role of lenders. Challenging the common perception that powerful banks possess superior monitoring capabilities (e.g., Petersen and Rajan, 1995; Dass and Massa, 2011), we show that bank market power can incentivize borrowers to manipulate information and hoard bad news, thereby increasing the incidence of stock price crashes. Importantly, unlike prior studies that typically focus on immediate effects, we

demonstrate a two-year-ahead impact of lenders' market power on borrowers' stock price crash risk. Our results suggest that it takes, on average, two years after loan origination for accumulated bad news to reach a tipping point and be revealed. We therefore encourage researchers and practitioners to consider crash risk over a longer horizon, because the absence of a short-term increase in risk does not imply the absence of future risk.

Third, our results shed new light on the relative efficacy of hard and soft monitoring. Existing research documents that large and powerful banks tend to rely on 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 less market power often gather soft information through more frequent interactions (e.g., Gustafson et al., 2021). Building on these insights, our finding that firms borrowing from powerful banks have stronger incentives to manipulate information and are more likely to experience stock price crashes implies that an overreliance on hard information can create incentives and opportunities for borrowers to manipulate financial information, leading to crashes and jeopardizing shareholders' wealth. Conversely, soft monitoring, which entails more frequent and direct interactions, serves as a vital complement for detecting hoarded bad news and preventing crashes. The detrimental effect of strong bank market power is mitigated when loans are issued to geographically closer borrowers or structured through concentrated syndicates, situations in which lead arrangers typically engage in more active, soft-monitoring activities.

Fourth, our findings enhance the understanding of how syndicated loan financing affects corporate performance. While earlier research has examined how corporate characteristics shape the structure and terms of syndicated loans (e.g., Chen, 2014; Graham et al., 2008; Kim and Song, 2011; Lin et al., 2012) and how loan covenants and their restrictiveness affect corporate decisions and outcomes (e.g., Chava and Roberts, 2008; Nini et al., 2009; Ersahin et al., 2021), the

consequences of syndicated lending for stock price crash risk remain under-studied. Beyond evidence that big and powerful banks sometimes lend to poorly performing firms, which improves borrowers' performance (i.e., Delis et al., 2017) and market value (Biswas et al., 2017), we document an adverse consequence of borrowing from powerful banks: higher crash risk. We also show that multiple other loan features, including loan size, cost, syndicate structure, collateral, and performance pricing provisions, are associated with borrowers' incentives to manipulate financial information and stock price crash risk for investors.

To clarify how our study differs from prior studies, Dang et al. (2022) show that firms' stock price crash risk decreases after U.S. intrastate branching reforms, whereas interstate deregulation has no significant effect. They argue that intrastate reforms increase bank consolidation, which strengthens acquiring banks' power and efficiency in monitoring local borrowers. Wu (2023) presents an opposing view, showing that increased city-level bank competition in China is associated with lower crash risk for firms, although causality is not established, and the mechanism is underdeveloped. Jiang et al. (2020) find that firms' stock return volatility falls after interstate banking deregulation, reasoning that competitive banking markets increase capital supply and help firms absorb negative shocks. Our research design differs from Dang et al. (2022) by using matched borrower-lender data and diverges from Jiang et al. (2020) by examining the third moment (skewness) of stock returns and comparing down- and up-volatility, rather than the second moment (variance). While our baseline finding is broadly consistent with Wu's (2023) from China, we provide further evidence regarding causal interpretation, delayed timing, the underlying mechanism, cross-sectional heterogeneity, and additional loan features beyond creditor market structure within the more developed U.S. banking market.

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

## 2 Literature Review and Hypothesis Development

This section contextualizes the ongoing debate regarding the relationship between bank market power and economic stability, followed by a review of the literature on stock price crash risk. We then develop competing hypotheses representing two distinct theoretical channels—one suggesting bank market power mitigates crash risk, and the other suggesting it exacerbates crash risk.

### *2.1 Bank Market Power and Economic Stability*

The relationship between bank market power and economic stability has been extensively studied, centering on the seminal "competition-fragility" versus "competition-stability" debate. The competition-fragility view posits that competition erodes franchise value and diminishes incentives for prudent risk management, thereby destabilizing the financial system (Beck et al., 2006; Jiang et al., 2022; Keeley, 1990). This perspective suggests that concentrated banking markets, where banks possess significant market power, enhance stability. Specifically, Keeley (1990) develops a model and demonstrates that banks in highly competitive markets face intense pressure and have to invest in risky projects to maintain returns, rendering the banking system more fragile. Conversely, banks in less competitive markets enjoy higher profitability and prioritize protecting their charter value, leading them to avoid excessively risky investments and thereby supporting financial system stability. A series of studies has provided 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 better withstand negative economic shocks,

reducing the probability of banking crises. Using household bankruptcy data, Dick and Lehnert (2010) document that U.S. banking deregulation led to an increase in personal bankruptcy rates, suggesting a detrimental effect of increased bank competition on economic stability. Danisman and Demirel (2019) examine banks in 25 developed countries and find that more powerful banks exhibit lower risk-taking across eight distinct risk dimensions. Jiang et al. (2022) construct bank-level measures of competitive pressure and demonstrate that heightened competition erodes profitability, pricing power, and charter values, which in turn increases risk-taking and fragility.

A competing strand of literature challenges the competition-fragility view and advocates the competition-stability view, arguing that a banking system dominated by a small number of powerful banks may be detrimental to economic stability. Excessive market power may destabilize the financial system through mechanisms such as "too-big-to-fail" expectations and borrower risk-shifting (Boyd and De Nicoló, 2005; Mishkin, 1999; Schaeck et al., 2009). For example, Mishkin (1999) posits that banks in less competitive markets take greater risks and pursue highly risky investment projects because they anticipate government bailouts. Boyd and De Nicoló (2005) offer a complementary explanation, suggesting that when banks use their market power to charge higher interest rates, borrowers are incentivized to undertake riskier projects to cover the higher cost of capital, thereby increasing the banks' own risk exposure. Using the H-statistics to measure bank competition at the country level, Schaeck et al. (2009) provide evidence that more competitive banking systems are less prone to financial crises, whereas greater concentration is associated with a higher probability of a systemic crisis. Examining macroeconomic volatility, Leroy and Lucotte (2019) show that weak bank competition exacerbates credit procyclicality and the impact of a shock to GDP. Examining bank reforms in postwar Germany, Huber (2021) finds that bank mergers did not improve profitability or efficiency; instead, their lending became riskier. Recent

theoretical advances suggest a U-shaped relationship (e.g., Martinez-Miera and Repullo, 2010), implying that bank failure is minimized at an intermediate level of competition that balances franchise value preservation against oligopolistic risk-taking.

While much prior work focuses on financial sector outcomes, evidence from non-financial sectors remains mixed and the theoretical debate persists. For instance, Dass and Massa (2011) show that stronger lending relationships in less competitive markets enhance banks' monitoring efficiency and improve borrowers' corporate governance, supporting the competition-fragility view. In contrast, Jiang et al. (2020) document that firms' stock return volatility declines following interstate banking deregulation, arguing that more competitive banking markets increase the supply of capital and help firms cope with negative shocks, which is consistent with the competition-stability view. By examining the impact of bank market power on corporate stock price crash risk through specifically identified lending relationships, our study provides crucial evidence that contributes to this debate 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 identifies the sudden release of stockpiled bad news as the primary driver of such crashes (Kothari et al., 2009). Driven by managerial incentives and agency concerns, managers tend to disclose good news promptly while delaying the release of bad news (Chen et al., 2001; Kothari et al., 2009). This behavior creates severe information asymmetries that prevent investors from adjusting portfolios or liquidating positions in a timely manner. When accumulated bad news reaches a critical threshold at which managers can no longer conceal it or resolve the underlying problem before mandatory disclosure, the stockpiled information is released all at once (Kothari et al., 2009). At this tipping point, shareholders respond with rapid selling,

triggering a collapse in the stock price. This phenomenon is statistically 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 more susceptible to stock price crashes (e.g., Jin and Myers, 2006; Hutton et al., 2009; Kim et al., 2016b). Qualitative evidence further supports the theory: Graham et al. (2005) surveyed senior executives and found that they indeed delay the release of bad news to buy time to study the negative information or attempt to improve the situation before it becomes public. The literature remains inconclusive regarding the specific impact of bank market power on corporate stock price crash risk, because two crucial mechanisms, the monitoring-enhancement channel and the manipulation-incentive channel, offer competing predictions for this relationship.

### *2.3 Hypothesis Development*

#### *2.3.1 Bank Market Power, Monitoring Enhancement, and Corporate Stock Price Crash Risk*

As financial intermediaries, banks possess a distinct informational advantage and the capability to monitor borrowers (Freixas and Rochet, 2008). Seminal work by Petersen and Rajan (1995) demonstrates that credit market concentration facilitates relationship lending, enabling banks to internalize long-term benefits of supporting borrowers and investing in the acquisition of soft information. Specifically, banks in less competitive markets wield greater market power, which allows them to screen and monitor borrowers more effectively. By fostering enduring lending relationships, these banks facilitate the collection of proprietary private information and develop industry-specific expertise, further enhancing their monitoring efficiency. This "information hypothesis" suggests that moderate concentration enhances monitoring incentives and reduces informational frictions, which has received empirical support from recent studies (e.g., Fungáčová et al., 2017). Furthermore, the literature suggests that powerful banks leverage their bargaining

power to negotiate and impose stringent accounting-based contract terms (Rajan, 1992; Dou, 2020). These covenants, combined with acquired private information, provide banks with the necessary control to monitor and intervene effectively when credit quality deteriorates. More recent studies suggest that relationship lending in concentrated markets serves a governance-enhancing role, improving borrowers' governance quality (Dass and Massa, 2011) and performance (Delis et al., 2017). Conversely, maintaining close lending relationships and restrictive covenants is more challenging in competitive markets, where borrowers have a broader range of alternative financing options (Boot and Thakor, 2000). Consequently, banks in competitive markets face higher costs and greater difficulty in collecting private information and monitoring borrowers.

The monitoring-enhancement channel predicts that strong bank market power reduces corporate stock price crash risk. Given that crash risk is primarily driven by information asymmetries between managers and investors, we expect that banks with strong market power utilize their networks, bargaining power, and resources to collect information and discipline managerial behavior. Strong lending relationships and the motivation to acquire private information should mitigate information asymmetries, curb managerial bad news hoarding, and decrease the amount of negative information hidden from outsiders, thereby lowering 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-rider" problem in information collection may discourage lead arrangers from gathering soft information and effectively monitoring borrowers (Marquez, 2002). This leads to greater information frictions and a failure to detect concealed bad news. Based on this logic, we propose our first hypothesis:

***H1a****: High bank market power reduces corporate stock price crash risk.*

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

Prior studies find that banks in less competitive banking markets with substantial market power rely more heavily on standardized quantitative (hard) criteria to screen and monitor borrowers. Specifically, Stein (2002) develops a model examining the optimal organizational form for allocating capital to investment projects and concludes that hard information (e.g., financial ratios) can be transmitted effectively within large and hierarchical organizations to allocate capital to the best projects. This model is particularly applicable to large and powerful banks, especially following periods of consolidation. Conversely, smaller banks often use qualitative information generated through loan officers' personal interactions with borrowers, which enables them to develop superior and borrower-specific knowledge and allocate capital efficiently. Empirically, Cole et al. (2004), using small business surveys, find that large banks are more likely to extend credit to borrowers who use 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, supporting the view that powerful banks favor hard-monitoring practices.

Consequently, firms borrowing from powerful banks may have stronger incentives than other borrowers to manipulate financial information to secure funding and satisfy loan covenant requirements. Evidence of manipulation around external financing is well documented; for instance, firms tend to manage or smooth earnings before issuing equity (e.g., Teoh et al., 1998; Cohen and Zarowin, 2010) and debt (Liu et al., 2010). Borrowers that have received loans also face pressure from capital market participants, which influences their accounting choices and can encourage manipulation to avoid covenant violations (Dechow et al., 2010). For example, Fan et al. (2019) investigate private loans and observe that firms subject to EBITDA-related covenants are more likely to misclassify core expenses as special items when they approach the violation threshold. Franz et al. (2014) show that firms close to violating current ratio covenants have a

stronger incentive to engage in earnings management. These studies collectively suggest that borrowers facing strict covenant restrictions may manipulate accounting figures to meet requirements and avoid consequences such as increased interest rates, early repayment demands, transfers of control rights to lenders, or closure of the credit line.

The manipulation-incentive channel predicts that strong bank market power increases corporate stock price crash risk. Powerful banks favor hard monitoring and create a rigid environment where borrowers are incentivized to manipulate financial reports and conceal negative information from outsiders to preserve the appearance of creditworthiness and avoid the loss of control. Moreover, powerful banks relying heavily on hard information for monitoring tend to conduct fewer site visits and interact less frequently with borrowers (Cole et al., 2004). As a result, less soft information is collected, which reduces banks' ability to detect concealed bad news, provides more room for manipulation, and increases the likelihood of a crash. Conversely, less powerful banks rely more on borrowers' soft information and engage in more frequent soft-monitoring activities (Gustafson et al., 2021), facilitating better information collection and helping to uncover concealed bad news. Therefore, we propose our second hypothesis:

***H1b****: High bank market power increases corporate stock price crash risk.*

These competing channels imply that the relationship between bank market power and crash risk is theoretically ambiguous; the net effect is therefore an empirical question that depends on which channel dominates in practice.

## 3 Method and Data Collection

### *3.1 Regression Model and Variables*

We employ the following baseline regression model to test the effect of bank market power on corporate stock price crash risk:

$$CRASH_{i,t+n} = \alpha + \beta_0 Bank_Lerner_{i,t} + \beta_1 Controls_{i,t+n-1} + \mu_j + \eta_{t+n} + \varepsilon_{i,t+n}, (1)$$

where $Bank_Lerner_{i,t}$ denotes bank market power at the time of loan origination ($t$). $CRASH_{i,t+n}$ represents the borrower's stock price crash risk $n$ years after origination, where $n$ is determined empirically. 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 measure crash risk with three indicators: negative conditional skewness (*NCSKEW*), down-to-up volatility (*DUVOL*), and a crash dummy (*CRASHD*, estimated with a probit model). The construction of these variables is provided in Appendix 1. For all three measures, higher values indicate more negatively skewed stock returns or a greater propensity for crashes. $Controls_{i,t+n-1}$ is a vector of control variables commonly used in the crash risk literature (e.g., Kim et al., 2011a; 2016a).[2] $\mu_j$ denotes industry-fixed effects (two-digit SIC codes), and $\eta_{t+n}$ denotes year-fixed effects. We apply heteroskedasticity-robust standard errors in the baseline model.

We measure individual bank market power using the Lerner index (*Bank_Lerner*), a standard metric in the banking literature (e.g., Beck et al., 2013; Delis et al., 2017; Danisman and Demirel, 2019).[3] The Lerner index, also known as the profit-cost margin, is calculated using the following formula, $Lerner\ index = (P - MC)/P$, where $P$ is the price of bank output and $MC$ is the marginal cost of production. Marginal cost is estimated parametrically using a standard translog cost function, as described in Delis et al. (2017). We present the detailed procedure in Appendix

[2] We do not include lagged crash risk in the baseline model, but our results are robust to controlling for potential autoregressive conditional skewness in stock returns (Harvey and Siddique, 1999), i.e., one-year lagged crash risk, and crash risk at loan origination (year $t$) to address concerns that the observed relationship might stem from risky firms attracting banks that seek a higher risk premium. These results, reported in Table A6 of the Online Appendix, indicate that high bank market power is associated with a subsequent increase in borrower crash risk.

[3] A limitation of the Lerner index is that it captures a bank's national rather than local market power. To address this, we use structural measures of banking market concentration, the Herfindahl–Hirschman Index (HHI) following Li et al. (2024), as a robustness check. Our results in Table A5 of the Online Appendix show that state-level and MSA-level HHIs produce results consistent with our baseline finding: higher banking market concentration predicts a two-year-ahead increase in borrowers' negative stock price skewness.

1. We use the Lerner index of the lead arranger because the lead bank bears the primary responsibility for monitoring (Lin et al., 2012; Gustafson et al., 2021).[4] Our results are robust to using the lender-weighted average Lerner index of the entire syndicate and to applying alternative cost function specifications. These results are not reported for brevity but are available upon request.

*3.2 Data Collection and Descriptive Statistics*

We construct our sample by linking syndicated loan data with banks as lenders and *Compustat* firms as borrowers of each loan facility. We retrieve syndicated loan data from the Thomson Reuters Loan Pricing Corporation (Dealscan) database, and the sample period spans 1992-2019.[5] We then match each loan facility with bank-level data from the Federal Deposit Insurance Corporation (FDIC), corporate stock price data from *CRSP*, and financial report data from *Compustat*. Our sample of U.S. firms accounts for approximately 45% of all syndicated loan borrowers. Consistent with the crash risk literature (e.g., Chen et al., 2001; Kim et al., 2011a, 2011b; Al Mamum et al., 2020), we exclude borrowers in financial (SIC codes 6000-6999) and utility (4900-4949) sectors, as well as firm-year observations with fewer than 26 active weeks or a year-end stock price below $1.[6] The final sample comprises approximately 27,105 loan facilities from 12,115 packages and contains 9,869 firm-year observations.[7] This sample size is comparable to those of prior studies using syndicated-loan data (e.g., Delis et al., 2017). We present the detailed

[4] Our results are robust to controlling for participants' market power. Because including the participant-average Lerner substantially reduces the number of observations (by 40%), we report these results in the Online Appendix (Table A8). About 8% of loan facilities have more than one lead arranger. For these facilities, we use the Lerner index of the lead arranger with the largest share. We also test whether having multiple lead arrangers moderates our baseline relationship and find no moderating effect (in Table A17 of the Online Appendix).

[5] Our findings are robust to excluding major crisis years, i.e., 2001, 2007-2008, and 2020 (as our main finding shows a two-year-ahead effect, our crash risk data also covers 2020 and 2021), during which crashes were exceptionally frequent. These results are not tabulated for brevity.

[6] Our findings are robust to relaxing these two restrictions, and those results are not tabulated for brevity.

[7] The relationship between bank market power and corporate stock price crash risk is not affected by lending relationships. These results are reported in Table A15 of the Online Appendix.

sample selection steps in Table A1 of the Online Appendix. The number of observations used in the regression analysis is slightly smaller because of missing values for control variables.

[Insert Table 1 here]

Table 1 reports descriptive statistics with all continuous variables winsorized at the 1st and 99th percentiles. *NCSKEW* has a mean of 0.069 and a standard deviation of 0.861. *DUVOL* has a mean of 0.023 and a standard deviation of 0.362. *CRASHD* has a mean of 0.203, indicating that 20.3% of loan-year observations experienced a stock price crash. *Bank_Lerner* has a mean of 0.314. These summary statistics are broadly comparable to those reported in prior studies of crash risk (e.g., Kim et al., 2011b; 2016a) and bank market power (e.g., Wang et al., 2020). We present the Pearson correlation matrix in Table A2 of the Online Appendix.

## 4 Empirical Results

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

Unlike prior studies that typically examine the contemporaneous effect of a covariate on crash risk, we analyze the effect of bank market power over a five-year horizon, from loan origination to 4 years thereafter.[8] This lead-lag approach allows us to identify whether an effect exists and, if so, how long it takes for bad news to accumulate and eventually surface.

The results in Table 2 demonstrate a positive effect of bank market power on two-year-ahead corporate stock price crash risk. Specifically, we find no significant relationship between bank market power and corporate stock price crash risk at loan origination (n=0). The coefficient of $Bank_Lerner_{i,t}$ in column (1) is negative and statistically insignificant. One year later (n=1), the coefficient changes sign but remains statistically insignificant (column 2). In the second year after loan origination (n=2), the positive effect increases in both economic magnitude and statistical

[8] We tested longer horizons and found no persistent effects beyond year 4. These results are not reported for brevity.

significance. Column (3) shows that a one-standard-deviation increase in $Bank_Lerner_{i,t}$ (0.19 units) is associated with a 0.04-unit increase in $NCSKEW_{i,t+2}$, equivalent to approximately 4.6% of its standard deviation.[9] The growth of the coefficient from 0.039 in year *t+1* to 0.210 in year *t+2* is substantial. The positive relationship is robust across alternative crash risk metrics: a one-standard-deviation increase in *Bank_Lerner* is associated with a 5.1%-standard-deviation increase in *DUVOL* and a 1.16-percentage-point increase in the probability of a crash, as reported in columns (8) and (13), respectively.[10] The relationship is economically meaningful, as a one-standard-deviation increase in *Bank_Lerner* is associated with an increase in *NCSKEW* that is equivalent to 45% of the effect of a one-standard deviation change in firm size or 2.9 times the effect from a one-standard-deviation change in *ROA*. The effect begins to attenuate in the third year (n=3): it remains statistically significant for *NCSKEW* (*t*=1.87 in column 4) and *CRASHD* (*t*=2.60 in column 14) but is insignificant for *DUVOL* (*t*=1.26 in column 9). By the fourth year (n=4), the effect becomes statistically insignificant (columns 5, 10 and 15).

[Insert Table 2 here]

One might question whether a positive relationship existed prior to loan origination, such that strong bank market power reduces this relationship in years *t* and *t+1*, or whether the coefficient of *Bank_Lerner* was already trending upward before loan origination. To address these concerns, we use Fig. 1 to plot the coefficients of *Bank_Lerner* from three years prior to loan origination (*t-3*) to four years after (*t+4*). We find no significant correlation between *Bank_Lerner* and crash risk

[9] The two-year-ahead increase in crash risk is robust to excluding the 3,665 loan facilities that mature within a year. Table A3 of the Online Appendix reports results by maturity subgroups: loans maturing within 12 months do not show the two-year-ahead effect, whereas loans maturing after 12 months do.

[10] To address the concern that the two-year-ahead effect is driven by the firm's earlier or subsequent borrowings, we create a dummy that equals 1 if the firm has other borrowings (including new facilities) during *t-2* to *t+2*. The presence of multiple borrowings does not affect the relationship between bank market power and two-year-ahead corporate stock price crash risk. These results are reported in Table A4 of the Online Appendix.

metrics prior to origination, nor an upward pre-trend. This lack of pre-event significance bolsters the internal validity of our findings.

[Insert Fig. 1 here]

The observed positive effect of bank market power on two-year-ahead corporate stock price crash risk supports *Hypothesis H1b* and suggests that greater bank market power increases managers' tendency to hoard bad news. This finding indicates that the manipulation-incentive channel provides a more compelling explanation for the documented relationship than the monitoring-enhancement channel. We observe a strong effect on crash risk in the second year after loan origination, with weaker effects in the first and third years, suggesting that it takes, on average, two years after loan origination for bad news to accumulate, reach a tipping point, and be revealed.[11] If firms' earnings manipulation persists through the first year after issuing securities (Cohen and Zarowin, 2010; Liu et al., 2010), the crash in the second year is plausible and may reflect the reversal of these accruals or the point at which the volume of hidden information becomes impossible to manage. Overall, our results demonstrate that strong bank market power can be detrimental to the stability of non-financial sectors.

*4.2 Robustness Checks and Addressing Endogeneity Concerns*

To verify the robustness of our primary findings and address potential endogeneity concerns inherent in this research context, we conduct a series of tests.

We begin by employing alternative estimation methods. First, we employ two-way clustering of standard errors at the firm and year levels to account for potential within-firm and within-year

[11] We acknowledge that our crash-risk metrics are based on calendar years, and crashes do not always occur exactly 24 months after loan origination. For example, a loan issued in December of year *t* that crashes in January of *t+2* spans 13 months, while a loan issued in January of *t* that crashes in December of *t+2* spans 35 months. Although our variables do not model this variation explicitly, they nevertheless show a concentrated increase in crashes during the second year, implying that crashes tend to materialize more than one year after loan origination rather than within the first year.

correlation in the error term, following Cameron and Miller (2015). Second, we include industry × year fixed effects to control for industry-specific shocks in each year. Third, we cluster standard errors at the bank-year level to address potential error correlations within bank-year clusters. Fourth, we include firm-fixed effects to account for unobservable time-invariant borrower characteristics that may influence bank selection. This specification relies on within-firm variation and omits borrowers with only one syndicated loan facility in the sample period. The results in Table A9 of the Online Appendix show that the coefficients of $Bank_Lerner_{i,t}$ remain positive and statistically significant across these alternatives, indicating that our main finding is robust to these estimation methods.

Next, we examine whether our findings are robust to the inclusion of bank- and loan-level covariates. Specifically, we control for bank-level attributes, including bank size, Tier 1 capital ratio, and lead bank reputation. We account for loan-specific characteristics, including loan cost, facility amount, maturity, number of lenders, loan purpose, loan type, the presence of performance pricing, and whether the loan is collateralized (secured status).[12] Columns (1)-(3) of Table 3 show that the effect of bank market power on corporate stock price crash risk remains positive and statistically significant after adding these controls. Besides the effect of bank market power, we find a negative coefficient of $Facility_Amount_{i,t}$, suggesting that firms granted larger loans are less susceptible to crashes, potentially because banks allocate more resources to monitoring larger exposures. $Performance_Pricing_{i,t}$ has a positive coefficient, indicating that such provisions may inadvertently incentivize managers to engage in earnings manipulation to meet contractual benchmarks and reduce borrowing costs. In columns (4)-(6), we include $\Delta Bank_Lerner_{i,t\sim t+2}$ to

[12] Our results are robust to controlling for macroeconomic variables including real GDP growth, inflation, real interest rate, term spread, NBER recession indicator, industrial production growth, and unemployment. These results are reported in Table A7 of the Online Appendix.

control for changes in bank market power over the two years following loan origination. This change measure is not significantly associated with crash risk, suggesting that the observed positive effect of bank market power on two-year-ahead corporate stock price crash risk is driven by the bank's market power at loan origination rather than by subsequent changes in bank market power after loan origination. Finally, in columns (7)-(9), we incorporate bank-fixed effects. While the significance levels for *NCSKEW* and *DUVOL* attenuate slightly, the effect on *CRASHD* is stronger. Overall, the results in Table 3 demonstrate that the positive relationship between bank market power and corporate stock price crash risk is robust to controlling for bank- and loan-level variables.

[Insert Table 3 here]

We employ an IV approach to address potential endogeneity arising from omitted variables that may simultaneously influence bank market power and borrowers' crash risk. We use the branching restrictiveness index developed by Rice and Strahan (2010) as the IV. This index captures the staggered relaxation of geographical restrictions on bank expansion across states in the U.S. Because these regulatory shifts represent exogenous shocks to local bank market power, the RS index serves as a valid instrument, and we use this state-level timing of regulatory changes as an IV for individual bank market power. The results in Table 4 confirm that our findings are robust to using an IV to address endogeneity concerns and estimate the relationship. In column (2), the second-stage coefficient of $Bank_Lerner_{i,t}$ is 1.689 ($t$=2.87), indicating that a one-standard-deviation increase in $Bank_Lerner_{i,t}$ causes a 37.3%-standard-deviation increase in $NCSKEW_{i,t+2}$. The positive effect is robust to using *DUVOL* and *CRASHD* (columns 3-4) as alternative outcome measures.[13] Column (1) reports the first-stage results and diagnostic tests. The IV has strong first-

[13] Our results are robust to controlling for borrowers' state-year fixed effects to guard against state-level deregulation confounds. These results are reported in Table A10 of the Online Appendix.

stage relevance and passes the under-identification test (Kleibergen-Paap LM statistics), the weak identification test (Kleibergen-Paap Wald rk F statistics) and the weak-identification robust test (Anderson-Rubin Wald chi-sq statistics), suggesting that it is relevant and does not suffer from a weak instrument problem.

[Insert Table 4 here]

While the IV approach addresses omitted-variable endogeneity, it does not entirely rule out the potential selection problem arising from powerful banks intentionally selecting or attracting firms with particular characteristics that independently drive crash risk. To investigate this, we test for reverse causality. As shown in Table A13 of the Online Appendix, we find no evidence that a borrower's past crash risk significantly predicts *Bank_Lerner* at origination, alleviating concerns about self-selection and reverse causality. We do find that borrower's past stock price performance (*DTURNOVER* and *RET*), size, and leverage are associated with *Bank_Lerner*, indicating that powerful banks tend to lend to firms with specific observable characteristics, though stock price crash risk is not on that list.

One may ask whether the observed relationship reflects banks' market power per se or instead reflects bank size and organizational complexity. To isolate these effects, we examine *Bank_Lerner* and *Bank_Size* and their interactions. To simplify interpretation, we construct a dummy variable, *Large_Bank*, equal to 1 if the lender's total assets exceed the annual median across lead arrangers and 0 otherwise. We also construct *Bank_Reputation*, equal to 1 if the lead arranger ranks among the top ten by loan arrangement volume over the prior three years. The results in Table A12 of the Online Appendix indicate that the baseline effect is driven primarily by lead arrangers' market power rather than by size or reputation. The standalone effect of bank size is negative, and the effect of bank reputation is insignificant. The interaction terms are not

consistently significant. These results suggest that large banks may leverage their organizational capabilities and internal controls to reduce borrowers' bad news hoarding and crash risk, but such organizational strengths do not offset the adverse effect of market power.

We conduct an event-study analysis as an alternative specification to test the baseline relationship. We treat borrowing from a powerful bank as an event and focus on firms that borrowed from a given lender only once during the sample period to avoid confounding effects of repeated lending relationships. We classify a bank as "powerful" if its Lerner index exceeds the annual median and we define the event indicator, *First_time_high*, which equals 1 if the loan is provided by a powerful bank and 0 otherwise. The "borrowing from a powerful bank" group comprises 16.6% of total loan facilities. When matched to the firm-year panel, 1.47% of firm-year observations are exposed to the event. We test whether firms' crash risk increases following this exposure. Table 5 reports the results that continue to show a positive relationship between bank market power and corporate stock price crash risk. In columns (1)-(3), $First_time_high_{i,t-2}$ has a positive effect on crash risk in year *t*. To ensure the validity of our model, columns (4)-(6) present a dynamic specification. We find that the pre-event indicators, *Pre_2* and *Pre_1*, are statistically insignificant, and F-test p-values range from 0.146 to 0.577, supporting the parallel-trends assumption. *Post_2* has a positive and significant effect on crash risk, consistent with our facility-level results. The positive effect persists through the third year after the event (*Post_3*) and diminishes thereafter (*Post_4+*). These results are robust across all three metrics of crash risk.

[Insert Table 5 here]

Finally, we estimate a Cox proportional hazards model (Andersen and Gill, 1982) as an alternative specification. Using a setup analogous to our event-study design above, we label the event as borrowing from a powerful bank if the lead arranger's Lerner index exceeds the annual

median. We map these events to the firm-quarter panel. We identify crashes using the *CRASHD* criterion that a specific weekly return is below the annual mean minus 3.09 standard deviations, applied at the quarterly frequency. *Post_event* is an indicator that equals 1 for quarters after the event and 0 otherwise. Table A11 of the Online Appendix shows that borrowing from a powerful bank increases the hazard of experiencing a crash. Fig. A1 plots the survival curve, illustrating that the probability of remaining crash-free is lower for firms borrowing from a powerful bank.

### *4.3 The Mechanism*

#### *4.3.1 The Manipulation-Incentive Channel*

Building on the baseline finding of a positive effect of bank market power on corporate stock price crash risk, this section investigates the underlying mechanism: the manipulation-incentive channel. Since firms' bad news hoarding is the primary driver of stock price crashes (e.g., Kothari et al., 2009), it is plausible that high bank market power incentivizes firms to manipulate financial information and conceal bad news, particularly because powerful banks tend to rely heavily on hard-information criteria to screen and monitor borrowers (Stein, 2002; Cole et al., 2004; Lian, 2018). Firms may manipulate their earnings and real activities to temporarily meet covenant requirements and thereby avoid technical default and subsequent transfers of control to creditors in the event of a covenant violation. Under this framework, we expect, from the lender's perspective, that *powerful banks are more inclined to impose stricter hard-monitoring requirements, as reflected in a larger number of financial covenants in loan contracts, and that higher covenant intensity is associated with greater crash risk for borrowers.* The literature shows that informational opaqueness and earnings manipulation contribute to the accumulation of bad news, ultimately leading to stock price crashes (e.g., Chen et al., 2017; Hutton et al., 2009; Kim et al., 2016b). From the borrower's perspective, we therefore expect *firms borrowing from powerful*

*banks to exhibit greater earnings manipulation, leading to higher crash risk.* We use the mediation analysis (Baron and Kenney, 1986) and the Sobel test to verify the manipulation-incentive channel from both the lender and borrower perspectives.

We first test the mediating role of covenant intensity, and the results in Table 6 support our conjecture. Column (1) shows a positive relationship between *Bank_Lerner* and *Financial_Covenants*, indicating that powerful banks rely more heavily on hard monitoring and impose more covenant restrictions in loan contracts. Columns (2)-(4) include *Financial_Covenants* in the crash risk models and the results show that covenant intensity is positively and significantly correlated with crash risk. The Sobel test results confirm that financial covenants mediate the relationship between bank market power and corporate stock price crash risk, suggesting that loan contract strictness is an important source of managerial pressure that is associated with stock price crash risk.

[Insert Table 6 here]

To verify the channel from the borrower's perspective, we examine two forms of manipulation: financial reporting opacity (accrual-based) and real activities manipulation. Our first measure, *Opaque*, is the three-year moving sum of the absolute value of discretionary accruals, following Hutton et al. (2009). Discretionary accruals are estimated using the modified Jones model (Dechow et al., 1995). Hutton et al. (2009) argue that accrual-based earnings management (AEM) obscures information about fundamentals and enables managers to hide bad news from external stakeholders; thus, *Opaque* serves as an indicator of information asymmetry, as firms with consistently large discretionary accruals are more likely to engage in earnings management. Our second set of metrics consists of real earnings management (REM) indicators, *RM_1* and *RM_2*, following Cohen and Zarowin (2010). *RM_1* captures reductions in discretionary expenses and

increases in abnormal production costs, while *RM_2* captures abnormal cash flows from operations combined with reductions in discretionary expenses. Given that our baseline results show a two-year-ahead effect on crash risk, we compute each firm's average *RM_1* and *RM_2* over the two years following loan origination and test whether this average mediates the relationship between bank market power and corporate stock price crash risk.

The results in Table 7 show that REM mediates the relationship between bank market power and corporate stock price crash risk. While column (1) displays a positive effect of bank market power on financial reporting opacity, the mediation analysis in columns (2)-(4) suggests that *Opaque* does not appear to be the primary mediator of crash risk and that the Sobel test for this path remains insignificant. However, we find that REM serves as a strong mediator. Columns (5) and (9) demonstrate that $Bank_Lerner_{i,t}$ is positively associated with REM in the two years after loan origination. *Avg_RM_1* (columns 6 and 7) and *Avg_RM_2* (columns 10 and 11) are significantly correlated with crash risk, and including these measures reduces the coefficient of $Bank_Lerner_{i,t}$ relative to our baseline results in Table 2. The Sobel test results are significant, confirming the mediating role of REM. Our results suggest that altering actual business operations to meet bank-imposed targets is a key mechanism through which bank market power translates into crash risk. One possible reason that REM, but not AEM, mediates the baseline relationship is that REM affects firms' underlying operating decisions and directly influences cash flows, and is therefore less detectable (Graham et al., 2005) and becomes the preferred tool for managers facing hard-monitoring pressures.

[Insert Table 7 here]

*4.3.2 Testing Alternative Explanations: Capital Supply Channel and Profitability and Creditworthiness Channel*

We test two alternative explanations for the baseline relationship. One potential mechanism underlying this relationship is the capital supply channel. Jiang et al. (2020) find that U.S. banking deregulation improved firms' access to external finance, allowing them to alleviate financial difficulties and reduce earnings volatility. Under this framework, one might expect banks with strong market power to restrict the supply of external finance, making it harder for borrowers to mitigate negative shocks before having to release the bad news and thereby increasing crash likelihood. Jiang et al. (2020) show that U.S. firms' investment-cash flow sensitivity decreases after banking deregulations, indicating that firms gain better access to external finance and 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 test whether firm investment is more sensitive to internal cash flows when bank market power is greater. 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 greater*. 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 use an alternative measure and define investment (*INVR*) as (*capital expenditures + M&A expenses + R&D expenses – sale of property, plant, and equipment + investment to maintain existing assets*) / *total assets*, following Richardson (2006) and Li et al. (2021). We interact *Bank_Lerner* with *CF*. A positive coefficient of the interaction term $CF_{i,t+1} \times Bank_Lerner_{i,t}$ would support the capital supply channel and indicate that firms rely more on internal cash flows when bank market power is greater. A negative coefficient would indicate the opposite.

The results in Panel A of Table 8 do not support the capital supply channel. The interaction term $CF_{i,t+1} \times Bank_Lerner_{i,t}$ is insignificant in column (1), indicating no impact of bank market

power on the cash flow sensitivity. The null result holds after controlling for bank- and loan-level variables in column (2). Using *INVR* in columns (3)-(4), the coefficient of the interaction term $CF_{i,t+1} \times Bank_Lerner_{i,t}$ is negative and statistically significant, indicating weaker cash flow sensitivity when bank market power is greater. This finding contradicts the capital supply channel but aligns with evidence that EU firms in concentrated banking markets may actually face fewer financial constraints due to strong relationship lending (Ratti et al., 2008).[14]

The second alternative explanation is that powerful banks may charge higher interest rates or reduce fund availability, thereby depressing borrowers' profitability and creditworthiness, which ultimately triggers a crash. If this were the case, we would expect to see a decline in firm profitability (i.e., *ROA* and *ROE*) and creditworthiness (i.e., *Altman Z-score*) in the second year after loan origination.

The results in Panel B of Table 8 do not support this channel. *Bank_Lerner* is not significantly correlated with borrowers' *ROA* (column 1), *ROE* (column 3) or the *Z-score* (column 5), indicating that bank market power at loan origination does not materially affect two-year-ahead corporate profitability and creditworthiness.[15] It is therefore unlikely that the documented crash risk is driven by a fundamental deterioration in firm health. Overall, the results in Table 8 rule out both the capital supply channel and the profitability and creditworthiness channel. This reinforces our conclusion that the impact of bank market power on corporate stock price crash risk operates primarily through the manipulation-incentive channel. Covenant intensity and real activities

[14] In addition to investment-cash flow sensitivity, we examine changes in firms' external financing and cash holdings. The results in Table A14 of the Online Appendix show that borrowers' cash holdings increase after loan origination, indicating that firms accumulate syndicated-loan proceeds to their balance sheets. Equity issuance capacity is unaffected at *t+2*. Debt issuance is positive at *t+2*, indicating that borrowers had not exhausted their debt capacity. These patterns do not suggest a funding squeeze, further ruling out the capital supply channel.

[15] Our results do not contradict Delis et al. (2017). We focus on the two-year-ahead effect, because crashes concentrate in year *t+2*. Although we do not report the one-year-ahead effect in this paper, we do observe a positive effect of *Bank_Lerner* on *ROA* at year *t+1*, which is consistent with Delis et al. (2017).

manipulation mediate the relationship. In short, hard monitoring by powerful banks appears to stimulate borrowers' incentives to manipulate information, conceal bad news, and satisfy covenant requirements, thereby increasing crash risk.

[Insert Table 8 here]

*4.4 Further Analysis of Timing*

Our baseline results indicate that bank market power influences corporate stock price crash risk with a two-year lag, suggesting that borrowers' bad news hoarding (e.g., REM) likely peaks during the two-year window following loan origination. To test this conjecture and provide further evidence on crash timing, we examine the correlation between $Bank_Lerner_{i,t}$ and REM before and after loan origination. As reported in Table 9, the correlation between $Bank_Lerner_{i,t}$ and REM is not statistically significant before loan origination (columns 1 and 2). The relationship is positive and statistically significant from loan origination ($t$) through the second year ($t+2$), but no significant relationship is observed beyond $t+2$. This result indicates that borrowing-associated manipulation increases during the initial two-year period (from $t$ to $t+2$) but does not continue to escalate thereafter, possibly because of the costs of maintaining REM (Graham et al., 2005; Cohen and Zarowin, 2010) and because firms discontinue manipulation after the bad news is released in year $t+2$. This pattern of REM provides a compelling explanation for why crashes predominantly occur in the second year following loan origination, marking the "tipping point" where the volume of hoarded bad news becomes unsustainable and is finally reflected in the stock price.

[Insert Table 9 here]

*4.5 Heterogeneous Effects of Bank Market Power*

*4.5.1 External Finance Dependence and Financial Constraints*

A natural question is how borrowers' demand for external finance influences their manipulation activities and stock price crash risk. Theoretically, two competing effects may exist. On the one hand, borrowers with greater external finance dependence rely more heavily on bank loans and therefore may have stronger incentives to hoard bad news to avoid signaling credit distress to lenders. This could increase manipulation and, in turn, elevate crash risk. On the other hand, firms with greater external financing needs may operate more cautiously and produce more transparent reporting, which could reduce manipulation and crash risk. To distinguish between these possibilities, we examine whether our baseline result varies with firms' external finance dependence and financial constraints. Following Dang et al. (2022), we define external finance dependence as (*capital expenditures + R&D expenses + M&A expenses – operating income before depreciation and amortization*) / (*capital expenditures + R&D expenses + M&A expenses*). Our second measure is the size-age index developed by Hadlock and Pierce (2010), which serves as a proxy for financial constraints. For both metrics, we construct dummy variables equal to 1 if the firm's value exceeds its industry-year median and 0 otherwise.

The results in Table 10 indicate that the effect of bank market power on corporate stock price crash risk is significantly more pronounced for firms that depend heavily on external finance. In column (1), the interaction term, $Bank_Lerner_{i,t} \times Financial_Dependence_{i,t+1}$, is positive and statistically significant (0.192, $t$=2.86), suggesting that the positive relationship between bank market power and two-year-ahead crash risk is amplified for firms with greater external finance dependence. These results are robust to using *DUVOL* and *CRASHD* to measure crash risk (columns 2 and 3). Similarly, in column (4), the interaction term $Bank_Lerner_{i,t} \times Financial_Constraints_{i,t+1}$ yields a positive and significant coefficient (0.212, $t$=2.90). These findings collectively imply that, when borrowers are heavily reliant on bank credit or face severe

financial constraints, the pressure to satisfy hard-monitoring requirements, such as strict covenants, overwhelms any potential cautionary behavior. It drives these firms toward aggressive earnings manipulation to maintain their credit access, ultimately heightening their susceptibility to stock price crashes.

[Insert Table 10 here]

*4.5.2 Loan Covenant Tightness*

We investigate whether the baseline effect varies with loan covenant tightness. The previous section has shown that powerful banks' reliance on hard monitoring, i.e., financial covenants, can incentivize borrowers to hide bad news and thus increase crash risk. The literature has also documented that firms close to violating current ratio covenants engage in significantly higher levels of earnings management (Franz et al., 2014). Accordingly, we expect that loans with narrower covenant headroom (higher violation probability) will exacerbate the pressure on managers, thereby amplifying the effect of bank market power on corporate stock price crash risk. To test this conjecture, we use the probability of covenant violation, *Prob_Violation*, developed by Demerjian and Owens (2016), and interact it with *Bank_Lerner*.

The results in Table 11 show that the effect of bank market power on crash risk is indeed greater for loans with a higher probability of covenant violation. In column (1), the interaction term $Lerner_{i,t} \times Prob_Violation_{i,t}$ has a positive coefficient (0.125, $t$=1.66), indicating that when covenant headroom is narrow, bank market power more severely increases the negative skewness of the borrower's stock returns. The results are robust to using *DUVOL* as an alternative crash risk metric (column 2). These findings provide further evidence that the monitoring-induced pressure from powerful lenders is an important driver of news-hoarding behavior that leads to crashes.

[Insert Table 11 here]

*4.5.3 Difficulty of Monitoring: Lending Distance*

We examine whether syndicated loan features that facilitate bank monitoring can mitigate the detrimental effect of bank market power on crash risk. The first feature is the geographic distance between the lender and the borrower. The literature shows that a greater distance between their headquarters hinders information collection and increases the cost of monitoring (e.g., DeYoung et al., 2008). Therefore, we expect *longer distances 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 test this conjecture with two measures. *Across_State* is a dummy that equals 1 if the borrower obtains the loan from a bank headquartered in a different state. *Ln_Distance* is the natural logarithm of the physical distance (in kilometers) between the headquarters of the lender and the borrower.

The results in Table 12 demonstrate that closer proximity, which facilitates monitoring, attenuates the effect of bank market power on corporate stock price crash risk. Columns (1)-(3) show that cross-state borrowers are more sensitive to the effect of bank market power. Specifically, column (1) indicates that the effect of *Bank_Lerner* on *NCSKEW* is 0.073 for within-state borrowers but rises to 0.196 for cross-state borrowers. The effect is robust to using *DUVOL* and *CRASHD* to measure crash risk (columns 2-3), and to using the physical distance between the lender and the borrower as an alternative measure of monitoring difficulty (columns 4-5). Collectively, these findings imply that closer proximity between borrower and lender facilitates soft monitoring and information collection, which complements powerful banks' hard-monitoring tools and improves the detection of hoarded bad news, thereby reducing the detrimental effect of bank market power on corporate stock price crash risk.

[Insert Table 12 here]

*4.5.4 Loan Syndicate Structure*

We examine whether the baseline effect is moderated by the structure of the loan syndicate. The literature suggests that syndicate concentration is a key determinant of monitoring efficiency and that more concentrated syndicates are associated with increased soft monitoring and resolution of moral hazard problems in the loan sales market. For example, Sufi (2007) demonstrates that lead banks retain larger loan proportions and conduct more intensive investigations when borrowers are more informationally opaque. Chen (2014) suggests that a smaller lender pool and higher lead retention reduce free-riding problems, thereby improving banks' monitoring efficiency and suppressing borrowers' excessive risk-taking. Furthermore, Gustafson et al. (2021) observe that lenders with a larger lead share have stronger incentives to engage in frequent soft-monitoring activities, such as site visits and third-party appraisals. Motivated by these insights, we expect that *the detrimental effect of bank market power on corporate stock price crash risk is weaker in loans with a more concentrated syndicate structure*. We employ three measures of syndicate concentration. The first measure is the logarithm of the number of lenders in the syndicate (*Number_of_Lenders*). The second measure is the lead bank's share of the loan (*Lead_Share*). The third measure is the Herfindahl-Hirschman Index for the syndicate (*Lender_Concentration*), computed as the sum of the squared lender shares.

The results in Table 13 show that bank market power has a smaller impact on corporate stock price crash risk when the syndicate is more concentrated. In column (2), the interaction term $Bank_Lerner_{i,t} \times Number_of_Lenders_{i,t}$ is positive (0.027, $t$=1.82), indicating that bank market power has a larger effect for loans with more lenders (i.e., less concentrated syndicates). In column (5), $Bank_Lerner_{i,t} \times Lead_Share_{i,t}$ is negative (-0.145, $t$=-2.25), suggesting that bank market power has a smaller impact if the lead bank retains a larger proportion of the loan. Similarly, in

column (8), $Bank_Lerner_{i,t} \times Lender_Concentration_{i,t}$ is negative (-0.145, $t$=-2.59), showing that bank market power has a smaller effect for loans with more concentrated syndicates. Overall, these results support our prediction that a concentrated syndicate structure improves monitoring efficiency and alleviates the adverse effect of bank market power on corporate stock price crash risk. Our findings imply that the soft monitoring inherent in concentrated syndicates serves as an important counterweight to powerful banks' hard monitoring and effectively reduces borrowers' propensity to hoard bad news.[16]

[Insert Table 13 here]

## 5 Conclusion

Using matched data on syndicated loan borrowers and lenders, this paper documents a positive and robust effect of bank market power on two-year-ahead corporate stock price crash risk. When lenders wield greater market power, borrowers are more inclined to conceal negative information, which increases the likelihood of stock price crashes. Our results challenge the common view that powerful banks are uniformly more effective at screening, monitoring, and controlling borrowers. We validate the manipulation-incentive channel from a dual perspective. From the lender's perspective, we observe that powerful banks tend to impose greater covenant intensity, reflecting a reliance on hard information for monitoring. From the borrower's perspective, we demonstrate that firms borrowing from powerful banks engage in more real activities manipulation following loan origination. These results suggest that high bank market power inadvertently amplifies

[16] A potential endogeneity concern in the heterogeneity tests is that an omitted variable could jointly determine lead bank's market power and the moderator (e.g., its syndicate share), resulting in biased estimates. Because we lack perfect IVs to separately instrument *Bank_Lerner* and the moderators, we implement a control function approach (Wooldridge, 2015) as an alternative way to estimate the relationship and address endogeneity issues. This approach uses first-stage regression residuals to isolate the endogenous component of the regressors and assumes that those controls are sufficient to render the endogenous regressor conditionally exogenous. The results in Table A16 of the Online Appendix show that, while some moderators appear endogenous, the interaction terms remain robust, validating our inferences in this section.

managerial incentives to hide bad news, thereby exacerbating information asymmetry. In the broader debate on banking market structure and economic stability, our findings align with the competition-stability view, offering novel evidence from the perspective of the non-financial sector. Our heterogeneity analysis further reveals that this detrimental effect is stronger for firms with greater demand for external finance and for loans with tighter covenants, but it can be mitigated by lending to geographically closer borrowers and by structuring syndicates to be more concentrated.

Our findings have significant implications for investors and regulators. First, borrowers that deal with powerful banks tend to conceal bad news, which leads to increased uncertainty and potential wealth destruction for investors. This suggests that more competitive banking markets, where banks have less market power and engage more in soft-monitoring activities, may reduce managerial incentives to manipulate, lower information asymmetries, and enhance stability in non-financial sectors. Second, lenders' soft-monitoring activities, for instance, through closer proximity between borrowers and lenders and frequent interactions motivated by a concentrated syndicate structure, complement hard monitoring and help mitigate the adverse effects of strong bank market power on borrowers' crash risk. Third, we recommend evaluating crash risk over a longer horizon, because the absence of short-term risk does not preclude a delayed effect. Overall, these findings deepen our understanding of lending relationships by highlighting creditors and loan contracts as important channels affecting borrowers' stock price crash risk and broader economic stability.

Our findings are based on the U.S. setting, where the banking system combines relationship-based and transactional lending, but they likely have implications for international financial markets as well. A compelling avenue for future research lies in exploring how cross-country

institutional frameworks influence these dynamics. For instance, in economies with less developed financial markets and weaker creditor rights, banks may find it even harder to verify hard information reported by corporate borrowers, potentially exacerbating the adverse effect of strong market power. Our findings contribute to the international finance literature by highlighting an underexplored mechanism through which banking market structure affects real-sector stability, with implications for credit markets in which lenders possess sufficient market power to impose hard-monitoring constraints.

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**Appendix 1** Construction of Main Variables

*1.1 Stock Price Crash Risk*

The first measure, *NCSKEW*, captures 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:

$$r_{i,\tau} = \alpha_i + \beta_{1i} r_{m,\tau-2} + \beta_{2i} r_{m,\tau-1} + \beta_{3i} r_{m,\tau} + \beta_{4i} r_{m,\tau+1} + \beta_{5i} r_{m,\tau+2} + \varepsilon_{i,\tau} \quad (A1)$$

where $r_{i,\tau}$ represents the stock return of firm *i* in week $\tau$. $r_{m,\tau}$ 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 logarithm of one plus the regression residual in Equation (A1): $W_{i,\tau} = \ln(1 + \varepsilon_{i,\tau})$. The value of *NCSKEW* for firm *i* in 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. (A2), where *n* denotes the number of weeks in the fiscal year:

$$NCSKEW_{i,t} = -\left[n(n-1)^{\frac{3}{2}} \sum W_{i,\tau}^3\right] / \left[(n-1)(n-2)\left(\sum W_{i,\tau}^2\right)^{3/2}\right] \quad (A2).$$

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. We then calculate the standard deviation for the two subgroups of returns separately. *DUVOL* for firm *i* in year *t* is measured as the natural logarithm of the ratio of the standard deviation of down-weeks to the standard deviation of up-weeks:

$$DUVOL_{i,t} = ln\{((n_u - 1)\sum_{Down} {W_{j,\tau}}^2)/((n_d - 1)\sum_{UP} {W_{j,\tau}}^2)\} \quad (A3).$$

Unlike *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 equal to 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 and 0 otherwise (Hutton et al., 2009).

*1.2 Bank Market Power*

We estimate bank-level marginal cost and market power using a parametric translog cost function, following the variable definitions and homogeneity restrictions used by Delis et al. (2017).

*A. Cost Function Specification*

Total cost $C_{it}$ for bank $i$ in year $t$ is defined as the sum of interest expenses and noninterest expenses. Bank output $Q_{it}$ is measured by total earning assets, which capture the core intermediation activity of banks. Input prices are defined as follows:

- The price of labor, $w_{l,it}$, is measured as personnel expenses divided by total assets
- The price of physical capital, $w_{k,it}$, is measured as noninterest expenses (net of personnel expenses) divided by fixed assets.
- The price of intermediation funds, $w_{d,it}$, is measured as total interest expenses divided by total customer deposits.

All variables are obtained from banks' Call Reports. Observations with nonpositive values are excluded to ensure meaningful logarithmic transformations.

To impose linear homogeneity in input prices, total cost and input prices are normalized by the price of deposits prior to taking logarithms. The resulting translog cost function is specified as:

$$\ln\left(\frac{C_{it}}{w_{d,it}}\right) = \partial_0 + \beta_1 lnQ_{it} + \frac{1}{2}\beta_2 ln(Q_{it})^2 + \gamma_1 ln\left(\frac{w_{l,it}}{w_{d,it}}\right) + \gamma_2 ln\left(\frac{w_{k,it}}{w_{d,it}}\right) + \frac{1}{2}\gamma_{11}\left[ln\left(\frac{w_{l,it}}{w_{d,it}}\right)\right]^2 + \frac{1}{2}\gamma_{22}\left[ln\left(\frac{w_{k,it}}{w_{d,it}}\right)\right]^2 + \gamma_{12} ln\left(\frac{w_{l,it}}{w_{d,it}}\right) ln\left(\frac{w_{k,it}}{w_{d,it}}\right) + \delta_1 lnQ_{it} ln\left(\frac{w_{l,it}}{w_{d,it}}\right) + \delta_2 lnQ_{it} ln\left(\frac{w_{k,it}}{w_{d,it}}\right) + \mu_i + \tau_t + \varepsilon_{it}, \quad (A4)$$

where $\mu_i$ captures unobserved time-invariant bank-level heterogeneity and $\tau_t$denotes year-fixed effects that control for common macroeconomic and regulatory shocks.

*B. Estimation method*

We estimate the translog cost function (A4) using a fixed-effects panel estimator, with standard errors clustered at the bank level. This parametric approach follows Delis et al. (2017) in its definition of costs, output, and input prices, as well as in the imposition of linear homogeneity. Delis et al. (2017) show that results based on such a parametric translog specification (OLS) are similar to those based on a semi-parametric estimator.

*C. Marginal cost*

Marginal cost is obtained as the derivative of the cost function with respect to output. From the estimated translog specification, the elasticity of cost with respect to output is given by:

$$\frac{\partial lnC_{it}}{\partial lnQ_{it}} = \beta_1 + \beta_2 lnQ_{it} + \delta_1 ln\left(\frac{w_{l,it}}{w_{d,it}}\right) + \delta_2 ln\left(\frac{w_{k,it}}{w_{d,it}}\right) \quad (A5)$$

Marginal cost at the bank-year level is then computed as:

$$MC_{it} = \left(\frac{C_{it}}{Q_{it}}\right)\frac{\partial lnC_{it}}{\partial lnQ_{it}} \quad (A6)$$

*D. Lerner index*

Finally, the Lerner index, our primary measure of bank market power, is defined as the price-cost markup:

$$Lerner_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \ (A7)$$

where the output price $P_{it}$is measured as total interest and noninterest income divided by total earning assets. This definition ensures consistency between the price measure and the output concept used in the cost function.

## **Appendix 2** Variable Definitions

| Variables | Definitions |
|---|---|
| *Variables for the crash risk* | |
| NCSKEW | Negative conditional skewness of a firm's weekly stock return distribution. The model is presented in Appendix 1. Source: CRSP. |
| DUVOL | Down-to-up volatility of stock return. The model is presented in Appendix 1. Source: CRSP. |
| CRASHD | A dummy variable equal to 1 for a crash and 0 otherwise. The model is presented in Appendix 1. Source: CRSP. |
| *Firm-level variables* | |
| DTURNOVER | Detrended average monthly stock turnover. Source: CRSP. |
| SIGMA | Standard deviation of firm-specific weekly returns. Source: CRSP. |
| RET | Arithmetic average of firm-specific weekly returns. Source: CRSP. |
| SIZE | Natural logarithm of the market value of equity. Source: CRSP and Compustat. |
| MB | Market value of equity divided by book value of equity. Source: CRSP and Compustat. |
| LEV | Long-term debt over total assets. Source: Compustat. |
| ROA | Income before extraordinary items divided by lagged total assets. Source: Compustat. |
| ROE | Net income divided by book value of total equity. Source: Compustat. |
| Z-score | 1.2×working capital / total assets + 1.4×retained earnings / total assets + 3.3×EBIT / total assets + 0.6×market value of equity / total liabilities + sales / total assets. Source: Compustat. |
| Opaque | The three-year moving sum of absolute discretionary accruals. Source: Compustat. |
| RM_1 | -1×abnormal discretionary expenses + abnormal production cost. Source: Compustat. |
| RM_2 | -1×abnormal cash flow from operations – abnormal discretionary expenses. Source: Compustat. |
| Sales_Growth | Sales growth divided by one-year-lagged sales. Source: Compustat. |
| INV | Capital expenditures divided by total assets. Source: Compustat. |
| INVR | (Capital expenditures + M&A expenses + R&D expenses – sale of property, plant, and equipment + investment to maintain existing assets)/ total assets. Source: Compustat. |
| CF | Operating cash flows divided by total assets. Source: Compustat. |
| Financial_Dependence | A dummy variable equal to 1 for the firms that are more dependent 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). Source: Compustat. |
| Financial_Constraints | A dummy variable equal to 1 for financially constrained firms (the top 50% of the industry-year group), where we measure financial constraints using the size-age index (-0.737×ln(assets) + 0.043×[ln(assets)]^2 - 0.040×age). Source: Compustat. |
| *Bank- and loan-level variables* | |
| Bank_Lerner | We use the Lerner index to measure the lead bank's market power. The model is presented in Appendix 1. Source: FDIC. |
| Bank_Size | Natural logarithm of book value of total assets of the lead bank. Source: FDIC. |
| Tier_One | The Tier 1 capital ratio of the lead bank. Source: FDIC. |
| Bank_Reputation | A dummy variable equal to 1 for the banks ranked in the top ten based on the amount of loans they provided in the past three years and 0 otherwise. Source: Dealscan. |
| RS index | The branching restrictiveness index capturing the staggered relaxation of geographical restrictions on bank expansion across states. Source: Rice and Strahan (2010). |
| Cost_of_Loan | The all-in drawn spread, measured in basis points, representing the interest rate borrowers pay over LIBOR plus annual fees. Source: Dealscan. |
| Financial_Covenants | The number of financial covenants of the loan facility. Source: Dealscan. |
| Non_Financial_Covenants | The number of non-financial covenants of the loan facility. Source: Dealscan. |
| Facility_Amount | The natural logarithm of the size of the loan facility. Source: Dealscan. |
| Maturity | The maturity of the loan in months. Source: Dealscan. |
| Across_State | A dummy variable equal to 1 if the firm borrows from a different state and 0 otherwise. Source: Dealscan, Compustat and FDIC |
| Ln_Distance | The natural logarithm of the physical distance between borrower and lender headquarters. We measure the distance using latitude and longitude. Source: Dealscan, Compustat and FDIC |
| Number_of_Lenders | The natural logarithm of the number of lenders in the syndicate. Source: Dealscan. |
| Performance_Pricing | A dummy variable equal to 1 for the loan with performance pricing and 0 otherwise. Source: Dealscan. |
| Secured | A dummy variable equal to 1 if the loan is secured with collateral and 0 otherwise. Source: Dealscan. |
| Loan_Purpose | A categorical variable for purpose of the loan, e.g., refinancing, working capital, and acquisition. Source: Dealscan. |

| | |
|---|---|
| Loan_Type | A categorical variable for loan type, e.g., revolver and term loan. Source: Dealscan. |
| Lead_Share | Lead bank's share in the loan syndicate. Source: Dealscan. |
| Lender_Concentration | The Herfindahl-Hirschman Index (sum of the squared lender shares in the syndicate). Source: Dealscan. |
| Prob_Violation | The probability of loan covenant violation. Source: Dealscan and Compustat. |

**Table 1** Descriptive Statistics

| Variable | N | Mean | Median | Std Dev | p5 | p95 |
|---|---|---|---|---|---|---|
| *Variables for the crash risk* | | | | | | |
| NCSKEW | 27,050 | 0.069 | 0.050 | 0.861 | -1.341 | 1.595 |
| DUVOL | 27,049 | 0.023 | 0.017 | 0.362 | -0.578 | 0.637 |
| CRASHD | 27,105 | 0.203 | 0.000 | 0.402 | 0.000 | 1.000 |
| *Firm-level variables* | | | | | | |
| DTURNOVER | 26,755 | 0.002 | 0.000 | 0.056 | -0.066 | 0.072 |
| SIGMA | 27,053 | 0.054 | 0.049 | 0.025 | 0.022 | 0.103 |
| RET | 27,055 | -0.002 | -0.002 | 0.008 | -0.016 | 0.010 |
| SIZE | 27,000 | 7.105 | 7.127 | 2.113 | 3.545 | 10.62 |
| MB | 26,987 | 2.890 | 2.083 | 5.539 | 0.313 | 10.130 |
| LEV | 27,035 | 0.296 | 0.268 | 0.215 | 0.000 | 0.698 |
| ROA | 27,039 | 0.019 | 0.038 | 0.131 | -0.164 | 0.140 |
| ROE | 27,019 | 0.050 | 0.102 | 0.887 | -0.654 | 0.589 |
| Z-score | 25,286 | 3.133 | 2.948 | 3.855 | -1.511 | 8.634 |
| Opaque | 21,135 | 0.224 | 0.179 | 0.179 | 0.042 | 0.553 |
| RM_1 | 22,740 | -0.015 | -0.024 | 0.431 | -0.704 | 0.705 |
| RM_2 | 24,622 | -0.007 | -0.008 | 0.257 | -0.422 | 0.421 |
| Sales_Growth | 26,198 | 0.114 | 0.065 | 0.343 | -0.249 | 0.566 |
| INV | 26,041 | 0.063 | 0.039 | 0.075 | 0.007 | 0.204 |
| INVR | 26,041 | 0.132 | 0.081 | 0.162 | 0.013 | 0.417 |
| CF | 26,190 | 0.081 | 0.087 | 0.119 | -0.091 | 0.229 |
| Financial_Dependence | 26,774 | 0.353 | 0.000 | 0.478 | 0.000 | 1.000 |
| Financial_Constraints | 27,062 | 0.274 | 0.000 | 0.446 | 0.000 | 1.000 |
| *Bank- and loan-level variables* | | | | | | |
| Bank_Lerner | 25,856 | 0.314 | 0.367 | 0.190 | -0.033 | 0.572 |
| Bank_Size | 27,105 | 19.23 | 19.62 | 1.998 | 15.29 | 21.45 |
| Tier_One | 27,105 | 0.073 | 0.067 | 0.020 | 0.055 | 0.106 |
| Bank_Reputation | 27,105 | 0.436 | 0.000 | 0.496 | 0.000 | 1.000 |
| RS index | 15,472 | 2.081 | 2.000 | 1.476 | 0.000 | 4.000 |
| Cost_of_Loan | 24,144 | 191.0 | 175.0 | 124.8 | 25.00 | 405.0 |
| Financial_Covenants | 27,105 | 1.123 | 1.000 | 1.314 | 0.000 | 4.000 |
| Non_Financial_Covenants | 27,105 | 1.683 | 0.000 | 2.226 | 0.000 | 6.000 |
| Facility_Amount | 27,105 | 18.73 | 18.98 | 1.835 | 15.25 | 21.42 |
| Maturity | 25,522 | 47.51 | 60.00 | 22.72 | 12.00 | 84.00 |
| Across_State | 27,105 | 0.563 | 1.000 | 0.496 | 0.000 | 1.000 |
| Ln_Distance | 22,721 | 6.620 | 6.874 | 1.269 | 3.623 | 8.125 |
| Number_of_Lenders | 27,105 | 1.582 | 1.792 | 1.059 | 0.000 | 3.178 |
| Performance_Pricing | 27,105 | 0.354 | 0.000 | 0.478 | 0.000 | 1.000 |
| Secured | 27,105 | 0.489 | 0.000 | 0.500 | 0.000 | 1.000 |
| Lead_Share | 23,205 | 0.491 | 0.376 | 0.305 | 0.095 | 1.000 |
| Lender_Concentration | 27,105 | 0.382 | 0.219 | 0.337 | 0.059 | 1.000 |
| Prob_Violation | 27,105 | 0.299 | 0.001 | 0.415 | 0.000 | 0.999 |

This table presents descriptive statistics. Stock price data are obtained from *CRSP*. Firm financial report data are sourced from *Compustat*. The sample consists of U.S. firms, excluding those in financial (SIC codes 6000-6999) and utility (4900-4949) sectors. Syndicated loan data are obtained from *Dealscan*, for the period from 1992 to 2019. Bank data are collected from the *Federal Deposit Insurance Corporation* (FDIC). All

continuous variables are winsorized at the 1% and 99% levels. Definitions of the variables are summarized in Appendices 1 and 2.

**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 |
| $Bank_Lerner_{i,t}$ | -0.041 | 0.039 | 0.210*** | 0.110* | 0.059 | -0.024 | 0.007 | 0.098*** | 0.031 | 0.033 | 0.074 | 0.105 | 0.223** | 0.260*** | 0.146 |
| | (-0.69) | (0.39) | (3.55) | (1.87) | (0.96) | (-0.98) | (0.31) | (3.97) | (1.26) | (1.29) | (0.78) | (1.11) | (2.34) | (2.60) | (1.38) |
| $DTURNOVER_{i,t+n-1}$ | -0.160 | 0.206** | 0.030 | 0.199** | 0.174* | -0.079* | 0.072 | 0.014 | 0.073* | 0.067** | 0.278 | 0.369* | 0.649*** | 0.338* | 0.116 |
| | (-1.58) | (1.99) | (0.33) | (2.14) | (1.75) | (-1.75) | (1.55) | (0.35) | (1.77) | (1.74) | (1.43) | (1.90) | (3.31) | (1.75) | (0.56) |
| $SIGMA_{i,t+n-1}$ | 1.452*** | 1.768*** | 0.888*** | -0.218 | -0.097 | 0.421*** | 0.454*** | 0.065 | -0.124 | -0.197 | -5.049*** | -5.008*** | -6.307*** | -7.330*** | -7.148*** |
| | (4.26) | (5.14) | (2.70) | (-0.65) | (-0.28) | (2.83) | (3.04) | (0.45) | (-1.61) | (-1.30) | (-8.09) | (-7.95) | (-10.03) | (-11.36) | (-10.47) |
| $RET_{i,t+n-1}$ | 4.282*** | 6.017*** | 6.142*** | 6.706*** | 8.727*** | 2.042*** | 2.532*** | 2.843*** | 3.478*** | 4.024*** | 1.091 | 3.902*** | 5.304*** | 6.320*** | 7.325*** |
| | (6.26) | (9.10) | (9.21) | (10.05) | (12.52) | (6.63) | (8.48) | (9.40) | (11.67) | (12.79) | (0.81) | (2.96) | (3.95) | (4.53) | (5.10) |
| $SIZE_{i,t+n-1}$ | 0.057*** | 0.036*** | 0.042*** | 0.040*** | 0.041*** | 0.023*** | 0.013*** | 0.016*** | 0.017*** | 0.017*** | 0.004 | 0.010 | 0.004 | 0.015** | 0.001 |
| | (14.67) | (9.38) | (11.21) | (10.29) | (10.14) | (13.93) | (8.03) | (9.90) | (10.01) | (9.88) | (0.62) | (1.53) | (0.53) | (2.17) | (0.10) |
| $MB_{i,t+n-1}$ | 0.002* | -0.003** | -0.002** | 0.001 | -0.002* | 0.001** | -0.001* | -0.001* | 0.000 | -0.000 | 0.002 | -0.002 | -0.002 | 0.001 | -0.007*** |
| | (1.81) | (-2.38) | (-2.17) | (0.59) | (-1.86) | (1.98) | (-1.66) | (-1.67) | (0.58) | (-0.78) | (0.86) | (-1.22) | (-1.31) | (0.77) | (-3.45) |
| $LEV_{i,t+n-1}$ | -0.140*** | -0.052* | -0.099*** | -0.062*** | -0.115*** | -0.054*** | -0.013 | -0.031*** | -0.009 | -0.053*** | -0.166*** | 0.025 | -0.134*** | -0.046 | -0.154*** |
| | (-4.51) | (-1.72) | (-3.51) | (-2.09) | (-3.74) | (-4.05) | (-1.04) | (-2.59) | (-0.71) | (-4.03) | (-3.14) | (0.49) | (-2.61) | (-0.86) | (-2.73) |
| $ROA_{i,t+n-1}$ | 0.058 | 0.157*** | 0.104*** | -0.019 | -0.023 | 0.023 | 0.099*** | 0.050*** | 0.009 | 0.009 | 0.800*** | 0.627*** | 0.646*** | 0.450*** | 0.633*** |
| | (1.47) | (3.51) | (2.85) | (-0.45) | (-0.60) | (1.28) | (4.77) | (2.79) | (0.48) | (0.48) | (6.91) | (5.05) | (5.44) | (3.91) | (4.87) |
| Intercept | -0.509*** | -0.334*** | -0.373*** | -0.359*** | -0.443*** | -0.237*** | -0.105** | -0.143*** | -0.181*** | -0.188*** | -0.722*** | -1.106*** | -0.566*** | -0.843*** | -0.996*** |
| | (-5.28) | (-3.45) | (-3.61) | (-3.94) | (-4.88) | (-5.86) | (-2.45) | (-3.12) | (-4.37) | (-4.35) | (-3.95) | (-5.74) | (-3.21) | (-4.51) | (-4.66) |
| 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 |
| Observations | 23,914 | 24,285 | 24,440 | 22,679 | 20,749 | 23,912 | 24,285 | 24,440 | 22,648 | 20,749 | 23,911 | 24,279 | 24,457 | 22,667 | 20,768 |
| $R^2$ | 0.047 | 0.034 | 0.040 | 0.050 | 0.057 | 0.056 | 0.042 | 0.049 | 0.063 | 0.070 | 0.056 | 0.056 | 0.057 | 0.065 | 0.062 |

This table presents the results of testing the effect of bank market power on corporate stock price crash risk. We use the OLS estimation, controlling for industry- and year-fixed effects in *NCSKEW* and *DUVOL* equations, and use probit regression in *CRASHD* equations. We test the effect from year *t* (n=0), when the syndicated loan is issued, through 4 years after origination. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

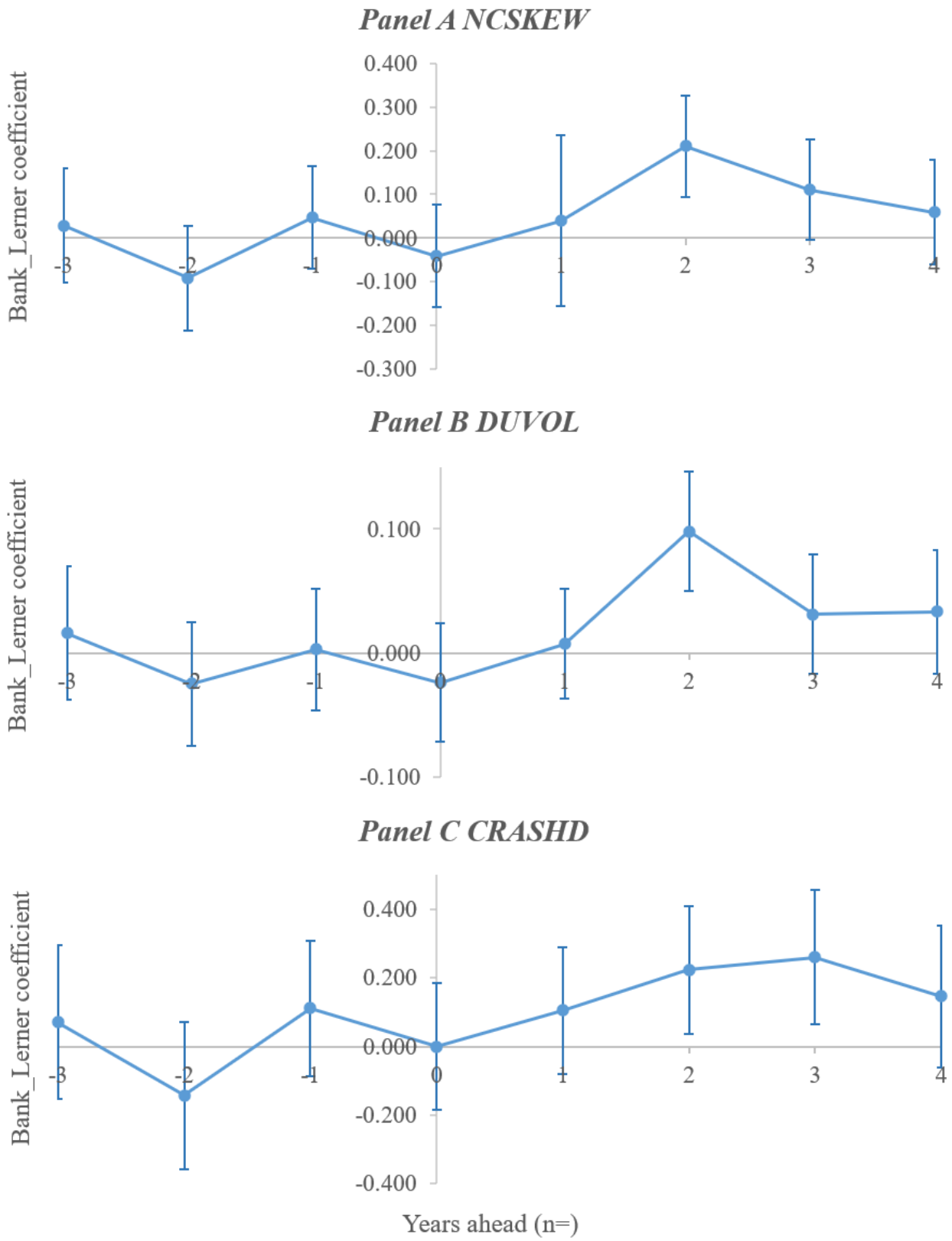



Fig. 1 displays the regression coefficient of *Bank_Lerner* in determining stock price crash risk. The error bar shows the 95% confidence interval.

**Table 3** Controlling for Bank- and Loan-Level Variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.152** | 0.078*** | 0.187* | 0.153** | 0.073** | 0.163 | 0.228* | 0.090* | 0.404* |
| | (2.30) | (2.82) | (1.74) | (2.08) | (2.37) | (1.60) | (1.79) | (1.65) | (1.79) |
| $\Delta Bank_Lerner_{i,t-t+2}$ | | | | -0.128 | -0.061 | -0.225 | -0.087 | -0.031 | -0.117 |
| | | | | (-1.34) | (-1.53) | (-1.33) | (-0.77) | (-0.65) | (0.59) |
| $DTURNOVER_{i,t+1}$ | -0.041 | -0.012 | 0.531** | -0.035 | 0.002 | 0.521** | -0.075 | -0.022 | 0.691*** |
| | (-0.42) | (-0.27) | (2.54) | (-0.33) | (0.05) | (2.38) | (-0.64) | (-0.44) | (2.95) |
| $SIGMA_{i,t+1}$ | 0.756** | 0.011 | -5.501*** | 0.888** | 0.115 | -5.801*** | 1.295*** | 0.314* | -5.165*** |
| | (2.04) | (0.07) | (-7.81) | (2.25) | (0.67) | (-7.84) | (2.99) | (1.66) | (-6.38) |
| $RET_{i,t+1}$ | 5.763*** | 2.666*** | 6.901*** | 5.491*** | 2.418*** | 7.902*** | 5.376*** | 2.267*** | 8.736*** |
| | (7.84) | (8.01) | (4.71) | (6.99) | (6.48) | (5.13) | (6.22) | (5.85) | (5.28) |
| $SIZE_{i,t+1}$ | 0.062*** | 0.025*** | 0.006 | 0.063*** | 0.025*** | 0.002 | 0.065*** | 0.027*** | -0.002 |
| | (11.14) | (10.45) | (0.57) | (10.59) | (10.00) | (0.21) | (9.87) | (9.79) | (-0.18) |
| $MB_{i,t+1}$ | -0.003** | -0.001* | -0.003 | -0.003** | -0.001* | -0.000 | -0.003** | -0.001** | 0.000 |
| | (-2.23) | (-1.64) | (-1.33) | (-2.06) | (-1.87) | (-0.18) | (-2.35) | (-2.17) | (0.04) |
| $LEV_{i,t+1}$ | -0.118*** | -0.040*** | -0.175*** | -0.127*** | -0.045*** | -0.172*** | -0.125*** | -0.047*** | -0.177*** |
| | (-3.47) | (-2.70) | (-2.83) | (-3.75) | (-2.97) | (-2.69) | (-3.18) | (-2.85) | (-2.56) |
| $ROA_{i,t+1}$ | 0.087** | 0.040** | 0.679*** | 0.110*** | 0.049** | 0.665*** | 0.125*** | 0.049** | 0.534*** |
| | (2.31) | (2.15) | (5.29) | (2.79) | (2.51) | (5.09) | (2.58) | (2.07) | (3.77) |
| $Bank_Size_{i,t}$ | -0.003 | -0.002 | 0.007 | -0.010 | -0.004 | 0.002 | 0.057** | 0.018 | 0.066 |
| | (-0.43) | (-0.58) | (0.63) | (-1.38) | (-1.44) | (0.13) | (2.21) | (1.60) | (1.31) |
| $Tier_One_{i,t}$ | 0.247 | -0.077 | 1.345 | -0.118 | -0.179 | 0.877 | 2.156** | 0.594 | 2.782* |
| | (0.44) | (-0.33) | (1.44) | (-0.18) | (-0.67) | (0.85) | (2.18) | (1.42) | (1.75) |
| $Bank_Reputation_{i,t}$ | -0.020 | -0.005 | -0.023 | -0.022 | -0.007 | -0.028 | -0.001 | 0.007 | 0.002 |
| | (-1.35) | (-0.88) | (-0.94) | (-1.42) | (-1.12) | (-1.10) | (-0.04) | (0.89) | (0.06) |
| $Cost_of_Loan_{i,t}$ | -0.000 | -0.001* | -0.001*** | -0.000 | -0.000 | -0.001*** | -0.000 | 0.000 | -0.001*** |
| | (-1.48) | (-1.70) | (-3.20) | (-1.42) | (-1.55) | (-3.67) | (-1.34) | (-1.20) | (-3.92) |
| $Facility_Amount_{i,t}$ | -0.025*** | -0.010*** | -0.019 | -0.023*** | -0.007*** | -0.019 | -0.018** | -0.008** | -0.018 |
| | (-3.63) | (-3.45) | (-1.59) | (-3.20) | (-2.98) | (-1.52) | (-2.38) | (-2.40) | (-1.34) |
| $Maturity_{i,t}$ | 0.015 | 0.009 | 0.029 | 0.015 | 0.009 | 0.024 | 0.007 | 0.005 | 0.012 |
| | (0.95) | (1.32) | (1.04) | (0.89) | (1.24) | (0.79) | (0.36) | (0.60) | (0.37) |
| $Number_of_Lenders_{i,t}$ | -0.000 | -0.003 | 0.029 | -0.000 | -0.004 | 0.004 | 0.005 | -0.001 | 0.002 |
| | (-0.05) | (-0.89) | (1.04) | (-0.01) | (-0.93) | (0.22) | (0.47) | (-0.33) | (0.11) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Performance_Pricing$_{i,t}$ | 0.065*** | 0.025*** | 0.064*** | 0.069*** | 0.028*** | 0.071*** | 0.072*** | 0.028*** | 0.077*** |
| | (4.62) | (4.03) | (2.65) | (4.63) | (4.49) | (2.82) | (4.51) | (4.28) | (2.88) |
| Secured$_{i,t}$ | 0.046*** | 0.022*** | -0.001 | 0.043*** | 0.018*** | 0.007 | 0.044** | 0.020*** | -0.004 |
| | (3.08) | (3.49) | (-0.23) | (2.67) | (2.67) | (0.27) | (2.51) | (2.72) | (-0.13) |
| Intercept | 0.039 | 0.020 | -0.503 | 0.137 | 0.055 | -0.350 | -1.400*** | -0.456** | -2.151** |
| | (0.21) | (0.24) | (-1.45) | (0.67) | (0.61) | (-0.95) | (-2.80) | (-2.05) | (-2.21) |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan purpose | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank effects | No | No | No | No | No | No | Yes | Yes | Yes |
| Observations | 21,179 | 21,179 | 21,127 | 19,283 | 19,283 | 19,227 | 17,470 | 17,470 | 17,152 |
| $R^2$ | 0.050 | 0.060 | 0.065 | 0.050 | 0.059 | 0.064 | 0.063 | 0.073 | 0.070 |

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 Appendices 1 and 2. Columns (4)-(9) control for the change in Lerner index after loan origination ($\Delta Bank_Lerner_{i,t\sim t+2}$). Columns (7)-(9) control for bank-fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 4** An Instrumental Variable Approach

| Dependent variables | (1) Bank_Lerner$_{i,t}$ | (2) NCSKEW$_{i,t+2}$ | (3) DUVOL$_{i,t+2}$ | (4) CRASHD$_{i,t+2}$ |
|---|---|---|---|---|
| RS index$_{i,t}$ | -0.012*** | | | |
| | (-14.87) | | | |
| Bank_Lerner$_{i,t}$ | | 1.689*** | 0.743*** | 0.531* |
| | | (2.87) | (2.90) | (1.90) |
| DTURNOVER$_{i,t}$ | 0.003 | -0.034 | 0.003 | 0.074 |
| | (0.20) | (-0.26) | (0.05) | (1.13) |
| SIGMA$_{i,t}$ | -0.034 | 1.105** | 0.142 | -1.432*** |
| | (-0.67) | (2.46) | (0.70) | (-6.80) |
| RET$_{i,t}$ | 0.044 | 5.939*** | 3.033*** | 0.820** |
| | (0.46) | (7.05) | (7.72) | (2.08) |
| SIZE$_{i,t}$ | -0.001 | 0.069*** | 0.028*** | 0.011*** |
| | (-1.00) | (10.05) | (9.43) | (3.38) |
| MB$_{i,t}$ | 0.000 | -0.001 | -0.001 | 0.000 |
| | (1.38) | (-0.36) | (-0.75) | (0.20) |
| LEV$_{i,t}$ | -0.009** | -0.056 | -0.011 | -0.002 |
| | (-2.02) | (-1.33) | (-0.59) | (-0.12) |
| ROA$_{i,t}$ | 0.022*** | 0.083* | 0.028 | 0.079*** |
| | (3.21) | (1.67) | (1.17) | (3.40) |
| Bank_Size$_{i,t}$ | 0.015*** | -0.045*** | -0.020*** | -0.007 |
| | (13.16) | (-3.73) | (-3.83) | (-1.20) |
| Tier_One$_{i,t}$ | 1.452*** | -3.331*** | -1.524*** | -0.546 |
| | (14.58) | (-2.74) | (-2.88) | (-0.97) |
| Bank_Reputation$_{i,t}$ | -0.015*** | 0.038* | 0.020** | 0.003 |
| | (-6.25) | (1.65) | (2.07) | (0.27) |
| Cost_of_Loan$_{i,t}$ | -0.000 | 0.000 | -0.000 | -0.000 |
| | (-0.84) | (0.21) | (-0.97) | (-0.16) |
| Facility_Amount$_{i,t}$ | -0.003*** | -0.017* | -0.006* | -0.012*** |
| | (-2.83) | (-1.94) | (-1.67) | (-2.78) |
| Maturity$_{i,t}$ | 0.005** | 0.010 | 0.007 | 0.001 |
| | (2.49) | (0.56) | (0.80) | (0.07) |
| Number_of_Lenders$_{i,t}$ | -0.007*** | -0.004 | -0.006 | 0.005 |
| | (-6.24) | (-0.39) | (-1.15) | (0.96) |
| Performance_Pricing$_{i,t}$ | 0.000 | 0.072*** | 0.029*** | 0.030*** |
| | (0.04) | (4.25) | (4.03) | (3.60) |
| Secured$_{i,t}$ | -0.002 | 0.029 | 0.016* | -0.010 |
| | (-1.04) | (1.46) | (1.86) | (-1.09) |
| Industry effects | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Loan purpose | Yes | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes | Yes |
| Kleibergen-Paap LM statistics | 217.95*** | | | |
| Kleibergen-Paap Wald rk F statistics | 221.06*** | | | |
| Anderson-Rubin Wald test chi-sq statistics | 8.45*** | | | |
| $R^2$ | | 0.027 | 0.039 | 0.055 |
| Observations | 12,266 | 12,266 | 12,266 | 12,266 |

This table presents results using staggered banking market deregulation, following Rice and Strahan (2010), as an instrumental variable (IV) to test the effect of bank market power on corporate stock price crash risk. The sample period is from 1992 to 2006. Column (1) shows the first-stage regression, and columns (2)-(4) show the second-stage regressions. We report the Kleibergen-Paap LM statistics for under-identification, the Kleibergen-Paap Wald rk F statistics for weak identification test, and the Anderson-Rubin Wald test chi-sq statistics for weak-identification-robust test. The Stock-Yogo weak ID test 10% critical value is 16.38. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 5** An Event-Study Design

| | (1) $NCSKEW_{i,t}$ | (2) $DUVOL_{i,t}$ | (3) $CRASHD_{i,t}$ | (4) $NCSKEW_{i,t}$ | (5) $DUVOL_{i,t}$ | (6) $CRASHD_{i,t}$ |
|---|---|---|---|---|---|---|
| $First_time_high_{i,t-2}$ | 0.073*** | 0.029*** | 0.114*** | | | |
| | (3.72) | (3.38) | (3.13) | | | |
| Pre_2 | | | | 0.030 | 0.008 | 0.073 |
| | | | | (1.03) | (0.67) | (1.44) |
| Pre_1 | | | | 0.027 | 0.009 | 0.058 |
| | | | | (1.03) | (0.79) | (1.21) |
| Post_0 | | | | -0.018 | -0.011 | 0.053 |
| | | | | (-0.73) | (-0.099) | (1.20) |
| Post_1 | | | | 0.005 | 0.005 | 0.031 |
| | | | | (0.21) | (0.51) | (0.72) |
| Post_2 | | | | 0.062*** | 0.028*** | 0.100** |
| | | | | (2.61) | (2.75) | (2.35) |
| Post_3 | | | | 0.056** | 0.019* | 0.091** |
| | | | | (2.38) | (1.92) | (2.20) |
| Post_4+ | | | | 0.003 | 0.001 | 0.035 |
| | | | | (0.19) | (0.12) | (1.31) |
| $DTURNOVER_{i,t-1}$ | 0.044 | 0.033* | -0.007 | -0.022 | 0.004 | 0.035 |
| | (1.17) | (1.92) | (-0.09) | (-0.41) | (0.18) | (1.31) |
| $SIGMA_{i,t-1}$ | 1.072*** | 0.229*** | -7.344*** | 0.943*** | 0.165** | 0.074 |
| | (7.47) | (3.57) | (-24.43) | (5.08) | (2.01) | (0.68) |
| $RET_{i,t-1}$ | 6.226*** | 2.969*** | 6.149*** | 6.194*** | 2.910*** | 5.556*** |
| | (21.38) | (21.97) | (9.22) | (16.08) | (16.65) | (6.82) |
| $SIZE_{i,t-1}$ | 0.054*** | 0.022*** | 0.028*** | 0.059*** | 0.025*** | 0.024*** |
| | (31.91) | (30.18) | (8.77) | (28.69) | (27.79) | (6.52) |
| $MB_{i,t-1}$ | 0.001** | 0.001*** | -0.001 | 0.000 | 0.000 | -0.001 |
| | (2.23) | (2.76) | (-0.73) | (0.30) | (0.62) | (-0.65) |
| $LEV_{i,t-1}$ | -0.050*** | -0.021*** | -0.025 | -0.043** | -0.021*** | -0.005 |
| | (-3.35) | (-3.24) | (-0.87) | (-2.20) | (-2.56) | (-0.15) |
| $ROA_{i,t-1}$ | 0.074*** | 0.034*** | 0.494*** | 0.138*** | 0.066*** | 0.548*** |
| | (7.04) | (6.60) | (12.77) | (8.58) | (8.53) | (10.49) |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes |
| F-stat for parallel trends | | | | 1.09 | 0.55 | 3.85 |
| P-value | | | | 0.338 | 0.577 | 0.146 |
| Observations | 90,582 | 90,576 | 90,667 | 61,537 | 61,532 | 61,589 |
| $R^2$ | 0.040 | 0.047 | 0.063 | 0.043 | 0.053 | 0.051 |

This table presents the results of using an event-study design to test the effect of bank market power on corporate stock price crash risk. We examine loans for which the firm used syndicated loan financing only once during the sample period. *First_time_high* is a dummy variable equal to 1 if the firm borrowed from a powerful bank (*Bank_Lerner* greater than the annual median). This test uses firm-year panel data rather than the pooled syndicated-loan data, with 1.47% of firm-year observations exposed to the event. We use two-way fixed-effects estimation to test the effect. Columns (4)-(6) use a dynamic model to demonstrate the change of the effect over time, where *Post_0* denotes the year of loan origination. Definitions of the variables are summarized in Appendices 1 and 2. We use firm and year two-way clustered standard errors. T-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 6** Mechanism Analysis: Financial Covenants

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variables | $Financial_Covenants_{i,t}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.212*** | 0.210*** | 0.097*** | 0.061** |
| | (3.46) | (3.55) | (3.96) | (2.26) |
| $Financial_Covenants_{i,t}$ | | 0.016*** | 0.006*** | 0.006** |
| | | (2.82) | (2.64) | (2.38) |
| $Non_Financial_Covenants_{i,t}$ | 0.348*** | 0.007* | 0.002 | 0.004*** |
| | (108.35) | (1.67) | (1.56) | (2.70) |
| Control variables | Yes | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Sobel test | | 0.003** | 0.001** | 0.001* |
| (z-value) | | (2.19) | (2.10) | (1.95) |
| Observations | 21,178 | 21,178 | 21,178 | 21,195 |
| $R^2$ | 0.506 | 0.041 | 0.050 | 0.056 |

This table presents mediation tests examining whether financial covenant intensity mediates the relationship between bank market power and corporate stock price crash risk. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 7** Mechanism Analysis: Earnings Manipulation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | $Opaque_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $Avg_RM_1_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $Avg_RM_2_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.046*** | 0.253*** | 0.109*** | 0.091*** | 0.071*** | 0.169*** | 0.081*** | 0.080*** | 0.038** | 0.173*** | 0.081*** | 0.086*** |
| | (4.20) | (2.87) | (4.02) | (3.01) | (2.69) | (2.59) | (2.99) | (2.68) | (2.55) | (2.75) | (3.10) | (2.98) |
| $Opaque_{i,t+2}$ | | -0.047 | -0.029* | 0.001 | | | | | | | | |
| | | (-1.26) | (-1.75) | (0.04) | | | | | | | | |
| $Avg_RM_1_{i,t+2}$ | | | | | | 0.039** | 0.022*** | -0.009 | | | | |
| | | | | | | (2.28) | (3.06) | (-1.06) | | | | |
| $Avg_RM_2_{i,t+2}$ | | | | | | | | | | 0.139*** | 0.071*** | -0.009 |
| | | | | | | | | | | (4.99) | (6.03) | (-0.65) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects | 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 |
| Sobel test | | -0.002 | -0.001 | 0.000 | | 0.003** | 0.002** | -0.001 | | 0.005** | 0.003** | -0.000 |
| (z-value) | | (-1.21) | (-1.62) | (0.04) | | (2.09) | (2.12) | (-0.99) | | (2.27) | (2.35) | (-0.63) |
| Observations | 20,080 | 20,080 | 20,080 | 20,097 | 20,206 | 20,206 | 20,206 | 20,214 | 21,874 | 21,874 | 21,874 | 21,890 |
| $R^2$ | 0.230 | 0.043 | 0.054 | 0.058 | 0.316 | 0.041 | 0.052 | 0.056 | 0.319 | 0.042 | 0.042 | 0.057 |

This table presents mediation tests examining whether earnings manipulation mediates the relationship between bank market power and corporate stock price crash risk. $Opaque_{i,t+2}$ captures a three-year moving sum of absolute discretionary accruals, from year $t$ to $t+2$. $Avg_RM_1_{i,t+2}$ and $Avg_RM_2_{i,t+2}$ are measures of real earnings management in the two years after loan origination. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 8** Testing Alternative Explanations

**Panel A:** Testing the Capital Supply Channel

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variables | $INV_{i,t+2}$ | | $INVR_{i,t+2}$ | |
| $CF_{i,t+1}$ | 0.099*** | 0.092*** | 0.164*** | 0.164*** |
| | (7.49) | (6.88) | (5.32) | (5.30) |
| $CF_{i,t+1} \times Bank_Lerner_{i,t}$ | -0.022 | 0.004 | -0.242** | -0.182** |
| | (-0.55) | (0.10) | (-2.96) | (-2.24) |
| $Bank_Lerner_{i,t}$ | 0.014*** | 0.005 | 0.060*** | 0.039*** |
| | (2.58) | (0.90) | (4.48) | (2.72) |
| $MB_{i,t+1}$ | 0.001*** | 0.001*** | 0.002*** | 0.003*** |
| | (7.76) | (8.71) | (10.86) | (11.82) |
| Intercept | 0.073*** | 0.129*** | 0.084*** | 0.486*** |
| | (12.74) | (9.02) | (7.73) | (14.03) |
| Bank- and loan-level variables | No | Yes | No | Yes |
| Industry effects | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes |
| Observations | 23,288 | 20,157 | 23,288 | 20,157 |
| $R^2$ | 0.375 | 0.395 | 0.120 | 0.152 |

**Panel B:** Testing the Profitability and Creditworthiness Channel

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variables | $ROA_{i,t+2}$ | $ROA_{i,t+2}$ | $ROE_{i,t+2}$ | $ROE_{i,t+2}$ | $Z\text{-score}_{i,t+2}$ | $Z\text{-score}_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.000 | -0.000 | -0.006 | 0.012 | 0.050 | -0.038 |
| | (0.01) | (-0.04) | (-0.10) | (0.19) | (0.41) | (-0.29) |
| $DTURNOVER_{i,t+1}$ | -0.024 | -0.020 | 0.269* | 0.188 | 0.458 | 0.193 |
| | (-1.07) | (-0.92) | (1.81) | (1.19) | (1.26) | (0.49) |
| $SIGMA_{i,t+1}$ | -0.933*** | -0.807*** | -2.788*** | -2.422*** | -14.56*** | -12.78*** |
| | (-13.89) | (-11.45) | (-6.30) | (-5.21) | (-12.80) | (-11.15) |
| $RET_{i,t+1}$ | 1.190*** | 1.194*** | 4.879*** | 4.925*** | 12.27*** | 12.28*** |
| | (8.30) | (7.69) | (4.81) | (4.51) | (5.40) | (5.10) |
| $SIZE_{i,t+1}$ | 0.002*** | 0.002* | 0.011*** | 0.007 | -0.066*** | -0.068*** |
| | (3.72) | (1.68) | (2.68) | (1.15) | (-7.18) | (-4.57) |
| $MB_{i,t+1}$ | 0.001*** | 0.001*** | 0.014*** | 0.009*** | 0.013*** | 0.014*** |
| | (3.13) | (3.25) | (5.03) | (3.17) | (4.58) | (4.59) |
| $LEV_{i,t+1}$ | 0.009* | 0.020*** | 0.024 | -0.017 | -0.455*** | -0.281*** |
| | (1.92) | (3.77) | (0.59) | (-0.34) | (-4.44) | (-2.76) |
| $ROA_{i,t+1}$ | 0.391*** | 0.380*** | | | | |
| | (15.43) | (13.67) | | | | |
| $ROE_{i,t+1}$ | | | 0.052*** | 0.066*** | | |
| | | | (2.67) | (3.25) | | |
| $Z\text{-score}_{i,t+1}$ | | | | | 0.860*** | 0.859*** |
| | | | | | (86.17) | (78.82) |
| Intercept | 0.045*** | 0.045 | 0.008 | -0.426** | 1.905*** | 1.584*** |
| | (2.78) | (1.36) | (0.12) | (-2.17) | (9.91) | (3.19) |
| Bank- and loan-level variables | No | Yes | No | Yes | No | Yes |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 24,407 | 21,146 | 24,397 | 21,139 | 22,798 | 19,771 |
| $R^2$ | 0.285 | 0.296 | 0.040 | 0.052 | 0.776 | 0.787 |

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 Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 9** The Timing of Crash: Corporate Real Earnings Management Before and After Loan Origination

| **Panel A:** RM_1 | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Dependent variables | $RM_1_{i,t-2}$ | $RM_1_{i,t-1}$ | $RM_1_{i,t}$ | $RM_1_{i,t+1}$ | $RM_1_{i,t+2}$ | $RM_1_{i,t+3}$ | $RM_1_{i,t+4}$ |
| $Bank_Lerner_{i,t}$ | -0.018 | 0.042 | 0.073** | 0.099*** | 0.098*** | 0.044 | 0.013 |
| | (-0.54) | (1.37) | (2.36) | (3.18) | (3.37) | (1.51) | (0.42) |
| Firm control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank- and loan-level variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16,032 | 17,361 | 18,742 | 19,017 | 18,892 | 17,994 | 16,569 |
| $R^2$ | 0.312 | 0.315 | 0.313 | 0.316 | 0.325 | 0.319 | 0.326 |
| **Panel B:** RM_2 | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Dependent variables | $RM_2_{i,t-2}$ | $RM_2_{i,t-1}$ | $RM_2_{i,t}$ | $RM_2_{i,t+1}$ | $RM_2_{i,t+2}$ | $RM_2_{i,t+3}$ | $RM_2_{i,t+4}$ |
| $Bank_Lerner_{i,t}$ | 0.010 | 0.019 | 0.041** | 0.042** | 0.054*** | 0.010 | 0.002 |
| | (0.55) | (1.59) | (2.28) | (2.45) | (3.22) | (0.60) | (0.09) |
| Firm control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank- and loan-level variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17,654 | 19,262 | 20,738 | 20,638 | 20,383 | 18,749 | 17,030 |
| $R^2$ | 0.310 | 0.298 | 0.301 | 0.304 | 0.313 | 0.309 | 0.316 |

This table presents the results of testing the effect of bank market power on corporate real earnings management. We test the effect from two years before loan origination (year *t-2*) to 4 years after loan origination. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 10** External Finance Dependence and Financial Constraints

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variables | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.086 | 0.056* | 0.107 | 0.100 | 0.065** | 0.217** |
| | (1.21) | (1.91) | (0.94) | (1.46) | (2.26) | (1.96) |
| $Bank_Lerner_{i,t} \times Financial_Dependence_{i,t+1}$ | 0.192*** | 0.062** | 0.277** | | | |
| | (2.86) | (2.23) | (2.50) | | | |
| $Financial_Dependence_{i,t+1}$ | -0.048* | -0.005 | -0.100** | | | |
| | (-1.82) | (-0.51) | (2.50) | | | |
| $Bank_Lerner_{i,t} \times Financial_Constraints_{i,t+1}$ | | | | 0.212*** | 0.054* | -0.158 |
| | | | | (2.90) | (1.79) | (-1.27) |
| $Financial_Constraints_{i,t+1}$ | | | | -0.076*** | -0.021* | 0.027 |
| | | | | (-2.67) | (-1.88) | (0.62) |
| 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 | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 20,997 | 20,997 | 20,958 | 21,178 | 21,178 | 21,139 |
| $R^2$ | 0.050 | 0.061 | 0.065 | 0.050 | 0.060 | 0.065 |

This table presents the results of testing the effect of external finance dependence and financial constraints on the relationship between bank market power and corporate stock price crash risk. $Financial_Dependence_{i,t+1}$ is a dummy variable equal to 1 for the firms that are more dependent 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). $Financial_Constraints_{i,t+1}$ is a dummy variable equal to 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, 35.3% of borrowers are classified as financially dependent and 27.4% of borrowers are classified as financially constrained. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 11** Loan Covenant Tightness

| Dependent variables | (1) $NCSKEW_{i,t+2}$ | (2) $DUVOL_{i,t+2}$ | (3) $CRASHD_{i,t+2}$ |
|---|---|---|---|
| $Bank_Lerner_{i,t}$ | 0.116 | 0.056* | 0.215* |
| | (1.63) | (1.87) | (1.83) |
| $Bank_Lerner_{i,t} \times Prob_Violation_{i,t}$ | 0.125* | 0.056* | -0.040 |
| | (1.66) | (1.82) | (-0.33) |
| $Prob_Violation_{i,t}$ | -0.041 | -0.021* | 0.034 |
| | (-1.55) | (-1.88) | (0.81) |
| Control variables | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes |
| Loan purpose | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes |
| Observations | 21,180 | 21,180 | 21,128 |
| $R^2$ | 0.050 | 0.060 | 0.065 |

This table presents the results of testing the effect of loan covenant tightness on the relationship between bank market power and corporate stock price crash risk. $Prob_Violation_{i,t}$ measures the probability of covenant violation, following Demerjian and Owens (2016). Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 12** Lending Distance

| Dependent variables | (1) $NCSKEW_{i,t+2}$ | (2) $DUVOL_{i,t+2}$ | (3) $CRASHD_{i,t+2}$ | (4) $NCSKEW_{i,t+2}$ | (5) $DUVOL_{i,t+2}$ | (6) $CRASHD_{i,t+2}$ |
|---|---|---|---|---|---|---|
| $Bank_Lerner_{i,t}$ | 0.073 | 0.027 | 0.024 | -0.266 | -0.085 | 0.171 |
| | (0.92) | (0.80) | (0.18) | (-1.22) | (-0.96) | (0.49) |
| $Bank_Lerner_{i,t} \times Across_State_{i,t}$ | 0.123* | 0.070** | 0.268** | | | |
| | (1.70) | (2.38) | (2.32) | | | |
| $Across_State_{i,t}$ | -0.086*** | -0.051*** | -0.099** | | | |
| | (-2.79) | (-4.14) | (-2.16) | | | |
| $Bank_Lerner_{i,t} \times Ln_Distance_{i,t}$ | | | | 0.070** | 0.027** | 0.003 |
| | | | | (2.23) | (2.13) | (0.06) |
| $Ln_Distance_{i,t}$ | | | | -0.036*** | -0.013** | -0.006 |
| | | | | (-2.68) | (-2.47) | (-0.28) |
| 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 | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21,179 | 21,179 | 21,127 | 17,880 | 17,880 | 17,822 |
| $R^2$ | 0.051 | 0.061 | 0.065 | 0.050 | 0.061 | 0.061 |

This table presents the results of testing the effect of lending distance on the relationship between bank market power and corporate stock price crash risk. Columns (1)-(3) test the effect of borrowing across state borders. Columns (4)-(6) test the effect of the physical distance between borrower and lender headquarters. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

**Table 13** Loan Syndicate Structure

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Dependent variables | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ | $NCSKEW_{i,t+2}$ | $DUVOL_{i,t+2}$ | $CRASHD_{i,t+2}$ |
| $Bank_Lerner_{i,t}$ | 0.097 | 0.029 | -0.128 | 0.240** | 0.129*** | 0.334** | 0.223*** | 0.122*** | 0.329*** |
| | (1.05) | (0.73) | (-0.83) | (2.35) | (3.06) | (2.08) | (2.81) | (3.70) | (2.61) |
| $Bank_Lerner_{i,t} \times Number_of_Lenders_{i,t}$ | 0.59 | 0.027** | 0.167*** | | | | | | |
| | (1.64) | (1.82) | (2.80) | | | | | | |
| $Number_of_Lenders_{i,t}$ | -0.010 | -0.013** | -0.051** | | | | | | |
| | (-0.65) | (-1.93) | (-1.98) | | | | | | |
| $Bank_Lerner_{i,t} \times Lead_Share_{i,t}$ | | | | -0.282* | -0.145** | -0.362 | | | |
| | | | | (-1.81) | (-2.25) | (-1.47) | | | |
| $Lead_Share_{i,t}$ | | | | 0.043 | 0.044 | 0.009 | | | |
| | | | | (0.57) | (1.37) | (0.07) | | | |
| $Bank_Lerner_{i,t} \times Lender_Concentration_{i,t}$ | | | | | | | -0.236* | -0.145*** | -0.514** |
| | | | | | | | (-1.80) | (-2.59) | (-2.28) |
| $Lender_Concentration_{i,t}$ | | | | | | | 0.103 | 0.069** | 0.060 |
| | | | | | | | (1.41) | (2.23) | (0.48) |
| 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 |
| Loan purpose | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan type | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21,179 | 21,179 | 21,127 | 18,035 | 18,035 | 18,006 | 21,179 | 21,179 | 21,127 |
| $R^2$ | 0.050 | 0.060 | 0.065 | 0.052 | 0.062 | 0.066 | 0.050 | 0.060 | 0.066 |

This table presents the results of testing the effect 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 syndicate. Columns (4)-(6) test the effect of the lead bank's share of the facility amount. Columns (7)-(9) test the effect of lender concentration. Definitions of the variables are summarized in Appendices 1 and 2. Heteroskedasticity-robust t-statistics are reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.