Monetary Policy and Debt Concentration

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Abstract

Analyzing a sample of U.S. listed firms from 2003 to 2022, we find robust evidence that firms tend to adopt more concentrated debt structures in response to monetary tightening shocks, while monetary easing shocks have no significant effect on debt concentration. Our cross sectional analyses indicates that the impact of monetary policy shocks (MPS) on debt concentration is primarily driven by heighted default risk, increased information asymmetry, and limited access to capital. This finding supports the view that concentrated debt structures reduce creditor coordination costs and facilitate successful debt renegotiation. Additionally, we observe that the positive relation between tightening shocks and debt concentration is more pronounced for firms with lower liquidation values, lower long-term debt ratios and higher stock return sensitivity to monetary policy. Collectively, our study highlights the role of monetary policy decisions in shaping corporate debt structure.

JEL Classifications: E52; G30; G32

Keywords: Monetary Policy Shocks; Debt Concentration

Data Availability: Data used in this study are available from the sources identified in the paper.

1. Introduction

Debt financing is one of the most important financing channels for firms, since it allows firms to raise capital without diluting ownership (Israel, 1992). Monetary policy set by central banks, which determines short-term nominal interest rates, can directly influence firms' debt financing by affecting the costs of external financing (Bernanke & Blinder, 1992). For instance, when interest rates are low, it is cheaper for firms to borrow, resulting in an increase in external debt used to finance their operations and investments. On the other hand, when interest rates are high, it can make borrowing more expensive, leading firms to reduce their reliance on external debt. As a result, monetary policy is unlikely to be ignored when corporate managers make financial decisions about firms' debt structures.

While there is a growing literature on how MPS affect corporate debt structure (Kashyap et al., 1993; Becker & Ivashina, 2014; Lhuissier & Szczerbowicz, 2021; Fabiani et al., 2024), little is known about whether and how MPS affect the composition of firms' debt (i.e., corporate debt concentration). Understanding this question is important, considering that the selection of debt concentration "is a first-order aspect of firm capital structure" (Li et al., 2021; Rauh & Sufi, 2010). Therefore, our study aims to fill this gap by empirically examining the impact of monetary policy shocks on debt concentration.

Prior literature on debt concentration has shown that firms consider the benefits and costs under different concentrations when making the debt financing decisions (Bolton & Scharfstein, 1996). By debt concentration, we refer to the extent to which the total debt is distributed across various debt types with different sources and priorities

(John et al., 2021). The higher the debt concentration, the more concentrated the debt structure, which means the firm use relatively fewer debt financing channels, with larger dependence on a certain type of debt financing (Colla et al., 2013). The advantage of a concentrated debt structure is that it increases the likelihood of successful debt renegotiation. This occurs because firms only need to communicate and coordination with a smaller number of creditors, which makes it easier to reach agreements. However, adopting concentrated debt structures can also be costly for firms as it increases the probability of strategic default by the manager, which motivates creditors to increase rates and makes it more difficult for firms to secure new debt financing in the future. Therefore, in order to determine the optimal debt structure, firms should weigh the benefits (i.e., reduced coordination costs among creditors and higher probability of successful debt renegotiation) and costs (i.e., higher likelihood of strategic default) of a concentrated debt structure.

Building on prior literature, we predict that firms should choose to increase (decrease) debt concentration in response to monetary tightening (easing) shocks. This can be explained through the impact of monetary policy shocks on firms' probability of debt default, information asymmetries and access to capital markets. For example, a monetary tightening shock can increase the costs of external financing, which may increase the risk of corporate default due to the inability to repay debts (Arellano et al., 2012). Therefore, firms are more likely to adopt concentrated debt structures to strengthen communication among creditors and increase the probability of successful debt renegotiation. In addition, a tightening shock exacerbates the degree of information asymmetry between firms and creditors, which ultimately hinders the successful debt renegotiation (Boivin et al., 2010). Consequently, firms require more concentrated debt structures to increase the probability of reaching agreements on debt renegotiation terms. Moreover, a tightening shock restricts firms' access to capital, which in turn increases their probability of financial distress (Davydenko, 2012). To resolve this distress, firms benefit from employing concentrated debt structures, as coordination across debt types is easier when there are fewer creditors.

To test this prediction, we measure firms' debt concentration in three ways. First, following Colla et al. (2013), our primary measure of debt concentration is a normalized Herfindahl-Hirschman index of seven diverse sources of debt (commercial paper, term loans, drawn credit lines, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt). Second, as in Colla et al. (2013) and Castro et al. (2020), we use a dummy variable *Excl90* as an alternative measure of debt concentration, which takes one if at least 90% of the company's debt is one debt type, and zero otherwise. Lastly, we count the number of different debt types that the firms use (see, Li et al., 2021). To measure the exogenous monetary policy shocks, we follow Nakamura and Steinsson (2018) and construct the MPS as the first principal component of the change in interest rate futures at different maturities that span the first year of the term structure in a tight window around the Federal Open Market Committee (FOMC) meetings, using all scheduled announcements from August 22, 2000, to May 4, 2022.

We then examine the empirical relation between monetary policy shocks and debt concentration in a sample consists of 36,612 firm-year observations for 4,786 individual U.S. listed firms from 2003 to 2022. We find that firms significantly increase debt concentration in response to monetary policy tightening shocks, while firms do not make significant changes in debt concentration when there are monetary easing shocks. This finding is consistent with our argument that firms exhibit higher debt concentration when facing monetary tightening shocks as a way to minimize creditor coordination costs and facilitate successful debt renegotiation.

Next, we address potential concerns about endogeneity problems. We contend that reverse causality is unlikely to exist in our research design, as the independent variable (i.e., the exogenous monetary policy shocks) is determined by the FOMC based on broader macroeconomic conditions, rather than firm-level variables. As a consequence, it is unlikely that changes in corporate debt concentration have a direct impact on these monetary policy shocks. We also rule out the effect of omitted variables by adopting three identification strategies. First, we perform the coefficient stability test proposed by Oster (2019). Second, following the suggestion of Gormley and Matsa (2014), we add the high-dimensional fixed effects to our baseline model to address for the unobserved heterogeneity. In particular, we control for firm-specific and interacted industry-year fixed effects, which helps alleviate the potential endogeneity concern arising from unobserved heterogeneity across firms and time-varying heterogeneity across industries. Third, following Larcker and Rusticus (2010), we further conduct the impact threshold of a confounding variable (ITCV) test to ensure our regression results are not driven by unobserved variables. Our baseline results remain robust after implementing these three identification methods, which effectively alleviates any potential endogeneity concerns.

We further investigate the mechanisms through which monetary tightening shocks influence firms' debt concentration decisions. Our cross-sectional analyses show that the positive relation between monetary tightening shocks and debt concentration is indeed more pronounced among firms with higher default risk, greater information asymmetry and restricted access to capital. These three types of firms typically face greater challenges in meeting their debt obligations and communicating effectively with creditors. As a consequence, they have a more pressing need for enhance coordination with creditors to prevent adverse economic outcomes. We further examine whether the positive relation between monetary tightening shocks and corporate debt concentration exhibits any cross-sectional variations with respect to firms' liquidation values, long-term debt ratios, and stock return sensitivities to monetary policy shocks. We find that firms with lower liquidation values, lower long-term debt ratios and larger stock price reactions are more responsive to monetary tightening shocks by increasing their level of debt concentration.

In our additional analysis, we examine the impact of monetary tightening shocks on firms' use of individual debt types. We find that firms significantly reduce their use of senior debt and capital leases in response to tightening shocks. This can be attributed to the adverse effects of higher interest rates, which dampens the overall economy and consequently reduce firms' total output and revenues, and their demand for senior debt and rented assets.

We also conduct multiple robustness checks to examine the validity of our findings. First, we show that our results are robust to alternative constructions of the debt concentration proxy variable (*HHI*). Second, we also show that our results still hold if we exclude firm-year observations during the recession or crisis periods. Third, to mitigate the concern that the documented relationship between monetary policy shocks and debt concentration can be driven by other debt structure characteristics, we include additional controls such as loan spread, maturity and number of covenants to our baseline model. We find that our results remain robust after adding these additional controls. Finally, we restrict our sample observations to those in which the sign of the largest monetary policy shocks (in absolute values) matches the sign of the aggregated shocks for the year. Our baseline results are robust to this adjustment.

Our study's key contributions are reflected in three aspects. First, we extend the literature that work on integrating corporate finance and macroeconomics (Rocheteau et al., 2018; Ottonello & Winberry, 2020; Crouzet, 2021). By focusing on the monetary policy shocks in macroeconomic policy and firms' debt concentration in corporate decisions, our study echoes with the call by Dechow et al. (2010) to connect macroeconomic factors with corporate activities. This integration can also help monetary policymakers better understand the implications of their policy decisions on different firms.

Second, this study adds novelty to the literature of how MPS impact corporate debt structures. Previous literature in this area is relatively scarce and mainly analyses the impact of MPS on corporate debt structures from the lens of debt substitution (e.g. the substitution between bank loan and bond debt) and debt maturity (Kashyap et al., 1993; Lhuissier & Szczerbowicz., 2021; Fabiani et al., 2024). To the best of our knowledge, this study is the first to provide a systematic analysis of the impact of monetary policy shocks on the corporate debt structure from the perspective of debt concentration (i.e., the number of debt types). By documenting a positive relation between monetary tightening shocks and debt concentration, we contribute to the literature on the effects of MPS on corporate debt structures from a previously unexplored perspective.

Third, this study enriches the body of research related to the factors influencing debt concentration. While existing research have shown that corporate debt concentration is associated with various factors such as accounting quality, CEO's risk-taking incentives, creditor protection, credit default swaps, and climate risk exposure (Castro et al., 2020; Li et al., 2021; John et al., 2021; Clark et al., 2023; Song et al., 2024), none of the studies investigate firms' debt concentration from the perspective of policy interventions. Our study explores how firms make choices regarding their debt structures in response to MPS, thus augmenting the relevant literature on the determinants of debt concentration.

The paper proceeds as follows. Section 2 summarizes related literature and discusses how MPS affect firms' degree of debt concentration. Section 3 describes our data, measurement of key variables and our model specification. Section 4 presents the empirical results. Section 5 concludes the paper.

2. Literature and hypothesis development

2.1. Literature on debt concentration

Prior studies highlight the role of firms' use of various debt types in shaping debt structure. A firm using fewer debt types implies a more concentrated debt structure, which can reduce financial distress costs due to fewer conflicts of interest among creditors (Bolton & Scharfstein, 1996; Bris & Welch, 2005; Hackbarth & Mauer, 2012). Different types of debt often come with unique cash flow requirements, control provisions, and collateral, and creditors may vary in investment horizons and non-financial interests (Ayotte & Morrison, 2009; Beatty et al., 2012; Lou & Otto, 2020). Bris and Welch (2005) argue that concentrated debt structures often minimize creditor coordination needs in restructuring or bankruptcy, lowering inefficient liquidation risks. Additionally, a concentrated structure reduces information collection and monitoring costs for creditors (Bris & Welch, 2005; Colla et al., 2013). However, high debt concentration may increase the likelihood of strategic default, where a firm intentionally defaults to reallocate cash, which can harm its credibility and future borrowing capacity (Bolton & Scharfstein, 1996; Li et al., 2021).

Previous studies have examined factors influencing debt concentration. Rauh & Sufi (2010) find that firms with lower credit quality tends to use multi-tiered debt structures, while Colla et al. (2013) find that more opaque firms with higher bankruptcy costs and limited market access employ fewer debt types. Castro et al. (2020) show that CEO risk-taking incentives lead to more concentrated debt. Li et al. (2021) suggest that high accounting quality facilitates creditor coordination, reducing debt concentration. John et al. (2021) find that firms in countries with strong creditor protection prefer concentrated debt. Yao et al. (2024) argue that a stable top management team lowers coordination costs, allowing for more diversified debt structures.

2.2. Literature on the transmission channels of monetary policy

Monetary policy shocks influence firms' financial decisions through several transmission channels. The primary channel is the interest rate channel, where tightening monetary policy raises real interest rates, increasing firms' borrowing costs and reducing their investment expenditures and labor hiring (Meltzer, 1995; Angeriz et al., 2008). Bernanke and Gertler (1995) and Mishkin (1995) expand on this by introducing the credit channel, which affects both the cost and availability of external financing.

According to the credit channel, in addition to affecting the general level of interest rates, monetary policy also impacts the cost of external financing and the availability of credit in the economy. The credit channel has two subchannels: (1) the balance sheet channel, which impacts firms' borrowing capacity as monetary policy changes their net worth. Prior studies such as Ashcraft and Campello (2007) and Angelopoulou and Gibson (2009) provide empirical evidence for the balance sheet channel; and (2) the bank lending channel, where tightening monetary policy reduces bank reserves, limiting loanable funds and increasing external financing costs. Empirical studies such as Kashyap and Stein (1995) support the bank lending channel.

A recent strand of literature empirically examines how monetary policy influences corporate activities. Gallo et al. (2016) find that aggregate firm earnings convey information about monetary policy, and the market reacts negatively to policy surprises, which leads to a negative relation between aggregate earnings and stock returns. Adra et al. (2020) indicate that an increase in the federal funds rate leads to a lower M&A announcement return, a greater likelihood of deal withdrawals, and greater financing difficulties for acquirers. Morlacco and Zeke (2021) develop a model to provide a rationale for the increase in market concentration and market power over the recent decades, during which interest rates generally fell. Ottonello and Winberry (2020) find that firms with lower default risk are more responsive to monetary policy shocks. Cloyne et al. (2023) show that younger, non-dividend-paying firms change their capital spending and borrowing to a much greater extent than older, dividend-paying firms in response to changes in interest rates.

In summary, MPS profoundly affect firms' investments, financing, and business practices. However, the impact of MPS on debt concentration remains underexplored.

2.3. Hypothesis

We posit that monetary tightening (easing) monetary policy shocks encourage firms to increase (decrease) debt concentration for three reasons. First, tightening shocks raise interest rates, increasing firms' costs of servicing external debt (Ippolito et al., 2018). The higher costs of external debt financing elevate firms' default risk (Arellano et al., 2012). In the event of default, firms with a more concentrated debt structure face fewer creditors, reducing conflicts of interest and facilitating debt renegotiation (John et al., 2021). Thus, firms may increase debt concentration to streamline coordination in debt restructuring.

Second, the balance sheet channel suggest that contractionary monetary policy reduces firms' net worth and collateral values, exacerbating adverse selection and moral hazard issues due to information asymmetry between firm managers and creditors. This increases creditors' information collection and monitoring costs, which ultimately hinders debt renegotiation (Boivin et al., 2010). Firms may therefore limit debt types to ease coordination and reduce creditors' costs of information collection and processing.

Third, tightening monetary policy shocks can restrict firms' access to capital markets by raising borrowing costs and reducing overall credit availability (Lo Duca et al., 2024). According to Davydenko (2012), limited access to capital increases financial distress risk, making it difficult for firms to quickly secure funds to address tightening shocks. Managing financial distress across multiple debt types with different cash flow claims, control provisions, investor preferences is complex (Lou & Otto, 2020; Li et al., 2021). Consequently, firms may choose more concentrated debt to reduce creditor coordination costs and facilitate resolution to financial challenges. Taken together, we hypothesize:

$\boldsymbol{H_0}$. *Firms adopt a more concentrated (diversified) debt structure in response to contractionary (expansionary) monetary policy shocks.*

3. Sample, variables, and model specification

3.1. Data sources and sample

The sample in this paper covers the period from 2003 to 2022. We collect U.S. public firms' debt structure data from Capital IQ and accounting data from Compustat. We restrict our sample to firms listed on AMEX, NASDAQ or NYSE, and further remove financial and utility firms (SIC codes 6000–6999 and 4900–4949, respectively). Following Colla et al. (2013), we exclude firm–year observations with missing or zero values of total assets or total debt; observations with book or market leverage outside the range of zero to one; and observations with the differences between total debt reported in Compustat and the sum of all debt types as reported in Capital IQ exceeding 10% of the total debt. Firm–year observations with missing values of control variables in our regression analysis are also excluded.

We construct monetary policy shock variables using high-frequency interest rate futures data obtained from CME Group (owner of the Chicago Board of Trade and Chicago Mercantile Exchange). FOMC meeting dates and times are obtained from the Federal Reserve Board website. After merging firm-level variables with the data on monetary policy shocks, our effective sample consists of 36,612 firm–year observations, representing 4,786 unique firms. We winsorize all continuous variables in our regression analysis at the 1st and 99th percentiles to mitigate the impact of outliers.

3.2 Variable definitions

3.2.1. Dependent variable: Debt concentration

We measure the degree of concentration in a firm's debt structure in three different ways to ensure the robustness of our findings. First, we compute the normalized Herfindahl-Hirschman Index (*HHI*) across various debt types used by a firm. Following Colla et al. (2013) and Li et al. (2021), we compute this index by summing the squares of the shares of the seven mutually exclusive debt types as reported in Capital IQ over the total debt for firm *i* in year *t* as shown below:

$$SS_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SBN_{it}}{TD_{it}}\right)^2 + \left(\frac{SUB_{it}}{TD_{it}}\right)^2$$

$$+\left(\frac{CL_{it}}{TD_{it}}\right)^2+\left(\frac{Other_{it}}{TD_{it}}\right)^2 \quad (1)$$

where CP represents commercial paper, DC represents drawn credit, TL refers to term loans, SBN refers to senior bonds and notes, SUB refers to subordinated bonds and notes, CL is capital leases, $Other$ includes all other types of debt as well as total trust-preferred stock, and TD is the total amount of debt. The normalized *HHI* is then defined as follows:

$$HHI_{it}=\frac{SS_{it}-\frac{1}{7}}{1-\frac{1}{7}} \quad (2)$$

The *HHI* index ranges from zero to one, where a value of zero indicates maximum borrowing diversity, with a firm using all seven debt types in equal proportions. An *HHI* index of one indicates a lack of borrowing diversity, with the firm relying on a single debt type exclusively.

Second, as in Colla et al. (2013), we measure the degree of a firm's debt concentration using an indicator variable, *Excl90*, which captures significant dependence on a single debt type. *Excl90* is defined as follows:

$$Excl90_{it}=1\ if\ a\ firm\ obtains\ at\ least\ 90\%\ of\ its\ debt\ from\ one\ debt\ type,$$

$$=0\ otherwise. \quad (3)$$

This measure allows us to identify firms that rely heavily on a single debt type, indicating a high level of debt concentration.

Third, we measure debt concentration by counting the number of different debt types in a firms' debt structure, *Count*, which captures the diversity of debt types. This measure differentiates among the seven types of debt mentioned above, with $Count_{it}$

ranging from one to seven, with higher values corresponding to a more diversified debt structure. Following Li et al. (2021), we include only debt types that constitute at least 5% of a firms' total debt to focus on the types of debt that are economically important.

In our baseline analysis, we forward the three debt concentration proxy variables by one year and use them as dependent variables: HHI_{it+1}, $Excl90_{it+1}$, and $Count_{it+1}$.

3.2.2. Independent variable of interest: Monetary policy shocks

We identify monetary policy shocks using high-frequency interest rate futures data around FOMC announcements, following the method of Nakamura and Steinsson (2018). Specifically, we construct our measure of monetary policy shocks as the first principal component of surprises within a 30-minute window around FOMC announcements, based on the following five series: the federal funds rate (FFR) immediately after the meeting, the expected FFR following the next meeting, and expected three-month Eurodollar interest rates at horizons of two, three, and four quarters. We calculate the surprises as the changes in interest rates futures from 10 minutes before to 20 minutes after each FOMC announcement (e.g., Gürkaynak et al., 2005; Gertler & Karadi, 2015; Nakamura & Steinsson, 2018).

This measure offers two key advantages. First, it captures the impact of both target rate changes and forward guidance by considering both unexpected changes in the current-month FFR and shifts in the future path of interest rates following FOMC announcements. Second, the use of a narrow time window around announcements ensures that the revisions of market expectations are solely driven by monetary policy actions.

Our effective sample includes 174 FOMC announcements. To minimize the influence of other confounding factors, we exclude unscheduled FOMC meetings and conference calls. To help us explain the economic impact of MPS on debt concentration, the obtained MPS series are re-scaled such that its effect on the one-year nominal Treasury yield is equal to one.[1]

Finally, to merge with our annual firm-level debt concentration data, we aggregate monetary policy shocks into an annual frequency, *MPS_Total*, by summing the shocks from all FOMC announcements in a fiscal year (e.g., Cloyne et al., 2020; Flodén et al., 2020; Ottonello & Winberry, 2020). To align with the fiscal year timing of the debt concentration data, we adjust the monetary policy shock series, originally in calendar years, to match fiscal years. For example, if a firm's fiscal year ends on May 31, 2002, its relevant financial data spans from June 1, 2001 to May 31, 2002. Accordingly, we aggregate monetary policy shocks occurring within this period. Since our sample period for monetary policy shocks covers fiscal years from 2002 to 2021, the aggregated MPS series based on calendar years begin in July 2000 and end in May 2022.

3.3. Baseline regression

Previous studies have shown that monetary policy shocks have asymmetric effects on corporate activities and asset prices. Contractionary (tightening) monetary

[1] Data on one-year nominal Treasury yield is available on the Federal Reserve Board's website: Finance and Economics Discussion Series.

policy generally has a stronger adverse impact on economic output, inequality, and firms' employment and sales compared to expansionary (easing) policy, as documented by Matthes and Barnichon (2015), Furceri et al. (2018), and Kurt (2024). Conversely, Guo et al. (2022) find that easing shocks have a larger effect on stock market returns, particularly when market sentiment is high, while Xu et al. (2024a, 2024b) show that expansionary policy reduces future stock price crash risk and boosts corporate cash holdings, with tightening shocks having no significant effects on these outcomes. To test the empirical relation between monetary policy shocks and debt concentration, we adopt the following baseline regression model:

$$Debt\ Concentration_{i,t+1} = \beta_0 + \beta_1 MPS\_Tightening_{i,t} + \beta_2 MPS\_Easing_{i,t} + Controls + \theta_j + \mu_t + \varepsilon_{i,t} \quad (4)$$

where *i* refers to firm, *t* refers to year, and *Debt Concentration* is one of the three proxy variables used to measure debt concentration: *HHI*, *Excl90*, and *Count*. *MPS_Tightening* and *MPS_Easing* represent monetary tightening and easing shocks, with missing values replaced by zero. θ_j and μ_t represent the Fama-French 48 industry fixed effects and year fixed effects, respectively.

Although MPS variables are annualized macroeconomic measures, they vary across firms within the same fiscal year due to differences in fiscal year schedule. In the U.S., firms follow diverse fiscal year timelines, leading to variations in their exposures to calendar-year MPS. For example, firm A's 2015 fiscal year may run from December 2014 to December 2015, while firm B's 2015 fiscal year may span September 2014 to September 2015. Only approximately 70% of our sample firms have fiscal year ending in December. Our MPS measures are calculated as the sum of tightening or easing shocks from all FOMC meetings occurring within a firm's fiscal year.[2] Therefore, MPS variables naturally differ across firms, even within the same fiscal year, mitigating the concerns about multicollinearity between *MPS* variables and year fixed effects. This variability reduces concerns about the multicollinearity between *MPS* and year fixed effects. To account for macroeconomic condition changes and temporal trends such as technological advancements and evolving regulatory requirements, we include year fixed effects in our analysis.[3] Additionally, industry effects are incorporated to control for sector-specific characteristics and varying sensitivities to monetary policy.

In line with prior literature (e.g., Colla et al., 2013; Castro et al., 2020; Li et al., 2021; Yao et al., 2024), we include a set of control variables, *Controls*, that may influence a firm's debt structure. *Leverage* is the ratio of total debt to total assets; *MTB* is measured as the sum of market value of equity, total debt, preferred stock liquidating value minus deferred taxes, and investment tax credit, divided by total assets; *Profitability* is the ratio of operating income before depreciation to total assets; *Size* is the natural logarithm of total assets; *Tangibility* is the ratio of net property, plant, and equipment to total assets; *CF_Volatility* is the standard deviation of operating cash flows calculated over the previous twelve quarters, scaled by total assets; *Firm_Age* is the natural logarithm of one plus the number of years that a firm has been recorded in

[2] In untabulated analysis, we also calculate MPS as the average of tightening and easing shocks from all FOMC meetings occurring within a firms' fiscal year and re-estimate the baseline regression models, our results remain robust to this alternative measure of MPS series.
[3] Our results remain robust when year fixed effects are omitted.

Compustat; *Dividend* is an indicator variable equal to one if common stock dividends are positive, and zero otherwise; *Unrated* is an indicator variable equal to one if a firm has no S&P domestic rating, and zero otherwise; *R&D* is the ratio of research and development expenses to total assets; *Analysts* is the number of financial analysts following a firm; and *Blockholder* is a firms' institutional blockholder ownership. The detailed definitions of all variables are provided in Appendix A.

In addition to Equations (4), we also employ the following regressions to examine the impact of monetary tightening and easing separately:

$$Debt\ Concentration_{i,t+1} = \beta_0 + \beta_1 MPS\_Tightening_{i,t} + Controls + \theta_j + \mu_t + \varepsilon_{i,t} \quad (5)$$

$$Debt\ Concentration_{i,t+1} = \beta_0 + \beta_1 MPS\_Easing_{i,t} + Controls + \theta_j + \mu_t + \varepsilon_{i,t} \quad (6)$$

In estimating Equations (4), (5) and (6), we use an Ordinary Least Squares (OLS) regression model and a Tobit model (censored at zero and one) with standard errors clustered at the firm level for our first measure of debt concentration, *HHI*. We then substitute *HHI* with our second measure of debt concentration, *Excl90*, and estimate our baseline regressions using a Probit model. When the dependent variable is the third measure, *Count*, we employ a Poisson model.

4. Empirical results

4.1. Summary statistics

Table 1 presents the summary statistics for the main variables in our study, with Panel A, B and C reporting the statistics for the full sample, the sample with monetary tightening shocks, and the sample with monetary easing shocks, respectively. From Panel A of Table 1, We observe a high degree of debt concentration among our sample firms, with a mean *HHI* of 0.714. This implies that if a firm only employs two types of debt, then one debt type accounts for 85.7% of total debt while the other accounts for only 14.3%. The other two debt concentration measures show similar results, with mean values of 0.474 for *Excl90* and 1.817 for *Count*. These statistics indicate that 47.4% of firm–year observations in our sample rely on a single debt type for at least 90% of their total debt, and on average, our sample firms finance at least 5% of their debt through 1.82 different sources. The standard deviations for *HHI*, *Excl90*, and *Count*, are 0.262, 0.499, and 0.823, respectively, showing substantial variation in debt concentration across firm–year observations. These statistics are generally consistent with findings in prior studies such as Colla et al. (2013) and Castro et al. (2020).

The summary statistics of MPS indicate significant variation in both the direction and magnitudes. *MPS_Total*, representing overall monetary policy shocks, has a mean of –0.001 and a standard deviation of 0.037. *MPS_Tightening*, which captures firm–year observations with contractionary monetary policy shocks (i.e., positive values of *MPS_Total*), has a mean value of 0.042 and a standard deviation of 0.035. In contrast, *MPS_Easing*, which captures firm–year observations subject to expansionary monetary policy shocks (i.e., negative values of *MPS_Total*), has a mean value of -0.021 and a standard deviation of 0.013.

With respect to the summary statistics of our control variables, the mean of *Size* is 6.768, corresponding to an average total asset value of $870 million among our sample firms. *Firm_Age* has a mean of 2.873, indicating an average firm age of 18.

Additionally, 67.5% of firms lack an S&P domestic credit rating (mean *Unrated* = 0.675), and 39.5% of firms pay dividends (mean *Dividend* = 0.395). The means (standard deviations) of other control variables *Leverage*, *MTB*, *Profitability*, *Tangibility*, *CF_Volatility*, *R&D*, *Analysts* and *Blokcholder* are 0.261 (0.198), 1.712 (1.671), 0.062 (0.247), 0.266 (0.239), 0.023 (0.028), 0.053 (0.146), 7.584 (7.386), and 0.259 (0.373), respectively. The statistics of our control variables are consistent with prior research, such as Li et al. (2021), Clark et al. (2023), and Hu et al., (2024).

< Insert Table 1 here >

4.2. Main findings

Table 2 presents the baseline regression results for the impact of MPS on debt concentration. In column (1) to (4), we jointly include monetary tightening and easing shocks in a single model and estimate their respective impacts on debt concentration. Specifically, we first estimate an OLS regression for HHI_{t+1} and report the results in column (1). The estimated coefficient on $MPS\_Tightening_t$ is positive and statistically significant at the 1% level, indicating a positive relation between monetary tightening shocks and debt concentration. However, the estimated coefficient on MPS_Easing_t is statistically insignificant, suggesting that firms do not significantly adjust debt concentration in response to easing shocks. Since *HHI* is censored between zero and one, we also employ a Tobit model to address this bounded nature and present the results in column (2). The average marginal effect of $MPS\_Tightening_t$ on HHI_{t+1} remains positive and statistically significant, while the average marginal effect of

$MPS\_Tightening_t$ on HHI_{t+1} is still statistically insignificant. In column (3), we replace the dependent variable HHI_{t+1} with $Excl90_{t+1}$, and estimate a Probit model. The average marginal effect of $MPS\_Tightening_t$ on $Excl90_{t+1}$ is positive and statistically significant at the 5% level, while the average marginal effect of MPS_Easing_t on $Excl90_{t+1}$ is not statistically significant. This suggests that firms are more likely to obtain at least 90% of its total debt from one debt type under monetary tightening shocks. Column (4) reports the regression results estimated by a Poisson model using the third debt concentration proxy variable, $Count_{t+1}$, as the dependent variable. The average marginal effect of $MPS\_Tightening_t$ on $Count_{t+1}$ is negative and statistically significant at the 5% level, indicating that firms borrow from fewer debt sources during monetary tightening shocks. The average marginal effect of MPS_Easing_t on $Count_{t+1}$ remains statistically insignificant, confirming that easing shocks do not influence debt concentration.

To explore the asymmetric effects of MPS, we further examine the relation between MPS and debt concentration separately in the sub-samples of firm–years with monetary tightening and easing shocks. Column (5) to (8) show that in the sub-sample of firm–years with tightening shocks, the estimated coefficients and average marginal effects of $MPS\_Tightening_t$ are consistently positive and statistically significant when the dependent variables are HHI_{t+1} and $Excl90_{t+1}$, and negative and statistically significant when the dependent variable is $Count_{t+1}$. In contrast, columns (9) to (12) show that in the sub-sample of firm–years with easing shocks, the estimated coefficients and average marginal effects of MPS_Easing_t are statistically insignificant for any of the three debt concentration measures.

The effect of monetary tightening shocks on debt concentration is also economically important. Column (5) suggests that a one standard deviation increase in $MPS\_Tightening_t$ is associated with an increase by 2.87% (=0.035*0.600/0.731), relative to the sample mean of *HHI*. For comparison, a one standard deviation change in $Tangibility_t$ is associated with a change in *HHI* by 3.3% relative to the sample mean of *HHI*. Column (7) shows that a one standard deviation increase in *MPS_Tightening* is associated with an increase of 1.84% (=0.035*0.525) in the probability of a firm obtaining at least 90% of its debt from one debt type, which is equivalent to 3.65% of *Excl90*'s sample mean. Column (8) indicates that a one standard deviation increase in $MPS\_Tightening_t$ is associated with 0.037 (=0.035*–1.065) fewer types of debt.

The coefficients of the control variables generally align with those reported in the previous literature (e.g., Colla et al., 2013; Li et al., 2021). Specifically, we find that debt concentration is negatively associated with leverage (*Leverage*), firm age (*Firm_Age*) and Tangibility (*Tangibility*), while positively related to market-to-book ratio (*MTB*), cash flow volatility (*CF_Volatility*), dividend payments (*Dividend*) and research and development expenses (*R&D*).

Overall, our baseline results show that MPS predominantly affect debt concentration through monetary tightening. This conclusion remains robust whether monetary tightening and easing shocks are analyzed jointly or separately. As a result, all subsequent analyses focus exclusively on the sub-sample with monetary tightening shocks.

< Insert Table 2 here >

4.3. Identification tests

In our research design, we use exogenous monetary policy shocks as the independent variable, which effectively mitigate concerns about reverse causality. This is because the Federal Reserve's monetary policy decisions, made by the FOMC, are primarily driven by broader macroeconomic conditions such as inflation, unemployment, and overall economic growth. Due to financial stability concerns, central banks may monitor aggregate corporate debt levels and structures as part of assessing financial stability risks. If widespread firm-level debt structures lead to constrained investment during monetary tightening, central banks may also factor this into their policy models to balance growth and stability objectives. While aggregate trends in corporate debt may influence central bank decision-making through financial stability concerns and economic growth impact, it is less likely that monetary policy directly responds to individual firms' debt structures. Therefore, the observed effects on firms' debt concentration are attributable to MPS themselves.

The primary endogeneity concern in our baseline regression arises from omitted variables that affect both MPS and debt concentration, but are not included as control variables. To address this endogeneity concerns due to unobserved variables, we adopt three identification tests: (i) Oster's (2019) coefficient stability test; (ii) the high dimensional fixed effects; (iii) the impact threshold of a confounding variable.

4.3.1. Oster's coefficient stability test

To formally assess the impact of the omitted variables in our baseline model, we conduct the coefficient stability test proposed by Oster (2019). Given that Oster's test is specifically designed for linear models, we apply it by estimating OLS regression models for our three debt concentration proxy variables in the sample with monetary tightening shocks. Rows (1)-(2) of Table 3 present the estimated coefficients of $MPS\_Tightening$ from the baseline regression model specified in Equation (5) and their corresponding R^2. Rows (3)-(4) present the assumptions for R_{max} and δ used in estimating the bounds of $MPS\_Tightening$'s coefficients. The value of R_{max} lies between the R^2 in our baseline regressions with observable control variables and one. The parameter δ represents the ratio of the effect of observable variables on the coefficient of $MPS\_Tightening$ to the effect of unobservable variables on the coefficient of $MPS\_Tightening$. Following the suggestions of Oster (2019), we set the upper bound (R_{max}) as 1.3 times the observed R^2 in the baseline regressions that control for all observables and assign a value of one to δ. We then estimate the bounds of $MPS\_Tightening$'s coefficients and verify whether the interval excludes zero.

Rows (5)-(6) of Table 3 indicate that the bounds of $MPS\_Tightening$'s coefficients exhibit minimal variations and do not include zero, suggesting that accounting for both observable and unobservable variables would not significantly alter our conclusions drawn from baseline regressions in Table 2. In rows (7)-(8), we report the values of Oster's δ. Oster's δ is defined as the degree of selection on unobservables relative to observables that would be necessary to drive away the results. As recommended by Oster (2019), we compare the absolute values of Oster's δ to one and validate that all δ estimates are larger than one. Such high δ values suggest that the $MPS\_Tightening$'s coefficients are less affected by the unobservable variables. Specifically, the absolute values of δ estimates range between 16.9-24.2 across the three specifications in our baseline regressions. It is very unlikely that unobservables are 16.9-24.2 times as important as all the observables included in our baseline model. Overall, Oster's coefficient stability test confirms that our results are unlikely to be driven by the unobservable variables.

< Insert Table 3 here >

4.3.2. High-dimensional fixed effects

To control for the unobserved heterogeneity, we follow Gormley and Matsa (2014) and employ high-dimensional fixed effects models.[4] Specifically, we re-estimate the relation between monetary tightening shocks and debt concentration by including firm and industry×year fixed effects. These controls accout for unobserved firm-level heterogeneity and time-varying heterogeneity across industries.

Table 4 presents the estimated results. In columns (1)–(3), the independent variable of interest is *MPS_Tightening*. We observe that the estimated coefficient on *MPS_Tightening* is positive and statistically significant at the 1% level when the dependent variable is *HHI*, and is negative and statistically significant at the 10% level when the dependent variable is *Count*. The estimated coefficient on *MPS_Tightening* is positive and statistically insignificant (t stat.=1.41) when the dependent variable is *Excl90*. These results demonstrate the robustness of our findings after controlling for

[4] Stata commands for estimating non-linear regressions, such as Tobit and Probit regressions, are not currently available. For linear regressions with high-dimensional fixed effects, we use the "reghdfe" Stata command developed by Correia (2016), when the dependent variables are *HHI* and *Excl90*. When the dependent variable is *Count*, we adopt the "ppmlhdfe" Stata command developed by Correia et al., (2020) to estimate Poisson regressions with high-dimensional fixed effects.

high-dimensional fixed effects. In columns (4)–(6), the independent variable of interest is *MPS_Easing*. The estimated coefficients on *MPS_Easing* are statistically insignificant across all three measures of debt concentration, consistent with our findings in Table 2.

< Insert Table 4 here >

4.3.3. Impact threshold of a confounding variable

As a final approach to addressing the endogeneity problem caused by omitted variable bias, we follow the suggestion of Larcker and Rusticus (2010) and estimate the impact threshold of a confounding variable. The ITCV approach assesses how strong an omitted variable must be correlated with both the dependent and independent variables in a regression (conditional on existing controls) to render a statistically significant coefficient of interest insignificant at the 10% level (Frank, 2000). A larger ITCV value indicates that our regression results are less influenced by potential omitted variable bias. We conduct the ITCV test for all three debt concentration proxy variables in our sample with monetary tightening shocks, and present the results in Table 5. In Panel A of Table 5, we test the ITCV test of the relation between *MPS_Tightening* and *HHI*. The estimated ITCV is 0.015, indicating the correlations between *MPS_Tightening* and *HHI* with the unobserved confounding variable each needs to be about 0.121 ($=\sqrt{0.015}$) to overturn our main findings. To assess the likelihood that such an omitted variable exists in our model, we compare the value of ITCV with the absolute value of the partial impact factor (*Impact*) of all the control variables. In particular, we find that the value of ITCV is greater than the absolute values of *Impact* for all control variables, suggesting that our findings are robust to the potential omitted variable bias. The same conclusions can be drawn when we replace the dependent variable with *Excl90* and *Count*.

< Insert Table 5 here >

4.4 Cross-sectional analyses

The empirical results discussed above indicate that firms tend to employ more concentrated debt structures in response to monetary tightening shocks. In Section 2.3, we posit three potential channels through which these shocks lead to increased debt concentration: heightened risk of corporate default, exacerbated information asymmetries between firms and their creditors, and restricted access to capital markets. Dur to these factors, firms may opt for greater debt concentration to reduce creditor coordination costs and enhance the likelihood of successful debt renegotiation. In this section, we provide empirical evidence supporting these channels. Following the methodologies outlined in John et al. (2021) and Li et al. (2021), we conduct sub-sample analyses based on default risk, information asymmetry, and access to capital markets.

Firms with higher default risk, greater information asymmetries, and limited access to capital markets are more vulnerable to challenges such as the inability to repay maturing debt, inefficient liquidation, and ineffective communication with creditors. These challenges may have severe consequences when firms face monetary tightening shocks, making it difficult for firms to renegotiate debt effectively and complicating bankruptcy liquidation. Therefore, it is important for these firms to adopt more concentrated debt structures so that they can coordinate efficiently with their creditors to mitigate these adverse outcomes (John et al., 2021; Li et al., 2021).

4.4.1 Default risk

When a firm defaults on its debt, it needs to renegotiate with its creditors. A more concentrated debt structure allows the firm to coordinate with fewer creditors, which can result in fewer disagreements and conflicts of interest among creditors. Therefore, we expect that the positive relation between monetary tightening shocks and debt concentration is more pronounced for firms with higher default risk. These firms face greater challenges in managing their debt obligations when interest rates are high, making the benefits of a concentrated debt structure particularly evident under such circumstances.

Following prior literature (Castro et al., 2020; Song et al., 2024), we measure firms' default risk using Altman's z-score (*Z_score*). A lower value of *Z_score* suggests a firm has higher bankruptcy risk. We then divide our sample into two sub-samples based on the annual median values of *Z_score* and estimate the baseline regressions as specified in Equation (5) in these two sub-samples. Panel A of Table 6 report the results of our sub-sample analysis. For brevity, we only report the estimated coefficients on *MPS_Tightening*.

We find that the estimated coefficients and average marginal effects of *MPS_Tightening* on the three debt concentration proxy variables are statistically significant in the sub-samples with low *Z_score*, while they are statistically insignificant in the sub-samples with high *Z_score*. Moreover, the absolute values of the coefficients and average marginal effects of *MPS_ Tightening* are greater in the sub-samples with low *Z_score* than those in the sub-samples with high *Z_score*. We also conduct tests to examine to the differences in the coefficients and average marginal effects of *MPS_Tightening* between the two sub-samples. The p-values of these tests, as reported in the bottom of Panel A, show that the differences are all statistically significant. Taken together, these results confirm our expectation that the positive relation between monetary tightening shocks and debt concentration is stronger for firms with higher default risk, highlighting the default risk as a channel through which monetary tightening shocks affect debt concentration.

4.4.2 Information asymmetry

Firms may strategically choose more concentrated debt structures to minimize the costs creditors incur associated with information collection and monitoring, thereby enhancing overall efficiency in coordination and renegotiation. When debt concentration is higher, creditors can more efficiently monitor the firm's performance, leading to more effective creditor coordination. Furthermore, with a concentrated debt structure, firms need to align their interests with only a limited number of creditor types, which can increase the likelihood of successful debt renegotiation. Therefore, we expect that the restricted access to external borrowings due to monetary tightening shocks have a larger impact on corporate debt structure for firms with greater information asymmetry.

To examine this potential mechanism, we use the variable *Bog_Index* proposed by Bonsall et al. (2017) to measure information asymmetry. *Bog_Index* is a multifaceted measure of readability that assess the clarity of firms' annual reports. It is constructed base on several plain English factors such as passive voice, weak verbs, and jargons (Bonsall et al., 2017). A higher *Bog_Index* indicates lower readability in annual reports, which corresponds to greater information asymmetry. We divide our sample into two sub-samples based on the annual median values of *Bog_Index*, and re-estimate the baseline regression for each sub-sample. The results are reported in Panel B of Table 6.

We observe that the positive effect of *MPS_Tightening* on debt concentration is only statistically significant in the sub-samples with high *Bog_Index*. The absolute values of the coefficients and average marginal effects of *MPS_Tightening* are larger in the sup-samples with high *Bog_Index* than those in the sub-samples with low *Bog_Index*. The differences in the coefficients and average marginal effects of *MPS_Tightening* between the two sub-samples are statistically significant, expect for columns (5) and (6). These findings corroborate our prediction that with monetary tightening shocks, firms are more likely to choose a concentrated debt structure to mitigate information asymmetry and facilitate better creditor coordination.

4.4.3 Access to capital

Monetary tightening shocks, which reduce overall credit availability, can further restrict firms' access to external capital markets. This limited access can lead to an increase in the likelihood of financial distress, thereby increasing the risk of bankruptcy (Davydenko, 2012; John et al., 2021). Consequently, firms with limited access to capital may choose more concentrated debt structures to reduce financial distress costs and mitigate disagreements among creditors. We posit that the positive relation between monetary tightening shocks and debt concentration is much stronger among firms with more restricted access to external capital markets.

A general approach to measure a firms' access to the capital market in the literature is to identify whether the firm has a credit rating (e.g., Colla et al., 2013). According to Adhikari et al. (2017), firms without credit ratings often struggle to access public bond markets. We measure credit rating using an indicator variable, *Unrated*, which equals one if a firm does not have a S&P domestic rating and zero otherwise. Based on *Unrated*, we then partition our sample into two sub-samples and re-estimate our baseline regression for each sub-sample. of firms and compare their coefficients.

As shown in Panel C of Table 6, the estimated coefficients and average marginal effects of *MPS_Tightening* are only statistically significant in the sub-samples of firms without credit ratings (*Unrated*=1). The absolute values of the coefficients and average marginal effects of *MPS_Tightening* are larger in the sup-samples of firms without credit ratings than those in the sub-samples of firms with credit ratings. The differences in the coefficients and average marginal effects of *MPS_Tightening* between the two sub-samples are all statistically significant. These findings support our prediction that monetary tightening shocks prompt firms with limited capital access to adopt more concentrated debt structures.

< Insert Table 6 here >

4.5 Further cross-sectional analysis

In this section, we further examine whether the positive relation between monetary tightening shocks and corporate debt concentration exhibits any cross-sectional variations with respect to firms' liquidation values, long-term debt ratios, and stock return sensitivities to monetary policy shocks.

4.5.1 Liquidation values

Firms with lower liquidation values often face challenges due to difficulties in creditor coordination and inefficient liquidation processes (Bolton & Scharfstein, 1996; Yao et al., 2024). As a result, effective creditor coordination becomes even more important for these firms to mitigate the risk of inefficient liquidation. In response to monetary tightening shocks, firms with lower liquidation values are more likely to adopt concentrated debt structures, which help reduce disagreements among creditors and facilitate creditor coordination. We expect a stronger positive relation between monetary tightening shocks and debt concentration among firms with lower liquidation values.

To test this conjecture, we follow Bradley et al. (1984) and use asset specificity (*Specificity*) as a proxy for liquidation value. Specifically, *Specificity* is measured as the ratio of operating expenses to operating income. A higher *Specificity* indicates stronger asset specificity and, consequently lower liquidation value. We partition our sample into two sub-samples based on the annual median of *Specificity* and then re-estimate our baseline regression for each sub-sample.

As reported in Panel A of Table 7, the estimated coefficients and average marginal effects of *MPS_Tightening* are only statistically significant in the sub-samples of firms with low liquidation values. The absolute values of the coefficients and average marginal effects of *MPS_Tightening* are also larger in the sub-samples of firms with low liquidation values than those in the sub-samples of firms with high liquidation values. The differences in the coefficients and average marginal effects between the two sub-samples are all statistically significant. These results support our prediction that the positive relation between monetary tightening shocks and debt concentration is more pronounced among firms with lower liquidation values.

4.5.2 Long-term debt ratios

Firms with more long-term debt may experience challenges in adjusting their debt structures according to monetary policy shocks compared to those with less long-term debt. According to Hoffmann et al. (2023), firms with higher long-term debt ratios are typically burdened by substantial interest and principal payment obligations. These financial commitments can reduce firms' net income, which negatively impacts their profitability and cash flows. In addition, a high level of long-term debt can restrict financial flexibility, making it difficult for firms to secure additional financing or adapt to changing market conditions. As a result, we expect that in response to monetary tightening shocks, firms with lower long-term debt ratios are more likely to choose concentrated debt structures.

We estimate firms' long-term debt ratios (*LDebt*) as the ratio of long-term debt to total debt. We then divide our sample with monetary tightening shocks into two sub-samples based on the annual median of *LDebt*, and re-estimate our baseline regression in the two sub-samples. As shown in the Panel B of Table 7, the positive effect of monetary tightening shocks on debt concentration is only statistically significant in the sub-samples of firms with lower long-term debt ratios. These findings are consistent with our expectation.

4.5.3 Stock price sensitivity to monetary policy shocks

Firms' exposure to monetary policy shocks can vary significantly. Those with higher exposure tend to experience greater fluctuations in stock returns in response to changes in monetary policy. As a result, the monetary policy shocks may impose a larger impact on firms with higher exposure and managers of these firms are more likely to incorporate monetary policy shocks in their debt structure decisions. n contrast, firms with lower exposure to monetary policy shocks exhibit minimal changes in stock prices, suggesting that these shocks have a limited impact on their financial outcomes. Therefore, we predict that the influence of monetary tightening shocks on debt concentration is stronger for firms with higher exposure to the shocks.

To measure a firm's monetary policy exposure, *MPE*, we adopt the beta of stock returns to monetary policy shocks on FOMC meeting days. Specifically, we focus on *MPE* values that are negative, as a theoretical unexpected increase (decrease) in interest rates should lead to a decrease (increase) stock prices. We then divide our sample into two sub-groups based on the median of the absolute values of *MPE*, and re-estimate our baseline regression in the two sub-samples. Panel C of Table 7 shows that the absolute values of the coefficients and average marginal effects of

MPS_Tightening are only statistically significant in the sub-samples of firms with higher exposure to monetary policy shocks. More importantly, the differences in the absolute values of the coefficients and average marginal effects between the high and low sub-samples are positive and statistically significant, except for columns (5) and (6), confirming our prediction.

< Insert Table 7 here >

4.6 Robustness checks

4.6.1. Alternative methods for measuring debt concentration

To assess the robustness of our main findings, we first employ two alternative measures of debt concentration, as outlined in Donato (2022). In the first alternative measure, we divide subordinated bonds and notes, one of the seven debt types used in Equation (1), further into three categories: *SrSub* (senior subordinated debt), *JrSub* (junior subordinated debt), and *OtherSub* (all subordinated debt not classified as either senior or junior). The other six debt types in Equation (1) remain the same. We then re-construct SS_{it} as SS_Alt1_{it} as follows:

$$SS\_Alt1_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SBN_{it}}{TD_{it}}\right)^2 + \left(\frac{SrSub_{it}}{TD_{it}}\right)^2 + \left(\frac{JrSub_{it}}{TD_{it}}\right)^2 + \left(\frac{OtherSub_{it}}{TD_{it}}\right)^2 + \left(\frac{CL_{it}}{TD_{it}}\right)^2 + \left(\frac{Other_{it}}{TD_{it}}\right)^2 \tag{7}$$

We then normalize SS_Alt1_{it} to construct HHI_Alt1_{it} as follows:

$$HHI\_Alt1_{it} = \frac{SS\_Alt1_{it} - \frac{1}{9}}{1 - \frac{1}{9}} \tag{8}$$

In our second alternative measure, we classify both senior and subordinated bonds and notes, the two of the seven debt types in Equation (1), into three categories: secured debt types (*SecDebt*), unsecured debt types (*UnsecDebt*), and all other senior or subordinated bonds and notes that are classified as either secured or unsecured (*OtherSec*). Then we calculate SS_Alt2_{it} as follows:

$$SS\_Alt2_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SecDebt_{it}}{TD_{it}}\right)^2 + \left(\frac{UnsecDebt_{it}}{TD_{it}}\right)^2 + \left(\frac{OtherSec_{it}}{TD_{it}}\right)^2 + \left(\frac{CL_{it}}{TD_{it}}\right)^2 + \left(\frac{Other_{it}}{TD_{it}}\right)^2 \quad (9)$$

The normalized *HHI_Alt2* index is:

$$HHI\_Alt2_{it} = \frac{SS\_Alt2_{it} - \frac{1}{8}}{1 - \frac{1}{8}} \quad (10)$$

We replace *HHI* with these two alternative measures of debt concentration in our baseline regression. Table 8 shows that the estimated coefficients and average marginal effects of *MPS_Tightening* are all positive and statistically significant at the 1% level. This indicates that our main findings are robust to alternative definitions of debt concentration.

< Insert Table 8 here >

4.6.2. Alternative sample selection

Another concern is that our baseline results can be driven away by firms' exposure to certain uncertainty shocks during the sample period of 2003-2022. For instance, the 2008 international financial crisis led to a great deal of uncertainty in firms' production and operation, which may increase the corporate risk of default and thus firms are more likely to concentrate their debt structures during this period (Lou & Wang, 2018; Liu et al., 2021). To rule out this possible explanation, we conduct two separate analyses. First, we exclude firm-year observations where more than six months of a fiscal year fall within recession periods as defined by the National Bureau of Economic Research, and present the results in Panel A of Table 9. Second, we exclude observations during the 2007-2009 financial crisis (Flannery et al., 2012), with the results shown in Panel B of Table 9.

In line with our baseline results, the estimated coefficients and average marginal effects of *MPS_Tightening* are positive and statistically significant when the dependent variables are *HHI* and *Excl90*, and negative and statistically significant when the dependent variable is *Count* in the sample with monetary tightening shocks. We can therefore conclude that our results do not apply specifically to these periods with uncertainty shocks.

< Insert Table 9 here >

4.6.3 Controlling for other debt structure characteristics

Monetary policy shocks may be related to other dimensions of its debt structure. For example, Kashyap et al. (1993) reveals that monetary policy tightening is associated with a decrease in bank loans and an increase in debt securities' issuance. Becker and Ivashina (2014) extend this discourse and find that U.S. non-financial firms tend to substitute bank loans with bonds at times of tight monetary policy. Additionally, Fabiani et al. (2024) show that a policy cut lengthens corporate debt maturity, encouraging firms to shift towards long-term financing. To the extent that firms simultaneously make decisions based on the different dimensions of debt structure (e.g., maturity and seniority), there may be a concern that the other dimensions of debt structure, rather than credit coordination costs, are the reasons for explaining the relation between monetary policy shocks and debt concentration. To mitigate this concern, we include different debt structure characteristics as additional controls, and re-estimate our baseline regressions. Following Li et al., (2021), we add the number of covenants (*Covenants*) specified in the firms' existing loans and debt maturity (*Maturity*) into our baseline model. We measure *Maturity* as the value-weighted average maturity of each debt type. In addition, we control for loan spread (*Loan_spread*), which is calculated as the natural logarithm of the all-in-drawn-spread reported by Dealscan. Similar to other control variables, these additional variables are also measured at fiscal year *t*.

Table 10 presents the results. We consistently find a positive relation between monetary tightening shocks and debt concentration, while the relation between monetary easing shocks and debt concentration remains statistically insignificant. Notably, the magnitudes of the estimated effects are very similar to those reported in Table 2. This finding alleviates the concern that the observed relation between monetary tightening shocks and debt concentration is driven by other characteristics of the debt structure.

< Insert Table 10 here >

4.6.4 Alternative monetary policy shocks

We further employ an alternative measure of monetary policy shocks to ensure the robustness of our baseline results. Specifically, we keep firm-year observations only if the sign of the largest monetary policy shocks (in absolute values) within the year matches the sign of the aggregated shocks. The results are reported in Table 11. In line with our baseline results, we observe a positive and statistically significant relationship between monetary tightening shocks and firms' debt concentration. In contrast, there is no significant relationship between monetary easing shocks and debt concentration. These findings show that our baseline results remain robust, after accounting for the impact of large-scale surprises.

< Insert Table 11 here >

4.7 Impact of tightening shocks on various debt types

Our analysis has examined the influence of monetary tightening shocks on corporate debt concentration, which we have measured using the three debt concentration proxy variables. In this section, we investigate how tightening shocks affect a firms' use of a specific type of debt. We follow the classification of Capital IQ described in Section 3.2.1 and re-estimate the baseline model by replacing the dependent variables into the indicator variables of the respective debt type.

Table 12 reports the results. The coefficients on column (1)-(3), column (5) and column (7) are statistically insignificant, suggesting that tightening shocks do not significantly affect firms' use of commercial paper, drawn credit lines, term loans, subordinated bonds and notes, and other debt types. However, in columns (4) and (6), we document a negative and significant coefficient on senior bonds and notes and capital leases, suggesting that companies significantly rely less on senior debt and capital leases when there are monetary tightening shocks. In particular, one standard deviation increase in the fraction of tightening shocks is associated with a decrease of 1.86% (1.14%) of the use of senior debt (capital leases).

When experiencing tightening shocks, firms may have the incentive to rely less on senior bonds and notes and capital leases in order to reduce their exposure to higher interest rates. The higher interest rates induced by monetary tightening shocks often reduce firms' net income both by increasing their interest expense and by reducing their revenues as the overall economy slows (Mishkin, 1995; Angeriz et al., 2008). Consequently, firms' costs of external financing become higher which significantly reduce their demand for senior bonds and notes. In addition, firms' production might be adversely affected in periods of monetary tightening shocks (Ahmad & Rangaraju, 2020). Therefore, the firms may not need to rent new assets, leading to a significant reduction in the use of capital leases.

< Insert Table 12 here >

4.8. Other predictions: supply-side argument

The hypothesis discussed in Section 2.3 is based on a demand-side argument, where firms' responses to monetary policy shocks drive the resulting debt concentration. We acknowledge, however, that a supply-side explanation cannot be ruled out – namely, that the dominant effect may arise from the supply of loans and bonds. From a supply-side perspective, one might intuitively predict that tightening monetary policy would lead to a decrease in overall credit availability. This could be attributed to higher funding costs for banks, stemming from higher interest rates, which subsequently reduce their lending capacity (Kashyap & Stein, 1995). As credit supply contracts, firms may face constraints in their borrowing options, potentially leading to a reduction in the diversity of debt sources they can access.

That said, the supply-side explanation is not without complications. For instance, private creditors might continue to provide credit at higher interest rates, thereby maintaining the overall credit supply despite the tightened monetary conditions. According to Degerli and Monin (2024), the private credit fundraising remains robust during periods of monetary tightening, indicating that the availability of credit does not necessarily decline. Furthermore, the supply-side argument struggles to explain why firms would inherently adjust their debt financing strategies in response to a reduction in the variety of available debt instruments (e.g., John et al., 2021).

Since our empirical analysis relies on firm-level variables, we focus on the demand-side mechanism that provides a more compelling framework for understanding the observed patterns of corporate debt concentration in response to tightening monetary policy shocks.

5. Conclusions

This study empirically examined the impact of monetary policy shocks on the debt structure choices of U.S. listed firms from 2003 to 2022. We find that monetary tightening shocks have a significant and positive impact on firms' degree of debt concentration, whereas easing shocks have insignificant effects on the debt concentration. This baseline result holds up after conducting several robustness tests. Additionally, our cross sectional analyses reveal that the impact of MPS on debt concentration is primarily driven by increased default risk, greater information opacity and restricted access to capital. These firms have greater needs to facilitate creditor coordination to prevent negative economic consequences, which prompts them to choose more concentrated debt structures. We also show that the positive relation of monetary tightening shocks on debt concentrated is more pronounced for firms characterized by lower liquidation values, lower long-term debt ratios and higher stock price sensitivity to monetary policy shocks.

Overall, our findings show that the impact of monetary policy shock on a firm's debt structure extends far beyond the documented impacts on debt maturity (Fabiani et al., 2022) and the substitution between bank loans and bond debt (Kashyap et al., 1993; Becker & Ivashina, 2014; Arce et al., 2020).

Appendix A

Table A1. Variable definitions

This table reports the variable definitions and data sources. CME Group refers to Chicago Mercantile Exchange Group, CRSP refers to the Centre for Research in Security Prices, TAQ refers to the NYSE Trade and Quote database, IBES refers to the Institutional Brokers Estimate System, Refinitiv refers to Thomson Refinitiv database, and BM refers to Brian Miller's website.

Variable	Definition	Source
Measures for debt concentration		
HHI	Following Colla et al. (2013), the Herfindahl-Hirschman index of debt is defined as: $SS_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SBN_{it}}{TD_{it}}\right)^2 + \left(\frac{SUB_{it}}{TD_{it}}\right)^2 + \left(\frac{CL_{it}}{TD_{it}}\right)^2 + \left(\frac{Other_{it}}{TD_{it}}\right)^2$ where CP, DC, TL, SBN, SUB, CL, and $Other$ refer to the seven types of debt recorded in Capital IQ: commercial paper, drawn credit lines, term loans, senior bonds and notes, subordinated bonds and notes, capital leases, and other debt, respectively. TD is the total amount of debt. Then, the normalized Herfindahl-Hirschman index of debt is: $HHI_{it} = (SS_{it} - 1/7)/(1 - 1/7)$.	Capital IQ
Excl90	An indicator variable that equals one if a firm has at least 90% of its debt from one debt type, and zero otherwise (Colla et al., 2013).	Capital IQ
Count	The number of different debt types in a firm's debt structure. We count only debt types that represent at least 5% of the total debt of the firm to identify debt types with economically significant amounts (Li et al., 2021).	Capital IQ
HHI_Alt1	Following Donato (2020), we disaggregate subordinated bonds and notes into three distinct categories: senior subordinated debt (*SrSub*), junior subordinated (*JrSub*), and all subordinated debt not classified as either senior or junior (*OtherSub*). The normalized Herfindahl-Hirschman index of debt concentration is then calculated as:	Capital IQ

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Table A1 – continued from previous page

	$$SS\_Alt1_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SBN_{it}}{TD_{it}}\right)^2 + \left(\frac{SrSub_{it}}{TD_{it}}\right)^2 + \left(\frac{JrSub_{it}}{TD_{it}}\right)^2 + \left(\frac{OtherSub_{it}}{TD_{it}}\right)^2 + \left(\frac{CL_{it}}{TD_{it}}\right)^2 + \left(\frac{Other_{it}}{TD_{it}}\right)^2$$ Then, SS_Alt1_{it} is normalized to obtain: $HHI\_Alt1_{it} = (SS_{it} - 1/9)/(1 - 1/9)$.	Capital IQ
HHI_Alt2	Following Donato (2020), we classify senior and subordinated bonds and notes into three distinct categories: senior secured debt (*SecDebt*), unsecured debt types (*UnSecDebt*), and all senior and subordinated debt not classified as either secured or unsecured (*OtherSec*). The normalized Herfindahl-Hirschman index of debt concentration is then calculated as: $$SS\_Alt2_{it} = \left(\frac{CP_{it}}{TD_{it}}\right)^2 + \left(\frac{DC_{it}}{TD_{it}}\right)^2 + \left(\frac{TL_{it}}{TD_{it}}\right)^2 + \left(\frac{SecDebt_{it}}{TD_{it}}\right)^2 + \left(\frac{UnSecDebt_{it}}{TD_{it}}\right)^2 + \left(\frac{OtherSec_{it}}{TD_{it}}\right)^2 + \left(\frac{CL_{it}}{TD_{it}}\right)^2 + \left(\frac{Other_{it}}{TD_{it}}\right)^2$$ Then, SS_Alt2_{it} is normalized to obtain: $HHI\_Alt2_{it} = (SS_{it} - 1/8)/(1 - 1/8)$.	Capital IQ
Measures for monetary policy shocks		
MPS_total	The first principal component of five interest rate futures: current-month federal funds rate (FFR) surprise, expected FFR surprise immediately following the next FOMC meeting, and surprises in the 2/3/4-quarters ahead Eurodollar futures over a 30-minute tight window around FOMC announcements (Nakamura & Steinsson, 2018). To merge with our annual debt concentration data, we aggregate the monetary policy shocks into yearly values by summing the shocks from all FOMC announcements within the fiscal year	CME Group

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Table A1 – continued from previous page

Variable	Definition	Source
	(Gertler & Karadi, 2015; Cloyne et al., 2020; Ottonello & Winberry, 2020).	
MPS_Tightening	Positive values of *MPS_total*, missing if *MPS_Total* is negative.	CME Group
MPS_Easing	Negative values of *MPS_total*, missing if *MPS_Total* is negative.	CME Group
Firm-level variables		
Leverage	The sum of long-term debt and current liabilities divided by total assets.	Compustat
MTB	Market value of equity plus total debt plus preferred stock liquidating value minus deferred taxes and investment tax credit divided by total assets.	Compustat
Profitability	Operating income before depreciation divided by total assets.	Compustat
Size	The natural logarithm of total assets.	Compustat
Tangibility	Net property, plant, and equipment divided by total assets.	Compustat
CF_Volatility	Standard deviation of operating cash flows calculated over a 5-year period divided by total assets.	Compustat
Firm_Age	The natural logarithm of one plus the number of years since a firm appears in Compustat.	Compustat
Dividend	An indicator variable that equals one if common stock dividends are positive, and zero otherwise.	Compustat
Unrated	An indicator variable that equals one if a firm does not have a Standard and Poor's domestic credit rating, and zero otherwise.	Capital IQ
R&D	Research and development expenses divided by total assets, with missing data treated as zero.	Compustat
Analysts	Number of analysts of a firm, with missing data treated as zero.	IBES
Blockholder	Institutional blockholder ownership, with missing data treated as zero.	Refinitiv
Z_score	Modified Altman's (1968) *Z_score* is calculated as: $z\_score = (1.2 \times WC + 1.4 \times RE + 3.3 \times EBIT + 0.999 \times Sales)/TA$ where WC is working capital, RE is retained earnings, $EBIT$ is the earnings before interest and taxes, and TA is the total assets.	Compustat

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Table A1 – continued from previous page

Variable	Definition	Source
	Following Graham et al. (2008), we exclude the ratio of market value of equity to the book value of total debt from the original computation of *Z_score* because a similar term, *MTB*, is included in our baseline regression model as a separate control variable.	Compustat
Bog_Index	An index that is a proprietary measure of readability designed using Editor Software's plain English software, *StyleWriter*. It is calculated based on several plain English factors such as passive voice, weak verbs, and jargon (Bonsall et al., 2017). High values of the Box index indicators lower readability.	BM
Specificity	The ratio of operating expenses to operating income (Bradley et al., 1984).	Compustat
LDebt	The ratio of long-term debt to total debt.	Capital IQ
MPE	The beta of stock returns to monetary policy shocks on the FOMC meeting days.	TAQ
Covenants	The number of covenants included in a debt contract.	Dealscan
Loan_spread	Value-weighted all-in-draw-spread.	Dealscan
Maturity	Value-weighted average maturity of a debt instrument.	Dealscan
CP_Dummy	An indicator variable that equals to one if a firm uses commercial paper, and zero otherwise.	Capital IQ
DC_Dummy	An indicator variable that equals to one if a firm uses drawn credit lines, and zero otherwise.	Capital IQ
TL_Dummy	An indicator variable that equals to one if a firm uses term loans, and zero otherwise.	Capital IQ
SBN_Dummy	An indicator variable that equals to one if a firm uses senior bonds and notes, and zero otherwise.	Capital IQ
SUBN_ Dummy	An indicator variable that equals to one if a firm uses subordinated bonds and notes, and zero otherwise.	Capital IQ
CL_ Dummy	An indicator variable that equals to one if a firm uses capital leases and notes, and zero otherwise.	Capital IQ
Other_ Dummy	An indicator variable that equals to one if a firm uses other types of debt, and zero otherwise.	Capital IQ

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Table 1. Summary statistics

This table reports the summary statistics for key variables used in our empirical analyses. Our full sample consists of 36,612 firm–year observations and 4,786 unique firms, among which 11,591 firm-year observations are during the periods with monetary tightening shocks and 25,021 firm–year observations are during the periods with monetary easing shocks. The effective sample period for monetary policy shocks spans from 2002 to 2021, while the effective sample for debt concentration variables and control variables is between 2003 and 2022. The number of observations, mean, standard deviation, 5th percentile, 25th percentile, median, 75th percentile, and 95th percentiles are reported from left to right, in sequence for each variable. The summary statistics for the full sample, sample with monetary tightening shocks and sample with monetary easing shocks are presented in Panel A, B and C of Table 1, respectively. All continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A.

Panel A. Full sample

Variables	Obs.	Mean	S.D.	5%	25%	Median	75%	95%
HHI_{t+1}	36,612	0.714	0.262	0.287	0.460	0.755	1.000	1.000
$Excl90_{t+1}$	36,612	0.474	0.499	0.000	0.000	0.000	1.000	1.000
$Count_{t+1}$	36,612	1.817	0.823	1.000	1.000	2.000	2.000	3.000
MPS_Total_t	36,612	-0.001	0.037	-0.043	-0.029	-0.013	0.015	0.078
$Leverage_t$	36,612	0.261	0.198	0.005	0.100	0.234	0.379	0.635
MTB_t	36,612	1.712	1.671	0.530	0.854	1.236	1.954	4.415
$Profitability_t$	36,612	0.062	0.247	-0.344	0.054	0.109	0.158	0.257
$Size_t$	36,612	6.768	2.018	3.410	5.366	6.804	8.119	10.130
$Tangibility_t$	36,612	0.266	0.239	0.021	0.084	0.182	0.385	0.794
$CF\_Volatility_t$	36,612	0.023	0.028	0.005	0.009	0.014	0.024	0.071
$Firm\_Age_t$	36,612	2.873	0.817	1.386	2.303	2.944	3.526	4.078
$Dividend_t$	36,612	0.395	0.489	0.000	0.000	0.000	1.000	1.000
$Unrated_t$	36,612	0.675	0.469	0.000	0.000	0.000	1.000	1.000
$R\&D_t$	36,612	0.053	0.146	0.000	0.000	0.001	0.044	0.257
$Analysts_t$	36,612	7.584	7.386	0.000	2.000	5.000	11.000	23.000
$Blockholder_t$	36,612	0.259	0.373	0.000	0.000	0.000	0.628	0.953

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Variables	Obs.	Mean	S.D.	5%	25%	Median	75%	95%
Panel B. Sample with monetary tightening shocks								
HHI_{t+1}	11,591	0.731	0.259	0.302	0.476	0.793	1.000	1.000
$Excl90_{t+1}$	11,591	0.504	0.500	0.000	0.000	1.000	1.000	1.000
$Count_{t+1}$	11,591	1.749	0.793	1.000	1.000	2.000	2.000	3.000
$MPS\_Tightening_t$	11,591	0.042	0.035	0.009	0.015	0.027	0.066	0.109
$Leverage_t$	11,591	0.261	0.198	0.004	0.104	0.234	0.377	0.635
MTB_t	11,591	1.462	1.221	0.478	0.776	1.111	1.709	3.590
$Profitability_t$	11,591	0.071	0.242	-0.280	0.058	0.112	0.162	0.259
$Size_t$	11,591	6.656	1.985	3.358	5.269	6.674	7.965	10.013
$Tangibility_t$	11,591	0.274	0.238	0.025	0.089	0.192	0.393	0.796
$CF\_Volatility_t$	11,591	0.022	0.025	0.005	0.009	0.014	0.024	0.065
$Firm\_Age_t$	11,591	2.872	0.795	1.386	2.303	2.890	3.526	4.060
$Dividend_t$	11,591	0.391	0.488	0.000	0.000	0.000	1.000	1.000
$Unrated_t$	11,591	0.620	0.485	0.000	0.000	1.000	1.000	1.000
$R\&D_t$	11,591	0.050	0.153	0.000	0.000	0.000	0.039	0.235
$Analysts_t$	11,591	7.196	6.997	0.000	2.000	5.000	10.000	21.000
$Blockholder_t$	11,591	0.301	0.385	0.000	0.000	0.000	0.699	0.967
Panel C. Sample with monetary easing shocks								
HHI_{t+1}	25,021	0.706	0.263	0.281	0.455	0.737	0.998	1.000
$Excl90_{t+1}$	25,021	0.460	0.498	0.000	0.000	0.000	1.000	1.000
$Count_{t+1}$	25,021	1.848	0.835	1.000	1.000	2.000	2.000	3.000
MPS_Easing_t	25,021	-0.021	0.013	-0.044	-0.030	-0.025	-0.013	-0.001
$Leverage_t$	25,021	0.261	0.198	0.005	0.099	0.234	0.380	0.635
MTB_t	25,021	1.828	1.830	0.564	0.895	1.298	2.074	4.809
$Profitability_t$	25,021	0.058	0.249	-0.377	0.053	0.107	0.157	0.256
$Size_t$	25,021	6.820	2.031	3.434	5.409	6.869	8.186	10.177
$Tangibility_t$	25,021	0.263	0.239	0.019	0.081	0.178	0.381	0.794
$CF\_Volatility_t$	25,021	0.023	0.030	0.005	0.009	0.014	0.024	0.074

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Table 1 – continued from previous page

Variables	Obs.	Mean	S.D.	5%	25%	Median	75%	95%
$Firm\_Age_t$	25,021	2.873	0.827	1.386	2.303	2.944	3.526	4.111
$Dividend_t$	25,021	0.396	0.489	0.000	0.000	0.000	1.000	1.000
$Unrated_t$	25,021	0.700	0.458	0.000	0.000	1.000	1.000	1.000
$R\&D_t$	25,021	0.054	0.143	0.000	0.000	0.002	0.046	0.268
$Analysts_t$	25,021	7.764	7.552	0.000	2.000	5.000	11.000	23.000
$Blockholder_t$	25,021	0.240	0.367	0.000	0.000	0.000	0.576	0.946

Table 2. Monetary policy shocks and debt concentration

This table reports the results of our baseline regressions, estimating the relation between monetary policy shocks and debt concentration. The dependent variables are three proxies for debt concentration: *HHI* $_{t+1}$, *Excl90* $_{t+1}$, and *Count* $_{t+1}$. The independent variables are the exogenous monetary policy shocks. In columns (1)–(4), we replace missing values of *MPS_Tightening* and *MPS_Easing* with zeros and include both monetary tightening and easing shocks in our baseline regressions. In column (5)–(12), we partition the full sample into two sub-samples based on the sign of *MPS_Total*. Columns (5)–(8) report the regression results estimated in the sub-sample with monetary tightening shocks (*MPS_Total*>0), and columns (9)–(12) report the regression results estimated in the sub-sample with monetary easing shocks (*MPS_Total*<0). We then estimate the regressions in the full sample. The model specifications include ordinary least squares (OLS), Tobit, Probit, and Poisson, as shown in each respective column. We report the regression coefficients for the OLS models, and average marginal effects for the Tobit, Probit and Poisson models. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	*HHI* $_{t+1}$	*HHI* $_{t+1}$	*Excl90* $_{t+1}$	*Count* $_{t+1}$	*HHI* $_{t+1}$	*HHI* $_{t+1}$	*Excl90* $_{t+1}$	*Count* $_{t+1}$	*HHI* $_{t+1}$	*HHI* $_{t+1}$	*Excl90* $_{t+1}$	*Count* $_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MPS_Tightening $_t$	0.364***	0.452***	0.433**	-0.872**	0.450***	0.600***	0.525**	-1.065***				
	(3.31)	(3.06)	(2.02)	(-2.44)	(3.51)	(3.49)	(2.06)	(-2.64)				
MPS_Easing $_t$	-0.280	-0.345	-0.385	0.819					0.037	0.081	-0.042	-0.191
	(-1.31)	(-1.24)	(-0.94)	(1.22)					(0.14)	(0.24)	(-0.09)	(-0.24)
Leverage $_t$	-0.321***	-0.452***	-0.529***	0.878***	-0.331***	-0.469***	-0.574***	0.842***	-0.315***	-0.443***	-0.505***	0.894***
	(-43.22)	(-47.88)	(-35.38)	(40.42)	(-24.92)	(-27.39)	(-21.36)	(22.16)	(-35.05)	(-39.17)	(-28.06)	(33.57)
MTB $_t$	0.008***	0.012***	0.014***	-0.031***	0.010***	0.014***	0.018***	-0.037***	0.008***	0.012***	0.014***	-0.030***
	(9.35)	(8.05)	(7.10)	(-9.11)	(4.98)	(3.90)	(3.56)	(-5.00)	(8.22)	(7.27)	(6.30)	(-7.89)
Profitability $_t$	0.041***	0.061***	0.075***	-0.149***	0.028*	0.033	0.024	-0.095*	0.052***	0.081***	0.105***	-0.184***
	(4.63)	(3.88)	(3.73)	(-4.92)	(1.89)	(1.16)	(0.63)	(-1.86)	(4.80)	(4.73)	(4.46)	(-4.98)
Size $_t$	-0.021***	-0.030***	-0.036**	0.073***	-0.019***	-0.030***	-0.035***	0.068***	-0.022***	-0.031***	-0.037***	0.075***
	(-16.82)	(-18.93)	(-14.77)	(18.90)	(-8.48)	(-10.25)	(-7.79)	(10.16)	(-14.46)	(-15.94)	(-12.53)	(15.87)
Tangibility $_t$	-0.048***	-0.059***	-0.087***	0.152***	-0.079***	-0.102***	-0.143***	0.274***	-0.033***	-0.039***	-0.063***	0.097***
	(-6.15)	(-6.16)	(-5.87)	(6.50)	(-5.81)	(-5.99)	(-5.37)	(6.89)	(-3.56)	(-3.43)	(-3.51)	(3.36)

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Table 2 – continued from previous page

Variables	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CF\_Volatility_t$	0.453***	0.662***	0.821***	-1.345***	0.893***	1.383***	1.801***	-2.302***	0.305***	0.434***	0.513***	-1.021***
	(8.73)	(7.82)	(7.07)	(-7.61)	(8.93)	(8.15)	(7.47)	(-6.63)	(5.07)	(4.53)	(3.94)	(-4.97)
$Firm\_Age_t$	-0.016***	-0.024***	-0.032***	0.060***	-0.016***	-0.024***	-0.029***	0.059***	-0.016***	-0.023***	-0.033***	0.059***
	(-9.08)	(-10.21)	(-9.13)	(10.65)	(-4.80)	(-5.55)	(-4.50)	(5.89)	(-7.42)	(-8.33)	(-7.76)	(8.58)
$Dividend_t$	0.026***	0.028***	0.045***	-0.060***	0.025***	0.027***	0.045***	-0.058***	0.026***	0.029***	0.044***	-0.061***
	(8.18)	(7.26)	(7.41)	(-6.35)	(4.48)	(3.86)	(4.23)	(-3.51)	(6.84)	(6.15)	(6.12)	(-5.29)
$Unrated_t$	0.005	0.013***	-0.002	-0.015	0.006	0.011	-0.003	-0.029	0.005	0.013**	0.000	-0.011
	(1.36)	(2.82)	(-0.23)	(-1.41)	(0.96)	(1.35)	(-0.21)	(-1.48)	(1.19)	(2.42)	(0.06)	(-0.85)
$R\&D_t$	0.050***	0.113***	0.097*	-0.230***	0.038	0.081	0.072	-0.179	0.062***	0.140***	0.119***	-0.266***
	(2.98)	(3.07)	(2.24)	(-3.62)	(1.20)	(1.21)	(0.89)	(-1.45)	(3.43)	(4.01)	(2.70)	(-3.97)
$Analysts_t$	0.004***	0.005***	0.006***	-0.009***	0.004***	0.006***	0.008***	-0.011***	0.004***	0.004***	0.005***	-0.009***
	(14.50)	(13.46)	(10.75)	(-11.23)	(9.01)	(8.65)	(7.78)	(-7.39)	(11.38)	(10.37)	(7.73)	(-8.55)
$Blockholder_t$	0.003	0.004	0.012*	-0.010	0.001	0.002	0.017	-0.013	0.004	0.005	0.009	-0.008
	(0.84)	(0.90)	(1.69)	(-0.94)	(0.20)	(0.32)	(1.45)	(-0.68)	(0.86)	(0.92)	(1.10)	(-0.57)
Constant	0.886***				0.869***				0.903***			
	(35.49)				(20.63)				(30.62)			
Model	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,612	36,612	36,612	36,612	11,591	11,591	11,591	11,591	25,021	25,021	25,021	25,021
Pseudo R^2		0.248	0.112	0.024		0.241	0.109	0.021		0.251	0.115	0.025
Adjusted R^2	0.179				0.174				0.183			
Model	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson

Table 3. Oster's coefficient stability test

This table reports the results of Oster's (2019) coefficient stability test, which is used to assess the impact of omitted variable bias. Since Oster's test is only applicable for linear models, we apply it by estimating OLS regression models for all three debt concentration proxy variables. Rows (1) and (2) present the coefficients of $MPS\_Tightening_t$ and R^2. Rows (3) and (4) present the assumption of δ and *Rmax* in estimating the bounds of $MPS\_Tightening_t$. According to Oster (2019), δ is set to be one so that the observable variables and unobservable variables have an equally significant impact on the $MPS\_Tightening_t$'s coefficients. *Rmax* is the upper bound of R^2 and is defined as 1.3 times R^2 from our baseline model that controls for all observable variables. Rows (5) and (6) present the bounds on the coefficient of $MPS\_Tightening_t$, which are estimated using the Stata command *psacalc*. Rows (7) and (8) report the values of Oster's δ, which are calculated when setting *Rmax* =1.3×R^2 and the coefficients on $MPS\_Tightening_t$ to be zero. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

		HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
		(1)	(2)	(3)
(1)	$MPS\_Tightening_t$	0.450***	0.513**	-1.062***
(2)	R^2	0.174	0.140	0.162
(3)	δ	1	1	1
(4)	*Rmax* = 1.3*R^2	0.226	0.182	0.211
(5)	Bounds on the treatment effect	(0.412, 0.451)	(0.449, 0.513)	(-0.974, -1.062)
(6)	Treatment effect excludes 0	Yes	Yes	Yes
(7)	Oster's δ	-24.134	-16.887	-24.189
(8)	$\mid \delta \mid > 1$	Yes	Yes	Yes

Table 4. High-dimensional fixed effects

This table reports the regression results from high-dimensional fixed effects models, following Gormley and Matsa (2014). Specifically, we include both firm and interacted industry×year fixed effects to control for unobserved heterogeneity. Columns (1)–(3) report the regression results estimated in the sub-sample with monetary tightening shocks, and columns (4)–(6) report the regression results estimated in the sub-sample with monetary easing shocks. The model specifications include ordinary least squares (OLS), linear probability model (LPM), and Poisson, as shown in each respective column. We report the regression coefficients for all the models. The coefficients of the Fama–French 48 industry and year fixed effects are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$MPS\_Tightening_t$	0.356***	0.406	-0.364*			
	(2.58)	(1.41)	(-1.72)			
MPS_Easing_t				0.250	0.311	-0.461
				(1.09)	(0.66)	(-1.23)
$Leverage_t$	-0.210***	-0.349***	0.323***	-0.153***	-0.259***	0.268***
	(-10.27)	(-8.20)	(9.50)	(-12.30)	(-10.11)	(12.52)
MTB_t	0.001	0.007	-0.001	0.001	0.001	0.001
	(0.41)	(1.07)	(-0.14)	(0.59)	(0.53)	(0.61)
$Profitability_t$	0.011	0.015	0.001	0.034**	0.075**	-0.040
	(0.59)	(0.41)	(0.04)	(2.38)	(2.57)	(-1.58)
$Size_t$	-0.048***	-0.087***	0.074***	-0.035***	-0.057***	0.062***
	(-7.90)	(-6.88)	(7.07)	(-9.66)	(-7.67)	(9.69)
$Tangibility_t$	-0.123***	-0.200***	0.271***	-0.149***	-0.268***	0.254***
	(-3.57)	(-2.78)	(4.67)	(-7.16)	(-6.24)	(7.11)
$CF\_Volatility_t$	0.188	0.652*	-0.340	-0.206**	-0.303	0.266*
	(1.04)	(1.74)	(-1.04)	(-2.28)	(-1.63)	(1.76)
$Firm\_Age_t$	-0.022	-0.001	0.031	-0.021**	-0.024	0.034**
	(-1.60)	(-0.03)	(1.32)	(-2.51)	(-1.36)	(2.31)

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Table 4 – continued from previous page

Variables	*HHI_{t+1}* (1)	*$Excl90_{t+1}$* (2)	*$Count_{t+1}$* (3)	*HHI_{t+1}* (4)	*$Excl90_{t+1}$* (5)	*$Count_{t+1}$* (6)
$Dividend_t$	0.004	0.012	0.006	-0.002	0.005	0.010
	(0.45)	(0.66)	(0.39)	(-0.37)	(0.42)	(1.13)
$Unrated_t$	0.005	0.017	-0.004	0.019***	0.021**	-0.013*
	(0.45)	(0.73)	(-0.22)	(3.60)	(2.00)	(-1.66)
$R\&D_t$	-0.036	-0.082	0.031	0.014	0.052	-0.021
	(-1.26)	(-1.39)	(0.86)	(0.57)	(1.03)	(-0.52)
$Analysts_t$	0.001	0.003	-0.001	0.001*	0.001	-0.000
	(1.49)	(1.58)	(-0.71)	(1.84)	(0.82)	(-0.55)
$Blockholder_t$	0.013	0.046**	-0.024	0.010*	0.033***	-0.010
	(1.35)	(2.32)	(-1.53)	(1.67)	(2.70)	(-1.06)
Constant	1.169***	1.149***	-0.120	1.067***	1.024***	-0.012
	(20.74)	(9.80)	(-1.22)	(31.53)	(14.75)	(-0.20)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,621	10,621	10,621	24,189	24,189	24,189
Pseudo R^2			0.074			0.074
Adjusted R^2	0.476	0.394		0.491	0.400	
Model	OLS	LPM	Poisson	OLS	LPM	Poisson

Table 5. Analysis of the impact of unobservable confounding variables

This table reports the results of the impact threshold of a confounding variable (ITCV) of the relation between monetary tightening shocks and debt concentration based on Frank (2000) and Larcker and Rusticus (2010). The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variables are the monetary tightening shocks ($MPS\_Tightening_t$). Column (1) reports the estimated ITCV value, which is the minimum product of the partial correlation between the dependent variable and the omitted confounding variable and the partial correlation between the independent variable and the omitted confounding variable that makes the coefficient on $MPS\_Tightening_t$ statistically insignificant. Column (2) presents the implied minimum correlation that a confounding variable must have with both the dependent variable and $MPS\_Tightening_t$, to cause the $MPS\_Tightening_t$'s coefficients to become statistically insignificant. Column (3) shows the raw correlations between $MPS\_Tightening_t$ and each control variable in our baseline model specified in Equation (5). Column (4) shows the raw correlations between the dependent variable and each control variable in our baseline model specified in Equation (5). Column (5) calculates the raw impact of each control variable by multiplying the two raw correlations shown in columns (3) and (4). Column (6) reports the partial correlation between $MPS\_Tightening_t$ and each control variable as outlined in Equation (5). Column (7) reports the partial correlation between the dependent variable and each control. Column (8) calculates the partial impact of each control variable by multiplying the two partial correlations shown in columns (6) and (7). We conduct the ITCV test for all three debt concentration proxy variables using OLS regressions, and report the results in Panel A, B, and C of Table 5, respectively.

Panel A. Debt concentration proxy variable: *HHI*								
	ITCV	ITCV implied correlations	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Raw_Impact*	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Impact*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$MPS\_Tightening_t$	0.015	0.121						
$Leverage_t$			-0.016	-0.306	0.005	-0.017	-0.235	0.004
MTB_t			-0.150	0.125	-0.019	-0.158	0.029	-0.005
$Profitability_t$			0.018	-0.116	-0.002	0.077	0.011	0.001
$Size_t$			-0.089	-0.177	0.016	-0.077	-0.072	0.006
$Tangibility_t$			0.022	-0.144	-0.003	0.026	-0.051	-0.001

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Table 5 – continued from previous page

	ITCV	ITCV implied correlations	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Raw_Impact*	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Impact*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$CF\_Volatility_t$			0.006	0.179	0.001	0.001	0.097	0.000
$Firm\_Age_t$			-0.049	-0.091	0.005	-0.045	-0.060	0.003
$Dividend_t$			-0.069	-0.064	0.004	-0.017	0.036	-0.001
$Unrated_t$			0.001	0.168	0.002	-0.072	0.006	-0.000
$R\&D_t$			0.010	0.151	0.002	0.078	0.028	0.002
$Analysts_t$			-0.103	-0.006	0.001	-0.020	0.094	-0.002
$Blockholder_t$			0.079	-0.001	-0.001	0.100	0.001	0.000
Panel B. Debt concentration proxy variable: *Excl90*								
$MPS\_Tightening_t$	0.008	0.087						
$Leverage_t$			-0.016	-0.301	0.005	-0.017	-0.224	0.004
MTB_t			-0.150	0.138	-0.021	-0.158	0.048	-0.008
$Profitability_t$			0.018	-0.100	-0.002	0.077	0.010	0.001
$Size_t$			-0.089	-0.179	0.016	-0.077	-0.079	0.006
$Tangibility_t$			0.022	-0.154	-0.003	0.026	-0.061	-0.002
$CF\_Volatility_t$			0.006	0.147	0.001	0.001	0.064	0.001
$Firm\_Age_t$			-0.049	-0.106	0.005	-0.045	-0.072	0.003
$Dividend_t$			-0.069	-0.072	0.004	-0.017	0.031	-0.001
$Unrated_t$			0.001	0.180	0.002	-0.072	0.015	-0.001
$R\&D_t$			0.010	0.135	0.001	0.078	0.015	0.001
$Analysts_t$			-0.103	-0.004	0.000	-0.020	0.099	-0.002
$Blockholder_t$			0.079	0.004	0.000	0.100	0.013	0.001
Panel C. Debt concentration proxy variable: *Count*								
$MPS\_Tightening_t$	-0.024	-0.156						
$Leverage_t$			-0.016	0.312	-0.005	-0.017	0.224	-0.004
MTB_t			-0.150	-0.152	0.023	-0.158	-0.061	0.010

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Table 5 – continued from previous page

	ITCV	ITCV implied correlations	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Raw_Impact*	ρ(x, *MPS_Tightening)*	ρ(x, *HHI)*	*Impact*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Profitability_t$			0.018	0.100	0.002	0.077	-0.013	-0.001
$Size_t$			-0.089	0.202	-0.018	-0.077	0.087	-0.001
$Tangibility_t$			0.022	0.167	0.004	0.026	0.070	0.002
$CF\_Volatility_t$			0.006	-0.139	-0.001	0.001	-0.047	-0.000
$Firm\_Age_t$			-0.049	0.116	-0.006	-0.045	0.074	-0.003
$Dividend_t$			-0.060	0.078	-0.005	-0.017	-0.035	0.001
$Unrated_t$			0.010	-0.210	-0.002	-0.072	-0.033	0.002
$R\&D_t$			0.010	-0.138	-0.001	0.077	-0.153	-0.001
$Analysts_t$			-0.103	0.020	-0.002	-0.020	-0.100	0.002
$Blockholder_t$			0.079	0.007	0.001	0.100	-0.002	-0.000

Table 6. Cross-sectional analyses

This table presents the results of cross-sectional analyses. Specifically, we test whether the effect of monetary tightening shocks on debt concentration is more pronounced in the sub-sample of firms with higher default risk, greater information asymmetry, and restricted access to capital markets. We measure firms' default risk using Altman's z-score (Altman, 1986), Z_Score_t; information asymmetry using the Bog index (Bonsall et al., 2017), Bog_Index_t; and firms' access to capital using credit rating, $Unrated_t$. The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is $MPS\_Tightening_t$. The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. We report the regression coefficients in columns (1) and (5), and average marginal effects for columns (2)-(4) and (6)-(8). The coefficients of control variables, and the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The statistical significance of the differences in the estimated coefficients on $MPS\_Tightening_t$ between two sub-samples is examined using Fisher's Permutation tests based on 1,000 bootstrap iterations. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Excl90_{t+1}$	$Count_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Variation in firms' default risk: Z_Score_t								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.770***	0.225	1.045***	0.316	1.012**	0.149	-1.758***	-0.517
	(3.90)	(1.32)	(3.69)	(1.45)	(2.57)	(0.44)	(-2.86)	(-0.95)
Constant	0.875***	0.927***						
	(15.54)	(13.90)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,797	5,794	5,797	5,794	5,785	5,793	5,797	5,794
Pseudo R^2			0.234	0.267	0.123	0.103	0.023	0.021
Adjusted R^2	0.194	0.168						
Difference in coef. of $MPS\_Tightening_t$	0.011**		0.011**		0.049**		0.069*	

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Table 6 – continued from previous page

Variables	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Excl90_{t+1}$	$Count_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	OLS		Tobit		Probit		Poisson	
Panel B. Variation in information asymmetry: *Bog_Index_t*								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.274	0.552***	0.397	0.714***	0.271	0.671*	-0.762	-1.231**
	(1.48)	(3.01)	(1.63)	(2.86)	(0.73)	(1.69)	(-1.29)	(-2.12)
Constant	0.856***	0.966***						
	(16.22)	(20.97)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,985	5,137	5,985	5,137	5,984	5,115	5,985	5,137
Pseudo R^2			0.238	0.261	0.104	0.125	0.019	0.025
Adjusted R^2	0.168	0.195						
Difference in coef. of *$MPS\_Tightening_t$*	0.090*		0.092*		0.140		0.099*	
Model	OLS		Tobit		Probit		Poisson	
Panel C. Variation in access to capital: *$Unrated_t$*								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.634***	0.110	0.948***	0.080	0.779**	0.091	-1.450***	-0.284
	(4.02)	(0.51)	(3.93)	(0.33)	(2.45)	(0.22)	(-3.07)	(-0.39)
Constant	0.864***	0.924***						
	(15.96)	(14.35)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,190	4,401	7,190	4,401	7,181	4,401	7,190	4,401
Pseudo R^2			0.184	0.107	0.110	0.107	0.020	0.018
Adjusted R^2	0.169	0.169						
Difference in coef. of *$MPS\_Tightening_t$*	0.000***		0.000***		0.005***		0.009***	
Model	OLS		Tobit		Probit		Poisson	

Table 7. Further cross-sectional analysis

This table reports the results of the further cross-sectional analyses of the impact of monetary tightening shocks on debt concentration. In Panels A–C, we divide our sample into two sub-samples based on the annual median values of liquidation values measured by asset specificity (Bradley et al., 1984), $Specificity_t$; long-term debt ratios defined as the ratio of long-term term to total debt, $LDebt_t$; and firms' stock price sensitivity to monetary policy shocks measured by the beta of stock returns to monetary policy shocks on FOMC meeting days, MPE_t, respectively. The dependent variables are three proxies for debt concentration: HHI_{t+1}, $Excl90_{t+1}$, and $Count_{t+1}$. The independent variable of interest is $MPS\_Tightening_t$. We report the regression coefficients in columns (1) and (5), and average marginal effects for columns (2)-(4) and (6)-(8). The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. The coefficients of control variables, as well as the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The statistical significance of the differences in the estimated coefficients on $MPS\_Tightening_t$ between two sub-samples is examined using Fisher's Permutation tests based on 1,000 bootstrap iterations. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Excl90_{t+1}$	$Count_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Liquidation value: *$Specificity_t$*								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.838***	0.137	1.201***	0.129	1.461***	-0.233	-2.005***	-0.318
	(4.42)	(0.79)	(4.44)	(0.59)	(3.86)	(-0.67)	(-3.40)	(-0.57)
Constant	0.956***	0.680***						
	(19.64)	(11.36)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,773	5,767	5,773	5,767	5,769	5,763	5,773	5,767
Pseudo R^2			0.266	0.245	0.134	0.102	0.026	0.018
Adjusted R^2	0.208	0.163						
Difference in coef. of $MPS\_Tightening_t$	0.001***		0.000***		0.000***		0.004***	

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Table 7 – continued from previous page

Variables	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Excl90_{t+1}$	$Count_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	OLS		Tobit		Probit		Poisson	
Panel B. Long-term debt ratios: *LDebt*$_t$								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.655***	0.269	0.909***	0.306	0.846**	0.234	-1.647***	-0.477
	(3.63)	(1.39)	(3.83)	(1.26)	(2.37)	(0.61)	(-2.84)	(-0.81)
Constant	0.815***	0.954***						
	(14.50)	(14.98)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,483	5,478	5,483	5,478	5,478	5,477	5,483	5,478
Pseudo R^2			0.258	0.291	0.119	0.122	0.024	0.022
Adjusted R^2	0.180	0.194						
Difference in coef. of $MPS\_Tightening_t$	0.066*		0.046**		0.108		0.070*	
Model	OLS		Tobit		Probit		Poisson	
Panel C. Monetary policy exposure (in absolute values): *MPE*$_t$								
	Low	High	Low	High	Low	High	Low	High
$MPS\_Tightening_t$	0.156	0.652**	0.209	0.878***	0.076	0.817*	-0.435	-1.606**
	(0.83)	(2.56)	(0.84)	(2.67)	(0.20)	(1.65)	(-0.72)	(-2.07)
Constant	0.864***	0.994***						
	(11.30)	(15.65)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,298	4,287	4,298	4,287	4,294	4,281	4,298	4,287
Pseudo R^2			0.264	0.269	0.121	0.118	0.023	0.023
Adjusted R^2	0.189	0.186						
Difference in coef. of $MPS\_Tightening_t$	0.057*		0.038**		0.116		0.090*	
Model	OLS		Tobit		Probit		Poisson	

Table 8. Alternative methods for measuring debt concentration

This table reports the relation between monetary tightening shocks and debt concentration, with alternative definition of debt types: HHI_Alt_{t+1} and HHI_Alt_{t+2}. The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. We report the regression coefficients for the OLS models, and average marginal effects for Tobit models. The coefficients of control variables, as well as the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

	HHI_Alt1_{t+1}	HHI_Alt1_{t+1}	HHI_Alt2_{t+1}	HHI_Alt2_{t+1}
Variables	(1)	(2)	(3)	(4)
$MPS\_Tightening_t$	0.584***	0.755***	0.434***	0.588***
	(4.43)	(4.49)	(3.40)	(3.50)
Constant	0.916***		0.961***	
	(20.67)		(21.84)	
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	11,591	11,591	11,591	11,591
Pseudo R^2		0.276		0.276
Adjusted R^2	0.189		0.194	
Model	OLS	Tobit	OLS	Tobit

Table 9. Excluding recession or crisis periods

This table reports the relation between monetary tightening shocks and debt concentration after excluding recession or crisis periods. In Panel A, we exclude firm-year observations where more than six months of a fiscal year during recessions, classified by the National Bureau of Economic Research. In Panel B, we exclude firm–year observations during the crisis periods, as identified by prior literature (Flannery et al., 2012). The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. We report the regression coefficients for column (1), and average marginal effects for columns (2)-(4). The coefficients of control variables, and the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)
Panel A. Excluding recession periods				
$MPS\_Tightening_t$	0.607***	0.830***	0.721*	-1.579**
	(2.89)	(2.99)	(1.69)	(-2.43)
Constant	0.811***			
	(14.57)			
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,618	6,618	6,618	6,618
Pseudo R^2		0.234	0.106	0.020
Adjusted R^2	0.167			
Model	OLS	Tobit	Probit	Poisson
Panel B. Excluding crisis periods				
$MPS\_Tightening_t$	0.428***	0.572***	0.557*	-1.152**
	(2.79)	(2.75)	(1.76)	(-2.35)
Constant	0.871***			
	(16.82)			
Controls	Yes	Yes	Yes	Yes

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Table 9 – continued from previous page

Variables	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8,043	8,043	8,043	8,043
Pseudo R^2		0.229	0.103	0.020
Adjusted R^2	0.164			
Model	OLS	Tobit	Probit	Poisson

Table 10. Controlling for other debt structure characteristics

This table shows the effects of monetary tightening shocks on debt concentration by adding additional control variables that can influence firms' debt structures. *Covenants* is the number of covenants included in the debt contract. *Loan_spread* is the value-weighted all-in-draw-spread reported by DealScan. *Maturity* is the value-weighted average maturity of each debt type. The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. We report the regression coefficients for columns (1) and (5), and average marginal effects for columns (2)-(4) and (6)-(8). The coefficients of control variables, as well as the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$MPS\_Ttightening_t$	0.491**	0.651**	0.546	-1.280*				
	(2.13)	(2.37)	(1.16)	(-1.65)				
MPS_Easing_t					0.186	0.125	0.560	-0.352
					(0.40)	(0.24)	(0.64)	(-0.24)
$Covenants_t$	-0.001	-0.001	0.004	-0.004	0.002	0.002	0.003	-0.011
	(-0.17)	(-0.30)	(0.51)	(-0.32)	(0.58)	(0.56)	(0.59)	(-1.21)
$Loan\_spread_t$	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.30)	(0.60)	(0.76)	(-1.22)	(-0.97)	(-0.75)	(-0.31)	(0.07)
$Maturity_t$	-0.001**	-0.000*	-0.001	0.001	-0.001***	-0.001***	-0.001*	0.001
	(-2.33)	(-1.90)	(-1.40)	(1.08)	(-3.69)	(-4.02)	(-1.89)	(1.59)
Constant	0.932***				0.887***			
	(10.98)				(16.23)			
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,733	3,733	3,729	3,733	7,720	7,720	7,719	7,720
Pseudo R^2		0.299	0.156	0.018		0.315	0.092	0.018
Adjusted R^2	0.160				0.150			
Model	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson

Table 11. Additional restrictions on monetary policy shocks

This table reports the relation between monetary policy shocks and debt concentration, incorporating additional restrictions on the shocks to further test the robustness of our main finding. Specifically, we keep only firm–year observations where the sign of the maximum monetary policy shocks (in absolute values) within a year matches the sign of the aggregated shocks for that year. The control variables are the same as those reported in Table 2. The model specifications are outlined in respective columns. We report the regression coefficients for the OLS models, and average marginal effects for Tobit, Probit and Poisson models. The coefficients of control variables, as well as the Fama-French 48 industry and year fixed effects, are suppressed for brevity in the respective columns. The t-statistics or z-statistics, reported in parentheses, are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Variables	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$	HHI_{t+1}	HHI_{t+1}	$Excl90_{t+1}$	$Count_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$MPS\_Tightening_t$	0.408***	0.565***	0.511*	-1.011**					0.347***	0.436***	0.444**	-0.887**
	(3.01)	(3.07)	(1.86)	(-2.35)					(3.05)	(2.85)	(1.99)	(-2.39)
MPS_Easing_t					0.062	0.102	0.005	-0.015	-0.061	-0.059	-0.146	0.308
					(0.23)	(0.29)	(0.01)	(-0.02)	(-0.26)	(-0.19)	(-0.32)	(0.42)
Constant	0.862***	0.977***	0.931***	0.243***	0.900***	1.009***	0.864***	0.243***	0.882***	0.990***	0.890***	0.243***
	(20.37)	(19.45)	(3.90)	(3.46)	(29.79)	(28.02)	(5.14)	(4.69)	(34.66)	(32.35)	(6.28)	(5.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,165	11,165	11,165	11,165	23,442	23,442	23,442	23,442	34,607	34,607	34,607	34,607
Pseudo R^2		0.241	0.109	0.021		0.258	0.117	0.026		0.250	0.113	0.024
Adjusted R^2	0.173				0.184				0.179			
Model	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson	OLS	Tobit	Probit	Poisson

Table 12. The impact across debt types

This table reports the relation between monetary tightening shocks and the likelihood of using various types of debt. In columns (1) –(7), the dependent variables are the seven debt type indicator variables: commercial paper (CP_Dummy_{t+1}), drawn credit lines (DC_Dummy_{t+1}), term loans ($TL\_ Dummy_{t+1}$), senior bonds and notes ($SBN\_ Dummy_{t+1}$), subordinated bonds and notes ($SUBN\_ Dummy_{t+1}$), capital leases ($CL\_ Dummy_{t+1}$), and other debt ($Other\_ Dummy_{t+1}$), respectively. For each debt type, the indicator variable equals one if a firm uses that type of debt, and zero otherwise. The control variables are the same as those reported in Table 2. Model specifications are outlined in the respective column. The same set of control variables and fixed effects are used as in Table 2. We report the average marginal effects for the profit models. The t-statistics or z-statistics reported in parentheses are based on standard errors clustered by firm. ***, **, and * denote significant level at 1%, 5%, and 10%, respectively. All variables are defined in Appendix A.

	CP_Dummy_{t+1}	DC_Dummy_{t+1}	TL_Dummy_{t+1}	SBN_Dummy_{t+1}	$SUBN\_Dummy_{t+1}$	CL_Dummy_{t+1}	$Other\_Dummy_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MPS\_Tightening_t$	0.115	-0.092	-0.077	-0.529**	0.019	-0.325*	-0.191
	(1.18)	(-0.37)	(-0.30)	(-2.30)	(0.13)	(-1.66)	(-1.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,364	11,570	11,570	11,589	11,450	11,451	11,540
Pseudo R^2	0.448	0.114	0.100	0.249	0.203	0.149	0.095
Model	Probit	Probit	Probit	Probit	Probit	Probit	Probit