Financial Shock Transmission to Heterogeneous Firms: the Earnings-Based Borrowing Constraint Channel *

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Abstract

We study the heterogeneous impact of jointly identified monetary policy and global risk shocks on corporate financing conditions. We disentangle these two shocks in a structural Bayesian Vector Autoregression framework and investigate their respective effects on financing of heterogeneous firms using micro-data for the US. We tease out mechanisms underlying the effects by contrasting financial frictions arising from traditional asset-based collateral constraints with the recently proposed earnings-based borrowing constraint, differentiating firms across leverage and earnings. Our empirical evidence strongly supports the earnings-based borrowing constraint. We find that global risk shocks have stronger and more heterogeneous effects on corporate financing conditions which depend on firms' position within the earnings distribution.

Keywords: corporate spreads; earnings-based borrowing constraint; heterogeneous firms; monetary policy shocks; global risk shocks.
JEL Classification: G12; E43; E52.

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1 Introduction

Heterogeneity in firm fundamentals plays a role in the transmission of monetary policy shocks to firms' funding costs. Other types of shocks, such as sudden shifts in global risk sentiment unrelated to monetary policy, may however also matter and transmit heterogeneously across firms, possibly via different channels. Insights into firm-level heterogeneity of funding costs responses to global risk and monetary policy shocks are limited because it is empirically challenging to disentangle the two shocks and their effects.

In this paper, we first propose an identification strategy to separate global risk and monetary policy shocks in a daily Bayesian Vector Autoregression (BVAR) framework. We then analyse two interrelated dimensions - firm heterogeneity and the type of shock - to understand how firms' financing conditions as well as their default probabilities respond to these shocks. We tease out potential mechanisms underlying the effects by contrasting canonical asset-based collateral constraints with the recently proposed earnings-based borrowing constraint hypothesis, differentiating firms across leverage and earnings. Understanding how monetary and global risk shocks transmit to firms depending on the type of their borrowing constraint matters because shocks that tighten firms' funding constraints can adversely affect real outcomes such as investment and production.

We add to our understanding of firms' funding constraints along three avenues. First, we draw a distinction between the effects of monetary policy shocks and global risk shocks. Recent geopolitical events, such as the Russian invasion of Ukraine, as well as the strong monetary policy tightening cycle in response to high inflation have underscored the need to disentangle heightened financing conditions due to either "pure" global risk or US monetary policy shocks. While previous papers have focused on firms' responses to high-frequency monetary policy shocks[1], recent evidence suggests that changes to the global risk environment that are unrelated to monetary policy also impact asset prices and hence affect firms' funding conditions (Bekaert, Hoerova, & Xu, 2021), notably in ways that differ both across firms and across sources of funding (debt versus equity).[2]

Our shock identification builds on a daily Bayesian Vector Autoregression (BVAR) framework with US financial market variables and a combination of sign and narrative restrictions (Brandt et al., 2021). Using a BVAR at daily frequency allows us to obtain both shocks from the same integrated model. This ensures that global risk shocks are purged of any confounding effects of actions by the Federal Reserve on global risk appetite. While US monetary policy has been identified as a driver of the Global Financial Cycle (Rey, 2015) and hence of global risk-off episodes (Miranda-Agrippino & Rey, 2020, 2022), there are numerous

[1] A non-exhaustive body of work includes Anderson and Cesa-Bianchi (2023), Arbatli Saxegaard et al. (2022), Cao et al. (2023), Cloyne et al. (2018), Fabiani et al. (2022), Ferreira et al. (2023), Jeenas (2019), Jungherr et al. (2022), Öztürk (2022), Palazzo and Yamarthy (2022), and Smolyansky and Suarez (2021).

[2] For example, Xu (2019) finds that global risk aversion explains a larger fraction of international return comovement in stocks relative to bonds. Bekaert, Engstrom, and Xu (2021) find that equity premia correlate more with risk aversion while corporate bond spreads and volatility correlate more with economic uncertainty.

episodes of heightened global risk that are disconnected from US monetary policy (Caldara et al., 2022). In contrast to previous studies, we do not focus exclusively on narrow time windows around FOMC meetings but instead retrieve the entire series of daily shocks to asset markets. Such shocks can stem e.g. from geopolitical events as well as from smaller narrative events.[3] We obtain a continuous series of shocks at daily frequency which allows us to estimate their impact across the entire series of corporate funding costs at each point in the sample period.

Second, we expand on existing insights on the heterogeneous transmission of financial shocks to firms' funding costs and default prospects across the distribution of firms (Anderson & Cesa-Bianchi, 2023; Palazzo & Yamarthy, 2022). We do so by contrasting traditional financial frictions arising from *asset-based* constraints with the recent *earnings-based* borrowing constraint (EBC) hypothesis, differentiating firms across their leverage and earnings distributions, respectively.[4] While firms' borrowing constraints are typically analysed based on the value of physical assets that firms can pledge as collateral - a building block of the classic financial accelerator literature - recent evidence suggests that borrowing constraints based on earnings have become an increasingly important determinant of firms' access to financing (Drechsel, 2023; Lian & Ma, 2020). This can have implications for the transmission of adverse financial shocks: financial acceleration through firms' balance sheet may be dampened under EBCs (Lian & Ma, 2020). Higher earnings can directly relax borrowing constraints when firms' borrowing capacity is not directly tied to the liquidation value of physical assets. Conversely, firms with low earnings can become relatively more constrained when adverse financial shocks impact both their discounted stream of cash flows and overall funding costs in capital markets.

We therefore conjecture that the responses of firms' financing conditions to financial shocks are more muted for the tails of firms within the *leverage* distribution but more pronounced for the tails of firms within the *earnings* distribution of firms. We find robust evidence that this is indeed the case. As a further possible determinant of firms' heterogeneous responses to financial shocks, we also consider firms' earnings-to-interest, i.e. interest coverage ratio, which can be seen as a hybrid indicator bridging the earnings-based and the collateral-based borrowing constraints (Drechsel & Kim, 2022; Greenwald, 2019).

Using a sample of large US corporates at weekly frequency over the period 2000-2021 and firm panel regressions, we analyse how bond spreads, equity prices and default probabilities of firms in the tails of the distribution respond to monetary policy and global risk shocks along these three dimensions of firm heterogeneity, i.e. leverage, earnings, and interest coverage ratios. We find that global risk shocks have stronger and more heterogeneous effects on corporate funding costs which depend on firms' position within the earnings distribution.[5] A global risk

[3] To ensure that we adequately separate the two forces, we show that both identified shocks correlate strongly with conventional measures of monetary policy surprises and global risk. Our global risk shock comoves well with the CBOE volatility index (VIX) and with measures of global uncertainty shocks (Bobasu et al., 2023). Our monetary policy shocks align with policy surprises around FOMC announcement dates.

[4] Anecdotal evidence suggests that the information content of firm leverage as an indicator of default risk may have lost ground in recent years. See, for example, Financial Times (2021, 2023a, 2023b).

[5] We obtain dynamic responses from firm-level local projections and confirm robustness of the main results at the bond-level as well.

shock equivalent to a 10 basis point unexpected decrease in US Treasury yields[6] pushes up a firm's corporate spread by an additional 12 basis points and depresses its equity price by additional 3.6 percentage points on average relative to a monetary policy shock.

Third, we zoom into the reaction of the pricing components of corporate bonds. We decompose bond spreads into an expected default risk component, capturing firm fundamentals, and an "excess bond premium" (EBP) component, a proxy for investor risk sentiment, following Gilchrist and Zakrajšek (2012). We assess via which of these two components the transmission of shocks is stronger. We find that a large share of the response in bond spreads is driven by their non-fundamental component, the EBP. Using panel local projections following Jordà (2005), we assess the persistence of the impact of the identified shocks on funding costs and default probabilities across firms and find persistent effects for both monetary policy and global risk shocks, with stronger impact for the latter and with more persistent effect on corporate spreads rather than on equity prices.

Related literature. This paper is at the intersection of two main strands of literature. The first strand relates to the identification of shocks based on sign restrictions (Arias et al., 2018) and narrative restrictions (Antolín-Díaz & Rubio-Ramírez, 2018). While high-frequency identification of monetary policy shocks has become a widely used approach, such identification does not lend itself to comparing these shocks to global risk shocks as event dates may not overlap. Our approach – a combination of sign, narrative, and relative magnitude restrictions – builds on the concept of "financial conditions", following in particular Brandt et al. (2021).[7] As an alternative way to identifying global risk shocks, some studies exploit changes in the price of gold around narrative events as an external instrument for uncertainty shocks in proxy SVARs (**Georgiadis2021**; Bobasu et al., 2023; Piffer et al., 2018). Our approach in turn does not depend on the strength of an external instrument and related sparsity of narrative events to retrieve a daily shock series.

The second strand of related literature investigates the role of firm heterogeneity in the transmission of shocks to firms' funding costs and real outcomes. The evidence on heterogeneous firm responses focuses mostly on monetary policy shocks, usually in an event study coupled with high-frequency shock identification frameworks.[8] A common finding of these papers is that firms with weaker fundamentals are worse off following a monetary tightening shock as they experience a more pronounced fall in their investment, employment, sales (Arbatli Saxegaard et al., 2022; Cloyne et al., 2018; Jeenas, 2019; Jungherr et al., 2022; Öztürk, 2022) or a more pronounced increase in credit spreads or default risk (Anderson & Cesa-Bianchi, 2023;

[6] The global risk shock captures flight-to-safety dynamics: heightened global risk aversion triggers a shift out of equity and into safe long-term US bonds, while strengthening the US dollar given its status as a safe haven.

[7] In a similar manner, Cieslak and Schrimpf (2019) combine monotonicity restrictions across maturities in the yield curve with high-frequency comovement in equity prices and interest rates to obtain monetary policy shocks purged of macroeconomic news from monetary policy communication.

[8] Examples of papers that employ high-frequency shock identification in this context include Anderson and Cesa-Bianchi (2023), Arbatli Saxegaard et al. (2022), Cloyne et al. (2018), Fabiani et al. (2022), Jeenas (2019), and Smolyansky and Suarez (2021).

Palazzo & Yamarthy, 2022; Smolyansky & Suarez, 2021).[9] An exception is Ottonello et al. (2022) who find that firms with low default risk are the most responsive to monetary shocks because they face a flatter marginal cost curve for financing investment.

Granular evidence from bond prices shows that monetary policy shocks trigger stronger responses of excess bond returns for risky, low-rated corporate bonds. Smolyansky and Suarez (2021) argue that this is due to the Fed's information effect on fundamentals: an unexpected monetary tightening signals positive news about the state of the economy, thus leading riskier corporate bonds with higher business cycle sensitivity to outperform. Guo et al. (2020) find that heterogeneous responses to monetary policy shocks in bond excess returns are driven more by news about (non-fundamental) risk premia than about cash flows. Ferreira et al. (2023) link heterogeneous responses to monetary policy shocks to ex-ante differences in firms' excess bond premium which they rationalize through firms' marginal product of capital curves. Closest to our paper is the work by Anderson and Cesa-Bianchi (2023) who also decompose corporate bond spreads into a fundamental and excess bond premium component and show evidence of a heterogeneous response of these components to monetary policy shocks across the leverage distribution of firms. As mentioned already above, our paper takes a broader perspective by investigating the responses of corporate financing conditions not only to monetary policy, but also to global risk shocks. Our results thus offer new insights as compared to the literature, as we find firms' financing conditions to respond rather homogeneously to monetary policy shocks but heterogeneously to global risk shocks, and this differential response to global risk shocks can be traced back to heterogeneity in the tightness of firms' earnings.

Our findings hence speak to the emerging literature that stresses the role of firms' earnings for access to funding. Earnings-based borrowing constraints have been found to be more prevalent than traditional asset-based collateral constraints particularly among large US firms (Greenwald, 2019; Lian & Ma, 2020). Lian and Ma (2020) show indeed that for large US non-financial firms only 20% of debt by value is collateralized by physical assets, whereas 80% is based predominantly on cash flows from firms' operations, with implications for firms' access to finance.[10] Drechsel (2023) argues that understanding whether asset repricing occurs as a result of changing expectations about the tightness of earnings-based constraints is also important from a macroeconomic perspective as it could affect policy trade-offs.

The remainder of the paper is structured as follows. Section 2 outlines our approach to identify monetary policy and global risk shocks in an integrated BVAR model and validates these shocks in the data. Section 3 presents the analysis of firm heterogeneity, including the firm level data and descriptive statistics, as well as the empirical approach to analyzing the heterogeneous shock transmission. Section 4 presents the results of the firm-level regressions and local projections, including robustness checks and Section 5 concludes.

[9] The heterogeneous impact of monetary policy on investment of riskier firms is also found to result from the structure of corporate debt maturity which makes firms with higher rollover risk and higher nominal debt burden more sensitive (Fabiani et al., 2022; Jungherr et al., 2022).

[10] Other studies show that the earnings-based borrowing constraint is prevalent also among small firms (Caglio et al., 2021) and emerging market firms (Camara & Sangiacomo, 2022).

2 BVAR model to identify shocks to financial conditions

BVAR model and identification. In a first step, we identify two types of shocks: a US monetary policy shock and a global risk shock. We rely on a structural daily Bayesian vector autoregression model (BVAR) whose structural form representation is as follows:

$$Ay_t = c + \sum_{l=0}^{p} B^l y_{t-l} + \varepsilon_t \ , \tag{1}$$

with vector y_t containing the endogenous variables, the vector c stacking the intercepts and ε_t containing the structural shocks. The lag length p is set to 4 to allow for sufficient dynamics in the responses of the endogenous variables.[11] We focus on shocks that are important determinants of funding constraints for firms by encompassing a set of key variables that together summarise how costly it is for corporations to finance themselves. For bank-based financing, short- and long-term interest rates matter, while for market-based financing the cost of equity and corporate bond pricing are important determinants of the cost of funding. Also fluctuations in the exchange rate can matter. Various measures of these so-called 'financial conditions' exist, which differ in coverage and setup; see, among others, Hatzius et al. (2010), Brave and Butters (2018), Koop and Korobilis (2014), Arrigoni et al. (2022). Financial conditions take a central role in monitoring the transmission of monetary policy and the risks to financial stability (Adrian and Liang, 2018).

To capture the wider concept of financial conditions, we include five endogenous variables in y_t which are key indicators for funding costs for firms: 3-month and 10-year US government bond benchmark yields, the cyclically-adjusted price to earnings ratio as a measure of equity prices (CAPE), the US nominal effective exchange rate and corporate spreads.[12] This choice of variables is in line with Arrigoni et al. (2022). We express yields and corporate spreads in plain differences and the other endogenous variables in first differences of the logarithm.

We exploit co-movements in this set of asset prices to identify five different structural shocks to financing conditions. We are mostly interested in the US monetary policy and global risk shock but simultaneously identify other important driving factors behind financial conditions to ensure that our shocks of interest are disentangled from these.[13] We estimate the model at daily frequency as financial conditions change on a daily basis, and taking a longer time interval would allow more room for possible confounding factors.[14]

[11] As shown in the Appendix Table A.1, the results are robust to choosing a smaller or larger number of lags.

[12] Data for the yields is taken from Refinitiv; CAPE is based on the US-DataStream Market from Datastream using as deflator US CPI, All Urban Consumers from the US Bureau of Labour Statistics; nominal effective exchange rate (against 48 main trading partners) is taken from J.P. Morgan; corporate spread is the spread between the ICE Bank Of America 15 + Year BBB United States Corporate Index taken from Merrill Lynch and the US 10-year Government Benchmark Bid Yield.

[13] As shown in the Appendix Table A.1, however, only identifying the US monetary policy and global risk shock generates median shock series that are highly correlated with the shocks as estimated in our fully identified model.

[14] When testing for firm heterogeneity in the responses to the shocks, the daily shocks are aggregated to match the weekly frequency of the US corporate dataset.

Table 1: Sign restriction identification

	US mon. policy	US macro risk	Global risk	Foreign mon. policy	Foreign macro risk
Short-term rate	+				
Long-term rate	+ (>foreign)	+	−	+	+
CAPE	−	+ (>foreign)	− (narrative)	−	+
Exchange rate	+	+	+ (>foreign)	−	−
Corporate spread		−			

Note: CAPE refers to cyclically-adjusted price to earnings ratio. A US monetary policy (macro risk) shock is assumed to have a stronger impact effect on US yields (US equities) than a foreign monetary policy (macro risk) shock, and a global risk shock is assumed to have a stronger impact effect on the US dollar effective exchange rate compared to a foreign macro risk shock. The narrative restriction imposes that the Lehman collapse in 2008 was characterised by an adverse shock to global risk sentiment and this shock was the largest relative driver of the fall in US equities on the day. All restrictions are imposed on impact.

Shock identification is achieved through a combination of sign, relative magnitude and narrative restrictions, in a similar vein as Brandt et al. (2021), Cieslak and Schrimpf (2019) and others. Table 1 summarises the sign restrictions: a + and - denote an increase or decrease respectively in the variable following a specific shock, while empty fields leave that response unrestricted. All restrictions are imposed on impact as markets typically react to news within the same day.

First, we identify a tightening US monetary policy shock as driving up US yields while depressing equity prices and appreciating the exchange rate. This set of restrictions finds strong empirical and theoretical support; Rigobon and Sack (2004) for example has shown that monetary policy shocks lead to increases in bond yields and cause stock prices to decline, while higher domestic interest rates, ceteris paribus, will also lead to an appreciation of the domestic currency (Engel, 2014; Ca'Zorzi et al., 2023). The imposed dynamics on yields, stock prices and the exchange rate are also supported in many studies tracing the effects of monetary policy shocks identified in a narrow time interval around the press conference (Jarociński and Karadi, 2020; Ca'Zorzi et al., 2023; Georgiadis and Jarociński, 2025). Second, to separate monetary policy from macro risk shocks, we follow the assumption made in several studies that the co-movement between bond yields and stock prices can be used to separate monetary news versus news related to the economy and risk (Matheson and Stavrev, 2014; Altavilla et al., 2019; Cieslak and Schrimpf, 2019; Jarociński and Karadi, 2020). That is, positive macro risk shocks are assumed to lift both yields and equity prices. Also the US dollar appreciates following this shock, as a response to higher yields, and corporate spreads are compressed due to improved risk sentiment.[15] Third, similar to Brandt et al. (2021), the global risk shock is identified to

[15]When leaving the restriction on corporate bond spreads out, the identified shocks of interest are hardly affected,

capture flight-to-safety dynamics that occurs when global investors rotate into safe assets amid heightened global risk aversion. Following this flight-to-safety shock, risky equity prices are assumed to fall while demand for safe US dollar-denominated assets such as US Treasuries rises, which causes Treasury yields to decline. Given its safe-haven status, the US dollar is assumed to appreciate following a rise in global risk aversion, which is in line with the findings of Georgiadis et al. (2024) and Kekre and Lenel (2024). A narrative restriction is imposed to strengthen the identification of this shock, assuming that on the day of the Lehman Brothers' collapse global risk sentiment dropped and was the largest factor behind the fall in US equity prices.[16]

Although these are not of main importance, we also separate out the foreign equivalents of the US monetary policy and macro risk shock to control for possible confounding factors. The foreign shocks are identified by imposing similar co-movements between yields and equity prices as imposed on their domestic shock counterparts, based on the fact that international asset prices tend to closely co-move following shocks (Forbes and Rigobon, 2002; Dedola and Lombardo, 2012; Dedola et al., 2013; Georgiadis and Jarociński, 2025). The key difference with the domestic shocks is that the effect on the exchange rate has the opposite sign as the shock comes from abroad. In addition, to better separate domestic from foreign shocks, US monetary policy shocks are restricted to have a stronger effect on US yields on impact than foreign monetary policy shocks, while US macro risk shocks are assumed to have a larger impact effect on US equity prices than foreign macro risk shocks. Finally, shocks to global risk sentiment are assumed to have a stronger impact on the US dollar than shocks to foreign macro risk, which reflects the importance risk sentiment in steering the US dollar given its safe haven status.[17] When leaving the foreign shocks unidentified, the identification of the US monetary policy and global risk shock are hardly affected, however, as shown in Table A.1.

The BVAR model is estimated over the period January 1995 to October 2022 at daily frequency in order to capture higher frequency changes in the perception of markets of the monetary policy stance of the Fed and global risk sentiment. We use Bayesian techniques for estimation and inference. We follow the techniques proposed by Arias et al. (2018) for the identification of the structural shocks using sign and magnitude restriction identification and assuming a normal-inverse-Wishart prior over the reduced form parameters. Narrative identification is imposed in line with Antolín-Díaz and Rubio-Ramírez (2018). The structural

which means that this restriction is well supported by the data, see Table A.1.

[16] This does not exclude that other shocks – such as an adverse US macro risk shock – drove equity prices on that day as well; we only assume that the contribution of adverse global risk sentiment was *larger* than each of the contributions of the other shocks individually. This restriction is supported by the data; on the day of the Lehman Brothers collapse, the US dollar appreciated, equity prices fell and 10-year US Treasury yields declined, which is how our global risk shock is identified. By contrast, should the domestic US macro shock have dominated, the US dollar would likely have depreciated overall.

[17] A noticeable part of the variation of the US dollar is driven by shifts in global risk sentiment (see e.g. Georgiadis et al., 2024 and the references therein). As such, a shift in global risk sentiments affects the US dollar *directly*. A foreign macro risk shock, by contrast, affects the US dollar effective exchange rate only *indirectly* via the trade weight of the country in question with the US, which on average is small. The shocks are however robust to leaving this restriction out, see Table A.1, which also indicates that the restriction is well reflected in the data.

shocks used in the firm heterogeneity analysis are based on the median over 10,000 draws that satisfy the full set of imposed restrictions.

Model discussion. Our model setup has clear advantages for our research question. A first benefit is that we can identify monetary policy and global risk shocks simultaneously, while still controlling for foreign spillovers. Changes in the monetary policy stance often go hand-in-hand with changes in global risk sentiment, particularly in the US given its dominant role in the international financial system (Miranda-Agrippino & Rey, 2020). As these shocks can affect firms differently, it is key to ensure that the identified US monetary policy shock is well separated from shocks to global risk. We need to account for foreign shocks as well as monetary policy shocks are often correlated across countries, which we do by simultaneously identifying a foreign counterpart for the monetary policy and macro risk shock.[18]

A second benefit is that the identification within a VAR setting will generate a continuous shock series which allows to incorporate daily dynamics in market pricing. In response to news, markets continuously reassess their interpretation of the monetary policy stance of the Federal Reserve and of global risk sentiment, which affects funding costs for firms. Important announcements of the Federal Reserve, as well as nuances in its communication, are often made on days other than those of FOMC meeting (Bauer & Swanson, 2022; Jayawickrema & Swanson, 2021). Moreover, shocks to global risk sentiment such as the 2008 global financial crisis or the COVID-19 pandemic take time to unfold as markets try to assess the economic implications of such a shock. Identifying monetary policy and global risk shocks on a daily basis might therefore capture important dynamics that might otherwise be overlooked.[19]

However, is important to note that our method of identifying structural shocks through daily asset price movements also influences what the structural shocks capture, and how they should be interpreted. Specifically, we identify the shocks through the lens of financial markets with shocks reflecting market participants' changing perceptions of daily news related to monetary policy, macroeconomic conditions and global risk. This approach results in a broader definition of structural shocks compared to certain other studies. For instance, unlike studies that identify high-frequency monetary policy shocks within narrow time frames (e.g. Jarociński and Karadi, 2020), our monetary policy shocks capture daily changes in market participants' view of the monetary policy stance, as reflected in changes in asset pricing. These include interest rate shifts on monetary policy meeting days and speeches, as well as changes prompted by news that cause market participants to adjust their expectations of monetary policy, such as significant data releases in a data-dependent monetary policy context. Similarly, the global

[18] An alternative, popular approach to identify monetary policy shifts is through high-frequency movements of interest rates and other asset prices within a narrow time window around the FOMC press release (Jarociński & Karadi, 2020). For our setup, this approach seems less well suited; while the event window is clearly defined for monetary policy shocks, it is less clear which window should be considered for other financial shocks such as shocks to global risk. In addition, markets often digest information outside of the specific window chosen, which might imply that important information might be lost when focusing on a narrow time window only.

[19] Our approach in addition accommodates the limitations of our sample of asset prices, which we obtain at weekly frequency, as well as the length of our sample period, which spans the past 20 years.

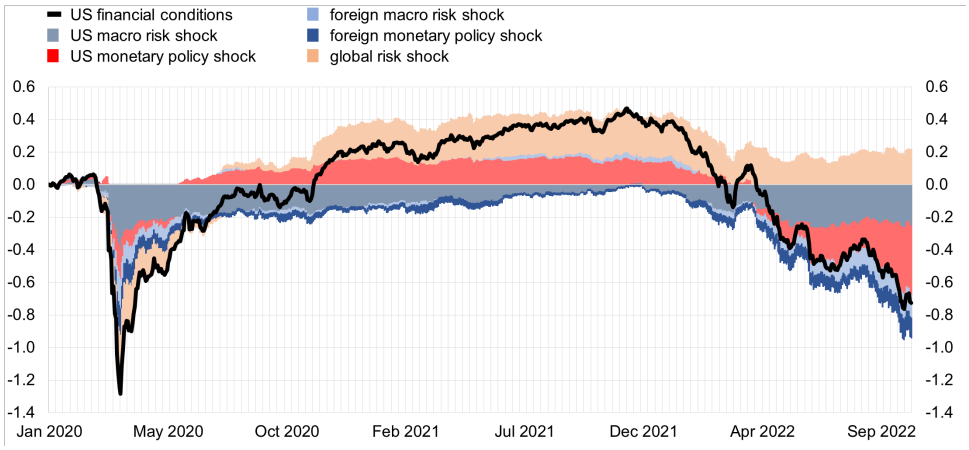


Figure 1: Model-based drivers of US financial conditions since the COVID-19 pandemic

Note: This figure shows accumulated contributions of the identified BVAR shocks to the US financial conditions index (FCI). An increase (decrease) in the FCI indicates a loosening (tightening) of financial conditions. The FCI index is constructed as an equally weighted average of the historical decomposition of the individual variables in the BVAR as proposed by Arrigoni et al. (2022).

risk shock reflects market reactions to events that lead investors to seek safer, risk-free assets. Each day typically involves identifying multiple shocks. For ease of reference throughout the paper, we continue labelling our shocks 'monetary policy', 'macro risk' and 'global risk' shocks, acknowledging that our identification rests on daily asset repricing by market participants.

Model validation. The identified structural shocks align well with events known to have been related to US monetary policy and global risk shocks. Regarding the US monetary policy shock, there is a close correlation between the monetary policy shocks of our daily BVAR model on the days of FOMC meetings with the high-frequency Fed monetary policy surprises identified in a narrow window around the press conferences of Jarociński and Karadi (2020), as shown in Figure A.1 in Appendix A.[20] Concerning the global risk shock, the shock series co-move well with the global economic uncertainty measure as constructed by Bobasu et al. (2023) who proxy global uncertainty by measuring the inherent difficulty to predict economic outcomes, following the work of Jurado et al. (2015), as shown in Figure A.3 in Appendix A.

The BVAR model results underline that US monetary policy shocks and global risk shocks are key determinants of financial conditions in the US. To illustrate that, Figure 1 shows the drivers of US financial conditions since the onset of the COVID-19 pandemic, with the financial conditions index calculated as an equally weighted combination of the five endogenous variables in the BVAR following Arrigoni et al. (2022). In the first weeks of the pandemic, financial conditions for US firms tightened substantially due to a combination of a worsening macro outlook and adverse global risk sentiment. When the Fed responded with unprecedented monetary policy stimulus, and global risk sentiment improved due to effective vaccine development, it again became substantially cheaper for firms to finance themselves with financial conditions reaching levels looser than pre-pandemic conditions. In the course of 2022, the steep

[20] For this exercise, we focus on the pure monetary policy shocks as filtered from informational effects.

monetary policy tightening of the Fed to fight record high inflation was effective in tightening financial conditions again. In sum, it is clear that shifts in the Fed's monetary policy stance and shocks to global risk sentiment are key drivers of financial conditions for firms in the US. The forecast error variance decomposition confirms that US monetary policy and global risk shocks together explain about a third of the total variability in US financial conditions over our sample.[21]

3 Analysis of firm heterogeneity

After having identified the two shocks, we next set up a firm-level regression framework to analyze the heterogeneous responses of firms' funding costs, as captured by their bond spreads and equity prices, together with their default prospects using a rich firm- and bond-level data of a sample of large US corporates.

3.1 Data and descriptive statistics

Firm-level data. The sample comprises listed companies included in the S&P 500 index. We consider both current and historical constituents, i.e. companies that were included in the S&P 500 index at any point in time between January 2000 and May 2021.[22] This results in an initial sample of 436 firms.[23] Focusing on the largest companies is instructive for several reasons. For one, it allows us to zoom in on the subset of US firms where EBCs are particularly likely to matter as documented by Lian and Ma (2020).[24] Firms selected into the S&P 500 are representative of the bulk of systemic macro-financial risks. They are "granular" as they account for a large share of business cycle activity in the US (Gabaix, 2011) and are exposed to both monetary policy and global risk shocks through their international activities. A sudden tightening in financial conditions is therefore likely to lead to substantial financial amplification in the macroeconomy, which EBCs more than traditional asset-based constraints may be able to dampen (Lian & Ma, 2020). In addition, limiting our attention to only firms that obtain a substantial share of their external financing through capital markets enables us to abstract from substitution effects between market- and bank-based financing which may apply for medium-sized corporations. At the same time, focusing on S&P 500 firms limits the external validity of our results with respect to smaller corporations with potentially less liquid bonds.

We analyze firm heterogeneity along a set of balance sheet indicators collected at quar-

[21] This is based on the 20-day ahead median forecast error variance decomposition (FEVD), taking the average over the FEVD of the different endogenous variables as a proxy for the FEVD for financial conditions. The variable-specific FEVD ranges between 22-46 percent.

[22] While listing and delisting of firms in the S&P 500 index is endogenous, such events do not occur as frequently as to warrant serious concerns about confounding effects in our analysis at weekly frequency.

[23] This sample size is similar to Palazzo and Yamarthy (2022) who estimate the reaction of CDS spreads to monetary policy surprises on a sample of 585 non-financial firms with an average of 300 firms around each FOMC announcement date.

[24] Lian and Ma (2020) find that cash-flow based borrowing is less common among small firms as they tend to exhibit low or negative earnings.

terly frequency from Thomson Reuters Datastream. To proxy for the extent of collateral-based constraints, we consider a firm's financial leverage measured by the debt-to-equity ratio (LEV). Arguably, firm leverage is an imperfect proxy for the degree of collateral-based borrowing. However, it reflects the extent to which creditors (relative to shareholders) have claims on the assets of the company in a liquidation scenario and therefore the financial constraints that are tied to the value of assets.[25] Figure C.1 in the Appendix shows that the debt-to-equity and debt-to-assets ratios of the firms in our sample, as expected, are highly correlated over the sample period and may therefore be used interchangeably.[26]

As an indicator of the tightness of a firm's EBC, we use the 12-month forward earnings per share (EPSE). Expected earnings per share is among the most commonly used, forward-looking indicators of profitability that captures the discounted stream of expected profits per share accruing to creditors.[27] It also facilitates comparison across firms' market size by way of normalizing earnings to the number of shares outstanding. In addition, we consider a firm's EBIT-to-interest expense ratio or "interest coverage ratio" (ICR) as a hybrid indicator of asset-based and earnings-based borrowing constraints. The ICR reflects a firm's ability to service debt out of current earnings. Because it is a function of both earnings as well as outstanding debt obligations, it can be interpreted as a hybrid indicator between leverage and profitability.[28]

We also collect weekly data on equity prices from the same source. To obtain a measure of firms' fundamental default risk, we use the expected default frequencies (EDFs) of publicly listed firms from Moody's KMV CreditEdge database.[29] We aggregate the daily series of EDFs to weekly averages. For robustness purposes, we complement the data with an additional model-free measure of a firm's credit risk by retrieving firm-level spreads on credit default

[25] Looking at the incidence of key terms in loan covenants, Drechsel (2023) finds that the maximum leverage ratio is the most common term that is unrelated to earnings (accounting for 21% of all covenants).

[26] While basic accounting would imply a perfect correlation between the two, in practice there can be measurement error and differences in data treatment. In our analysis, we confirm that our results are not driven by the choice of proxy for financial leverage.

[27] Alternative measures such as the return on equity (ROE) come with the caveat that they are backward looking and reflect book values as compared to market values (e.g. price-earnings ratio). Since EPS are scaled by the number of shares outstanding of a given firm, there may be concerns about comparability across firms. In Appendix F.5, we additionally classify firms according to their ROE and PE ratio as well as the growth rates of expected and realized EPS.

[28] Some may argue that high leverage or low profitability may not necessarily be a clear sign of weak firm fundamentals. High leverage can, on the one hand, be costly because it can affect investors' expectations of the firm's ability to remain in business; on the other hand, it can be beneficial by improving managerial incentives (Asgharian, 2003; Jensen, 1986; Wruck, 1990). A high leverage/low profitability firm could also be a successful, possibly young, firm that based on its good expected performance is able to borrow a large multiple of its equity/profits. What matters for our question, however, is the relative position of a firm in the leverage or profitability distribution, with leverage and profitability used as (indirect) proxies of the asset-based vs earnings-based borrowing constraints, respectively. Moreover, the growth prospects of a young firm should be captured by the forward-looking nature of *expected* earnings. Finally, the fact that we look at large S&P500 firms demands a certain level of maturity from firms in the sample that distinguishes them from the "high-leverage, low-profitability" type of start-ups.

[29] Moody's Analytics (2011) derive EDFs from a proprietary model of corporate default in the spirit of Merton (1974). The model takes a firm's market value of asset, its asset volatility, and leverage as inputs, defines a default threshold, and converts the resulting distance to default into a model-implied probability of default over a 12-month horizon. The EDF is thus a market-based summary statistic of publicly available information on corporate credit risk.

swaps (CDS) with a 5-year tenor from Bloomberg.

Bond-level data. We obtain data from Bloomberg covering information on corporate bonds issued by our sample of firms. Bonds are selected according to the following criteria: (i) active or matured, traded on any day between 7 January 2000 and 17 December 2021, (ii) issued by non-financial firms, (iii) denominated in USD, (iv) excluding private placements, (v) subject to a fixed coupon schedule, (vii) a remaining time to maturity between one and 30 years, and (viii) a minimum volume of USD 1 mn and a maximum volume of USD 5 bn. Criteria (i)-(iv) yield an initial sample of 12,996 bonds.

Cross-sectional information on bond characteristics as well as weekly time series of option-adjusted spreads (OAS) and option-adjusted bond duration are obtained from Bloomberg. An OAS is a model-based measure of a bond's credit risk above and beyond the maturity-matched risk-free rate (a zero-coupon US Treasury yield).[30] The underlying spread model takes embedded options such as early redemption into account. These options change the stream of discounted cash flows in the spread calculation. OAS therefore not only control for credit risk but also for contingent cash flow risk and make bonds of various different characteristics more comparable.[31]

As an additional measure of credit risk at the bond level, we retrieve bond-level composite credit ratings, a measure of the average credit rating of a security across four major rating agencies, from Bloomberg.[32] Due to limited data availability, the sample of bonds for which the weekly OAS and duration series can be obtained reduces to 10,679 bonds. We run additional cleaning steps on the series of OAS to ensure that stale bonds, i.e. bonds traded infrequently, do not bias the analysis. Appendix Table B.1 outlines the steps and how they affect the sample size. Cleaning as well as filtering the data according to criteria (v)-(viii) further reduces the sample to 7,364 bonds with which we proceed our analysis. Notwithstanding the reduction in the sample size, the overall count of bond-week observations at each point in time is sufficient and well-distributed across the distribution of credit risk (see Appendix Figure C.2).

Descriptive statistics. Table 2 presents summary statistics for the sample of cleaned and matched bonds. The median bond has a volume of USD 500 mn, a 10-year tenor, a BBB+ composite credit rating, and trades at a 138 basis point spread. The median firm has 12 bonds outstanding in an average week with some firms trading more than 23 bonds in a given week. About 46% of bonds feature embedded options, which makes the use of OAS all the more salient. Note that the distribution of OAS is fairly skewed, ranging from 86 basis points to 209 basis points for the 25^{th} and 75^{th} percentiles with some values above 1500 basis points in

[30] For further details about OAS, see Gabaix et al. (2007) and O'Kane and Sen (2005). OAS have been used in similar contexts e.g. by Anderson and Cesa-Bianchi (2023), Caballero et al. (2019), Cavallo and Valenzuela (2009) and others.

[31] Appendix D details how our data choices and estimation deviate from Gilchrist and Zakrajšek (2012).

[32] The Bloomberg Composite Credit Rating is an equally weighted average of the ratings by Moody's, Standard & Poor's, Fitch, and DBRS.

Table 2: Bond and firm characteristics – Summary statistics

	Mean	SD	P25	Median	P75
(a) Bond characteristics					
No. of bonds per firm/week	38.24	82.29	6.00	12.00	23.00
Bond volume (mil)	640.72	636.10	250.00	500.00	800.00
Maturity at issue (years)	15.73	10.02	9.50	10.03	29.98
Term to maturity (years)	10.49	8.61	3.93	7.31	16.43
BB Composite Bond Rating	BBB+		BBB	BBB+	A
OAS spread (bsp)	174.25	167.40	85.56	138.24	209.36
Duration (years)	6.91	4.53	3.29	5.91	10.09
Coupon rate (pct)	5.18	1.89	3.75	5.05	6.62
Bond options (pct)	0.46				
(b) Firm characteristics					
EDF 1-Year (%)	0.41	1.95	0.03	0.05	0.19
Leverage ratio	47.68	38.77	30.70	42.46	57.51
Realized earnings per share	4.04	8.68	1.51	2.68	4.60
Expected earnings per share	4.52	9.91	1.69	2.94	5.03
Interest coverage ratio	12.92	46.56	3.45	7.25	13.72
S&P Issuer Rating	BBB+		BBB-	BBB+	A-

Note: Sample period: 2000/01/07 – 2021/12/17; Number of bond-week observations: 2,274,822; Number of bonds: 7,674; Number of firms: 407. The sample statistics are based on trimmed data following the procedure described in Appendix Table B.1.

the right tail. This is partly mechanical due to the underlying pricing model used to compute OAS.[33] It also reflects the overall distribution of default risk in the sample that is skewed towards a tail of very risky firms. The bottom panel of Table 2 shows that this skew in firms' default risk is also reflected in the EDF.

We also verify that the distribution of firms across our measures of LEV, EPSE, and ICR are not identical or overlapping. In other words, those firms that are at the top of the leverage distribution and hence closer to their asset-based borrowing constraint are not at the same time also at the bottom of the earnings distribution and hence close to their earnings-based constraint. Figure 2 plots quantiles of EPSE against quantiles of LEV and ICR. The scatter cloud is very dispersed, suggesting that firms do not necessarily have the same position in the ICR/LEV-distribution as they have in the EPSE-distribution. The stronger bunching of observations along the 45-degree line in panel (ii) also supports the role of ICR as a hybrid indicator of both collateral-based and earnings-based borrowing constraints. It may add information above and beyond a firm's expected earnings.

Figure 3 illustrates the development of credit spreads across the leverage (left panel) and earnings distribution (right panel) of firms. Up until the Great Recession, highly levered and cash-flow constrained firms paid a multiple of safer firms' credit spreads on their debt. However,

[33]The OAS is not the price at which the security is exchanged. It reflects the net present value of the bond's cash flows once state-contingent claims are taken into account.

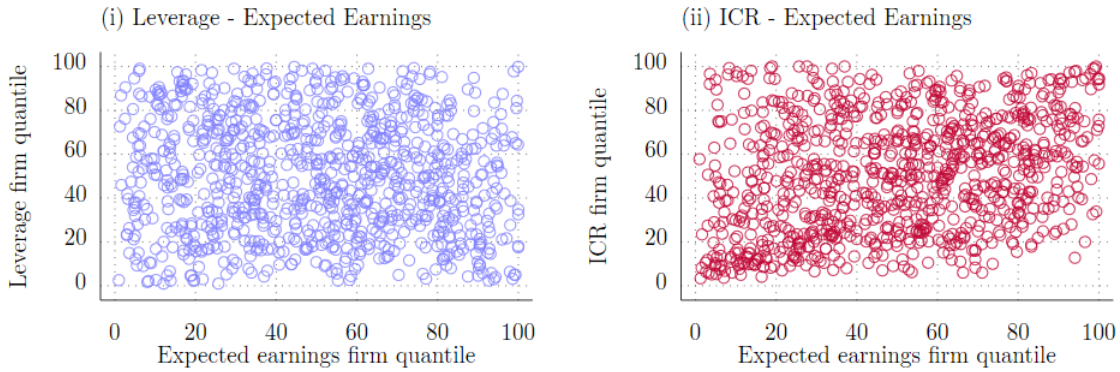


Figure 2: Distribution of firms' earnings against leverage and interest coverage ratio

Note: This figure shows the distribution of firms' earnings as measured by their expected earnings per share plotted against the distribution of (i) leverage as measured by debt-to-equity and (ii) their EBIT-to-interest ratio. Each circle represents a given firm's position in the leverage and earnings distribution, respectively.

the decade following the GFC saw a strikingly less pronounced difference in credit spreads across firms with strong versus weak fundamentals. In particular, the period of monetary policy normalization indicates that investors demanded little compensation for bearing highly levered firms' credit risk. These compressed spreads may not come as a surprise: companies were able to tap cheap funding during a period of abundant liquidity provided by central banks. Figure 3 highlights that investors nevertheless did price risk across the earnings distribution of firms during the past decade. One possible reason for greater attention to profitability measures could stem from the increasing sensitivity of indebted firms' cash flows and debt servicing costs to changes in interest rates. This observation motivates us to explore the sensitivity of corporate funding costs to monetary policy and global risk shocks.

3.2 Decomposing Credit Spreads into Fundamental and Excess Bond Premium Components

Since credit spreads are ultimately a summary statistic of various types of risk, we are also interested in shedding light on how monetary policy and global risk shocks move different components of credit spreads. To better understand the transmission channels of these shocks, we follow the seminal approach of Gilchrist and Zakrajšek (2012) and decompose corporate bond spreads into a fundamental component that captures *expected* default risk based on firm fundamentals and a non-fundamental component, the so called "excess bond premium" (EBP). The EBP is the compensation required by investors beyond the risk of default. Narrowly interpreted, the EBP captures investor risk sentiment. However, it has also been shown to relate to the liquidity constraints faced by financial intermediaries in the intermediation of corporate bonds (Gilchrist & Zakrajšek, 2012).

Our spread model linearly relates an individual firm j's credit spread $s_{j,t}[k]$ paid on bond k to the firm's probability of default $EDF_{j,t}$, a vector of bond characteristics capturing

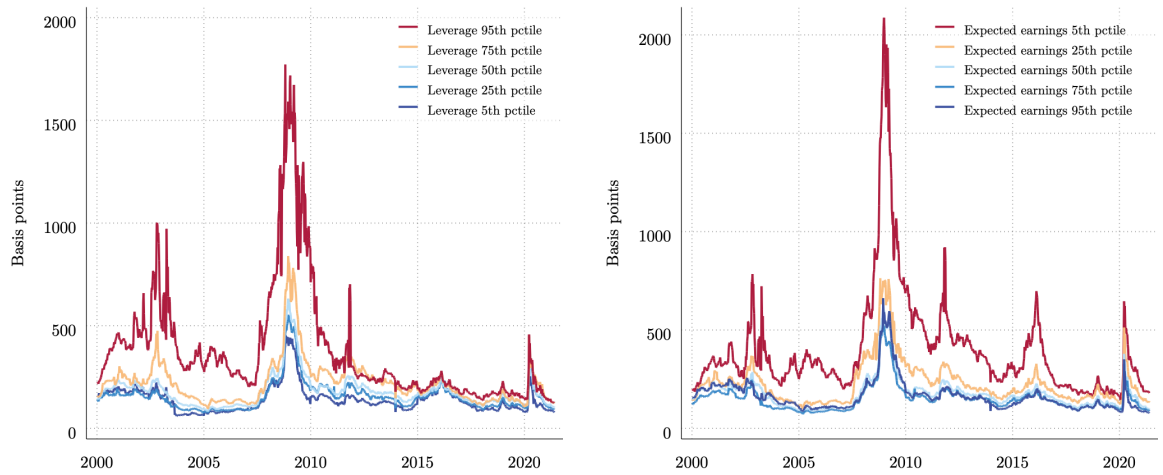


Figure 3: Option-adjusted spreads (OAS) across the firm distribution according to leverage (left) and earnings (right)

Note: This figure shows option-adjusted spreads (OAS) across the distribution of firms computed based on leverage (left panel) and expected earnings (right panel). Leverage is measured as the debt-to-equity ratio. Expected earnings are based on earnings per share projected 12 months forward.

the bond's liquidity risk $\boldsymbol{X}_{j,t}[k]$, and an industry fixed effect a_j,

$$s_{j,t}[k] = a_j + \Lambda^j EDF_{j,t} + \Lambda^k \boldsymbol{X}_{j,t}[k] + u_{j,t}[k] \tag{2}$$

where $u_{j,t}[k]$ denotes the pricing error.[34] The vector of bond characteristics $\boldsymbol{X}_{j,t}[k]$ comprises the option-adjusted bond duration, the coupon rate, the age of the traded bond since issuance, the bond volume, and an indicator variable for bonds with underlying options. Appendix D presents results of the estimation of (2) in Table D.1 as well as an overview of how our spread model and data deviate from Gilchrist and Zakrajšek (2012).[35]

Having obtained the pricing errors $u_{j,t}[k]$ of bonds from (2), we compute the predicted spread and the EBP at the firm level,

$$\hat{s}_{j,t} = \sum_k w_{j,t}[k]\, \hat{s}_{j,t}[k] \qquad \text{and} \qquad EBP_{j,t} \equiv \hat{u}_{j,t} = \sum_k w_{j,t}[k]\, \hat{u}_{j,t}[k] \tag{3}$$

where the weight is $w_{j,t}[k] = 1/N_{j,t}$, i.e. we take the simple average over all bonds of firm j.[36] Defining the predicted spread and EBP at the firm-level instead of the aggregate level allows us to study the heterogeneous responses of these components to financial shocks depending on

[34] We refrain from using the natural logarithm of the credit spread as the dependent variable because the transformation would eliminate all observations of negative spreads. Negative OAS observations are not uncommon since the spreads are produced by an underlying model. We confirm in separate robustness checks that using spreads in logs does not change our conclusions.

[35] Several robustness checks in Section 4 however confirm that small departures from their setup still deliver qualitatively similar results.

[36] For robustness, we verify that the weighting is immaterial by defining the weight on each individual bond k by its face value $V_{j,c,t}[k]$ relative to the total volume of bonds of firm j outstanding at time t, $w_{j,c,t}[k] = V_{j,c,t}[k]/\sum_k V_{j,c,t}[k]$.

firms' risk profile in the next section.

3.3 Estimating Heterogeneous Responses to Risk and Monetary Policy Shocks

We quantify the impact of identified US monetary policy shocks and global risk shocks on corporate funding costs in a panel local projections framework following Jordà (2005). Specifically, we are interested in the heterogeneous responses of corporate bond spreads (and their components) and equity prices depending on whether firms are relatively closer to their earnings constraint (low EPSE) or to their asset-based constraint (high LEV). We dynamically sort firms according to these weak/strong fundamentals and include interaction terms with the respective shocks to test for differential sensitivities.[37] To that end, we specify a model that interacts the shocks with indicator variables for "tail firms", i.e. firms at the bottom and top of the distribution of leverage and earnings.

To identify tail firms, let $z_{j,t}$ be the firm-level metric of leverage or profitability, respectively, that we use to categorize firms into "buckets". We compute the top and bottom τ^{th} quantiles $q \in \{\tau, 1-\tau\}$ of the distribution of z_t over roughly five-year subperiods between January 2000 and December 2021. For each subperiod $t_i \in \{t_1, t_2, t_3, t_4\}$, we then categorize firms into quantile buckets based on their median value $\bar{z}_{j,t_i}$ in subperiod t_i. Note that we do not re-assign firms to quantile buckets at each point in time but only every subperiod t_i to guarantee a long enough time series for each firm in the estimation.[38] At the same time, computing quantiles over subperiods rather than over the sample period ensures that firms are correctly classified according to their time-varying risk profile. We define the indicator variable that classifies firm j in the *bottom* τ^{th} quantile,

$$\mathbb{1}_{z,\tau,t} = \begin{cases} 1 & \text{if } \bar{z}_{j,t_i} \leq z^*_{t_i}(\tau) \quad \text{for } t_i \in \{t_1, t_2, t_3, t_4\} \\ 0 & \text{else} \end{cases} \tag{4}$$

where $z^*_{t_i}(\tau)$ denotes the cutoff value at quantile τ for subperiod t_i in the firm distribution of $z_{j,t}$. Analogously, we define the indicator variable that classifies firm j in the *top* τ^{th} quantile,

$$\mathbb{1}_{z,1-\tau,t} = \begin{cases} 1 & \text{if } \bar{z}_{j,t_i} \geq z^*_{t_i}(1-\tau) \quad \text{for } t_i \in \{t_1, t_2, t_3, t_4\} \\ 0 & \text{else} \end{cases} \tag{5}$$

In our benchmark analysis, we consider the top and bottom 20^{th} percentiles, i.e. $\tau = 0.2$, of the firm distribution according to their debt-to-equity ratio, $LEV_{j,t}$, their interest coverage ratio,

[37] In contrast to Arbatli Saxegaard et al. (2022) who define leverage cutoffs according to the average over the entire sample period, we dynamically sort firms into weak and strong categories every five years. This approach allows us to strike a balance between on the one hand ensuring that firms are correctly represented in the distribution when their risk profile changes as they grow and mature, and on the other hand ensuring stability in the estimation.

[38] For example, a firm whose median leverage ratio over the period 2000-2005 is below the 20th percentile leverage ratio computed over the same period will remain in the bottom quantile bucket over this five-year period. In addition, as pointed also by Gomes et al. (2016), since leverage is sticky, one would assume there are no frequent substantial changes.

$ICR_{j,t}$, and their expected earnings per share, $EPSE_{j,t}$, i.e. $z \in \{LEV, ICR, EPSE\}$.

The objective is to analyze whether levered and unprofitable firms in the tails are particularly sensitive to global risk and monetary policy shocks. This would manifest in significant effects of these shocks when interacted with the indicator variables for tail firms, $\mathbb{1}_{z,\tau,t}$ and $\mathbb{1}_{z,1-\tau,t}$. Let $y_{j,t}$ represent our asset price variable of interest of firm j at time t. We are interested in estimating the dynamic multiplier, or cumulative response, of $\Delta_h y_{j,t-1} = y_{j,t+h} - y_{j,t-1}$ for $h = 0, 1, ...H$ with respect to an exogenous shock s_t. We thus estimate a series of panel regressions for each horizon h,

$$\Delta_h y_{j,t-1} = \beta_h \varepsilon_t^i + \sum_{q \in \{\tau, 1-\tau\}} \beta_{h,q} \varepsilon_t^i \times \mathbb{1}_{z,q,t} + \phi_{j,h}(L) X_{j,t-1} + e_{j,t+h} \qquad h = 0, ..., H \tag{6}$$

where ε_t^i denotes the respective identified monetary policy or global risk shock ($i \in \{m, r\}$), $X_{j,t-1}$ is a vector of control variables, and $\phi_{j,h}(L)$ denotes its polynomial lag operator. The specification controls for economic activity, interest rates, and market uncertainty. More precisely, the vector $X_{j,t-1}$ includes four lags of the VIX, the 2-year US Treasury yield, and the Citigroup Economic Surprise Index (CESI), as well as crises dummies for the peak weeks of the Global Financial Crisis and of the Covid-19 pandemic, and industry fixed effects.[39]

4 Results

Baseline results. This section presents the baseline results of the responses of firm-level bond spreads and equity prices to monetary policy and global risk shocks. We are particularly interested in whether firms with different risk profiles exhibit heterogeneous sensitivities to the two shocks. Table 3 presents the responses of the estimated series of local projections in model (6) following a shock from tighter monetary policy s_t^m (panel a) and higher global risk s_t^r (panel b) at horizon $h = 1$, i.e. upon impact of the respective shocks. Columns (1) through (4) show the responses of corporate spreads, the excess bond premium, the probability of default, and (log) equity price. The shocks are calibrated to a 10-basis point negative (positive) impact on long-term Treasury yields over 5 days for the global risk shock (monetary policy tightening shock).

We first consider the dynamic responses based on the full sample of firms in the first row of panel (a) in Table 3. Monetary tightening leads to a significant initial jump in corporate spreads by 7 basis points. Most of this reaction is driven by the response of the non-fundamental component to the shock in column (2) – the excess bond premium accounts for around 6 basis points of the increase in spreads. Unexpected monetary tightening raises firms' probability of

[39] The specification is estimated with pooled OLS and industry fixed effects rather than with a firm fixed effects estimator. The baseline estimates are close to invariant to whether industry or firm fixed effects are used. Note also that in the current setting with $N < T$, the fixed effects estimator may yield biased estimates, in particular when the sample is split into subsamples.

default on average by about 0.03 percentage points (column (3)), albeit with little statistical significance. Equity prices drop significantly in response to the shock: on average a 10 basis point equivalent increase in US yields leads to a fall in a firm's equity price by 3.5 percent.[40] Overall, the results are in line with a typical reaction of asset prices to an unexpected monetary contraction. Similar results obtain for the global risk shock in the first row in panel (b). A sudden spike in global risk aversion triggers a sharp rise in spreads, with the brunt of the spread reaction again being driven by the non-fundamental EBP. The responses are about twice as large in magnitude compared to the monetary policy shock.

To shed light on how these responses differ across the distribution of firms, we repeat the exercise by augmenting the baseline specification with interaction terms of the shock with dummies for tail firms (see Section 3.3). Table 3 reports the estimates of the augmented models in subsequent rows below the baseline estimates for both the monetary policy shock (panel a) and global risk shock (panel b). As described in Section 3.3, we classify firms by their dynamic position in the distribution of firms according to leverage (LEV), the interest coverage ratio (ICR), and expected earnings per share (EPSE). Firms between the 20% and 80% percentile of this distribution, henceforth denoted the "average" firms, constitute the base relative to the firm dummies. We emphasize again that both the interest coverage ratio – the ability to cover debt payment out of current earnings – and expected earnings per share – investors' stake in the profits of the firm for each share owned – essentially serve as indicators of *profitability*.[41] A number of instructive comparisons can be drawn along several dimensions.

First, we start by comparing the overall responses to monetary policy (panel a) and global risk shocks (panel b). Interactions with tail firms are largely insignificant, suggesting that monetary tightening does not transmit disproportionately more or less to the funding conditions of strong or weak firms. This result obtains broadly across both bond and equity prices as well as fundamental and non-fundamental credit risk components. By contrast, global risk shocks hit the tail of least profitable firms disproportionately more. Weak firms, both defined by a low ICR and low expected earnings per share, see their funding costs increase significantly more relative to all other firms. The additional cost paid in terms of credit spreads can amount to 15 to 19 basis points more relative to their peers.

Second, we compare the heterogeneous responses according to leverage (LEV) and profitability indicators (EPSE) of firm risk, while also considering the interest cover ratio as a hybrid indicator bridging the earnings-based and the asset-based borrowing constraints, in a similar spirit as Greenwald (2019) and Drechsel and Kim (2022). Overall, investors do not appear to differentiate much across highly and weakly levered firms, neither in response to monetary tightening nor during global risk-off episodes. The interaction terms for LEV are

[40] As the response of equity prices is restricted for shock identification, a significant response is expected. The magnitude of the effect, and the relative strength of the response of equity following monetary policy versus global risk shocks, is left over to the data.

[41] However, they are forward-looking complements rather than substitutes as the ICR captures the extent to which debt and additional future borrowing are sustainable while expected earnings per share feature in the overall valuation of a company.

Table 3: Sensitivity of asset prices of tail firms upon impact of shocks.

	(1) Δ Spread	(2) Δ EBP	(3) Δ EDF	(4) Δ ln(PI)
Panel (a): Monetary policy shock				
ε_t^m	7.395***	5.889**	0.028*	-0.035***
ε_t^m	7.261***	6.220***	0.020**	-0.035***
LowLEV $\times$ ε_t^m	-1.167	-1.277	-0.003	0.000
HighLEV $\times$ ε_t^m	1.842	-0.537	0.045	-0.002
ε_t^m	7.001***	6.145***	0.016**	-0.034***
LowICR $\times$ ε_t^m	2.670	-1.178	0.073	-0.007*
HighICR $\times$ ε_t^m	-0.358	-0.126	-0.005**	0.001
ε_t^m	7.140***	5.938***	0.021**	-0.034***
LowEPSE $\times$ ε_t^m	1.861	-0.652	0.048*	-0.004*
HighEPSE $\times$ ε_t^m	0.034	0.468	-0.006	-0.001*
Panel (b): Global risk shock				
ε_t^r	18.628***	15.472***	0.056*	-0.069***
ε_t^r	17.502***	15.406***	0.039**	-0.068***
LowLEV $\times$ ε_t^r	-4.942	-5.107**	-0.006	-0.003
HighLEV $\times$ ε_t^r	10.456	5.000*	0.099	-0.002
ε_t^r	15.858***	14.366***	0.027**	-0.065***
LowICR $\times$ ε_t^r	18.773**	9.504**	0.176*	-0.022*
HighICR $\times$ ε_t^r	-3.616**	-2.995*	-0.011*	0.002
ε_t^r	16.439***	14.232***	0.037**	-0.065***
LowEPSE $\times$ ε_t^r	15.194***	8.416***	0.126**	-0.019***
HighEPSE $\times$ ε_t^r	-1.695	-0.788	-0.013	-0.005
Industry FE	YES	YES	YES	YES
Observations	222,060	219,513	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$, i.e. upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)). The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(5). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

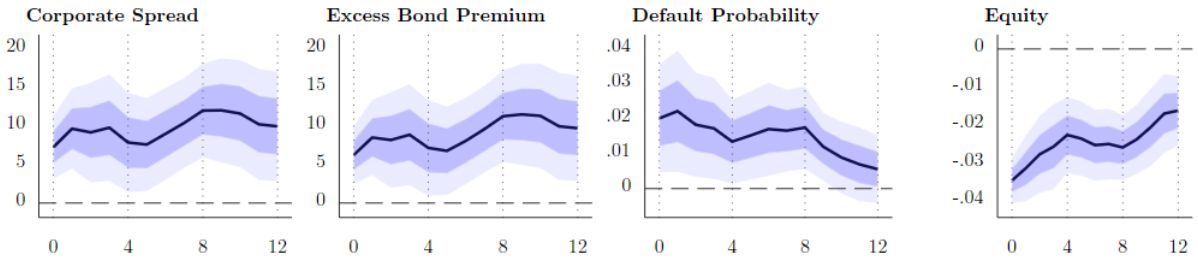
largely insignificant. Conversely, investors seem to discount least profitable firms relatively more. Weak firms with low expected earnings (low EPSE) see their debt funding costs increase and their equity prices fall significantly more when global risk sentiment deteriorates. This pattern also emerges for weak firms with lower ability to cover their interest expense out of current earnings (low ICR), albeit with modest statistical significance. Overall, we find that global risk shocks have stronger and more heterogeneous effects on corporate funding costs which depend on firms' position within the earnings distribution. These findings suggest that the earnings-based borrowing constraint discussed above appears to be more binding relative to the asset-based borrowing constraint. This is in line with evidence by Jeenas (2019) who finds that liquid asset holdings more than leverage explain the heterogeneous pass-through of monetary policy shocks to borrowing costs of listed US firms.

Third, we compare strong versus weak firm responses. Overall, we find significant evidence supporting a greater sensitivity to shocks for weak firms but not for strong firms. When looking at the profitability distribution of firms, only the less profitable firms seem to be more sensitive to global risk shocks. but very profitable firms are not significantly better off. However, very profitable firms do not seem to be affected, as the interaction term is insignificant, a further suggestive evidence that financial amplification through firms balance sheet might be alleviated when the earnings-based borrowing constraint is more binding.

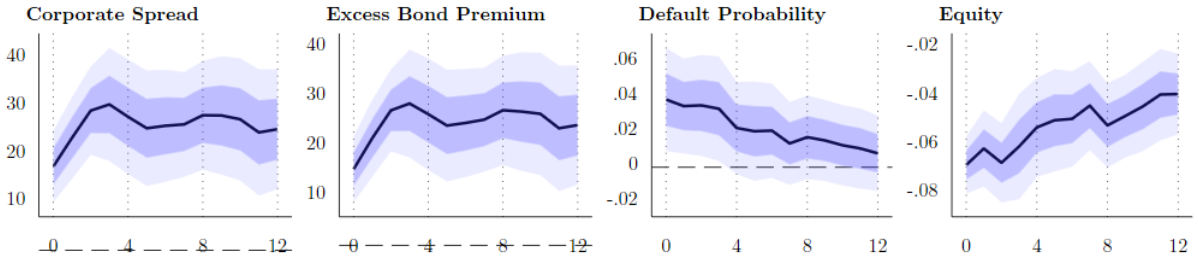
When splitting firms by interest coverage ratio, however, strong firms with high ICR are hit relatively less by global risk shocks. They pay on average 4 basis points less on their bonds relative to the average firm upon impact of the shock and their expected default probability deteriorates by less relative to average and weak firms. This observation may suggest some rebalancing behavior by investors away from risky towards the least risky firms, to the extent that the rebalancing occurrs within the corporate bond markets.[42] Flights to safety, in particular to quality in the US corporate bond market, have been documented for example by Baele et al. (2019).

Finally, we compare asset price reactions across columns (1) to (4). It is worth noting that all asset pricing variables and components significantly respond to monetary policy and global risk shocks. The strong reactions provide backing for the identification of shocks through the BVAR based on financial conditions. A large share of the response in credit spreads is driven by the non-fundamental component, the EBP. This suggests that both types of shocks tend to move investor sentiment beyond fundamental considerations of firms' riskiness. However, while monetary policy transmits through the non-fundamental component to all firms' funding conditions, shifts in global risk sentiment disproportionately affect investors' sentiment to invest in weak, risky firms. We also find a significant response of firms' default probability (EDF) to both shocks, as well as a strong negative equity price reaction of firms, which remains significant even after allowing for heterogeneous exposure, in most cases.

[42] There is some indication of rebalancing behavior of investors, e.g. the response of the EBP of highly levered firms to a global risk shocks is a mirror image of the response of less levered firms (-5.0 vs. + 5.1). This is only suggestive and could be due to different reasons however.



(a) Monetary policy shock s_t^m



(b) Global risk shock s_t^r

Figure 4: Cumulative responses of asset pricing variables to identified shocks

Note: This figure presents the impulse responses of a set of asset pricing variables to a monetary policy shock ϵ^m and a global risk shock ϵ^r. The responses are obtained from estimating model (6) over a 12-week horizon $h = 12$ over the sample period from 01/2000-12/2021. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The excess bond premium and fitted corporate spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the period 01/2000-12/2021. Shaded areas denote 95% and 68% confidence bands.

Overall, we find that investors tend indeed to discount the least profitable firms to a greater extent but they do not tend to differentiate much across highly or weakly levered firms. Only the least profitable firms tend to be more sensitive to global risk shocks, while very profitable firms are not symmetrically better off, with a few exceptions. Funding costs responses of least profitable firms to global risk shocks are not only strongly significant but also much larger in magnitude.

While the previous findings provide important insights into the responses of asset prices upon impact of the shocks, we also explore the *persistence* of the dynamic responses over time. Figure 4 presents the impulse responses of the estimated series of local projections following a shock from tighter monetary policy (panel (a)) and higher global risk (panel (b)) for the full baseline sample of firms. Again, the responses represent the reaction of asset prices and their components to a 10 basis point exogenous tightening (panel (a)) and easing (panel (b)) of US yields. Appendix E.1 presents the impulse responses for the subsets of weak and strong firms.[43] Appendix E.2 presents an additional exercise of asymmetric responses to tightening versus easing shocks of both monetary policy and global risk.[44]

[43] We caveat that the estimation on subsamples suffers from lack of power due to the smaller sample size of tail firms. Results should therefore be interpreted with caution.

[44] We note that overall the persistence in asset price responses to both shocks remains overall symmetric around

As seen in the first chart in panels (a) and (b), credit spreads jump by 7 and 19 basis points, respectively, upon impact of the shock and further rise to 15 and 35 basis points during the first weeks after the shocks. They remain persistently elevated for at least 12 weeks. The responses of the EBP and the probability of default in the second and third chart indicate that the spike in credit spreads is mainly driven by forces that are disconnected from fundamentals. In particular at longer horizons, firms' probability of default declines but the EBP remains persistently elevated. Financial shocks thus do not merely affect the *expected* default risk of firms but more so the risk sentiment of investors and the risk-bearing capacity of financial intermediaries, as reflected in the EBP (Gilchrist & Zakrajšek, 2012). Equity prices are similarly adversely affected upon impact of both shocks but recover slightly faster. Thus, while pessimistic sentiment in equity markets in response to tighter monetary policy and heightened global risk halves within three months, risk-averse sentiment in corporate bond markets remains persistently scarred for longer. This in turn suggests that corporate funding becomes particularly strained in debt markets.

Extensions and Robustness. We perform several robustness tests. The baseline firm-level results remain broadly robust with respect to (i) shortening the sample period to 2005-2021 to exclude earlier observations with fewer bonds outstanding (Table F.3), (ii) changing the estimation specification to include lagged dependent variables to account for autocorrelation in asset prices (Table F.4), (iii) adding week fixed effects (Table F.5) and week-industry fixed effects (Table F.6) to control for systematic variation in macro variables and time-varying industry-exposure, and (iv) using alternative measures of firm profitability (Table F.7).

We also sort firms not only according to the bottom and top 20^{th} percentiles, but also according to the 15^{th} percentiles and resort into groups every 2 years instead of every 5 years. While the results of the panel regressions remain broadly qualitatively similar, we note that statistical power starts to diminish as fewer firms in the tails are considered in each subgroup.[45] Relatedly, one might hence argue that our sample including only S&P 500 non-financial firms may pose limitations, as making statements about the tails of the distribution of these firms may not be fully representative of the wider distribution of small and large firms. However, as already previously mentioned, we need large firms to enable us to pick up and test the earnings-based borrowing constraint hypothesis. Other recent studies also use large, well-established firms (Anderson and Cesa-Bianchi (2023), Gürkaynak et al. (2022).[46] Having a large degree of heterogeneity in the sample is the crucial requirement to allow us to identify

zero. One exception is the EBP which tends to persistently decline over the next 12 weeks following a monetary easing shock.

[45] The dynamic sorting of firms into groups every two years makes the panel of firms more unbalanced, hence worsening the problem for statistical inference. The same holds when we sort firms into the top and bottom tails based on the 20^{th} and 80^{th} percentiles computed once over the entire sample period. The results remain however qualitatively similar also in this case. They are not reported here for sake of conciseness, but are available upon request from the authors.

[46] For instance, Gürkaynak et al. (2022) also consider firms that were part of the S&P500 to analyse their stock price reactions to monetary policy announcements.

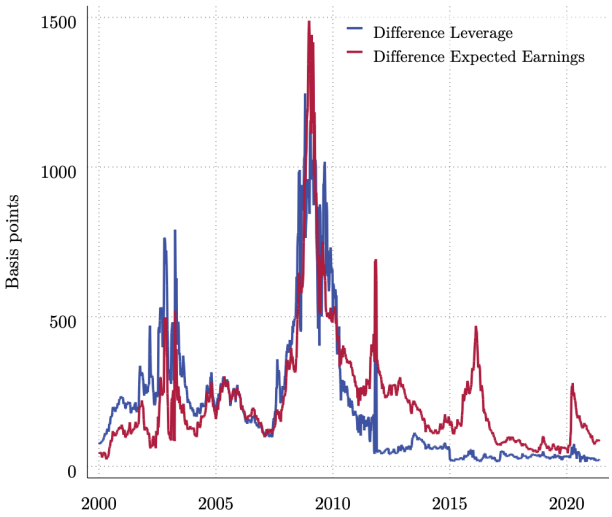


Figure 5: Difference in option-adjusted spreads (OAS) between the tail of weakest firms and the median firm computed based on leverage and profitability

Note: This figure shows the difference between the average option-adjusted spread (OAS) for the bottom 5^{th} pct. and the 50^{th} pct. (median) of firms computed based on the distribution of firms across leverage (blue) and expected earnings (red). Leverage is measured as the debt-to-equity ratio. Expected earnings are based on earnings per share projected 12 months forward. The tail of weakest firms is the top 95^{th} percentile for leverage and the bottom 5^{th} percentile for expected earnings.

the effects of financial shocks on those firms which are relatively more financially constrained than others, as argued also in Anderson and Cesa-Bianchi (2023). This is indeed the case as shown above. Finally, the "granular hypothesis" put forward in Gabaix (2011) suggests that aggregate phenomena can be rationalized by looking at the behavior of large firms.[47]

Unlike other studies (e.g. Anderson and Cesa-Bianchi (2023) and Palazzo and Yamarthy (2022)), we run our baseline analysis at the firm-level rather than at the security-level. As already explained above, we aggregate spreads and the EBP to the firm-level to make estimates across bonds and equities comparable. The impact of such aggregation should be negligible considering that the spread decomposition accounts for bond-specific characteristics. We nevertheless confirm that our results do not suffer from aggregation bias by rerunning the analysis at the bond-level. Table G.1 in Appendix G presents the results of model (6) estimated at the bond-level including bond, firm, and industry fixed effects. The results remain broadly in line with the firm-level results in Table 3.

A further cause for concern could be that the strong differential response of the non-fundamental component, the EBP, to shocks could be the omission of leverage and profitability from the spread model. That is, if systematic variation in leverage and earnings that is not controlled for drove the bond-level residual, this would mechanically lead to a stronger reaction of the EBP of more levered and less profitable firms. In other words, if fundamental risk factors like leverage and profitability were already fully capture in the spread model, then any

[47] Gabaix (2011) shows that idiosyncratic movements of the largest 100 US firms appear to explain about one-third of variations in output growth.

remaining differential impact of shocks on the EBP should represent truly *non-fundamental* reasons for investors pricing reactions. To ensure that our results are not driven by these potentially omitted variables, we run the spread decomposition on an augmented model where we include leverage and profitability in turn. Neither do they turn out significant in bond-level regressions, nor do they change the results of the firm-level analysis.[48]

5 Conclusion

In this paper, we study the heterogeneous impact of jointly identified monetary policy and global risk shocks on corporate funding costs and their default prospects. We disentangle these two shocks in a structural Bayesian Vector Autoregression framework and investigate their respective effects on funding costs of heterogeneous firms using micro-data for the US. We tease out mechanisms underlying the effects by contrasting financial frictions arising from traditional asset-based collateral constraints with the recent earnings-based borrowing constraint hypothesis, differentiating firms across leverage and earnings. Our empirical evidence strongly supports the earnings-based borrowing constraint hypothesis. We find that global risk shocks have stronger, persistent and more heterogeneous effects on corporate funding costs which depend on firms' position within the earnings distribution.

[48] Similarly, the results remain robust to a number of other checks, including (i) an alternative specification of the spread model that interacts regressors with an indicator variable, $\text{CALL}_{j,t}[k]$, to account for differential sensitivity of bonds with embedded options; (ii) augmenting the spread model with additional balance sheet indicators; (iii) including firm fixed effects instead of industry fixed effects; (iv) restricting the sample to only senior unsecured bonds.

References

Adrian, T., & Liang, N. (2018). Monetary policy, financial conditions, and financial stability. *International Journal of Central Banking*, *14*(1).

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., & Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, *108*, 162–179.

Anderson, G., & Cesa-Bianchi, A. (2023). Crossing the Credit Channel: Credit Spreads and Firm Heterogeneity. *American Economic Journal: Macroeconomics*, *forthcoming*.

Antolín-Díaz, J., & Rubio-Ramírez, J. F. (2018). Narrative Sign Restrictions for SVARs. *American Economic Review*, *108*(10), 2802–29. https://doi.org/10.1257/AER.20161852

Arbatli Saxegaard, E. C., Firat, M., Furceri, D., & Verrier, J. (2022). *U.S. Monetary Policy Shock Spillovers: Evidence from Firm-Level Data* (IMF Working Paper No. 2022/191). International Monetary Fund.

Arias, J. E., Rubio-Ramirez, J. F., & Waggoner, D. F. (2018). Inference Based on Structural Vector Autoregressions Identified With Sign and Zero Restrictions: Theory and Applications. *Econometrica*, *86*(2), 685–720. https://doi.org/10.3982/ECTA14468

Arrigoni, S., Bobasu, A., & Venditti, F. (2022). Measuring financial conditions using equal weights combination. *IMF Economic Review*, 1–30.

Asgharian, H. (2003). Are highly leveraged firms more sensitive to an economic downturn? *The European Journal of Finance*, *9*(3), 219–241.

Baele, L., Bekaert, G., Inghelbrecht, K., & Wei, M. (2019). Flights to Safety. *The Review of Financial Studies*, *33*(2), 689–746. https://doi.org/10.1093/rfs/hhz055

Bauer, M. D., & Swanson, E. T. (2022). *A reassessment of monetary policy surprises and high-frequency identification* (tech. rep.). National Bureau of Economic Research.

Bekaert, G., Engstrom, E. C., & Xu, N. R. (2021). The Time Variation in Risk Appetite and Uncertainty. *Management Science*, *68*(6), 3975–4004. https://doi.org/10.1287/MNSC.2021.4068

Bekaert, G., Hoerova, M., & Xu, N. R. (2021). *Risk, Monetary Policy and Asset Prices in a Global World* (mimeo No. -).

Bobasu, A., Quaglietti, L., & Ricci, M. (2023). Tracking Global Economic Uncertainty: Implications for the Euro Area. *IMF Economic Review 2023*, 1–38. https://doi.org/10.1057/S41308-023-00216-9

Brandt, L., Saint-Guilhem, A., Schröder, M., & Van Robays, I. (2021). *What drives euro area financial market developments? The role of US spillovers and global risk* (ECB Working Paper Series No. 2560). European Central Bank.

Brave, S., & Butters, R. A. (2018). Diagnosing the financial system: Financial conditions and financial stress. *29th issue (June 2012) of the International Journal of Central Banking*.

Caballero, J., Fernández, A., & Park, J. (2019). On corporate borrowing, credit spreads and economic activity in emerging economies: An empirical investigation. *Journal of In-*

ternational Economics, *118*, 160–178. https://doi.org/http://dx.doi.org/10.17632/6szztjpmdn.1

Caglio, C. R., Darst, M. R., & Kalemli-Özcan, S. (2021). *Collateral heterogeneity and monetary policy transmission: evidence from loans to SMEs and large firms* (NBER Working Paper No. 28685). National Bureau of Economic Research.

Caldara, D., Iacoviello, M., Kane, A., Cole-Smith, B., Singer, C., Markiewitz, E., Choudhary, F., Herman, J., Husted, L., Penn, M., Molligo, P., Conlisk, S., & Dhin, T. (2022). Measuring Geopolitical Risk. *American Economic Review*, *112*(4), 1194–1225. https://doi.org/10.1257/AER.20191823

Camara, S., & Sangiacomo, M. (2022). *Borrowing Constraints in Emerging Markets* (Mimeo No. -).

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust Inference With Multiway Clustering. *Journal of Business & Economic Statistics*, *29*(2), 238–249. https://doi.org/10.1198/jbes.2010.07136

Cao, J., Hegna, T., Holm, M. B., Juelsrud, R., König, T., & Riiser, M. (2023). *The Investment Channel of Monetary Policy: Evidence from Norway* (Norges Bank Working Paper No. 5/2023). Norges Bank.

Cavallo, E. A., & Valenzuela, P. (2009). The determinants of corporate risk in emerging markets: an option-adjusted spread analysis. *International Journal of Finance & Economics*, *15*(1), 59–74. https://doi.org/10.1002/ijfe.398

Ca'Zorzi, M., Dedola, L., Georgiadis, G., Jarocinski, M., Stracca, L., & Strasser, G. (2023). Making waves: Monetary policy and its asymmetric transmission in a globalized world. *International Journal of Central Banking*, *19*(2), 95–144.

Cieslak, A., & Schrimpf, A. (2019). Non-monetary news in central bank communication. *Journal of International Economics*, *118*, 293–315. https://doi.org/10.1016/J.JINTECO.2019.01.012

Cloyne, J., Ferreira, C., Froemel, M., & Surico, P. (2018). *Monetary Policy, Corporate Finance and Investment* (NBER Working Paper No. 25366). NBER.

Dedola, L., Karadi, P., & Lombardo, G. (2013). Global implications of national unconventional policies. *Journal of Monetary Economics*, *60*(1), 66–85.

Dedola, L., & Lombardo, G. (2012). Financial frictions, financial integration and the international propagation of shocks. *Economic Policy*, *27*(70), 319–359.

Drechsel, T. (2023). Earnings-Based Borrowing Constraints and Macroeconomic Fluctuations. *American Economic Journal: Macroeconomics*, (-).

Drechsel, T., & Kim, S. (2022). *Macroprudential policy with earnings-based borrowing constraints* (CEPR Discussion Paper No. DP17561). Center for Economic Policy Research.

Engel, C. (2014). Exchange rates and interest parity. *Handbook of international economics*, *4*, 453–522.

Fabiani, A., Falasconi, L., & Heineken, J. (2022). *Monetary Policy and Corporate Debt Maturity* (Mimeo No. -).

Ferreira, T. R. T., Ostry, D. A., & Rogers, J. (2023). *Firm Financial Conditions and the Transmission of Monetary Policy* (Finance and Economics Discussion Paper No. 2023-037). Federal Reserve Board. Washington, DC.

Financial Times. (2021, May). Is leverage still the best benchmark of credit risk?

Financial Times. (2023a, January). Opinion unhedged: Japan, inflated.

Financial Times. (2023b, January). Opinion unhedged: What we know about inflation. Are we heading for a corporate debt crisis? (Part 2).

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The journal of Finance*, *57*(5), 2223–2261.

Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica*, *79*(3), 733–772. https://doi.org/10.3982/ECTA8769

Gabaix, X., Krishnamurthy, A., & Vigneron, O. (2007). Limits of Arbitrage: Theory and Evidence from the Mortgage-Backed Securities Market. *The Journal of Finance*, *62*(2), 557–595. https://doi.org/10.1111/J.1540-6261.2007.01217.X

Georgiadis, G., & Jarociński, M. (2025). Global spillovers from multi-dimensional us monetary policy. *Journal of International Economics*, 104169.

Georgiadis, G., Müller, G. J., & Schumann, B. (2024). Global risk and the dollar. *Journal of Monetary Economics*, *144*, 103549.

Gilchrist, S., & Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, *102*(4), 1692–1720. https://doi.org/10.1257/aer.102.4.1692

Gomes, J., Jermann, U., & Schmid, L. (2016). Sticky Leverage. *American Economic Review*, *106*(12), 3800–3828. https://doi.org/10.1257/AER.20130952

Greenwald, D. L. (2019). *Firm Debt Covenants and the Macroeconomy: The Interest Coverage Channel* (MIT Sloan Research Paper No. 5909-19). Massachusetts Institute of Technology.

Guo, H., Kontonikas, A., & Maio, P. (2020). Monetary Policy and Corporate Bond Returns. *The Review of Asset Pricing Studies*, *10*(3), 441–489. https://doi.org/10.1093/RAPSTU/RAAA005

Gürkaynak, R. S., Karasoy-Can, G. H., & Lee, S. S. (2022). Stock Market's Assessment of Monetary Policy Transmission: The Cash Flow Effect. *Journal of Finance*, *77*(4), 2375–2421.

Hatzius, J., Hooper, P., Mishkin, F. S., Schoenholtz, K. L., & Watson, M. W. (2010). *Financial conditions indexes: A fresh look after the financial crisis* (tech. rep.). National Bureau of Economic Research.

Jarociński, M., & Karadi, P. (2020). Deconstructing Monetary Policy Surprises–The Role of Information Shocks. *American Economic Journal: Macroeconomics*, *12*(2), 1–43. https://doi.org/10.1257/MAC.20180090

Jayawickrema, V., & Swanson, E. (2021). Speeches by the fed chair are more important than fomc announcements: An improved high-frequency measure of us monetary policy shocks.

Jeenas, P. (2019). *Monetary Policy Shocks, Financial Structure, and Firm Activity: A Panel Approach* (mimeo No. -).

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *American Economic Review*, *76*(2), 323–329.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182. https://doi.org/10.1257/0002828053828518

Jungherr, J., Meier, M., Reinelt, T., & Schott, I. (2022). *Corporate Debt Maturity Matters For Monetary Policy* (Mimeo No. -).

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177–1216.

Kekre, R., & Lenel, M. (2024). The flight to safety and international risk sharing. *American Economic Review*, *114*(6), 1650–1691.

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101–116.

Lian, C., & Ma, Y. (2020). Anatomy of Corporate Borrowing Constraints. *The Quarterly Journal of Economics*, *136*(1), 229–291. https://doi.org/10.1093/QJE/QJAA030

Matheson, T., & Stavrev, E. (2014). News and monetary shocks at a high frequency: A simple approach. *Economics Letters*, *125*(2), 282–286.

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470. https://doi.org/10.1111/J.1540-6261.1974.TB03058.X

Miranda-Agrippino, S., & Rey, H. (2020). U.S. Monetary Policy and the Global Financial Cycle. *The Review of Economic Studies*, *87*(6), 2754–2776. https://doi.org/10.1093/restud/rdaa019

Miranda-Agrippino, S., & Rey, H. (2022). The Global Financial Cycle. *Handbook of International Economics*, *5*.

Moody's Analytics. (2011). *EDF (Expected Default Frequency) Overview* (Credit Research and Risk Measurement Brochure No. -). Moody's Analytics.

O'Kane, D., & Sen, S. (2005). Credit spreads explained. *The Journal of Credit Risk*, *1*(2), 61–78. https://doi.org/10.21314/JCR.2005.009

Ottonello, P., Perez, D. J., & Varraso, P. (2022). Are collateral-constraint models ready for macroprudential policy design? *Journal of International Economics*, 103650. https://doi.org/10.1016/J.JINTECO.2022.103650

Öztürk, Ö. (2022). *Debt Contracts, Investment, and Monetary Policy* (Mimeo No. -).

Palazzo, B., & Yamarthy, R. (2022). Credit Risk and the Transmission of Interest Rate Shocks. *Journal of Monetary Economics*, (forthcoming). https://doi.org/https://doi.org/10.1016/j.jmoneco.2022.06.004

Piffer, M., Podstawski, M., Bachmann, R., Große Steffen, C., Hachula, M., Pinder, J., Pothier, D., Mumtaz, H., Ravn, M., & Rieth, M. (2018). Identifying Uncertainty Shocks Using the Price of Gold. *The Economic Journal*, *128*(616), 3266–3284. https://doi.org/10.1111/ECOJ.12545

Rey, H. (2015). *Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence* (NBER Working Paper No. 21162).

Rigobon, R., & Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of monetary economics*, *51*(8), 1553–1575.

Smolyansky, M., & Suarez, G. (2021). *Monetary policy and the corporate bond market: How important is the Fed information effect?* (Finance and Economics Discussion Series No. 2010-010). Federal Reserve Board. Washington, DC.

Wruck, K. H. (1990). Financial distress, reorganization, and organizational efficiency. *Journal of Financial Economics*, *27*(2), 419–444. https://doi.org/10.1016/0304-405X(90)90063-6

Xu, N. (2019). *Global Risk Aversion and International Return Comovements* (Mimeo No. -).

Appendices

Appendix A BVAR Model Validation

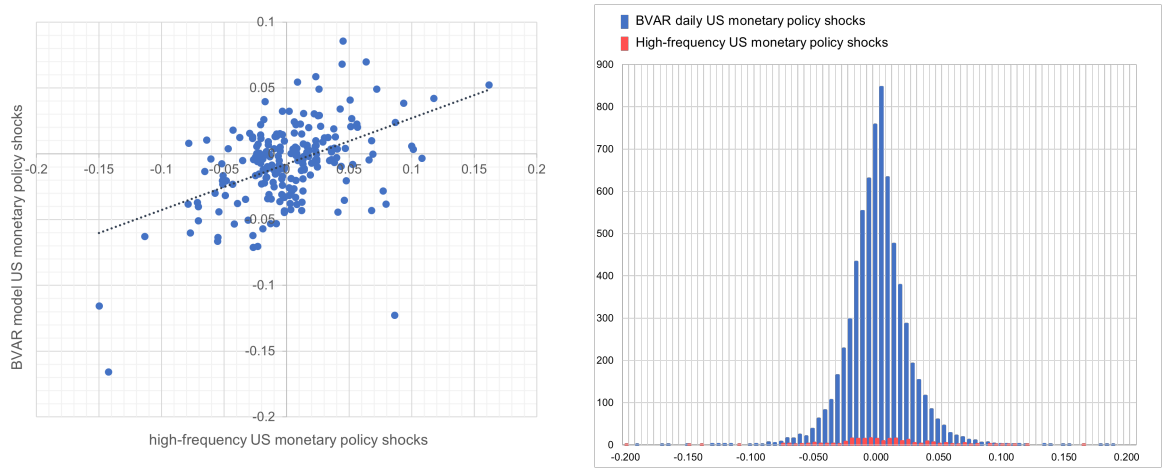


Figure A.1: Comparison BVAR monetary policy shocks versus high-frequency approach

Note: The left panel shows the correlation between the US monetary policy shocks identified in the BVAR and the high-frequency shocks on days of FOMC meetings following Jarociński and Karadi (2020), using the contribution of the US monetary policy shocks to the 10-year interest rate of the BVAR model on the day of the FOMC meeting and the 10-year interest rate instrument for the high-frequency shocks. This scatter plot leaves out the monetary policy shock linked to the strong reaction of the Fed in the wake of the global financial crisis, which in terms of magnitude is an outlier but which is very similarly identified in both empirical approaches and makes the correlation stronger than depicted on the chart. The right panel compares the histogram of the daily US monetary policy shock contribution to 10-year yields of the BVAR with that of the high-frequency shocks on FOMC dates using the 10-year rate as instrument.

Table A.1: Robustness BVAR: shock correlations

	US monetary policy shock	global risk shock
Test 1: no rel. restriction on US NEER	0.9993	0.9910
Test 2: corp. spread not restricted after US macro	0.9944	0.9865
Test 3: US policy and global risk shock only	0.9634	0.9671
Test 4: 1 lag	0.9972	0.9792
Test 5: 2 lags	0.9991	0.9817
Test 6: 3 lags	0.9988	0.9838
Test 7: 5 lags	0.9979	0.9834
Test 8: 6 lags	0.9973	0.9838

Notes: The table shows the correlation between the US monetary policy and global risk shock of the benchmark BVAR model and the shocks as identified in alternative versions. Test 1 does not impose the relative magnitude restriction that a global risk shock should have larger effects on the US nominal effective exchange rate than a foreign macro risk shock; test 2 leaves out the sign restriction on corporate bond spreads following a US macro risk shock; test 3 only identifies the US monetary policy and the global risk shock in the BVAR model (using the same restrictions for the two shocks as in Table 1), leaving the other shocks unidentified; test 4-8 test the structural shock correlations for different lag lengths of the endogenous variables in the BVAR.

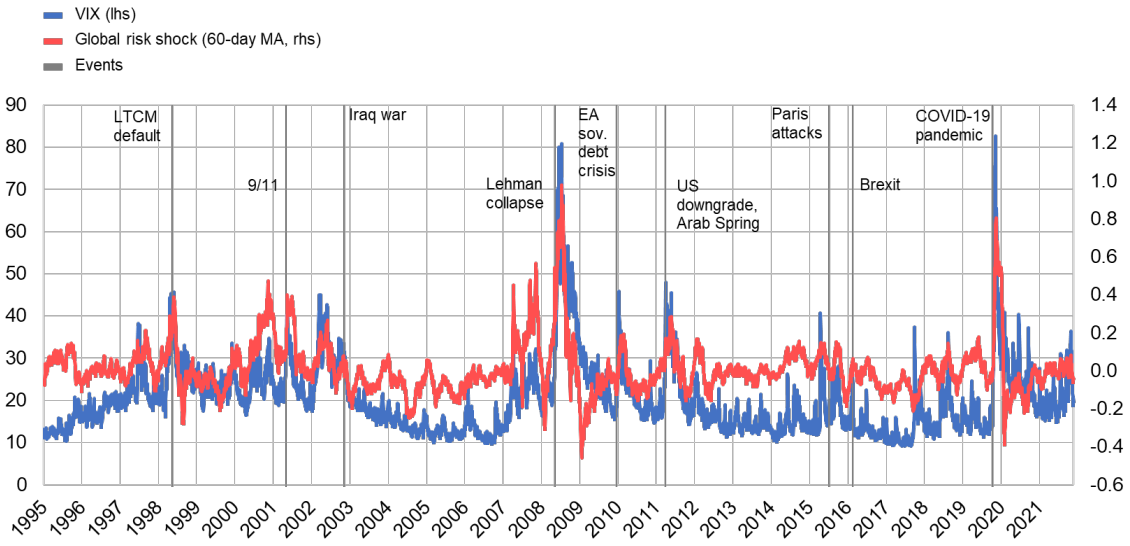


Figure A.2: Comparison global risk shocks series with VIX

Note: The chart shows the 60-day moving average of the global risk shock obtained from the daily BVAR, the CBOE volatility index (VIX), and selected narrative events.

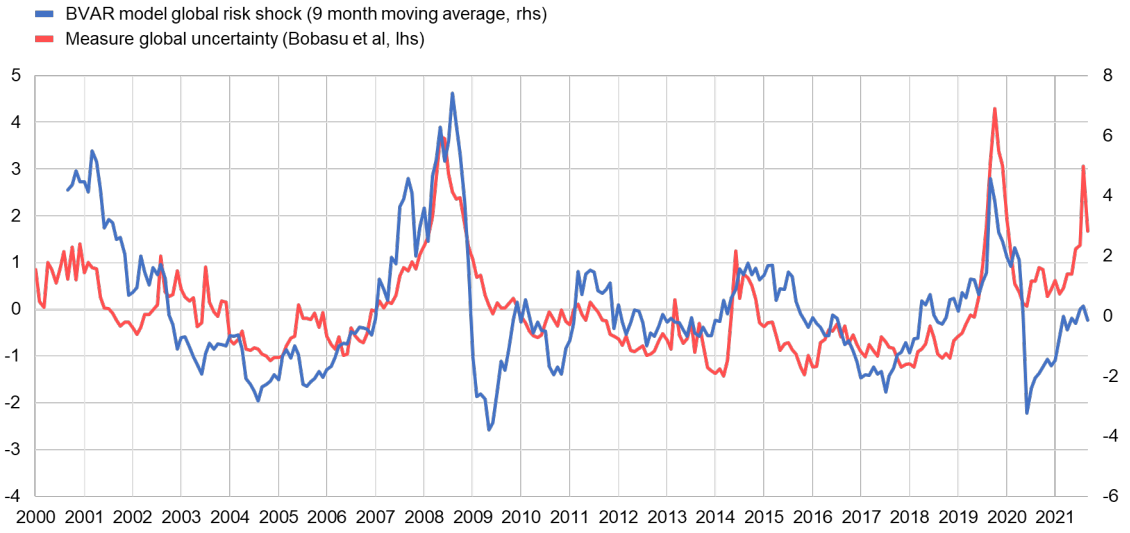


Figure A.3: Comparison global risk shocks with global uncertainty measure

Note: This chart shows the 9-month moving average of the global risk shock obtained from the daily BVAR and the measure of global uncertainty by Bobasu et al. (2023).

Appendix B Details of Bond- and Firm-Level Data

Table B.1: Reduction in OAS bond-week observations for each data trimming step

	No. of remaining bond-week obs.
No. OAS observations before trimming	2,272,931
(i) Drop volume $<$ 1mil and volume $>$ 5bn	2,262,348
(ii) Drop term-to-maturity $<$ 1 year and $>$ 30 years	2,194,404
(iii) Drop OAS < -500 and OAS $> 4,500$	2,186,060
(iv) Drop OAS if illiquid $>$ 26 weeks in a row	2,186,060
(v) Drop bond if there exist $<$ 26 consecutive bond-week obs.	2,185,478
No. OAS observations after trimming	**2,185,478**

Note: This table presents the total count N of bond-week observations of option-adjusted spreads (OAS) after each step in the data trimming process. The cut-offs in steps (i) and (ii) are calibrated in line with Gilchrist and Zakrajšek (2012). The cut-offs in steps (iii)-(v) are conservatively chosen to remove extreme outliers and stale bond observations, yet preserve important characteristics of the tails of the OAS distribution.

Table B.2: Industry coverage of estimation sample

	Unique bonds	Unique firms
Basic Industry	314	20
Capital Goods	1200	54
Communications	779	28
Consumer Cyclical	914	64
Consumer Non-Cyclical	1913	88
Electric	388	23
Energy	639	39
Insurance	188	6
Natural Gas	70	4
Other Industrial	4	2
Technology	726	62
Transportation	383	13

Note: This table presents details on the unique number of bonds and firms by industry covered in the estimation sample that is used in the credit spread decomposition. The estimation sample is an *unbalanced* panel at the bond-firm level.

Appendix C Additional Descriptive Statistics

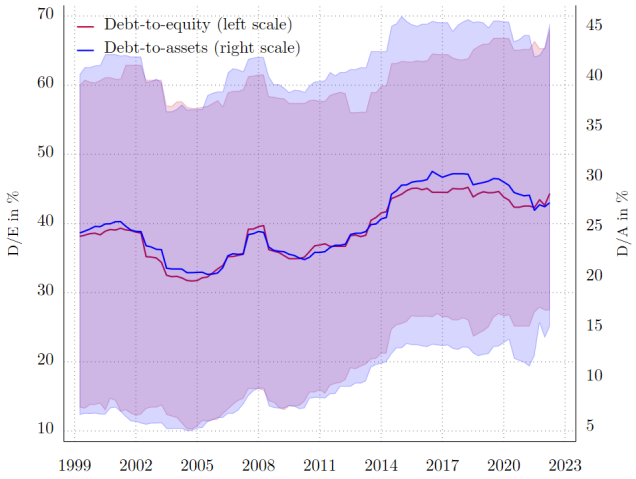


Figure C.1: Distribution of balance sheet proxies for financial leverage

Note: This chart presents the median (solid line) and 20th and 80th percentiles (shaded area) of the debt-to-equity and debt-to-asset ratios across the sample of S&P 500 firms.

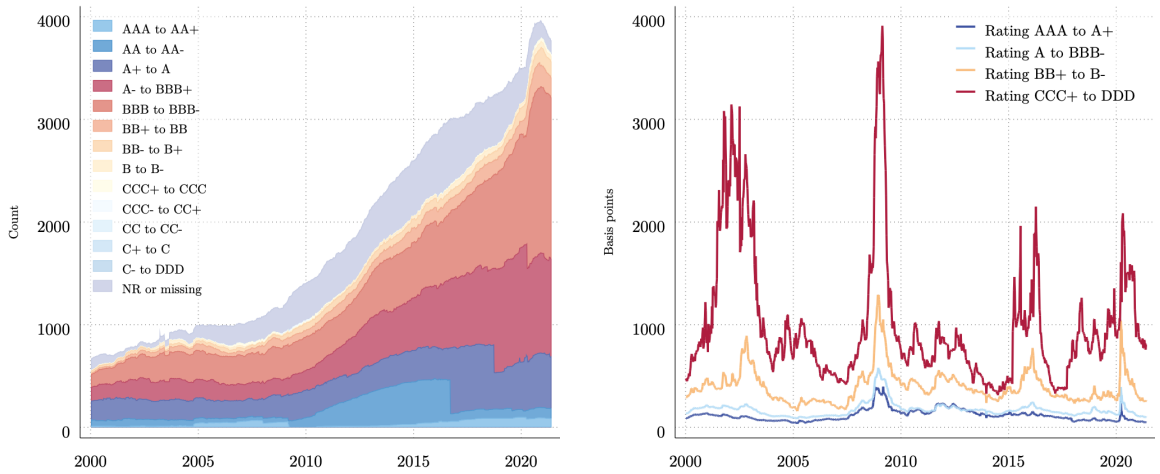


Figure C.2: Count of bond-week observations by rating category and the distribution of option-adjusted spreads (OAS) across ratings

Note: The left panel shows the count of bond-week observations for which the option-adjusted spread (OAS) series is available across Bloomberg composite bond rating categories. The right panel shows the average OAS across subsets the same rating categories.

Appendix D Spread Decomposition

D.1 Comparison with GZ spread model

Our estimation of the excess bond premium (EBP) differs from Gilchrist and Zakrajšek (2012) (GZ) in two ways. First, the choice of data and resulting sample differ. While we use S&P500 firms, GZ use a broader set of firms. Our sample period spans weekly observations from January 2000 to December 2021, GZ's monthly data starts in 1973 and ends in 2010. GZ use month-end credit spreads and estimate at monthly frequency. We use week-end credit spreads and estimate the EBP at weekly frequency. We believe that the high frequency feature of our data is more conducive to studying the reactions of asset prices to financial shocks and their channels. Note also that it is unclear how often GZ update their sample of bonds used to compute the EBP. We include all bonds issued before 28 May 2021 with a remaining term to maturity of at most 30 years.

Our measure of spreads is the option-adjusted spread (OAS) and our measure of credit risk is based on Moody's EDFs. By contrast, GZ employ a bottom up approach to both of these measures. They construct the so-called "GZ spread" based on a synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate debt instrument (following Gürkaynak, Sack and Wright, 2007). Moreover, they estimate the distance to default based on a Merton-type model. Following the choice of spread measure, GZ spreads range from 5 bsp to 3500 bsp. Our trimmed spreads range from -500 bsp to 4500 bsp due to the nature of OAS spreads.

Second, our estimation of the EBP departs from GZ's spread model in a number of ways. GZ use bond characteristics and, additionally, interaction terms of callable bond indicator variables with bond characteristics. We use only bond characteristics as option-adjusted spreads correct for pricing effects of embedded options. GZ also control for liquidity premia by interacting regressors with the slope, level, and curvature of the yield curve. Again, the OAS already accounts for these liquidity premia. Notwithstanding, we ascertain in Section 4 that the results of the panel LP exercise remain virtually invariant to augmenting the spread model with additional interaction terms. By virtue of the distribution of positive as well as negative OAS values, we refrain from estimating the spread model with log-spreads in contrast to GZ. Robustness checks however indicate that excluding bonds with negative OAS values from the sample does not materially affect the results.

To control for systematic variation across firms and industries, GZ include firm-level ratings fixed effects (S&P rating) and industry fixed effects based on three-digit NAICs industry codes. We limit the granularity of industry fixed effects by using Bloomberg's BICS industry classification. Irrespective of the exclusion of firm fixed effects, our EBP remains highly correlated with the GZ-EBP at the aggregate level. While not part of the baseline specification, for some specifications we include bond-level ratings fixed effects based on Bloomberg's composite bond rating. The results remain robust to this inclusion.

D.2 Estimation results of spread model

Table D.1: Credit spread decomposition based on the *full* sample

	(1) Est.	SE	(2) Est.	SE
$EDF_{j,t}$	59.396***	9.207	54.617***	17.333
$Duration_{j,t}[k]$	3.316***	0.448	4.680***	0.681
$Coupon_j[k]$	27.350***	2.312	20.905***	2.901
$Age_{j,t}[k]$	-1.986***	0.565	-0.684	0.601
$Volume_j[k]$	-5.979	4.838	-9.527	6.120
$CALL_j[k]$	3.599	4.657	-34.402**	13.505
$EDF_{j,t}$ x $CALL_j[k]$			7.258	16.264
$Duration_{j,t}[k]$ x $CALL_j[k]$			-2.257***	0.674
$Coupon_j[k]$ x $CALL_j[k]$			12.778***	2.881
$Age_{j,t}[k]$ x $CALL_j[k]$			-4.463***	0.871
$Volume_j[k]$ x $CALL_j[k]$			7.611	5.961
Industry FE	YES		YES	
Observations	2,207,373		2,207,373	
Adjusted R^2	0.424		0.430	

Note: The sample period covers 2000/01/07 – 2021/12/17. The dependent variable is the option-adjusted spread (OAS). Standard errors are clustered in the firm and time dimension following Cameron et al. (2011). Daily expected default frequencies (EDFs) at the 1-year horizon are converted into weekly averages. The indicator variable $CALL_j[k]$ is one for bonds with any type of underlying call option. Industry fixed effects are based on the BICS industry level 3 classification system.

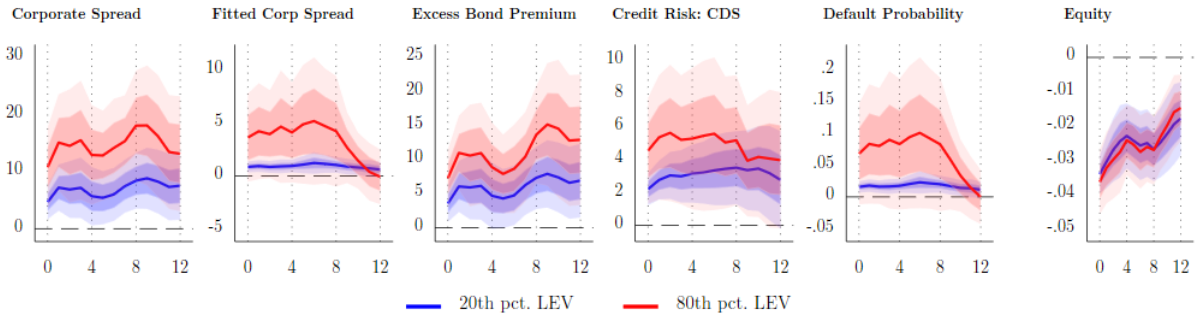
Table D.2: Credit spread decomposition based on a restricted sample of only *senior unsecured* bonds

	(1) Est.	SE	(2) Est.	SE
$EDF_{j,t}$	55.651***	12.542	47.456***	16.470
$Duration_{j,t}[k]$	3.131***	0.561	3.715***	0.940
$Coupon_j[k]$	26.266***	2.879	22.747***	3.744
$Age_{j,t}[k]$	-1.598***	0.559	-0.849	0.582
$Volume_j[k]$	-9.948**	4.963	-13.050**	6.178
$CALL_j[k]$	-3.497	4.620	-31.098**	13.678
$EDF_{j,t}$ x $CALL_j[k]$			17.568	14.931
$Duration_{j,t}[k]$ x $CALL_j[k]$			-0.875	0.910
$Coupon_j[k]$ x $CALL_j[k]$			7.545**	3.498
$Age_{j,t}[k]$ x $CALL_j[k]$			-2.783***	0.911
$Volume_j[k]$ x $CALL_j[k]$			7.070	5.979
Industry FE	YES		YES	
Observations	1,776,736		1,776,736	
Adjusted R^2	0.403		0.411	

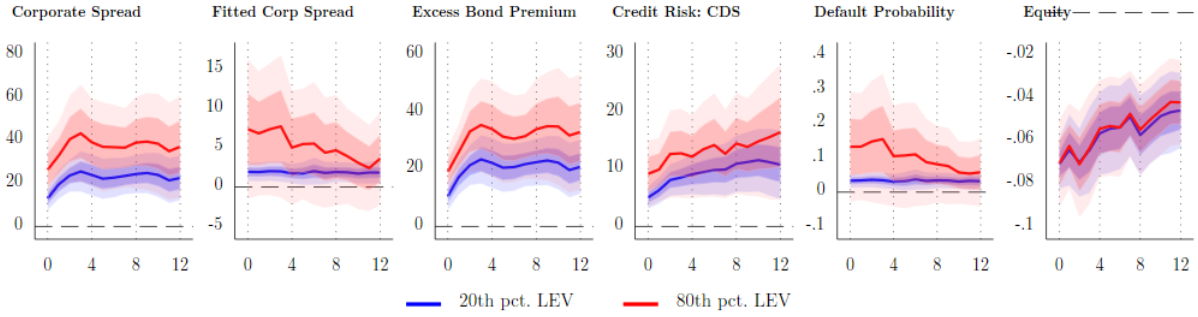
Note: The sample period covers 2000/01/07 – 2021/12/17. The dependent variable is the option-adjusted spread (OAS). Standard errors are clustered in the firm and time dimension following Cameron et al. (2011). Daily expected default frequencies (EDFs) at the 1-year horizon are converted into weekly averages. The indicator variable $CALL_j[k]$ is one for bonds with any type of underlying call option. Industry fixed effects are based on the BICS industry level 3 classification system.

Appendix E Supplementary results: firm-level local projections

E.1 Responses to shocks across weak and strong firms



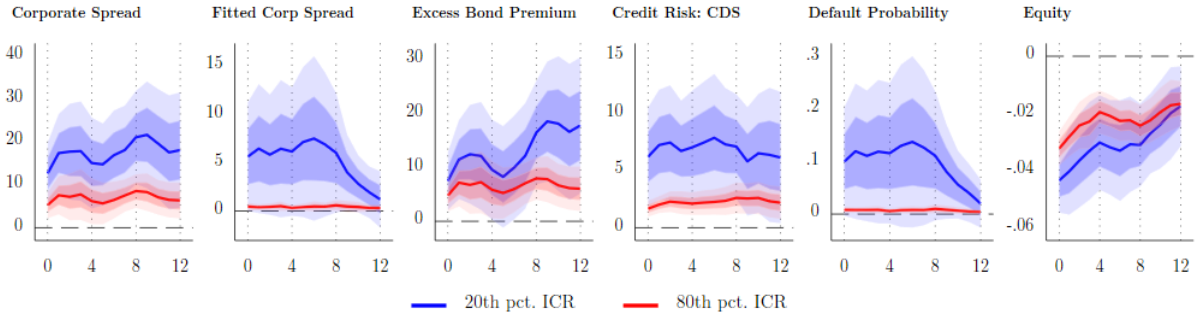
(a) Monetary policy shock s_t^m



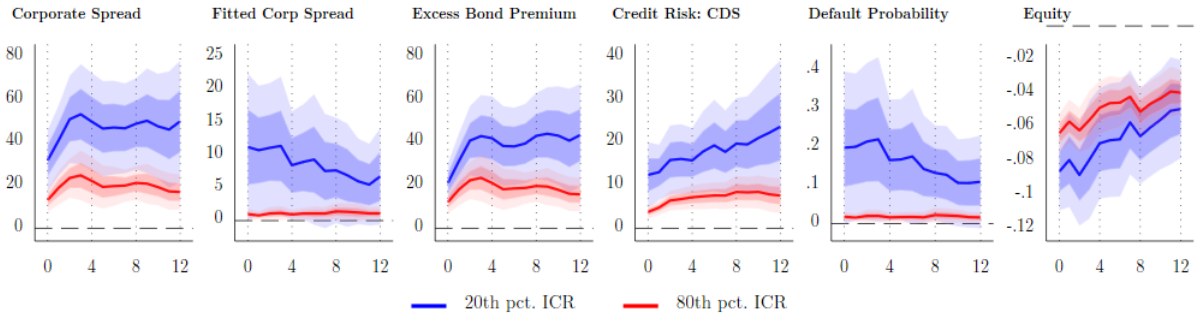
(b) Global risk shock s_t^r

Figure E.3: Cumulative responses of asset pricing variables to identified shocks for weak/strong firms by leverage (**LEV**)

Note: This figure presents the impulse responses of a set of asset pricing variables to a monetary policy shock s_t^m and a global risk shock s_t^r. The responses are obtained from estimating model (6) over a 12-week horizon $h = 12$ over the sample period from 01/2000-12/2021. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The excess bond premium and fitted corporate spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the period 01/2000-12/2021. Shaded areas denote 95% and 68% confidence bands.



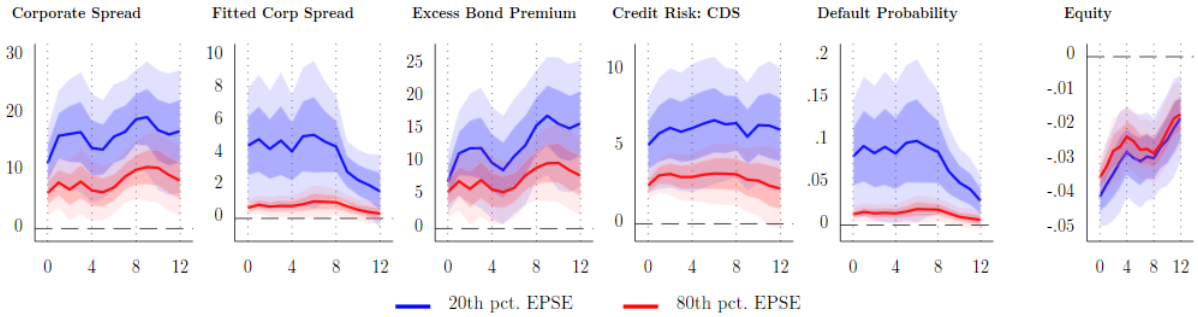
(a) Monetary policy shock s_t^m



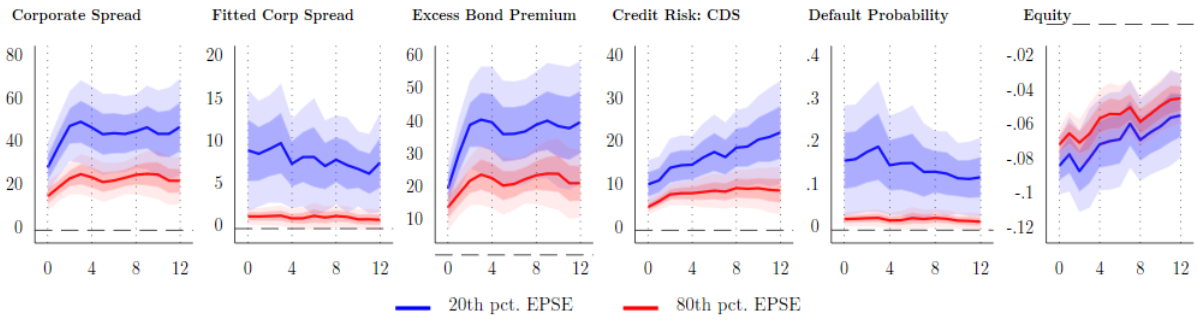
(b) Global risk shock s_t^r

Figure E.4: Cumulative responses of asset pricing variables to identified shocks for weak/strong firms by interest coverage ratio (**ICR**)

Note: This figure presents the impulse responses of a set of asset pricing variables to a monetary policy shock s_t^m and a global risk shock s_t^r. The responses are obtained from estimating model (6) over a 12-week horizon $h = 12$ over the sample period from 01/2000-12/2021. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The excess bond premium and fitted corporate spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the period 01/2000-12/2021. Shaded areas denote 95% and 68% confidence bands.



(a) Monetary policy shock s_t^m

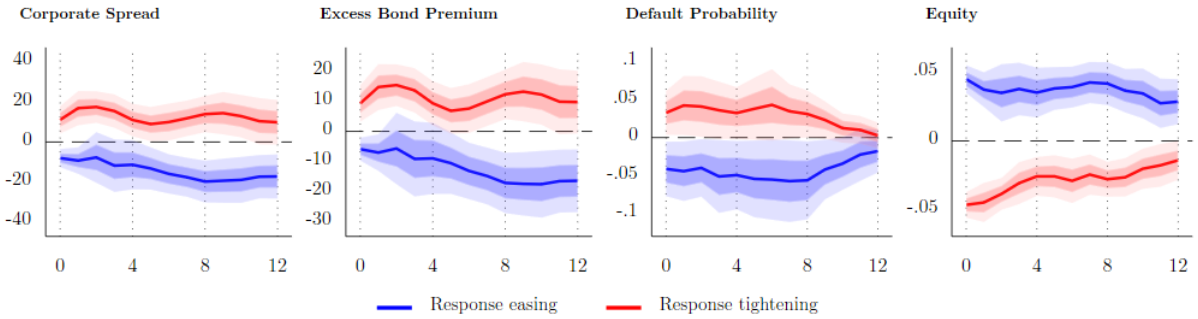


(b) Global risk shock s_t^r

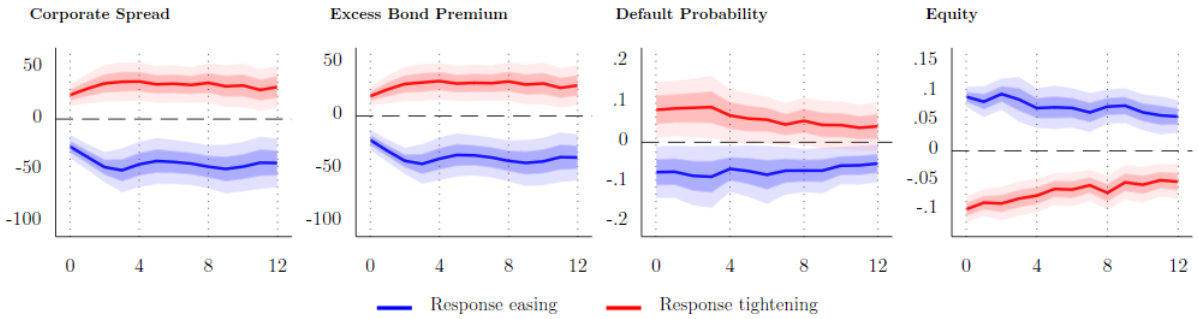
Figure E.5: Cumulative responses of asset pricing variables to identified shocks for weak/strong firms by expected earnings per share (**EPSE**)

Note: This figure presents the impulse responses of a set of asset pricing variables to a monetary policy shock s_t^m and a global risk shock s_t^r. The responses are obtained from estimating model (6) over a 12-week horizon $h = 12$ over the sample period from 01/2000-12/2021. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The excess bond premium and fitted corporate spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the period 01/2000-12/2021. Shaded areas denote 95% and 68% confidence bands.

E.2 Asymmetric responses to tightening and easing shocks



(a) Monetary policy tightening (+) and easing (−) shocks s_t^m



(b) Global risk tightening (−) and easing (+) shocks s_t^r

Figure E.6: Cumulative responses of asset pricing variables to identified tightening and easing shocks

Note: This figure presents the impulse responses of a set of asset pricing variables to a monetary policy shock ϵ^m and a global risk shock ϵ^r. The responses are obtained from estimating model (6) over a 12-week horizon $h = 12$ over the sample period from 01/2000-12/2021. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The excess bond premium and fitted corporate spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the period 01/2000-12/2021. Shaded areas denote 95% and 68% confidence bands.

Appendix F Robustness: firm-level panel regressions

F.1 Baseline results: Extended set of estimates of asset price reactions

Table F.1: Baseline results: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

1

	(1) ΔSpread	(2) $\Delta\widehat{\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
ε_t^m	7.395***	1.547*	5.889**	3.118***	0.028*	-0.035***
ε_t^m	7.261***	1.106**	6.220***	2.932***	0.020**	-0.035***
LowLEV $\times$ ε_t^m	-1.167	-0.136	-1.277	-0.431**	-0.003	0.000
HighLEV $\times$ ε_t^m	1.842	2.462	-0.537	1.351	0.045	-0.002
ε_t^m	7.001***	0.850**	6.145***	2.795***	0.016**	-0.034***
LowICR $\times$ ε_t^m	2.670	4.182	-1.178	2.494	0.073	-0.007*
HighICR $\times$ ε_t^m	-0.358	-0.219*	-0.126	-0.722**	-0.005**	0.001
ε_t^m	7.140***	1.166**	5.938***	2.894***	0.021**	-0.034***
LowEPSE $\times$ ε_t^m	1.861	2.715*	-0.652	1.544*	0.048*	-0.004*
HighEPSE $\times$ ε_t^m	0.034	-0.385	0.468	-0.149	-0.006	-0.001*
Panel (b): Global risk shock						
ε_t^r	18.628***	3.200*	15.472***	6.615***	0.056*	-0.069***
ε_t^r	17.502***	2.246**	15.406***	6.125***	0.039**	-0.068***
LowLEV $\times$ ε_t^r	-4.942	-0.357	-5.107**	-1.195*	-0.006	-0.003
HighLEV $\times$ ε_t^r	10.456	5.370	5.000*	3.643	0.099	-0.002
ε_t^r	15.858***	1.542**	14.366***	5.558***	0.027**	-0.065***
LowICR $\times$ ε_t^r	18.773**	9.965*	9.504**	7.758*	0.176*	-0.022*
HighICR $\times$ ε_t^r	-3.616**	-0.628*	-2.995*	-2.036***	-0.011*	0.002
ε_t^r	16.439***	2.139**	14.232***	5.872***	0.037**	-0.065***
LowEPSE $\times$ ε_t^r	15.194***	7.041**	8.416***	5.022**	0.126**	-0.019***
HighEPSE $\times$ ε_t^r	-1.695	-0.700	-0.788	-0.603	-0.013	-0.005
Industry FE	YES	YES	YES	YES	YES	YES
Observations	222,060	219,575	219,513	219,821	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$, i.e. upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)). The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(5). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table F.2: Baseline results: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6) **normalized to 1 stdev**.

	(1) ΔSpread	(2) $\widehat{\Delta\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
ε_t^m	1.989***	0.416*	1.584**	0.839***	0.008*	-0.009***
ε_t^m	1.953***	0.298**	1.673***	0.789***	0.005**	-0.009***
LowLEV $\times$ ε_t^m	-0.314	-0.037	-0.343	-0.116**	-0.001	0.000
HighLEV $\times$ ε_t^m	0.495	0.662	-0.145	0.363	0.012	-0.001
ε_t^m	1.883***	0.229**	1.653***	0.752***	0.004**	-0.009***
LowICR $\times$ ε_t^m	0.718	1.125	-0.317	0.671	0.020	-0.002*
HighICR $\times$ ε_t^m	-0.096	-0.059*	-0.034	-0.194**	-0.001**	0.000
ε_t^m	1.920***	0.314**	1.597***	0.778***	0.006**	-0.009***
LowEPSE $\times$ ε_t^m	0.501	0.730*	-0.175	0.415*	0.013*	-0.001*
HighEPSE $\times$ ε_t^m	0.009	-0.104	0.126	-0.040	-0.002	-0.000*
Panel (b): Global risk shock						
ε_t^r	2.643***	0.454*	2.195***	0.939***	0.008*	-0.010***
ε_t^r	2.483***	0.319**	2.186***	0.869***	0.005**	-0.010***
LowLEV $\times$ ε_t^r	-0.701	-0.051	-0.725**	-0.170*	-0.001	-0.000
HighLEV $\times$ ε_t^r	1.484	0.762	0.709*	0.517	0.014	-0.000
ε_t^r	2.250***	0.219**	2.038***	0.789***	0.004**	-0.009***
LowICR $\times$ ε_t^r	2.664**	1.414*	1.348**	1.101*	0.025*	-0.003*
HighICR $\times$ ε_t^r	-0.513**	-0.089*	-0.425*	-0.289***	-0.002*	0.000
ε_t^r	2.332***	0.303**	2.019***	0.833***	0.005**	-0.009***
LowEPSE $\times$ ε_t^r	2.156***	0.999**	1.194***	0.713**	0.018**	-0.003***
HighEPSE $\times$ ε_t^r	-0.240	-0.099	-0.112	-0.085	-0.002	-0.001
Industry FE	YES	YES	YES	YES	YES	YES
Observations	222,060	219,575	219,513	219,821	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$, i.e. upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)), normalized to a 1 standard deviation adverse shock. The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(5). The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for p < 0.01, ** for p < 0.05, * for p < 0.1).

F.2 Results of baseline model for shorter sample period 2005-2021

Table F.3: Shorter time period 2005-2021: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

	(1) ΔSpread	(2) $\Delta\widehat{\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
ε_t^m	7.507***	1.563*	5.985**	3.195***	0.028*	-0.035***
ε_t^m	7.362***	1.110**	6.321***	2.994***	0.020**	-0.035***
LowLEV $\times$ ε_t^m	-1.297	-0.139	-1.432	-0.468**	-0.003	0.000
HighLEV $\times$ ε_t^m	2.002	2.528	-0.433	1.461	0.043	-0.002
ε_t^m	7.068***	0.846**	6.214***	2.853***	0.016**	-0.034***
LowICR $\times$ ε_t^m	2.910	4.309	-1.035	2.660	0.072	-0.007*
HighICR $\times$ ε_t^m	-0.369	-0.253*	-0.107	-0.796***	-0.005**	0.001
ε_t^m	7.216***	1.143**	6.036***	2.951***	0.021**	-0.034***
LowEPSE $\times$ ε_t^m	2.060	2.928*	-0.646	1.705*	0.049*	-0.004*
HighEPSE $\times$ ε_t^m	0.041	-0.370	0.457	-0.186	-0.006	-0.001
Panel (b): Global risk shock						
ε_t^r	18.886***	3.249*	15.684***	6.724***	0.056*	-0.069***
ε_t^r	17.767***	2.308**	15.610***	6.225***	0.039**	-0.069***
LowLEV $\times$ ε_t^r	-5.054	-0.370	-5.211**	-1.176	-0.007	-0.003
HighLEV $\times$ ε_t^r	10.520	5.316	5.136*	3.676	0.095	-0.002
ε_t^r	16.085***	1.585**	14.546***	5.662***	0.027**	-0.066***
LowICR $\times$ ε_t^r	18.983**	9.962	9.783**	7.791*	0.172*	-0.022*
HighICR $\times$ ε_t^r	-3.717**	-0.615*	-3.099*	-2.065***	-0.011*	0.002
ε_t^r	16.627***	2.143**	14.418***	5.949***	0.037**	-0.065***
LowEPSE $\times$ ε_t^r	15.674***	7.260**	8.705***	5.187**	0.125**	-0.019***
HighEPSE $\times$ ε_t^r	-1.736	-0.657	-0.880	-0.582	-0.012	-0.005
Industry FE	YES	YES	YES	YES	YES	YES
Observations	204,863	202,558	202,521	202,654	203,245	203,608

Note: This table presents the estimates of model (6) at horizon $h = 0$, i.e. upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)), for a shorter time period from 2005 to 2021. The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(4). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2005/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

F.3 Results of baseline model augmented with lagged dependent variable

Table F.4: Lagged dependent variables: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

	(1) ΔSpread	(2) $\widehat{\Delta\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
ε_t^m	7.228***	1.567*	5.718**	3.166***	0.029*	-0.035***
ε_t^m	7.109***	1.160**	6.046**	2.994***	0.021**	-0.035***
LowLEV × ε_t^m	-1.065	-0.146	-1.100	-0.420**	-0.003	0.000
HighLEV × ε_t^m	1.666	2.297	-0.674	1.268	0.043	-0.002
ε_t^m	6.811***	0.900**	5.963***	2.855***	0.017**	-0.034***
LowICR × ε_t^m	2.628	4.031	-1.289	2.431	0.072	-0.007*
HighICR × ε_t^m	-0.197	-0.230*	0.034	-0.726**	-0.005**	0.001
ε_t^m	6.993***	1.186**	5.782**	2.942***	0.021**	-0.034***
LowEPSE × ε_t^m	1.822	2.691*	-0.670	1.545*	0.049*	-0.004*
HighEPSE × ε_t^m	-0.040	-0.366	0.399	-0.151	-0.005	-0.001
Panel (b): Global risk shock						
ε_t^r	18.189***	3.235*	15.093***	6.634***	0.058*	-0.069***
ε_t^r	17.030***	2.344**	14.970***	6.175***	0.040**	-0.068***
LowLEV × ε_t^r	-4.825	-0.377	-4.924**	-1.176	-0.007	-0.003
HighLEV × ε_t^r	10.482	5.067	5.106*	3.456	0.097	-0.002
ε_t^r	15.226***	1.655**	13.841***	5.614***	0.028**	-0.065***
LowICR × ε_t^r	19.565**	9.533*	10.146**	7.486*	0.171*	-0.022*
HighICR × ε_t^r	-3.413*	-0.616**	-2.866*	-1.983***	-0.010**	0.002
ε_t^r	15.948***	2.193**	13.795***	5.897***	0.038**	-0.064***
LowEPSE × ε_t^r	15.778***	6.875**	9.011***	4.950**	0.125**	-0.019***
HighEPSE × ε_t^r	-1.974	-0.641	-1.056	-0.562	-0.012	-0.005
Industry FE	YES	YES	YES	YES	YES	YES
Observations	222,060	219,575	219,513	219,821	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$ augmented with 4 lags of the dependent variable. Hence the results show the initial impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)). The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(4). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for p < 0.01, ** for p < 0.05, * for p < 0.1).

F.4 Results with additional fixed effects

Table F.5: Week fixed effects: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

	(1) ΔSpread	(2) $\Delta\widehat{\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
LowLEV × ε_t^m	-0.450	-0.188	-0.385	-0.592**	-0.004	0.000
HighLEV × ε_t^m	2.203	2.447	-0.200	1.302	0.044	-0.002
LowICR × ε_t^m	2.466	4.174	-1.518	2.458*	0.072	-0.007*
HighICR × ε_t^m	-0.468*	-0.165	-0.298	-0.627**	-0.004**	0.001
LowEPSE × ε_t^m	1.986	2.730*	-0.597	1.529*	0.048*	-0.004*
HighEPSE × ε_t^m	0.374	-0.380	0.767	-0.175	-0.006	-0.001
Panel (b): Global risk shock						
LowLEV × ε_t^r	-3.329	-0.429	-3.173	-1.611*	-0.008	-0.004
HighLEV × ε_t^r	11.232*	5.351	5.759**	3.503	0.099	-0.003
LowICR × ε_t^r	18.292**	9.950*	8.821***	7.715*	0.175*	-0.021*
HighICR × ε_t^r	-3.962**	-0.559**	-3.403**	-1.941***	-0.010**	0.002
LowEPSE × ε_t^r	15.542***	7.078**	8.675***	4.944**	0.126**	-0.019***
HighEPSE × ε_t^r	-1.005	-0.686	-0.227	-0.734	-0.013	-0.005
Industry FE	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES
Observations	222,060	219,575	219,513	219,821	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$ with week fixed effects. Hence the results show the initial impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)) for the tails of firms. The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(4). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table F.6: Week-industry fixed effects: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

	(1) ΔSpread	(2) $\Delta\widehat{\text{Spread}}$	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
LowLEV × ε_t^m	-1.297	-0.928*	-0.587	-0.718**	-0.016*	0.001
HighLEV × ε_t^m	2.325	2.500	-0.128	1.199	0.045	-0.003***
LowICR × ε_t^m	2.151	4.535*	-2.200	2.217	0.078	-0.007**
HighICR × ε_t^m	-0.896	-0.531**	-0.366	-0.499***	-0.010**	0.002***
LowEPSE × ε_t^m	1.335	2.177*	-0.701	1.253**	0.039	-0.004**
HighEPSE × ε_t^m	0.519	-0.241	0.820	0.075	-0.003	-0.001
Panel (b): Global risk shock						
LowLEV × ε_t^r	-7.243**	-2.449**	-5.258**	-2.676**	-0.043**	0.004
HighLEV × ε_t^r	11.432*	5.606	5.707**	3.357*	0.102	-0.006
LowICR × ε_t^r	18.221**	10.680*	8.157***	7.063*	0.185*	-0.023***
HighICR × ε_t^r	-6.708***	-1.642***	-5.031**	-2.065***	-0.029***	0.009***
LowEPSE × ε_t^r	12.797**	5.602*	7.400***	3.528**	0.100*	-0.015**
HighEPSE × ε_t^r	-0.397	-0.360	0.107	-0.164	-0.006	-0.001
Industry FE	NO	NO	NO	NO	NO	NO
Week x Industry FE	YES	YES	YES	YES	YES	YES
Observations	221,914	219,429	219,367	219,675	220,564	220,818

Note: This table presents the estimates of model (6) at horizon $h = 0$ with week-industry fixed effects. Hence the results show the initial impact of the identified monetary policy shock s_t^m (panel (a)) and the global risk shock s_t^r (panel (b)) for the tails of firms. The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(4). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for p < 0.01, ** for p < 0.05, * for p < 0.1).

F.5 Results with alternative earnings-based measures

Table F.7: Earnings-based tails of firms: estimated shock impact on corporate spreads (1), their predicted and excess bond premium components (2-3), CDS spreads (4), equity prices (5), and default probabilities (6).

	(1) ΔSpread	(2) ΔSpread	(3) ΔEBP	(4) ΔCDS	(5) Δln(PI)	(6) ΔEDF
Panel (a): Monetary policy shock						
s_t^m	7.007***	1.048*	5.982***	2.790***	0.019**	-0.035***
LowROE × s_t^m	2.026	3.227**	-0.988	2.531*	0.057**	-0.004*
HighROE × s_t^m	0.351	-0.037	0.367	-0.427	0.000	0.002*
s_t^m	6.838***	0.782**	6.018***	2.770***	0.014**	-0.034***
LowPE × s_t^m	4.269*	4.455**	0.018	2.281	0.076**	-0.009**
HighPE × s_t^m	0.680	1.348	-0.549	0.662	0.022	-0.002*
s_t^m	7.051***	1.097*	6.036***	2.767***	0.020*	-0.034***
LowEPSEgrowth × s_t^m	3.275	3.080**	-0.084	3.196*	0.052***	-0.007*
HighEPSEgrowth × s_t^m	1.229	2.412*	-1.385	1.075	0.044*	-0.008***
s_t^m	6.900***	1.271*	5.695***	2.852***	0.024*	-0.034***
LowEPSTgrowth × s_t^m	5.016*	1.915**	2.947	1.972*	0.032**	-0.005*
HighEPSTgrowth × s_t^m	0.357	1.086*	-0.818	0.886	0.016*	-0.006***
Panel (b): Global risk shock						
s_t^r	16.414***	1.979*	14.521***	5.686***	0.035*	-0.068***
LowROE × s_t^r	15.342***	7.769***	8.024**	7.423**	0.135***	-0.015***
HighROE × s_t^r	-1.553	-0.028	-1.568	-1.543*	0.003	0.010*
s_t^r	14.898***	1.294**	13.516***	5.329***	0.023**	-0.064***
LowPE × s_t^r	25.218**	11.454***	14.385**	8.297**	0.194***	-0.036***
HighPE × s_t^r	5.048**	2.856	2.364	2.143	0.048	-0.006
s_t^r	16.652***	2.134*	14.653***	5.605***	0.038*	-0.065***
LowEPSEgrowth × s_t^m	18.337***	7.637***	10.039**	8.501***	0.128***	-0.025***
HighEPSEgrowth × s_t^m	6.455	5.267*	0.889	3.607	0.093*	-0.020**
s_t^r	15.756***	2.447*	13.431***	5.810***	0.044*	-0.065***
LowEPSTgrowth × s_t^m	21.520***	5.583***	15.593**	6.133***	0.093***	-0.028***
HighEPSTgrowth × s_t^m	9.726*	2.656	6.816*	2.673	0.041	-0.018***
Industry FE	YES	YES	YES	YES	YES	YES
Observations	222,060	219,575	219,513	219,821	220,710	220,964

Note: This table presents the estimates of model (6) at horizon $h = 0$, i.e. upon impact of the identified monetary policy shock ε_t^m and the global risk shock ε_t^r. The columns indicate the dependent variable. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as outlined in (4)-(5). ROE ≡ return on equity, PE ≡ price-earnings ratio, EPSEgrowth ≡ y-o-y percentage change in expected earnings-per-share, EPSTgrowth ≡ y-o-y percentage change in realized earnings-per-share. The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. Sample period: 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the full sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Appendix G Robustness: Bond-level Results of Shock Impact

Table G.1: Impact of shocks on the change $\Delta_{t,t-1}$ in corporate and CDS spreads

	(1) $\Delta_{t,t-1}$ Spread	(2) $\Delta_{t,t-1}$ Pred. Spread	(3) $\Delta_{t,t-1}$ EBP	(4) $\Delta_{t,t-1}$ CDS
Panel (a): Monetary policy shock				
ε_t^m	9.835***	1.832**	7.977***	3.020***
ε_t^m	9.231***	1.022**	8.232***	2.750***
LowLEV $\times$ ε_t^m	-2.187**	-0.186	-2.270**	-0.285
HighLEV $\times$ ε_t^m	0.338	0.835	-0.466	0.639
ε_t^m	8.394***	0.687***	7.676***	2.507***
LowICR $\times$ ε_t^m	3.404*	2.765*	0.863	2.151*
HighICR $\times$ ε_t^m	-0.079	-0.325**	0.264	-0.542***
ε_t^m	9.109***	0.935**	8.152***	2.709***
LowEPSE $\times$ ε_t^m	0.939	1.709	-0.699	1.214
HighEPSE $\times$ ε_t^m	-0.631	-0.180	-0.489	-0.203
Panel (b): Global risk shock				
ε_t^r	23.454***	3.918**	19.461***	6.487***
ε_t^r	20.378***	2.093**	18.296***	5.541***
LowLEV $\times$ ε_t^r	-6.105***	-0.350	-6.266***	-0.485
HighLEV $\times$ ε_t^r	6.542**	1.682	4.870***	2.351*
ε_t^r	18.037***	1.191***	16.829***	4.962***
LowICR $\times$ ε_t^r	18.623***	6.769**	12.086***	6.638**
HighICR $\times$ ε_t^r	-2.925*	-0.806**	-2.080	-1.779***
ε_t^r	19.308***	1.624**	17.626***	5.313***
LowEPSE $\times$ ε_t^r	14.909***	4.837*	10.169**	4.950**
HighEPSE $\times$ ε_t^r	-2.646	-0.224	-2.453	-0.613
Bond FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	1,895,150	1,875,950	1,875,269	1,884,174

Note: This table presents the estimates of bond-level regressions upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)). The columns indicate the dependent variable in levels: (1) credit spreads s_t, (2) predicted credit spread $\hat{s}_t$, (3) excess bond premium component $\hat{e}_t$, and (3) CDS spreads. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(5). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).

Table G.2: Impact of shocks on the change $\Delta_{t+1,t-1}$ in corporate and CDS spreads

	(1) $\Delta_{t+1,t-1}$ Spread	(2) $\Delta_{t+1,t-1}$ Pred. Spread	(3) $\Delta_{t+1,t-1}$ EBP	(4) $\Delta_{t+1,t-1}$ CDS
Panel (a): Monetary policy shock				
ε_t^m	12.213***	2.018**	10.232***	3.591***
ε_t^m	11.233***	1.085**	10.161***	3.252***
LowLEV $\times$ ε_t^m	-2.237**	-0.163	-2.288**	-0.271
HighLEV $\times$ ε_t^m	1.359	1.077	0.316	0.747
ε_t^m	10.380***	0.742***	9.608***	2.968***
LowICR $\times$ ε_t^m	5.197	3.162	2.269	2.560*
HighICR $\times$ ε_t^m	-0.771	-0.371**	-0.385	-0.676***
ε_t^m	11.332***	1.148**	10.160***	3.255***
LowEPSE $\times$ ε_t^m	1.848	1.474	0.449	1.178
HighEPSE $\times$ ε_t^m	-1.206	-0.318	-0.937	-0.211
Panel (b): Global risk shock				
ε_t^r	29.829***	4.158**	25.737***	7.553***
ε_t^r	25.581***	2.000*	23.608***	6.434***
LowLEV $\times$ ε_t^r	-6.134***	-0.477	-6.051***	-0.097
HighLEV $\times$ ε_t^r	8.289	1.820	6.418*	2.663
ε_t^r	21.985***	0.827**	21.159***	5.778***
LowICR $\times$ ε_t^r	27.560***	8.234**	19.666***	7.729**
HighICR $\times$ ε_t^r	-4.556**	-0.944**	-3.581**	-2.078***
ε_t^r	23.504***	1.371**	22.089***	6.164***
LowEPSE $\times$ ε_t^r	23.012**	5.840*	17.337***	5.681**
HighEPSE $\times$ ε_t^r	-3.307	-0.298	-3.121	-0.533
Bond FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	1,888,147	1,868,980	1,868,306	1,877,258

Note: This table presents the estimates of bond-level regressions upon impact of the identified monetary policy shock ε_t^m (panel (a)) and the global risk shock ε_t^r (panel (b)). The columns indicate the dependent variable in levels: (1) credit spreads s_t, (2) predicted credit spread $\hat{s}_t$, (3) excess bond premium component $\hat{e}_t$, and (3) CDS spreads. The indicator variables for the tails of firms (20^{th} and 80^{th} percentiles) are computed as formally outlined in (4)-(5). The shocks are calibrated to a 10 basis point increase (panel (a)) and decrease (panel (b)) in the 10-year US Treasury yield. The sample period covers 2000/01/07 – 2021/12/17. Standard errors and controls are omitted to preserve space. The excess bond premium (EBP) and fitted spread are obtained from a decomposition of corporate spreads following the methodology of Gilchrist and Zakrajšek (2012) which is estimated over the sample period. The asterisks denote statistical significance (*** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$).