Firm Financial Conditions and Monetary Policy Transmission in Capital Markets*

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Abstract

We examine how the transmission of monetary policy to firm-level investment depends on firms' financial conditions, as measured by their excess bond premia (EBPs), which we show encode the cyclicality of firms' default risk. We find that surprise monetary policy easings compress credit spreads more for higher-EBP firms—i.e., for firms whose default risk loads more on aggregate risk—whereas lower-EBP firms increase their investment by more. We also show that firms' heterogeneous responses to credit supply shocks closely resemble their reactions to monetary policy. A model in which firm-specific EBPs arise from the interaction between firms' default-risk cyclicality and aggregate financial intermediary constraints can explain our results. From micro to macro, we show that the distribution of EBPs across firms influences the aggregate effectiveness of monetary policy.

Key Words: Monetary Policy; Investment; Credit Spreads; Excess Bond Premium; Firm Heterogeneity; Credit Supply; Financial Frictions.
JEL Classification: E22, E44, E50.

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1 Introduction

How do firms' investment responses to monetary policy depend on their financial conditions? A large literature addressing this question is grounded in theories in which firms' access to external funds is subject to financial frictions (e.g., Bernanke and Gertler, 1989 and Kiyotaki and Moore, 1997). Empirically, the severity of these frictions has been proxied by firm characteristics, such as size (Gertler and Gilchrist, 1994), default risk (Ottonello and Winberry, 2020), liability structure (Gürkaynak et al., 2022), and age (Cloyne et al., 2023). We study a new dimension of firm-level financial conditions: firms' excess bond premia (EBPs), the component of firms' credit spreads in excess of their expected default risk (Gilchrist and Zakrajšek, 2012). Motivated by the average EBP's central role in the monetary transmission mechanism (Gertler and Karadi, 2015) and its predictive power for aggregate investment, we evaluate how *firm-level* EBPs shape firms' responsiveness to monetary policy in capital markets.

Our analysis proceeds in four stages. We first document that firm-specific EBPs embed firm-specific default-risk premia, which compensate investors for the covariance between firms' default risk and aggregate risk, i.e., their default-risk 'betas'. This provides a novel rationale for differences in EBPs across firms and complements interpretations of the average EBP as a measure of the financial sector's aggregate risk-bearing capacity. Second, we show that firms' EBPs affect their responsiveness to monetary policy. While monetary easings compress credit spreads more for firms with higher ex-ante EBPs, it is firms with lower EBPs that increase their investment more. Furthermore, we show that firms' heterogeneous responses to credit supply shocks closely resemble those from monetary shocks. Third, we build a stylized model in which firm-specific EBPs arise endogenously from the interaction between firms' default-risk betas and aggregate financial intermediary constraints. The model can rationalize our wide set of empirical moments when (i) monetary policy and credit supply shocks adjust intermediaries' capital supply curves more than firms' capital demand curves and (ii) firms' capital demand curves are convex or adjust more for low-EBP firms. Finally, consistent with our firm-level results, we show that distribution of firms' EBPs matters empirically for the aggregate potency of monetary policy.

We begin by documenting key facts about the cross-sectional EBP distribution. To do so, we use a dataset that combines bond-level corporate yields and firm-level balance sheet information for U.S. public non-financial firms from 1985 to 2021. We find limited cross-sectional association between firms' EBPs and their leverage or liquid asset shares. In contrast, older and larger firms as well as firms with higher Tobin's Qs tend to have lower EBPs. Most importantly, controlling for these other characteristics, we find that low-EBP firms' default risks—as proxied by their Merton (1974) distance-to-defaults—rise by about 50% less than high-EBP firms' when aggregate risk rises, as measured by equity index returns or changes in intermediary capital. Thus, firm-specific EBPs encode firm-specific default-risk premia, which compensate investors for the cyclicality of firm default risk.

Next, we study how firms' investment and credit spread responses to monetary policy shocks depend on their EBPs. We find that while surprise monetary policy easings compress credit spreads more for firms with higher EBPs—i.e., for firms with higher default-risk betas—lower-EBP firms increase their investment by more. In both cases, the magnitudes of these heterogeneous effects are economically meaningful: the relative responses of low-EBP firms' investment and credit spreads are comparable to the average responses observed across all firms. By including sector-time fixed effects, these findings reflect the differential reactions of low- versus high-EBP firms in the same sector and time period. These results are robust to many variants of our empirical approach, including conditioning on other measures of firm financial conditions. This highlights that firms' EBPs contain unique information beyond these other firm characteristics.

Motivated by the evidence that changes in credit supply are an important conduit for the transmission of monetary policy (e.g, Bernanke and Gertler, 1995; Anderson and Cesa-Bianchi, 2024), we also evaluate how firms' respond to credit supply shocks conditional on their EBPs. To do so, we use the high-frequency credit supply shocks of Ottonello and Song (2022), which are measured as changes in financial intermediaries' net worth around their earnings announements, purged of information related to non-financial firms. We find that the heterogeneous effects of credit supply shocks strongly resemble those of monetary policy. While a surprise increase in credit supply compresses credit spreads more for firms with higher EBPs, it is firms with lower EBPs that increase investment by more.

To interpret these empirical results, we build a model of capital markets in which homogeneous financial intermediaries, subject to skin-in-the-game balance sheet constraints à la Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), lend capital to firms that differ in the covariance between their idiosyncratic default risk and aggregate risk. Intermediaries' constraints imply that firms face upward sloping capital supply curves. Importantly, firms that tend to default in worse aggregate states—i.e., when recovery values if firms default are low[1]—tighten intermediaries constraints more, and so face steeper and higher-intercept capital supply curves. We close the model by assuming that all firms share the same downward sloping and convex capital demand curves. In equilibrium, while intermediaries' aggregate balance-sheet capacity drives the average EBP across firms, firms whose default risks co-move less with aggregate risk have lower EBPs, as in the data, due to their flatter capital supply curves. Crucially, low-EBP firms' flatter capital supply curves push them on to flatter segments of their convex capital demand curves in equilibrium.

Within our stylized setup, we follow Ottonello and Winberry (2020) by modeling a monetary policy easing as a rightward shift and flattening of firms' capital supply curves—due to an increase in intermediary net worth—as well as a rightward shift of firms' capital demand curves—due to a decrease in the risk-free rate. Increases in capital supply trace along low-EBP firms' locally more-elastic capital demand curves, generating a larger investment response and a smaller fall in credit spreads for low-EBP firms compared to high-EBP firms, as in the data. Increases in capital demand trace along low-EBP firms' flatter capital supply curves, which further reinforces their relative investment response but partially offsets the heterogeneous response of spreads. Thus, our model can qualitatively reproduce the observed heterogeneous effects when (i) monetary policy adjusts capital supply more than capital demand and (ii) there is meaningful convexity in firms' capital demand curves.[2] In addition, larger shifts in low-EBP firms' capital demand curves in general equilibrium may play a role as well, provided these shifts are sufficiently small so that credit spreads do not widen when monetary policy eases. The same restrictions are needed for the model to match the effects of credit supply shocks. Overall, our model highlights that changes in

[1]Modeling default recovery values as an aggregate state is in line with empirical evidence (see, e.g., Altman et al., 2004).

[2]That monetary policy shocks cause credit spreads to fall on average is consistent with restriction (i).

credit supply are important to explain firms' heterogeneous responses to monetary policy.

Finally, consistent with our firm-level findings, we show that the cross-sectional distribution of firms' EBPs is an important empirical driver of the aggregate effectiveness of monetary policy. Specifically, we document that when a larger mass of firms has lower EBPs, as measured by either a lower median or more left-skewed EBP distribution, monetary policy easings induce larger increases in aggregate investment growth. These findings showcase the aggregate relevance of our firm-level results.

Literature Review: Our paper relates to three strands in the literature. The first investigates firms' heterogeneous responses to monetary policy. Much of this literature is motivated by theories in which firms' access to external funds is subject to financial frictions, such as agency costs (Bernanke and Gertler, 1989, and Bernanke et al., 1999), collateral constraints tied to firms' physical capital (Kiyotaki and Moore, 1997) and earnings (Lian and Ma, 2021), as well as frictions in financial intermediation (e.g., Gertler and Kiyotaki, 2010, and Gertler and Karadi, 2011). Importantly—as highlighted by Ottonello and Winberry (2020), for example—financial frictions influence the shape of the marginal cost curve faced by firms. On the empirical front, the literature has used many firm-level characteristics to proxy for the severity of these financial frictions, such as liability structure (Ippolito et al., 2018; Gürkaynak et al., 2022), age (Bahaj et al., 2022; Durante et al., 2022), age & dividends (Cloyne et al., 2023), size (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020), leverage (Anderson and Cesa-Bianchi, 2024; Caglio et al., 2021; Wu, 2018; Lakdawala and Moreland, 2021), credit default swap spreads (Palazzo and Yamarthy, 2022), liquid assets (Jeenas, 2019; Jeenas and Lagos, 2022), liquidity-constraints (Kashyap et al., 1994), marginal productivity (González et al., 2021), and information frictions (Ozdagli, 2018; Chava and Hsu, 2020).[3] We contribute to this literature by showing that firms' EBPs play a key role in shaping firms' investment and credit spread responses to both monetary policy and credit supply shocks, even after controlling for other sources of firm heterogeneity.

Second, our paper relates to the longstanding literature on the determinants of investment, especially the user cost of capital theory (Jorgenson, 1963) and the Q theory (Tobin,

[3] Focusing on firm cyclicality, Crouzet and Mehrotra (2020) highlight that as a state variable, firm size may not be capturing the extent of firms' financial frictions, but rather their industry scope.

1969).[4] To address the empirical weakness of Q theory when assessed using equity prices, Philippon (2009) builds a model in which the "bond market's Q" is captured predominantly by firm credit spreads, which he finds to be a strong predictor of U.S. aggregate investment.[5] Relatedly, Gilchrist and Zakrajšek (2007) and Gilchrist et al. (2014) find similar results for firm-level credit spreads, which are the main source of variation in firms' user-cost of capital. Gilchrist and Zakrajšek (2012) clarify that it is the EBP component of credit spreads—which they link to financial intermediaries' aggregate risk aversion—that best predicts aggregate economic activity. Our contribution to this literature is to provide a firm-level rationale for differences in EBPs across firms based on differences in default risk-premia, i.e., the covariance between firms' default risk and aggregate risk. That firm-level fundamentals are embedded in firms' EBPs helps connect financial-sector and firm-centered theories of investment.

Third, our paper relates to the literature investigating the time-varying aggregate effects of monetary policy. Vavra (2014) and McKay and Wieland (2021) build models in which monetary policy is less effective in recessions due to cyclicality in the cross-sectional distribution of price adjustments and durable expenditures, respectively. Tenreyro and Thwaites (2016) document that the decreased power of U.S. monetary policy in recessions is particularly evident for durables expenditure and business investment, while Jordà et al. (2020) show this pattern holds internationally. Our paper contributes to this literature by showing that the moments of the cross-sectional EBP distribution are important empirical drivers of monetary policy's aggregate effectiveness, even after controlling for its weaker power in recessions.

[4]These literatures have their roots in the prima facie incompatibility between the stock and flow theories of capital and investment, respectively (e.g. Clark, 1899, Fisher, 1930, Keynes, 1936, Hayek, 1941). Beginning with Lerner (1953), q-theory has appealed to adjustment costs to resolve this incompatibility (see e.g. Lucas and Prescott, 1971, Abel, 1979 and Hayashi, 1982).

[5]Lin et al. (2018) extend the model to stochastic interest rates and empirically support their theory.

2 Data and Descriptive Statistics

In this section, we discuss our data sources and describe the EBP calculation (Section 2.1); document how the cross-sectional EBP distribution evolves over time and relates to other firm characteristics (Section 2.2); detail common features of our regression specifications (Section 2.3); and show that lower-EBP firms have less cyclical default risk (Section 2.4).

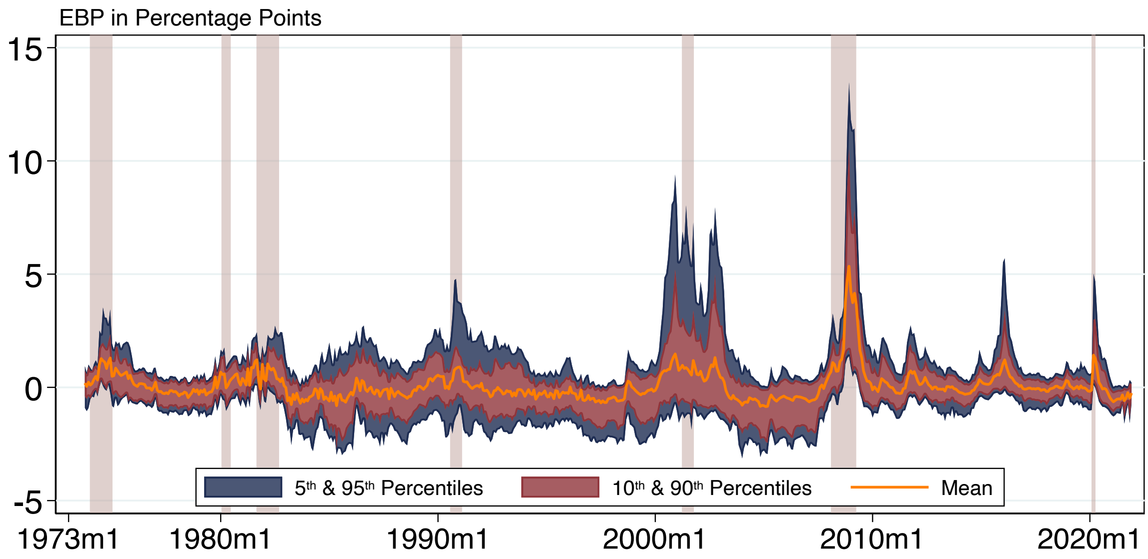
2.1 Data Sources and EBP Calculation

To provide a comprehensive picture of the firm, we use four databases: (i) the Center for Research in Security Prices (CRSP) Database, Wharton Research Data Services for firms' equity prices; (ii) the CRSP/Compustat Merged Database, Wharton Research Data Services for firms' balance sheets; and both the (iii) Arthur D. Warga, Lehman Brothers Fixed Income Database and (iv) the Interactive Data Corporation, ICE Pricing and Reference Data, for monthly corporate bond yields quoted in secondary markets. Merging these databases enables our investigation into monetary policy's effects on U.S. non-financial firms' quantities (investment) and prices (credit spreads).

Using our data, we first compute the credit spread S_{ikt} on the bond k issued by firm i at time t as the difference between the bond's yield and the yield on a U.S. Treasury that shares the same maturity, with the latter calculated by Gürkaynak et al. (2007). Following Gilchrist and Zakrajšek (2012), we then calculate the excess bond premium by decomposing each bond's credit spread S_{ikt} into two components. The first is the predicted spread $\hat{S}_{ikt}$ computed from a regression of bond-level credit spreads on firm-level expected default risk—as measured by firms' distance to default (Merton, 1974)—and a vector of bond characteristics. The second, and residual, component is the excess bond premium, EBP_{ikt}. A higher EBP_{ikt} implies that firm i's bond k carries a larger credit spread than what is justified by its expected default risk, and the bond's characteristics. Appendix A.3 provides more details on the EBP calculation.[6]

[6] Appendix A.3 also shows that (i) the correlation between our mean credit spreads and that of Gilchrist and Zakrajšek (2012) is 96%, and (ii) the correlation between our EBP and that of those authors is 86%.

FIGURE 1
Cross-Sectional Distribution of Bond-Level EBPs over Time



Note. Figure 1 shows the mean and selected percentiles (5$^{\text{th}}$, 10$^{\text{th}}$, 90$^{\text{th}}$, and 95$^{\text{th}}$) of the cross-sectional distribution of monthly bond-level EBPs. Shaded columns correspond to periods classified as recessions by the National Bureau of Economic Research.

After calculating the EBPs for all the bonds in the Lehman-Warga (1973–1998) and ICE (1997–2021) databases whose firm's balance sheet information and equity prices are available in Compustat and CRSP, respectively, our dataset contains 11,319 bonds from 1,913 firms at a monthly frequency from 1973 to 2021. While our focus on bond-financed firms tilts our sample towards large firms, using data on both marginal borrowing rates and investment is crucial to distinguish between different monetary transmission mechanisms. Further, since large firms have been shown to play an outsized role in driving U.S. business cycles (Carvalho and Grassi, 2019), our firm-level results should be relevant for monetary policy's aggregate effects. For more details about our dataset, including variable definitions, sample selection, cleaning of outliers, and summary statistics, see Appendix A.

2.2 The Cross-Sectional EBP Distribution

We document that the cross-sectional EBP distribution displays considerable heterogeneity and contains important firm-level information beyond what is reflected by the mean EBP

Table 1
Transition Matrix for Monthly Bond-Level EBPs

		$EBP_{ik,t+1}$ Quintiles				
		1	2	3	4	5
$EBP_{ik,t}$ Quintiles	1	0.85	0.11	0.02	0.01	0.01
	2	0.13	0.67	0.16	0.03	0.02
	3	0.02	0.18	0.62	0.16	0.02
	4	0.01	0.04	0.18	0.66	0.11
	5	0.01	0.01	0.02	0.13	0.83

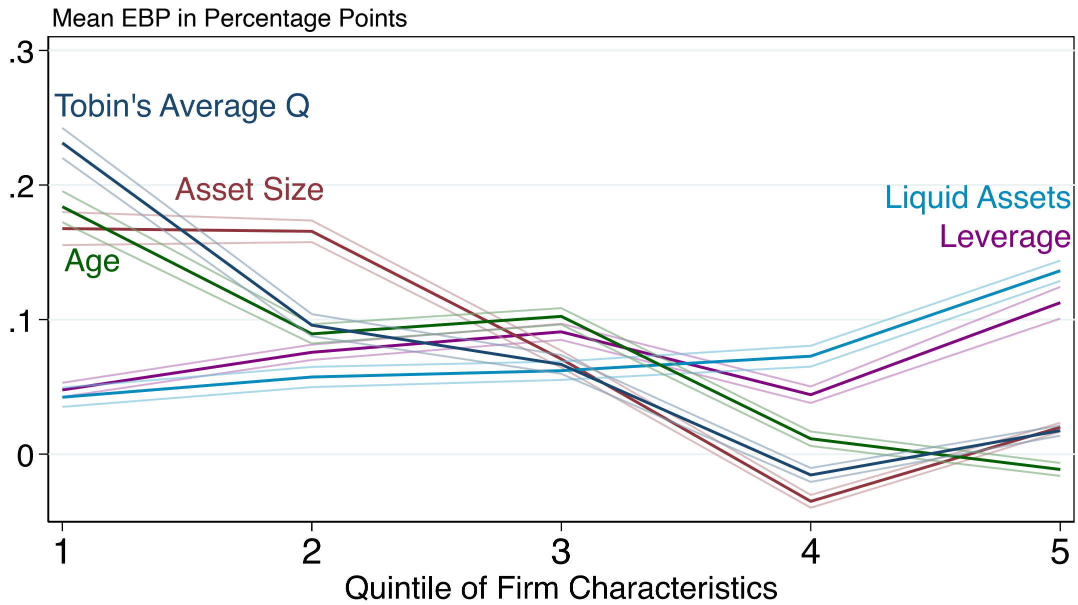
Note. Table 1 provides transition probabilities for monthly bond-level EBPs based on 5 states. Entry in row i and column j refers to the probability of transitioning from state (quintile) i to state (quintile) j in the subsequent month. Probabilities are calculated as an average over the sample.

(Gilchrist and Zakrajšek, 2012). Figure 1 plots the bond-level cross-sectional EBP distribution over the period 1973-2021. For most of this period, the left-tail percentiles are below zero, indicating that an appreciable segment of bonds receive a discount on their credit spreads relative to what is predicted by their expected default risk. Left-tail percentiles also have more muted cyclical fluctuations than the mean EBP, with a noticeable rise above zero only during the 2008 crisis. In contrast, right-tail percentiles are not only more volatile than the mean, but are also generally above zero. Thus, right-tail firms usually pay a premium on their borrowing costs relative to their expected default risk, especially in recessions. In all, this suggests that high-EBP firms may be more cyclically sensitive than low-EBP firms.

Although the percentiles of the EBP distribution vary considerably over time, a bond's place within the EBP distribution is reasonably persistent. Table 1 displays the Markov transition matrix for bond-level EBPs. It shows that the probability of a bond's EBP staying in its quintile in the next month (diagonal entries) is much higher than transitioning to any other quintile, with this result being particularly strong in the lowest and highest quintiles of the distribution. We see this result as necessary for firm-level EBPs to encode important information about the financial state of firms.

We also document the cross-sectional relationship between firm EBPs and other firm

FIGURE 2
Firm EBPs vs. Firm Characteristics in the Cross-Section



Note. Figure 2 reports firms' average EBP (y-axis) in each quintile of the following firm characteristics (x-axis): leverage (debt over assets), liquid assets (cash over assets), age (months since IPO), size (assets), and Tobin's average Q (market over book value of assets). Lines of lighter colors correspond to 90% confidence intervals. For each firm characteristic, (i) we sort firms into quintiles using the historical average of the characteristic, then (ii) we calculate the average EBP (and associated confidence interval) for the firms in each quintile.

characteristics (Figure 2). Specifically, we focus on the average relationship between the EBP and the following variables: leverage (debt over assets), liquid assets (cash over assets), age (time since IPO), size (asset value), and average Tobin's Q (market over book value of assets). First, there is limited cross-sectional association between firms' EBPs and their leverage or liquid asset share, two prominent measures of firms' financial constraints. In contrast, older and larger firms as well as firms with higher Tobin's Qs tend to have lower EBPs. Despite these cross-sectional correlations, the results in the remainder of the paper highlight that the information contained in firms' EBPs are statistically and economically distinct from these other characteristics.

2.3 Common Features of Regression Specifications

To estimate monetary policy's effects conditional on firms' EBPs, we follow an approach similar to Gertler and Gilchrist (1994) and Cloyne et al. (2023) by constructing indicator variables that denote whether a firm's EBP is below a particular threshold of the cross-sectional EBP distribution. We then interact these indicator variables with monetary policy shocks in panel local projections à la Jordà (2005).[7] As a baseline, we focus on the 20^{th} percentile of the cross-sectional distribution, such that $\mathbf{1}EBP^{low}_{ikt}$ is equal to 1 if the EBP of firm i's bond k at time t is in the bottom quintile of the time-t EBP distribution, and is 0 otherwise. We focus on firms in the bottom quintile in our baseline since these firms' investment are particularly responsive to monetary policy, highlighting their importance for monetary policy's effects on the macroeconomy. Our conclusions are robust to using other thresholds, such as the median, as we show in Appendix B.3.

In our baseline specifications, we use the monetary policy shocks of Bu et al. (2021). These shocks combine three appealing features, which together distinguish them from other monetary policy shocks. First, by extracting high-frequency interest-rate movements from the entire U.S. Treasury yield curve, these shocks stably bridge periods of conventional and unconventional monetary policy. Second, these shocks are devoid of the central bank information effect, the notion that monetary policy announcements, in addition to providing a pure monetary policy surprise, may also reveal information about the central bank's views on the macroeconomy. Third, the shocks are not predicted ex-ante by available information, such as Blue Chip forecasts, "big data" measures of economic activity, news releases, and consumer sentiment.[8] We calculate these shocks for the period January 1985 to July 2021, and, for regressions at a monthly (quarterly) frequency, aggregate the shocks by summing them within the month (quarter). In our regressions, we normalize the shocks so that positive values refer to monetary policy easings. Appendix A.1 provides further details. Appendix B.6 shows that our results are robust to using alternative monetary policy shocks.

Throughout the paper, we include in our regressions sector-time fixed effects to control

[7]We lag the interaction by one period to ensure it is not affected by the monetary policy shock.

[8]For critiques of earlier monetary policy shocks that exhibited predictability, see, for example, Ramey (2016), Miranda-Agrippino (2016), and Bauer and Swanson (2020).

for differences in sectoral sensitivities to time-varying factors, as well as firm fixed effects to control for permanent differences across firms. Our specifications also include a series of firm-level controls, denoted by $\mathbf{Z}_{it}$. These controls include firms' leverage, (log) size, sales growth, age, share of liquid assets, short-term asset share (current over total assets), and Tobin's (average) Q. They also include the indicator variables used in the interaction terms (i.e., $\mathbf{1}EBP_{ikt}^{low}$). Further, we include the interaction between the monetary policy shock and $\mathbf{1}\hat{S}_{ikt}^{low}$, an indicator variable equal to 1 if the predicted spread of firm i's bond k at time t is in the bottom quintile of the time-t predicted spread distribution, and 0 otherwise. This allows us to control for the role of the expected default-risk component of credit spreads (e.g., Ottonello and Winberry, 2020 and Palazzo and Yamarthy, 2022) for monetary policy transmission. In addition, inference is conducted using standard errors that are two-way clustered by firm and time period.

To measure the average response of firms' spreads and investment to monetary policy, we include aggregate controls $\mathbf{Y}_t$ en lieu of sector-time fixed effects. These aggregate controls include three lags of the following variables: Chicago Fed's national activity index for monthly regressions and GDP growth for quarterly regressions; CPI inflation; unemployment rate; the economic policy uncertainty index of Baker et al. (2016); and the first three principal components of the U.S. Treasury yield curve.

2.4 Firms' EBPs and the Cyclicality of their Default Risk

In this section, we provide evidence that differences in EBPs across firms embed differences in firms' default risk premia, as measured by the covariance between their default risk and aggregate risk. In our baseline, we use the log-return on the U.S. S&P500 index as our proxy for the aggregate state.

To measure default-risk loadings on aggregate risk for low- and high-EBP firms, we estimate two types of firm-level regressions at a monthly frequency. First, we estimate regressions of the following form separately for low-EBP firms—defined as firms in the bottom quintile of the cross-sectional EBP distribution in a given month—and high-EBP

TABLE 2
Firms' Default Risk and Aggregate Risk: Low- vs. High-EBP Firms

$\Delta DD_{i,t}$	(1) Low-EBP	(2) High-EBP	(3) Relative Low-EBP
R_t^{Mkt}	0.68***	1.06***	
	(.13)	(.22)	
$R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$			-0.29***
			(.08)

Note: Table 2 reports the loadings of firms' default risk on the U.S. S&P500 index (market) return. The first row reports β^{Mkt} from regression (1), which is estimated separately for low-EBP firms (column 1)—firms in the bottom quintile of the cross-sectional EPB distribution—and high-EBP firms (column 2)—firms in the upper quintiles. The second row reports $\beta^{Mkt,Rel}$ from regression (2), which measures how low-EBP firms' ($\mathbf{1}EBP_{it-1}^{low} = 1$) default risk loads on the market return relative to high-EBP firms' (column 3). Standard errors are two-way clustered by firm and month. *** denotes statistical significance at the 1% level.

firms—firms in the upper four quintiles:

$$\Delta DD_{i,t} = \alpha_i + \alpha_{s,m} + \beta^{Mkt} R_t^{Mkt} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + \varepsilon_{i,t}, \tag{1}$$

where $\Delta DD_{i,t}$ is the change in firm i's distance to default; R_t^{Mkt} is the log-return of the U.S. S&P500 index; α_i is a firm fixed effect; $\alpha_{s,m}$ is a sector-month seasonal fixed effect; and $\mathbf{Z}_{it-1}$ and $\mathbf{Y}_{t-1}$ are, respectively, the vectors of standard firm-level and aggregate control variables described in Section 2.3.

Second, we estimate the cyclicality of low-EBP firms' default risk *relative* to high-EBP firms' using the following specification:

$$\Delta DD_{i,t} = \alpha_i + \alpha_{s,t} + \beta^{Mkt,Rel}(R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \varepsilon_{i,t}, \tag{2}$$

which includes sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the U.S. S&P500 index return R_t^{Mkt} and $\mathbf{1}EBP_{it-1}^{low}$, an indicator variable that equals 1 if firm i's EBP is in the bottom quintile of the cross-sectional EBP distribution in $t-1$, and 0 otherwise.

The positive coefficients in the first two columns of Table 2—β^{Mkt} from regression (1)—indicate that when S&P500 index returns decline, firms' distance to defaults decline as well, that is, their default risk rises. However, comparing the point estimates reveals that low-EBP firms' default risk rises by about 50% less than high-EBP firms' when aggregate risk rises. That is, low-EBP firms' default risk is significantly less countercyclical than high-EBP firms'. We see this also in column (3), which displays $\beta^{Mkt,Rel}$ from regression (2) and highlights that low-EBP firms' default risk loads significantly less on aggregate risk than high-EBP firms', even after isolating for within-sector and within-time period variation.

In Appendix B.1, we show that these results are robust to (i) replacing the S&P500 return with the intermediary capital risk factor of He et al. (2017) as a measure of aggregate risk; (ii) interacting the S&P500 return simultaneously with other firm characteristics; and (iii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$.

Overall, the results in this section highlight that firms whose default risks load less on aggregate risk have lower EBPs. Henceforth, we adopt the interpretation that differences in EBPs across firms reflect differences in the cyclicality of their default risk, i.e., a default risk premium. We rationalize this interpretation with a theoretical framework in Section 5

3 Monetary Policy Shocks, Spreads and Investment

In this section, we study the response of firms' credit spreads and investment to monetary policy shocks, both on average and conditional on firms' *ex-ante* EBPs.

3.1 Monetary Policy and Bond-Level Credit Spreads

We begin by investigating the transmission of monetary policy to bond-level credit spreads. We find that while expansionary monetary policy shocks decrease credit spreads on average, the decrease is less pronounced for firms with lower-EBP bonds compared to those with higher-EBP bonds.

To measure the unconditional response of credit spreads to monetary policy, we estimate the following regressions at a monthly frequency for a series of horizons h:

$$S_{ikt+h} - S_{ikt-1} = \alpha_i^h + \alpha_{s,m}^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + e_{ikth}, \tag{3}$$

where S_{ikt} denotes firm i's bond k credit spread; ε_t^m refers to the monetary policy shock (where positive values reflect easings); α_i^h is a firm fixed effect; $\alpha_{s,m}^h$ is a sector-month seasonal fixed effect; and $\mathbf{Z}_{it-1}$ and $\mathbf{Y}_{t-1}$ are, respectively, the vectors of firm-level and aggregate control variables described in Section 2.3. To measure the response of credit spreads conditional on bonds' ex-ante EBPs, we estimate the following regressions:

$$S_{ikt+h} - S_{ikt-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{ikt-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{4}$$

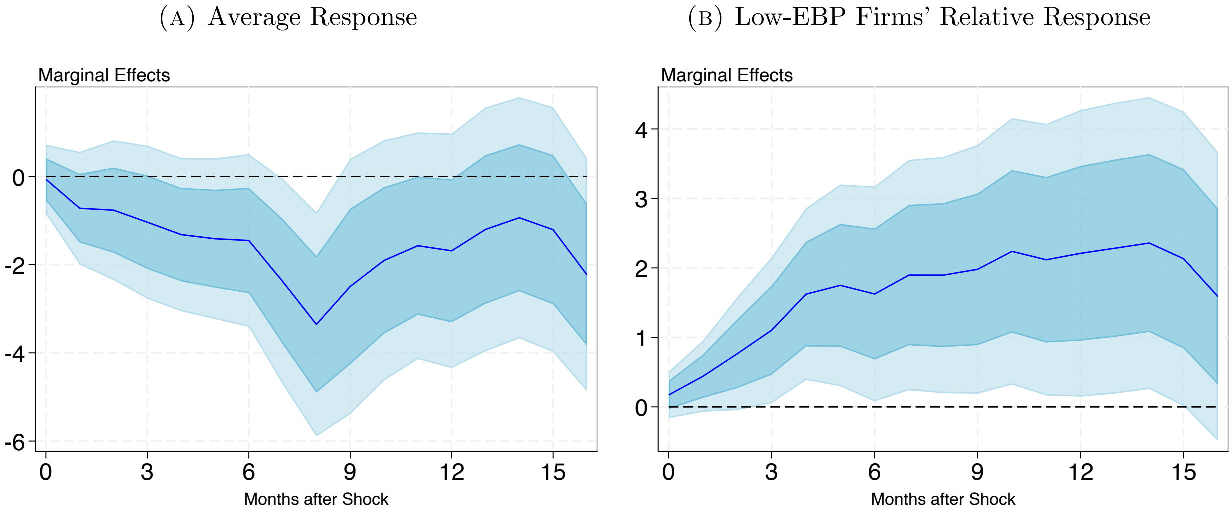
which include sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the monetary policy shock ε_t^m and $\mathbf{1}EBP_{ikt-1}^{low}$, an indicator variable that equals 1 if the EBP of firm i's bond k is in the bottom quintile of the cross-sectional EBP distribution in $t-1$, and 0 otherwise. With sector-time fixed effects, β_1^h measures the response of credit spreads to monetary policy for low-EBP bonds *relative* to high-EBP bonds, by comparing bonds within the same sector and time period.

Figure 3 shows that monetary policy has a significant, and heterogeneous, effect on bond credit spreads. Panel 3a reports the β_1^hs from regression (3), which trace the average response of bond-level credit spreads to a surprise monetary policy easing. We find that a 1 percentage point easing shock induces a decline in the average bond's credit spread of over 3 percentage points eight months after the shock, albeit with wide confidence bands. This result suggests a delayed peak effect of monetary policy on firms' marginal borrowing rates, an issue overlooked by short-horizon studies.[9]

Panel 3b reports the β_1^hs from regression (4), which trace the relative response of low-EBP bonds' credit spreads compared to high-EBP bonds'. The positive marginal effects imply that low-EBP bonds' spreads decrease by significantly less than high-EBP bonds' following a monetary policy easing. Quantitatively, eight months after the shock, the credit

[9]This delayed peak effect of monetary policy on bond-level credit spreads is in line with the findings in several aggregate studies e.g., Jarociński and Karadi (2020) and Bu et al. (2021).

FIGURE 3
Response of Bond-Level Credit Spreads to Monetary Policy



Note. Figure 3 reports the dynamic response of the h-month change in bond-level credit spreads, $S_{ikt+h} - S_{ikt-1}$, to a 1 percentage point monetary policy easing shock, ε_t^m. Panel 3a plots the β_1^hs from regression (3), which trace the unconditional (average) credit spread response. Panel 3b plots the β_1^hs from regression (4), which trace the credit spread response of low-EBP firms' bonds, defined as bonds with EBPs in the bottom quintile of the cross-sectional EBP distribution at $t-1$ ($\mathbf{1}EBP_{ikt-1}^{low} = 1$), relative to high-EBP firms' bonds, i.e., bonds not in the bottom quintile. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

spreads of bonds in the bottom quintile of the EBP distribution are estimated to have fallen by 2 percentage points less than those of firms in upper quintiles. Overall, monetary policy easings compress credit spreads meaningfully more for higher-EBP firms, that is, for firms with more countercyclical default risk. Of note, Appendix B.4 shows that it is the EBP-component of credit spreads itself that adjusts to monetary policy, as in Anderson and Cesa-Bianchi (2024).

Robustness: We show that our results are robust to many variants of our empirical approach, including: (i) interacting the monetary policy shock simultaneously with other state variables emphasized in the literature, namely leverage, distance to default, age, liquid asset share, credit rating, Tobin's average Q, size, and sales growth (Appendix B.2); (ii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ (Appendix B.3); and (iii) using alternative monetary policy shocks (Appendix B.6).

3.2 Monetary Policy and Firm-Level Investment

Turning to quantities, we document that low-EBP firms' investment increases more than that of high-EBP firms' following a monetary policy easing. Thus, low-EBP firms' investment is more responsive to monetary policy while their credit spreads are less responsive.

Following a similar structure to the previous section, we study the transmission of monetary policy to firm-level investment both unconditionally and conditional on a firm's ex-ante EBP. To evaluate the unconditional investment response, we estimate the following local projections at a quarterly frequency for a series of horizons h:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,q}^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + e_{ith}, \tag{5}$$

where K_{it} is the real book value of firm i's tangible capital stock; ε_t^m refers to the monetary policy shock (where positive values reflect easings); α_i^h is a firm fixed effect; $\alpha_{s,q}^h$ is a sector-quarter seasonal fixed effect; and $\mathbf{Z}_{it-1}$ and $\mathbf{Y}_{t-1}$ are, respectively, the vectors of firm-level and aggregate control variables described in Section 2.3.[10] To assess the investment response conditional on firms' EBPs, we estimate the following regressions:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{6}$$

which include sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the monetary policy shock ε_t^m and $\mathbf{1}EBP_{it-1}^{low}$, an indicator variable that equals 1 if firm i's EBP is in the bottom quintile of the cross-sectional EBP distribution in $t-1$, and 0 otherwise.[11]

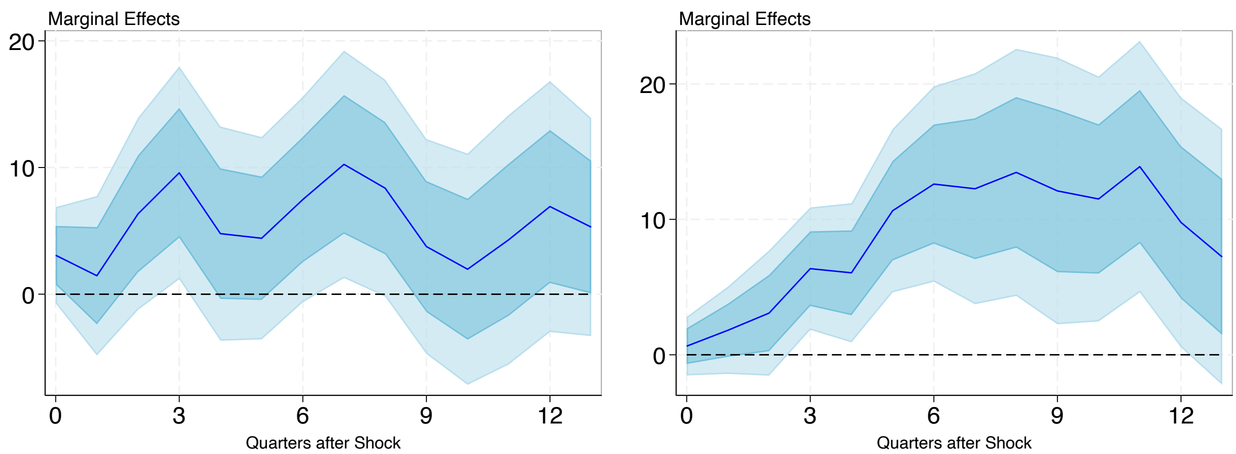
Analogous to the previous section, Figure 4 highlights that monetary policy exerts a sizeable, but heterogeneous, effect on firms' investment. The average investment response to monetary policy across firms is traced in Panel 4a. The response is hump-shaped and carries wide confidence bands, with a 1 percentage point monetary easing estimated to increase investment for the average firm by 12 percent at its peak, which occurs seven quarters after

[10] We also include firms' EBPs and predicted spreads in $\mathbf{Z}_{it-1}$.

[11] The indicator variable EBP_{it-1} is constructed as the average EBP_{ikt-1} on all firm i's bonds within the quarter prior to the monetary policy shock.

Figure 4
Firm-Level Investment Response to Monetary Policy

(A) Average Response (B) Low-EBP Firms' Relative Response



Note. Figure 4 reports the dynamic response of firm-level investment, $\log(K_{it+h}/K_{it-1})$, to a 1 percentage point monetary policy easing shock, ε_t^m. Panel 4a plots the β_1^hs from regression (5), which trace the unconditional investment response. Panel 4b plots the β_1^hs from regression (6), which traces the investment response of low-EBP firms, defined as firms with EBPs in the bottom quintile of the cross-sectional EBP distribution at $t-1$ ($\mathbf{1}EBP_{it-1}^{low} = 1$), relative to high-EBP firms, i.e., firms not in the bottom quintile. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

the shock.[12] This average effect, however, masks considerable heterogeneity based on firms' ex-ante EBPs, as shown in Panel 4b. The positive marginal effects, in this case, indicate that low-EBP firms, i.e., those with less-countercyclical default risk, increase investment considerably more than high EBP firms following a monetary easing. Quantitatively, seven quarters after the shock, low-EBP firms' investment is estimated to have increased by 12 percentage points more than high-EBP firms'. Consistent with these results, Appendix B.5 provides evidence that low-EBP firms also increase debt issuance significantly more than high-EBP firms following a monetary easing.

Robustness: We show that our results are robust to many variants of our empirical approach, including: (i) interacting the monetary policy shock simultaneously with other state variables emphasized in the literature, namely leverage, distance to default, age, liquid asset share, credit rating, Tobin's average Q, size, and sales growth (Appendix B.2); (ii) using

[12]The magnitude of this unconditional effect lies between the estimates of Jeenas (2018) and Ottonello and Winberry (2020).

alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$ (Appendix B.3); and (iii) using alternative monetary policy shocks (Appendix B.6).

4 Credit Supply Shocks, Spreads and Investment

This section shows that the EBP's relevance as a firm-level state variable extends also to credit supply shocks. The heterogeneous effects of such shocks provide additional empirical moments which help better understand the transmission of monetary policy.

To measure credit supply shocks, we use the high-frequency shocks identified by Ottonello and Song (2022). These shocks are constructed, over the period 2002 to 2020, by measuring changes in the market value of intermediaries' net worth in narrow windows around their earnings announcements. Using sign restrictions, the shocks are then purged of information related to non-financial firms (e.g., credit demand), with the residual purged shocks reflecting pure changes in credit supply.

We then re-estimate our baseline regressions from Sections 3.1 and 3.2 using the credit supply shocks. Specifically, we estimate:

$$Y_{i(k)t+h} - Y_{i(k)t-1} = \alpha_i^h + \alpha_{s,m/q}^h + \beta_1^h \varepsilon_t^{CS} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + +\boldsymbol{\delta}^h \mathbf{Y}_{t-1} e_{i(k)th}, \tag{7}$$

$$Y_{i(k)t+h} - Y_{i(k)t-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^{CS} \times \mathbf{1}EBP^{low}_{i(k)t-1}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{i(k)th}, \tag{8}$$

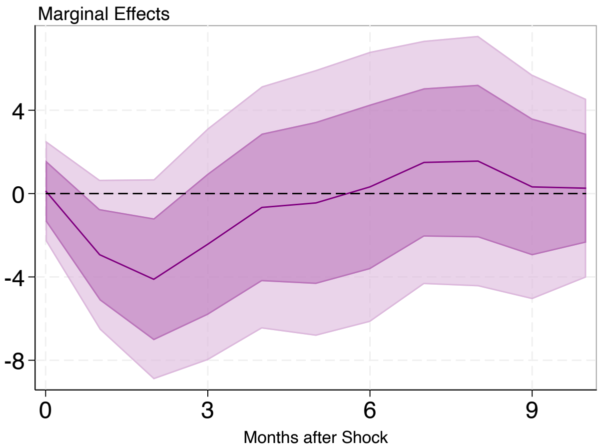
where $Y_{i(k)t}$ is either the bond-level credit spread (S_{ikt}) or firm-level (log) capital stock ($\log K_{it}$); ε_t^{CS} is the credit supply shock normalized to have the same variance as our monetary policy shock; and the remaining variables are the same as described previously.

Figure 5 presents the dynamic responses of bond-level credit spreads and firm-level investment to an expansionary credit supply shock. The key takeaway is that there is a clear similarity between how firms respond to credit supply shocks and monetary policy shocks conditional on their EBPs. Specifically, while low-EBP firms' credit spreads decline relatively little in response to a surprise easing of credit supply (Panels 5a and 5b), they increase investment considerably more in comparison to high-EBP firms (Panels 5c and 5d).

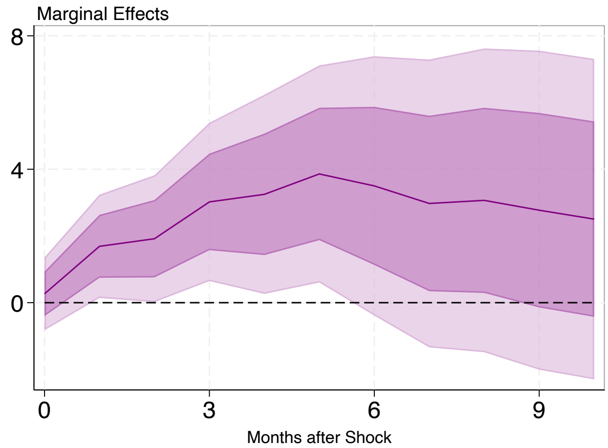
FIGURE 5

Response of Firms' Credit Spreads and Investment to Credit Supply Shocks

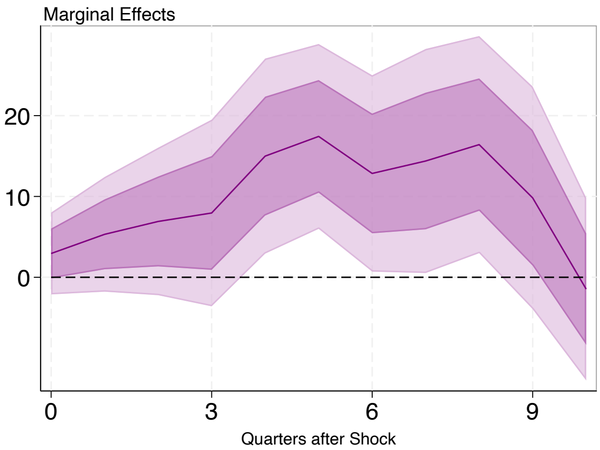
(A) Average Spread Response



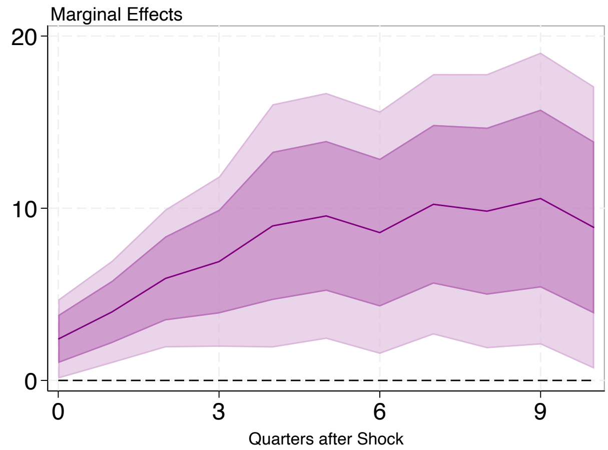
(B) Low-EBP Firms' Relative Spread Response



(C) Average Investment Response



(D) Low-EBP Firms' Relative Investment Response



Note. Figure 5 reports the dynamic responses of bond-level credit spreads and firm-level investment to an expansionary credit supply shock ε_t^{fin}, as calculated by Ottonello and Song (2022). Panels 5a and 5c plot in purple the β_1^hs from regression (7), tracing the average credit spread $S_{ikt+h} - S_{ikt-1}$ and investment $\log(K_{it+h}/K_{it-1})$ response, respectively. Panels 5b and 5d plot in purple the β_1^hs from regression (8), tracing the credit spread and investment response of low-EBP firms relative to high-EBP firms, respectively. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and time.

We also find that it is the EBP-component of firms' credit spreads that reacts to credit supply shocks (Appendix B.4) and that low-EBP firms increase debt issuance relative to high-EBP firms following expansionary credit supply shocks (Appendix B.5), consistent with the effects of monetary policy shocks.

Robustness: As for our monetary policy results, these findings are robust to the following variants of our empirical approach: (i) interacting the credit supply shock simultaneously with other variables used in the literature, namely leverage, distance to default, age, liquid asset share, credit rating, Tobin's average Q, size, and sales growth (Appendix B.2); and (ii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ (Appendix B.3).

5 Interpretation of Empirical Results

In this section, we develop a stylized model through which we interpret our empirical results from Sections 3 and 4. We first present a theoretical framework (Section 5.1) and characterize the key features of the model's capital market equilibrium (Section 5.2). We then use comparative statics exercises to rationalize our findings for the transmission of both monetary policy and credit supply shocks in capital markets (Section 5.3).

5.1 Theoretical Framework

The economy is composed of two islands indexed by j. Each island is populated by (i) a unit mass of identical firms that borrow capital for production; and (ii) a representative financial intermediary that, subject to financial frictions à la Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), lends capital to firms.

The economy features both idiosyncratic and aggregate risk. Idiosyncratic risk takes the form of island-specific firm default risk: with some probability p_j, a random variable, firms on island j draw the low productivity state $Z_j = 0$, which leads them to default on their loans. Aggregate risk comes from a random loss share $\mu \in (0, 1)$ for intermediaries on defaulted loans that is common to both islands, in line with empirical evidence linking recovery values with aggregate economic and financial conditions (e.g., Altman et al., 2004). Crucially, the random variables p_j and μ are drawn from a joint probability distribution $F_j(p_j, \mu)$ such that they may be correlated, with the island-specific covariance denoted by ρ_j. While firms and intermediaries know the joint probability distribution F_j, they make their borrowing and lending decisions, respectively, prior to the realization of the random variables.

To streamline the analysis, we assume that all firms carry the same expected default risk, $\mathbb{E}[p_j] \equiv \overline{p}$. Firms on the two islands only differ in the covariance ρ_j between their default risk and aggregate risk. A higher ρ_j implies that island-j firms' default risk is more *countercylical*, since it increases more in worse aggregate states, i.e., when the loss share on defaulted loans is higher.

Firms produce goods using a decreasing returns to scale technology $Y_j = Z_j \cdot K_j^{\alpha}$, where K_j denotes their capital stock and $\alpha \in (0, 1)$. Since firms lack internal funds, they must borrow capital to produce, but may default depending on their realized productivity. Firms' default probabilities p_j are drawn from distribution F_j. Given a realized default probability $\tilde{p}_j$, island-j firms' productivity Z_j follows a scaled Bernoulli distribution $Z_j \in \{0, Z\}$, with associated probabilities $\{\tilde{p}_j, (1 - \tilde{p}_j)\}$. Thus, firms default ex-post in the low productivity state ($Z_j = 0$). Since firms on both islands carry the same expected default risk ($\mathbb{E}[p_j] \equiv \overline{p}$), expected productivity is equalized across islands as well ($\mathbb{E}[Z_j] \equiv \overline{Z}$).

Given this setup, all firms solve the same expected profit maximization problem:

$$\max_{K_j} \; \overline{Z} K_j^{\alpha} - R_j^K K_j,$$

where R_j^K denotes the borrowing rate on capital. The first order condition of this problem yields firms' marginal benefit (MB), i.e. demand, curve for capital:

$$\frac{R_j^K}{R} = \frac{1}{R} \alpha \overline{Z} K_j^{\alpha - 1}, \tag{9}$$

where R denotes the gross risk-free interest rate and R_j^K / R is island-j firms' credit spread. Since $\alpha \in (0, 1)$, firms' MB curves in equation (9)—which trace their marginal products of capital—are downward sloping. In addition, $\alpha \in (0, 1)$ implies that firms' MB curves are convex—i.e., their slope flattens at higher levels of capital—reflecting the slower rate at which firms' marginal products decline as they accumulate capital. Thus, firms with more capital operate on more-elastic portions of their MB curves, where their credit spreads decline relatively little as capital increases.[13]

Financial intermediaries on both islands are endowed with the same net worth N. They also issue deposits D to households (not explicitly modeled here) at the risk-free rate R. These intermediaries have access to a capital producing technology that transforms N and D on a one-to-one basis into capital K_j, which they supply to firms for a return R_j^K. In the event of firm default, intermediaries on both islands lose the same fraction μ of their promised return on capital $R_j^K K_j$ (e.g., Bernanke et al., 1999), where μ is drawn from probability distribution F_j.

We assume, as in Anderson and Cesa-Bianchi (2024), that intermediaries only lend to firms on their own island, in line with empirical evidence on segmentation in corporate bond markets based on firm risk (see, e.g., Chernenko and Sunderam, 2012; Manconi et al., 2012). Motivated by regulatory capital requirements and internal risk-management practices, intermediaries face a constraint that requires them to have sufficient skin in the game when lending to firms. This is modeled as an agency friction in which intermediaries may abscond with a fraction θ of their expected revenue, since we assume intermediaries decision to abscond occurs prior to the realization of shocks. In turn, households only fund intermediaries that satisfy this incentive compatibility constraint.

The optimization problem of the intermediaries is the following:

$$\max_{K_j} \ (1-\mathbb{E}[p_j])R_j^K K_j + \mathbb{E}[p_j(1-\mu)]R_j^K K_j - R(K_j - N) \quad \text{s.t.} \tag{10}$$

$$(1-\mathbb{E}[p_j] + \mathbb{E}[p_j(1-\mu)])R_j^K K_j - R(K_j - N) \geq \theta((1-\mathbb{E}[p_j] + \mathbb{E}[p_j(1-\mu)])R_j^K K_j. \tag{11}$$

Our model's main innovation is the interaction between firm-specific default risk and intermediaries' aggregate loss share when firms default: $\mathbb{E}[p_j(1-\mu)] = \overline{p}(1-\overline{\mu}) - \rho_j$. In particular, we highlight that intermediaries' total expected payoff (10) is lower on islands where firms' default risk is more countercyclical (higher ρ_j) since these firms tend to default in worse aggregate states. In turn, this tightens these intermediaries' incentive compatibility

[13]The relationship between credit spreads $\frac{R^K}{R}$ and log capital $x = \log(K)$ is also (i) downward sloping and (ii) convex. This can be verified by rewriting equation (9) as $\frac{R_j^K}{R} = f(x) = \frac{\alpha \overline{Z}}{R} \exp[(\alpha-1)x]$, and showing that $f'(x) < 0$ and $f''(x) > 0$.

constraints (11).

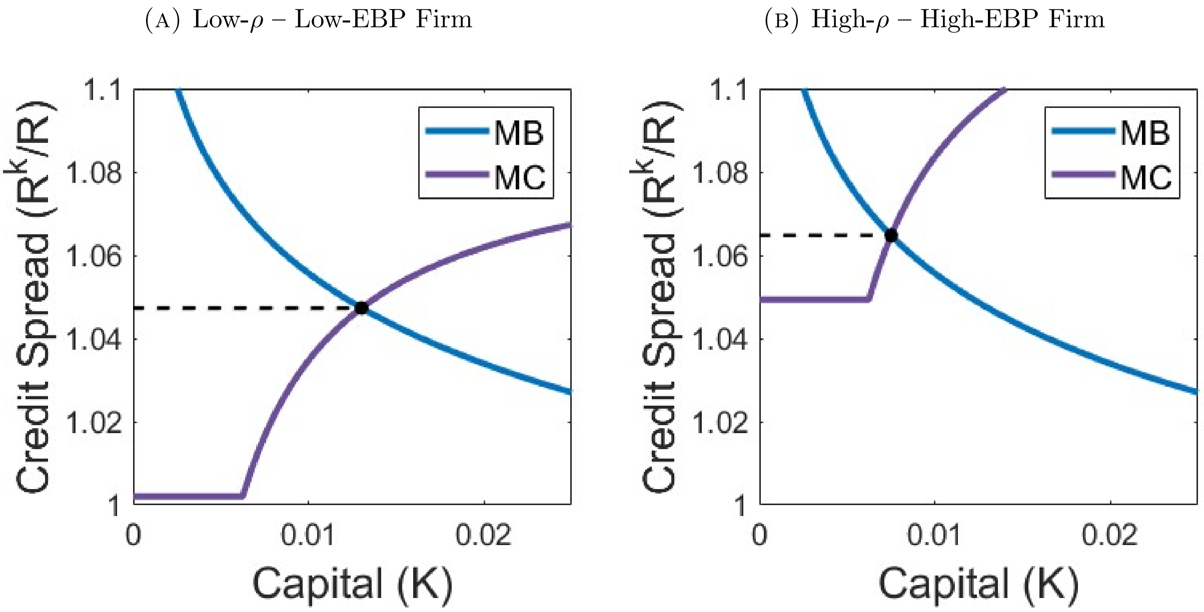
The solution to the problem above provides a schedule for how much capital intermediaries supply to firms for a given credit spread R_j^K/R. We focus on equilibria in which the expected return on capital is at least as large as the risk-free rate: $[1-\overline{p}\,\overline{\mu}-\rho_j]R_j^K \geq R$. When $R_j^K > R/[1-\overline{p}\,\overline{\mu}-\rho_j]$, intermediaries leverage-up until the point in which their incentive compatibility constraint binds. Additionally, when $R_j^K = R/[1-\overline{p}\,\overline{\mu}-\rho_j]$, financial intermediaries are indifferent between any level of lending that satisfies this constraint. Thus, we obtain the following marginal cost (MC), i.e., supply, curve for capital:

$$\frac{R_j^K}{R} = \begin{cases} \frac{1}{1-\overline{p}\overline{\mu}-\rho_j} & K_j < \frac{N}{\theta} \\ \frac{1}{1-\overline{p}\overline{\mu}-\rho_j}\frac{K_j-N}{K_j(1-\theta)} & K_j \geq \frac{N}{\theta}, \end{cases} \tag{12}$$

where $K_j = N/\theta$ is the cutoff value of capital supply for which the intermediaries' constraint binds. Importantly, when $K_j \geq N/\theta$, the capital supply curve is upward sloping.

To focus on the EBP-component of credit spreads and match the evidence from Section 2.4, our analysis focuses on firms' default risk cyclicalities ρ_j by equalizing all other parameters across islands. Thus, differences in the cyclicality of default risk ρ_j across firms is the key fundamental shaping differences in their MC curves. Per equation (12), a lower ρ_j (less cyclical default risk) reduces the compensation intermediaries need to lend to firms through both: (i) a lower intercept, reflecting a lower expected return; and (ii) a flatter slope, reflecting a lower risk premium due to the relaxation of intermediaries' incentive compatibility constraint. While cross-sectional differences in default risk cyclicality are key to generate a firm-level EBP distribution, the average EBP across firms is also shaped by intermediaries' aggregate net worth (N) and the tightness of their financial constraint (θ). This is in line with the original interpretation of the average EBP as a measure of intermediaries' risk-bearing capacity (Gilchrist and Zakrajšek, 2012).

FIGURE 6
Capital Market Equilibria for Low- & High-EBP Firms



Note. Figure 6 presents the capital market equilibrium for two types of firm, which differ in how much their default risk co-moves with aggregate risk. While both types of firm share the same marginal benefit (MB) curve, since they carry the same expected default risk ($\overline{p}$), differences in the cyclicality of firms' default risk (ρ_j) lead low-ρ_j (less-cyclically sensitive) firms in Panel 6a to face flatter and lower marginal cost (MC) curves compared to the high-ρ_j firms in Panel 6b. When markets are segmented according to firm risk, equilibrium occurs at the intersection of the MB curve and the MC curve in each panel. Low-ρ_j firms in Panel 6a have lower equilibrium credit spreads (EBPs) and are on flatter segments of both their MB and MC curves in equilibrium compared with the high-ρ_j firms in Panel 6b. Appendix C provides full details on the parameterization.

5.2 Capital Market Equilibrium, Firm EBPs and Curve Slopes

Figure 6 displays capital market equilibrium on the two islands, which occurs at the intersection of the MB curves (in blue) and the MC curves (in purple) in each panel. While the MB curves are the same for the two types of firm, the low-ρ_j firms in Panel 6a face flatter and lower-intercept MC curves compared to those faced by high-ρ_j firms in Panel 6b, and hence have lower credit spreads in equilibrium. We normalize $\rho_j = 0$ (i.e., acylical default risk) on the low-ρ_j island and describe the calibration of the model in Appendix C.

Since all firms carry the same expected default risk $\mathbb{E}[p_j] \equiv \overline{p}$, differences in equilibrium credit spreads across Panels 6a and 6b arise from differences in the cyclicality of firms' default risk ρ_j. These differences in credit spreads should therefore be interpreted as differences in firms' EBPs.[14] Thus, firms' with relatively low ρ_js, i.e., cyclically safer firms, have lower EBPs in our framework, reproducing the motivating evidence from Section 2.4.

In addition to differences in the slopes of firms' MC curves, we also highlight salient differences in the slopes of firms' MB curves in *equilibrium*. Specifically, low-EBP firms' flatter MC curves, in combination with convex MB curves, place them on flatter segments of their MB curves compared to high-EBP firms in equilibrium. Low-EBP firms' locally more-elastic MB curves will help the model to match the empirical responses of credit spreads and investment to shocks from monetary policy and credit supply.

5.3 Monetary Policy Comparative Statics by Firm EBPs

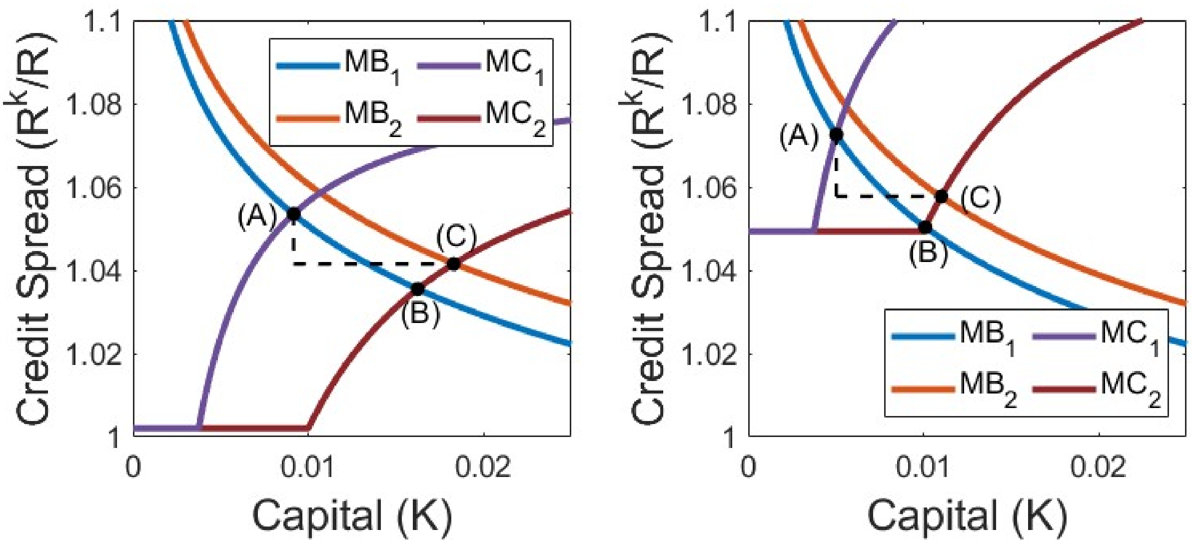
Within our stylized setup, we use comparative statics exercises to rationalize our empirical results from Sections 3 and 4. In the spirit of Ottonello and Winberry (2020), we model a monetary policy easing as both (i) a rightward shift and flattening of firms' MC curves, due to an increase in intermediaries' net worth N; and (ii) an outward shift in firms' MB curves, due to a reduction in the risk-free rate R. Our goal is to provide restrictions on the relative sizes of these shifts and tilts, as well as on the curve slopes, that are needed to match low- and high-EBP firms' differential responses to monetary policy shocks from the data. In our baseline exercises, changes in R and N are assumed to be common across islands. We then discuss the role of heterogeneous movements in firms' MC and MB curves, which might result from general equilibrium price effects that we do not explicitly model. Overall, the model can qualitatively match our empirical results under two conditions: (a) monetary policy adjusts firms' MC curves more than their MB curves; and (b) MB curves are meaningfully convex or shift more for low-EBP firms.

We first consider the effects of movements in firms' MC curves. In response to an expansionary monetary policy shock that increases intermediary net worth (N) uniformly across islands, firms' MC curves shift rightward and flatten. This MC-curve flattening is

[14] As in Gilchrist and Zakrajšek (2012), we use the Merton (1974) model to calculate firms' expected default risk, their predicted credit spread and their EBP. This model assumes a zero covariance between firms' default risk and aggregate risk ($\rho_j = 0$), with default risk dependent only on firm fundamentals. Thus, differences in default-risk cyclicality would be captured in the EBP component of firms' credit spreads.

Figure 7
Monetary Policy Effects on Spreads & Investment for Low- & High-EBP Firms

(a) Low-ρ – Low-EBP Firm (b) High-ρ – High-EBP Firm



Note. Figure 7 presents the comparative statics to a monetary policy easing, modeled as a uniform increase in financial intermediaries' net worth N and a decline in the risk-free interest rate R across both islands. These shocks (i) shift and flatten (non-uniformly) firms' MC curves, from MC_1 to MC_2, and (ii) shift firms' MB curves, from MB_1 to MB_2. We calibrate the (relative) size of these shifts so that credit spreads decline and investment increases on both islands, as in the data. Panel 7a shows the response of the low-ρ – low-EBP firm, while Panel 7b shows the response of the high-ρ – high-EBP firm. The low-EBP firms' investment increases relative to the high-EBP firms', although their credit spreads decline by less. Appendix C provides details on the parameterization.

more pronounced for low-EBP firms, per equation (12). Crucially, because low-EBP firms are on more elastic portions of their convex MB curves at their initial equilibrium (A), movements in MC curves alone generate larger investment increases and smaller spread reductions for low-EBP firms compared to high-EBP firms. This result is consistent with the empirical evidence from Section 3, and is illustrated by comparing the transition from equilibrium (A) to (B) in Panels 7a and 7b.

We then consider the effects of shifts in firms' MB curves. Incorporating rightward shifts in MB curves, from the lower risk-free rate (R), does not qualitatively change the heterogeneous effects produced by MC-curve shifts in our parameterization. For low-EBP firms, MB-curve shifts trace along flatter MC curves, inducing a larger increase in investment but a smaller increase in credit spreads relative to high-EBP firms. This is visible in the transition from equilibrium (B) to (C) in Panels 7a and 7b. Thus, while MB-curve shifts reinforce the investment heterogeneity produced by MC-curve shifts, they partially undo the heterogeneous effects on spreads. Still, if the MB-curve shifts are not too large as in Figure 7, the combined effect of monetary policy on firms' MC and MB curves—i.e., the transition from equilibrium (A) to (C)—remains consistent with our empirical results.

These comparative statics highlight that uniform changes in N and R can rationalize monetary policy's heterogeneous effects under two restrictions: (i) firms' MC curves adjust more than their MB curves and (ii) there is meaningful convexity in firms' MB curves. Reassuringly, the average effect of monetary policy across firms in the data is consistent with this first restriction. Specifically, the model matches the result that monetary policy easings cause a decline in credit spreads and an increase in investment for the average firm when MC curves react more than MB curves. This suggests that changes in credit supply are key to explain the heterogeneous effects of monetary policy, consistent with their important role in the overall monetary policy transmission (e.g., Bernanke and Gertler, 1995).[15]

Indeed, to match the heterogeneous effects of credit supply shocks from Section 4, the model with uniform curve shifts requires the same restrictions as for monetary policy shocks. Through the lens of our model, expansionary credit supply shocks correspond to an increase in intermediary net worth N, which shifts rightward and flattens firms' MC curves. When firms' MB curves are convex, these MC curve movements generate a larger investment response and a smaller reduction in spreads for low-EBP firms, as in the data. Since firms' MB curves may also shift rightward due to unmodeled general equilibrium increases in aggregate demand, credit supply shocks must again induce larger movements in firms' MC curves compared to their MB curves to fit our empirical results.

Next, we extend our analysis to consider asymmetric moves in firms' MC and MB curves. We first emphasize that adding heterogeneous shifts and tilts in firms' MC curves, if sufficiently small, does not qualitatively change the heterogeneous effects presented in Figure 7. Starting from equilibrium (C) in either panel, a further rightward shift or flattening of a given firm's MC curve—due to, for instance, a further increase in their intermediaries'

[15] Of note, since credit spreads adjust due to changes in N and R, and not default risk, it is the EBP component of firms' credit spreads that moves, consistent with our empirical results. In addition, firms' investment is financed by issuing debt, as in the data.

net worth N—generates both a further decline in the firm's credit spread *and* a further increase in its investment. Accordingly, such asymmetric shifts must be sufficiently small so as not to undo either low-EBP firms' relatively smaller reduction in credit spreads or high-EBP firms' relatively smaller increase in investment. Thus, while our framework can accommodate asymmetric movements in firms' MC curves, significant asymmetries in our setup would produce counterfactual predictions for credit spreads and investment.

Finally, we highlight that larger MB-curve shifts for low-EBP firms can play an important role in driving the heterogeneous effects of monetary policy. Starting from equilibrium (C) in either panel of Figure 7, a further rightward shift in a given firm's MB curve—due, for instance, to greater exposure to aggregate demand changes in general equilibrium—increases its investment response and dampens the decline in its credit spread. For high-EBP firms, this partially offsets the heterogeneous effects shown in Panel 7a, and so would need to be sufficiently small. For low-EBP firms, by contrast, relatively larger MB-curve shifts reinforce the heterogeneous effects both on investment and spreads from Panel 7b. Thus, larger monetary-policy induced shifts in low-EBP firms' MB curves can help account for our results, provided these shifts remain small relative to MC shifts so that credit spreads do not increase overall.

6 Firm EBPs & Monetary Policy's Aggregate Effects

In this section, we examine whether our cross-sectional result that firms' investment responses to monetary policy depend on their EBPs matters in the aggregate. In light of our empirical findings from Section 3, when more firms in the economy have lower EBPs—as captured by a lower median or a left-skewing of the cross-sectional EBP distribution—monetary policy should be more effective at stimulating aggregate investment. While the effect of a more-dispersed EBP distribution is ex-ante ambiguous, it helps indicate whether firms in the left or right tail of the EBP distribution exert a greater influence over the aggregate effectiveness of monetary policy.

To test these predictions, we run time-series local projections of a similar form to regression (5) from Section 3, but with two main modifications: (i) we use U.S. aggregate investment as our dependent variable, and (ii) we use the first three cross-sectional moments of the EBP distribution as state variables. Specifically, we estimate the following local projections at a quarterly frequency for a series of horizons h:

$$\frac{400}{h+1}\log\left(\frac{I_{t+h}}{I_{t-1}}\right) = \beta_0^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\beta}_2^h(\varepsilon_t^m \times \boldsymbol{M}_{t-1}) + \boldsymbol{\delta}_l^h \mathbf{Y}_{t-1} + e_{th}, \tag{13}$$

where I_t is aggregate investment; $\boldsymbol{M}_{t-1}$ is a vector that contains the median, dispersion and Kelly-skewness of the bond-level cross-sectional EBP and predicted spread distributions, normalized to be have zero mean and unit variance; and $\mathbf{Y}_{t-1}$ includes the aggregate controls of Section 2.3 along with the vector $\boldsymbol{M}_{t-1}$.[16] We measure dispersion and skewness using the 20th and 80th percentiles of the EBP distribution and use Newey-West standard errors with 12 lags for inference.

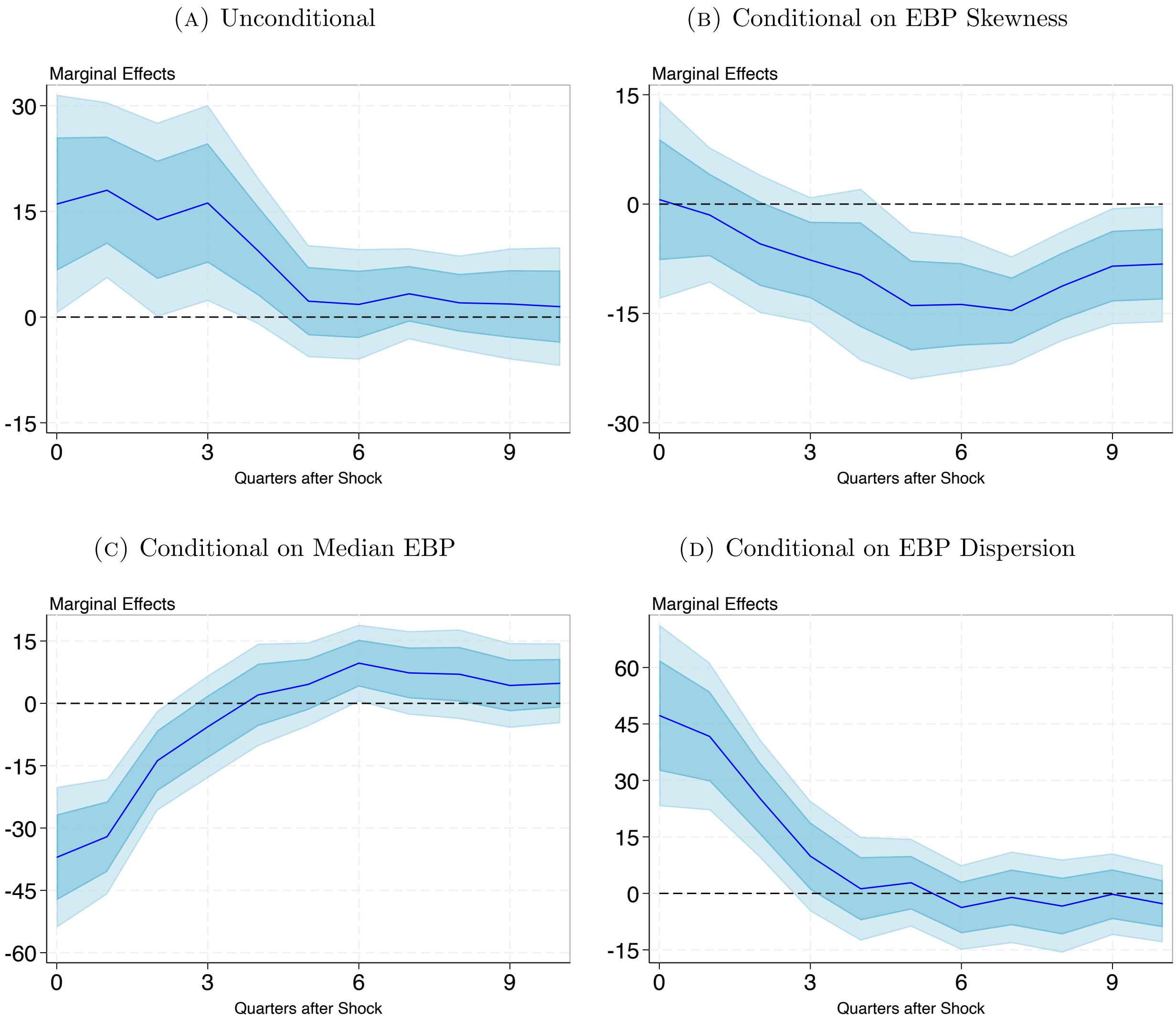
The results from these regressions, which are shown in Figure 8, are consistent with our cross-sectional results. First, Panel 8a shows that, on average, aggregate investment growth increases following a surprise monetary policy easing, with a 1pp easing estimated to generate a peak increase in investment growth of 15pp 3 quarters after the shock. Second, a more right-skewed EBP distribution is associated with a weaker pass-through from monetary policy to aggregate investment (Panel 8b), with a 1-standard-deviation more right-skewed distribution predicted to reduce investment by 15pp 6 quarters after the shock. A higher median EBP also predicts a significantly weaker transmission of monetary policy (Panel 8c), although the effects are relatively short-lived. Finally, a more dispersed EBP distribution predicts a stronger pass-through from monetary policy to aggregate investment, suggesting that the added stimulus from a lower left tail of the EBP distribution seems to overcome the drag from a higher right tail (Panel 8d). Overall, the findings of this section complement our firm-level results by highlighting that cross-sectional variation in firms' EBPs can carry significant macroeconomic consequences.

Importantly, we show in Appendix B.7 that monetary policy's aggregate effects con-

[16] For consistency, in these regressions, we substitute GDP growth for investment growth in the aggregate controls $\mathbf{Y}_{t-1}$ to again align ourselves with the existing forecasting literature (e.g., Ferreira, 2024).

Figure 8

Monetary Policy's Effect on Aggregate Investment Growth By EBP Moments



Note. Figure 8 reports the dynamic response of annualized aggregate investment growth to a 1 percentage point monetary policy easing shock ε_t^m, which we estimate using regression (13). Panel 8a shows unconditional effects, β_1^h. Panels 8b, 8c and 8d show the effects conditional on the skewness, median and dispersion of the EBP distribution, measured in standard deviations, which are three of the elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

ditional on the moments, especially the skewness, of the EBP distribution are robust to controlling for the interaction between monetary policy shocks and recession indicators similar to those used by Tenreyro and Thwaites (2016). Thus, the aggregate conditioning effects of firms' EBPs appear statistically distinct from variation in the potency of monetary policy over the business cycle.

7 Conclusion

We examine how and why the responsiveness of firms' credit spreads and investment to monetary policy depends with their financial conditions, as measured by their EBPs. Our paper has four main parts. First, we provide a firm-level rationale for heterogeneity in EBPs across firms. Specifically, we show that firm-specific EBPs embed firm-specific default-risk premia, which compensate intermediaries for the covariance between firms' default risk and aggregate risk, as measured by either equity index returns or changes in intermediary capital. Second, we show that firms' EBPs help regulate firms' sensitivity to monetary policy. In particular, we find that while expansionary monetary policy shocks compress credit spreads more for firms with higher ex-ante EBPs, it is firms with lower EBPs that invest more. Furthermore, we find that the heterogeneous effects of credit supply shocks strongly resemble those from monetary policy. Third, we build a model in which firm-specific EBPs arise from the interaction between firm-specific default risk cyclicality and aggregate financial intermediary constraints, which jointly determine the slope of the capital supply curve faced by firms. We use this stylized framework to place restrictions on the magnitudes of different economic mechanisms that are needed to match our empirical results. We emphasize that when firms' capital demand curves are convex, our model rationalizes our empirical results when monetary policy induces larger increases in capital supply than capital demand. This suggests that changes in credit supply play a key role in explaining the heterogeneous effects of monetary policy across firms. We also highlight that a greater sensitivity of low-EBP firms' capital demand curves to monetary policy in general equilibrium may contribute to our results as well. Finally, we show that our firm-level results appear to matter in the aggregate, with the distribution of firms' EBPs regulating monetary policy's pass-through to aggregate investment growth.

Policymakers and researchers often discuss three key aspects of the transmission of monetary policy: its distributional effects, its aggregate potency, and the channels through which it operates. Our paper touches on these three aspects. On the distributional front, we show that monetary policy is more effective at stimulating the investment of firms with lower EBPs. On the aggregate front, our paper offers a specific observable—the moments of the cross-sectional EBP distribution—to monitor monetary policy's time-varying aggregate effects. On the channels front, our paper provides empirical evidence of a link between financial frictions, which affect firms' capital supply curves, and the slope and interest-rate sensitivity of firms' capital demand curves, which can hopefully be useful to construct richer models of capital markets.

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Internet Appendix (for online publication only)

Firm Financial Conditions and Monetary Policy Transmission in Capital Markets

by T. Ferreira and D. Ostry

December 11, 2025

A Data Summary

A.1 Monetary Policy Shocks

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C Model Appendix

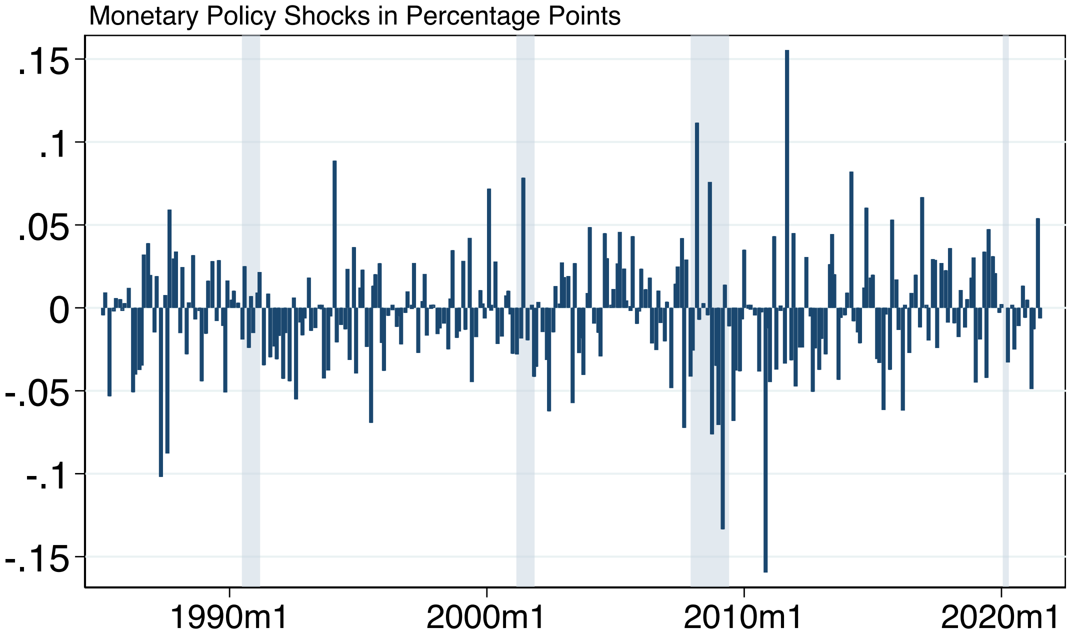
A Data Summary

In this section, we present further details on our baseline monetary policy shock series (Appendix A.1), provide variable definitions and outline our sample (Appendix A.2), discuss in more detail the EBP and distance to default calculations (Appendix A.3), and provide summary statistics for our main variables of interest (Appendix A.4).

A.1 Monetary Policy Shocks

This section provides more details about the Bu, Rogers and Wu (2021) monetary policy shocks, which we use in our baseline specifications throughout the paper. The start-date of our sample is January 1985, while the end-date is July 2021. Figure A.1 shows the times series of shocks at a monthly frequency. This "extended" series is longer than the original series of the paper, which runs from January 1994 to September 2019.

FIGURE A.1
Monetary Policy Shocks



Note. Figure A.1 plots the time series of Bu et al. (2021) monetary policy shocks at a monthly frequency from January 1985 to July 2021. Positive values here represent tightenings. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.

As discussed in the original paper, the Bu et al. (2021) monetary policy shocks are constructed using a two-step Fama-Macbeth procedure with identification achieved via a heteroskedasticity-based instrumental variable approach. The resulting shocks display a moderately-high correlation with other shock series in the literature, but have a number of notable properties: (i) they stably bridges periods of conventional and unconventional policy, providing us with a longer sample than many other papers in this area; (ii) they are devoid of the central bank information effects; and (iii) they are unpredictable from the information set available at the time of the shock. That said, as shown in Appendix B.6, our results are robust to using monetary policy shocks constructed as high-frequency changes in Federal Funds futures rates around FOMC announcements, as in Ottonello and Winberry (2020). For more details on the calculation of the Bu et al. (2021) shock series, see the original paper. Summary statistics for the Bu et al. (2021) monetary policy shock series are presented in Appendix A.4.

A.2 Variable Definitions and Sample Selection

In this subsection, we first define the variables used in our paper and then discuss our sample. All variable definitions are standard in the literature; we draw particularly on those used in Ottonello and Winberry (2020) and Gilchrist and Zakrajšek (2012). The variables are:

1. *Real Investment*: defined as $log(\frac{K_{it+h}}{K_{it-1}})$ for $h = 0, 1, 2...$, where K_{it-1} denotes the book value of the nominal capital stock of firm i at the end of period $t-1$ deflated by the BLS implicit price deflator (IPDNBS in FRED database). This is the same timing convention as Ottonello and Winberry (2020), although they label the real capital stock of firm i at the end of period $t-1$ as K_{it}. As in Ottonello and Winberry (2020), for each firm, we set the first value of their nominal capital stock to be the level of gross plant, property, and equipment (ppegtq in Compustat) in the first period in which this variable is reported in Compustat. From this period onwards, we compute the evolution of the capital stock using the changes of net plant, property, and equipment (ppentq in Compustat), which is a measure of net of depreciation investment with significantly more observations than

ppegtq. If a firm has a missing observation of ppentq located between two periods with non-missing observations we estimate its value by linear interpolation. We consider only investment spells of 15 quarters or more and we winsorize the top and bottom 0.5% of investment observations per period to remove outliers.

2. *Credit spread*: defined as $S_{ikt} = y_{ikt} - y_t^T$, where y_{ikt} is the yield quoted in the secondary market of corporate bond k issued by firm i in month t from the Lehman-Warga and ICE databases and y_t^T is the yield on a U.S. Treasury with the exact same maturity as the corporate bond k, using estimates from Gürkaynak et al. (2007). We winsorize the top and bottom 0.5% of (changes in) credit spread observations per period to remove outliers.

3. *Distance to default*: firm's expected default risk defined in the Merton (1974) model. Calculated as in Gilchrist and Zakrajšek (2012); see Appendix A.3 for further details.

4. *EBP*: defined as $EBP_{ikt} = S_{ikt} - \hat{S}_{ikt}$ where $\hat{S}_{ikt}$ is the predicted value of firm i's bond k credit spread at time t, which as in Gilchrist and Zakrajšek (2012), is calculated from a regression of $log(S_{ikt})$ on firm i's distance to default and bond k's characteristics. See Appendix A.3 for further details.

5. *Leverage*: defined as the ratio of total debt (sum of dlcq and dlttq in Compustat) to total assets (atq in Compustat).

6. *Share of liquid assets*: defined as the ratio of cash and short-term investments (cheq in Compustat) to total assets (atq in Compustat), as in Jeenas (2019).

7. *Size*: measured as log total assets (atq in Compustat) deflated using the BLS implicit price deflator (IPDNBS in FRED database).

8. *Sales growth*: measured as the log-difference of sales (saleq in Compustat) deflated using the BLS implicit price deflator (IPDNBS in FRED database).

9. *Age*: defined as age since initial public offering (begdat in Compustat).

10. *Tobin's (average) Q*: defined as the ratio of the market value of assets to book value of assets. Market value of assets is equal to (i) book value of assets (atq in Compustat) plus

(ii) market capitalization (share price times oustanding shares) minus common equity plus deferred taxes ((prccq * cshoq) - ceqq + txditcq, in Compustat), as in Cloyne et al. (2023). Since txditcq is sparsely available and is also a relatively small component of Tobin's q, we impute the value to be zero if an observation is missing.

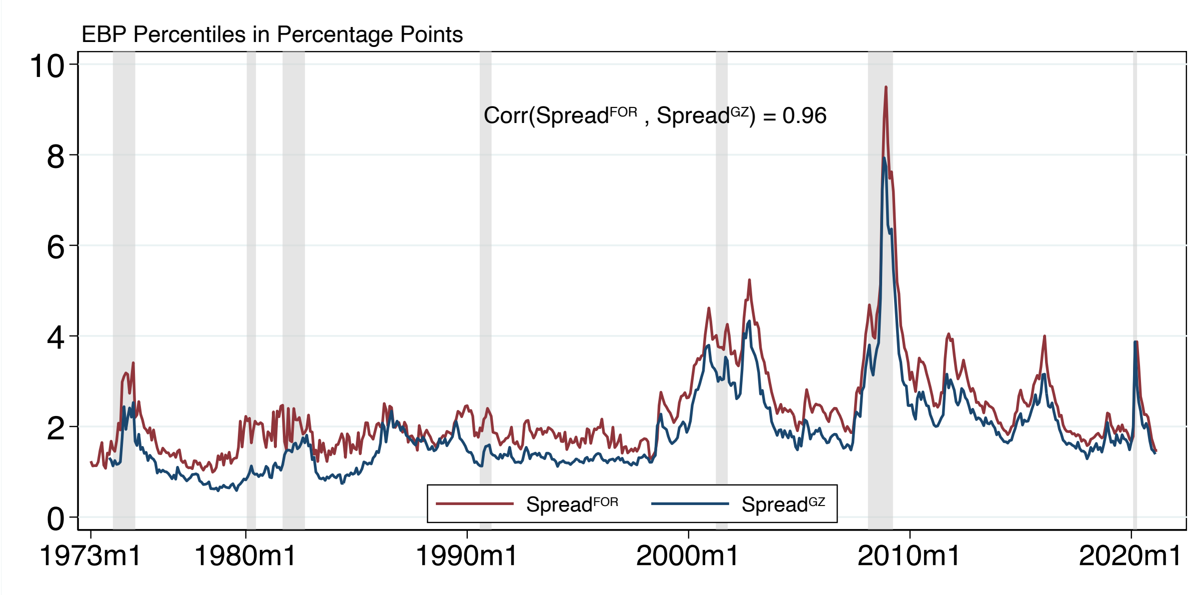
11. *Short-Term Assets*: defined as the ratio of current assets (actq in Compustat) to total assets (atq in Compustat).

12. *Sectors*: we consider 8 sectors based on 4-digit SIC codes: 1. SIC $\in$ [0,999] (agriculture, forestry, and fishing); 2. SIC $\in$ [1000,1499] (mining); 3. SIC $\in$ [1500,1799] (construction); 4. SIC $\in$ [2000,3999] (manufacturing); 5. SIC $\in$ [4000,4999] (transportation, communications, electric, gas, and sanitary services); 6. SIC $\in$ [5000,5199] (wholesale trade) 7. SIC $\in$ [5200,5999] (retail trade); 8. SIC $\in$ [7000,8999] (services).

13. *GDP, Aggregate Investment, CPI and Unemployment Rate*: measured as real chained gross domestic product (GDPC1 in FRED), real chained investment (RINV in FRED), consumer price index for cities (CPIAUCSL in FRED) and unemployment rate (UNRATE in FRED), respectively. Growth rates calculated as log-differences.

Sample selection: we focus on the non-financial firms whose equity prices are available in the Center for Research in Security Prices (CRSP) database, whose balance sheets are available from the CRSP/Compustat Merged Database, Wharton Research Data Services and whose bond yields data are available in the Arthur D. Warga, Lehman Brothers Fixed Income Database and the Interactive Data Corporation, ICE Pricing and Reference Data. To clean the data, similar to Gilchrist and Zakrajšek (2012), we first drop bond-time observations that display any of the following characteristics: they are puttable; they have spreads larger than 35% or below 0%; they have a residual maturity of less than 6 months or more than 30 years. After this, we drop bonds that have no spells of at least one year of consecutive observations. We then merge this bond-level dataset with the firm-level Compustat and CRSP databases for non-financial firms. To determine whether a firm is non-financial, we make use of both their NAICS/SIC code as well as the classification scheme internal to the Lehman-Warga/ICE databases. Specifically, if the NAICS/SIC code is available, we

FIGURE A.2
Credit Spreads: Comparison with Gilchrist and Zakrajšek (2012)



Note. Figure A.2 compares the mean credit spread calculated in this paper, in red, with the mean credit spread calculated by Gilchrist and Zakrajšek (2012), in blue. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.

exclude those firms classified as financial according to their NAICS/SIC code; otherwise, we exclude firms classified as financial according to the Lehman-Warga/ICE databases.

A.3 Calculating Distance to Default and the EBP

Our starting point is the credit spread S_{ikt} for bond k issued by firm i at time t. Figure A.2 plots the time series of our mean credit spread and that of Gilchrist and Zakrajšek (2012) and highlights that the correlation is 96%.

To derive each bond's EBP_{ikt}, we follow Gilchrist and Zakrajšek (2012) by estimating:

$$\log S_{ikt} = \beta DD_{it} + \gamma' \mathbf{Z}_{ikt} + v_{ikt}, \tag{A.1}$$

where DD_{it} is firm i's distance to default (Merton, 1974), and $\mathbf{Z}_{ikt}$ includes: (i) the bond's duration, age, par value, coupon rate (all in logs); (ii) a dummy for if the bond is callable; (iii) interactions between the characteristics listed in (i) and the call dummy in (ii); (iv)

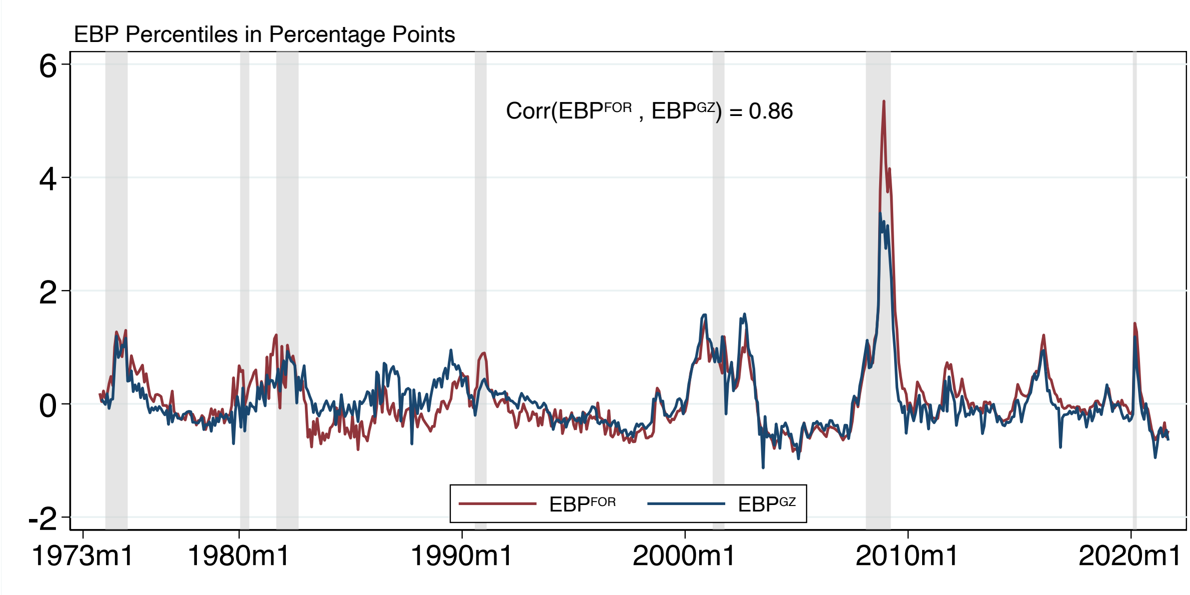
TABLE A.1
Bond-Level Credit Spreads and Firm Default Risk

$\log(S_{ikt})$	Est.	S.E.	T-stat
DD_{it}	-0.022	0.002	-13.37
$\log(Dur_{ikt})$	0.170	0.018	9.47
$\log(Age_{ikt})$	0.094	0.010	9.51
$\log(Par_{ikt})$	0.085	0.014	6.25
$\log(Coupon_{ikt})$	0.040	0.043	0.94
$\mathbf{1}_{Call_{ikt}}$	0.057	0.149	0.39
$DD_{it} \times \mathbf{1}_{Call_{ikt}}$	0.010	0.001	7.27
$\log(Dur_{ikt}) \times \mathbf{1}_{Call_{ikt}}$	0.030	0.018	1.65
$\log(Age_{ikt}) \times \mathbf{1}_{Call_{ikt}}$	-0.110	0.011	-9.89
$\log(Par_{ikt}) \times \mathbf{1}_{Call_{ikt}}$	-0.094	0.015	-6.05
$\log(Coupon_{ikt}) \times \mathbf{1}_{Call_{ikt}}$	0.503	0.045	11.28
$LEV_t \times \mathbf{1}_{Call_{ikt}}$	-0.042	0.007	-6.07
$SLP_t \times \mathbf{1}_{Call_{ikt}}$	-0.009	0.029	-0.29
$CRV_t \times \mathbf{1}_{Call_{ikt}}$	0.191	0.087	2.17
$VOL_t \times \mathbf{1}_{Call_{ikt}}$	0.002	0.000	8.37
Adj. R^2		0.679	
Industry Fixed Effects		Yes	
Credit-Rating Fixed Effects		Yes	

Note. Table A.1 present the estimated coefficients, standard errors and T-statistics from estimating regression (A.1) by OLS. The sample period is October 1973 to December 2021 and includes 682,316 observations. LEV_t, SLP_t, CRV_t refer to the level, slope and curvature (first three principal components) of the U.S. Treasury Yield Curve (Gürkaynak et al., 2007); VOL_t refers to the realized volatility of daily 10-year Treasury yield. Standard errors are two-way clustered by firm and month.

interactions between the call dummy in (ii) and DD_{it}, the first three principal components of the U.S. Treasury yield curve, and the volatility of the 10-year Treasury yield; and (v) industry and credit rating fixed effects. Table A.1 provides the results from estimating regression (A.1). Moreover, while the regression model is simple, it explains a significant share of the variation in credit spreads—the R^2 is 0.68—driven largely by firms' default risk. We discuss how we calculate DD_{it} later in this section.

FIGURE A.3
Excess Bond Premium: Comparison with Gilchrist and Zakrajšek (2012)



Note. Figure A.3 compares the mean EBP calculated in this paper, in red, with the mean EBP calculated by Gilchrist and Zakrajšek (2012), in blue. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.

Assuming the error term is normally distributed, the predicted spread $\hat{S}_{ikt}$ is given by:

$$\hat{S}_{ikt} = exp\left[\hat{\beta}DD_{it} + \hat{\gamma}'\mathbf{Z}_{ikt} + \frac{\hat{\sigma}^2}{2}\right], \tag{A.2}$$

where $\hat{\beta}$ and $\hat{\gamma}$ denote the OLS estimated parameters and $\hat{\sigma}^2$ denotes the estimated variance of the error term. Finally, we define the excess bond premium as

$$EBP_{ikt} = S_{ikt} - \hat{S}_{ikt}. \tag{A.3}$$

Implementing this procedure for the bonds in ICE and Lehman-Warga whose firm's balance sheet data and equity prices are available from Compustat and CRSP, respectively, yields, after data cleaning as described in Appendix A.2, a sample of monthly EBPs for 11,319 bonds from 1,913 firms. Figure A.3 plots the time series of our mean EBP and that of Gilchrist and Zakrajšek (2012) and highlights that the correlation is 86%.

The key predictor in the Gilchrist and Zakrajšek (2012) credit spread model is the firm's Merton (1974) distance to default (DD), an indicator of the firm's expected default risk. The DD framework assumes that the total value of the firm, denoted by V, is governed by following the stochastic differential equation:

$$dV = \mu_V V dt + \sigma_V V dZ_t, \tag{A.4}$$

where μ_V is the expected growth rate of V, σ_V is the volatility of V, and Z_t denotes the standard Brownian motion. Assuming that the firm issues a single bond with face-value D that matures in T periods, Merton (1974) shows that the value of the firm's equity E can be viewed as a call option on the underlying value of the firm V, with a strike price equal to the face-value of the firm's debt D maturing at T.

Using the Black and Scholes (1973) pricing formula for a call option, the value of the firm's equity is then

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2) \tag{A.5}$$

where r denotes the risk-free interest rate, $\Phi(.)$ denotes the cdf of standard normal distribution, and

$$\delta_1 = \frac{log(V/D) + (r + 0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}} \quad \text{and} \quad \delta_2 = \delta_1 - \sigma_V\sqrt{T}.$$

Using equation (A.5), by Ito's lemma, one can relate the volatility of the firm's value to the volatility of the firm's equity

$$\sigma_E = \frac{V}{E}\Phi(\delta_1)\sigma_V \tag{A.6}$$

Assuming a time to maturity of one year ($T = 1$) and daily data on one-year Treasury yields r, the face value of firm debt D, the market value of firm equity E, and its one-year historical volatility σ_E, equations (A.5) and (A.6) provide a two equation system that can be used to solve for the two unknowns V and σ_V.[17] Due to the issues raised in Vassalou

[17] Daily data for E is from CRSP ($prc * shrout$) and is used to calculate a daily 252-day historical rolling-window equity volatility σ_E. Quarterly data on firm debt $D =$ Current Liabilities$+\frac{1}{2}$Long-Term Liabilities is from Compustat ($dlcq + 0.5 * dlttq$) and is linearly interpolated to form a daily series.

and Xing (2004), we follow Gilchrist and Zakrajšek (2012) by implementing the two-step iterative procedure of Bharath and Shumway (2008). First, we set $\sigma_V = \sigma_E$ for each day in a one-year rolling window and then substitute σ_V into equation (A.5) to solve for the market value V for each of these days. Second, from our new estimated V series, we calculate a year-long series of daily log-returns to the firm's value, $\Delta \log V$, which we then use to compute a new estimate for σ_V as well as for μ_V.[18] We then iterate on σ_V until convergence.

Given solutions (V, σ_V, μ_V) to the Merton DD model, we are able to calculate the firm's Distance to Default over a one-year horizon as

$$DD = \frac{\log(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V} \tag{A.7}$$

Since default at T occurs when a firm's value falls below the value of its debt ($\log(V/D) < 0$), the DD captures the expected distance a firm is above default, given an expected asset growth rate μ_V and volatility σ_V until T, in units of standard deviations.

A.4 Summary Statistics

In this section, we provide summary statistics for our main monthly bond-level and quarterly firm-level variables of interest, as well as for the monetary policy shocks at both a monthly and quarterly frequency. These are displayed in Table A.2.

The first columns in Panels A.2a and A.2b report summary statistics for bond-level EBPs at a monthly frequency and firm-level EBPs at a quarterly frequency, respectively. The quarterly firm-level EBP series is constructed by averaging the bond-level EBP series across a firm's outstanding bonds in a given month and then across the months in a given quarter.[19] The summary statistics for the monthly bond-level and quarterly firm-level EBPs are broadly in line with one another. Further, unsurprisingly given the results documented in Appendix A.3, our mean monthly bond-level EBP is very similar to the corresponding mean value from Gilchrist and Zakrajšek (2012).

[18] Using the formulas $\sigma_V = \sqrt{252} * \sigma(\Delta \log V)$ and $\mu_V = 252 * \mu(\Delta \log V)$.

[19] The difference in the number of observations between the quarterly firm-level EBP series and the monthly bond-level EBP series reflects these two levels of averaging.

TABLE A.2
Monthly Bond-level and Quarterly Firm-level Summary Statistics

(A) Monthly Variables

	EBP_{ikt}	S_{ikt}	ε_t^m
Mean	.076	2.04	-.003
Median	-.065	1.30	0
S.D.	1.58	2.37	0.028
5^{th} Perc.	-1.39	.371	-.045
95^{th} Perc.	1.79	5.84	.042
# Obs.	581,845	638,717	439

(B) Quarterly Variables

	EBP_{it}	$\Delta log(K_{it})$	ε_t^m
Mean	.160	.496	-.008
Median	-.067	-.024	-.007
S.D.	2.04	6.93	.048
5^{th} Perc.	-1.84	-3.87	-.091
95^{th} Perc.	2.62	6.35	.072
# Obs.	59,471	52,052	147

Note. Table A.2 presents summary statistics for our main monthly bond-level variables and the monetary policy shock series at a monthly frequency (Panel A.2a) and for our main quarterly firm-level variables and the monetary policy shock series at a quarterly frequency (Panel A.2b) from 1973 to 2021 (1985 to 2021 for the monetary policy shocks). Values are in percentage points, except for investment $\Delta log(K_{it})$ which is in percent, and are calculated from the fully cleaned and merged dataset (see Appendix A.2). The monthly monetary policy shock series is summed within each quarter to generate the quarterly series. Of note, the mean *absolute* value of the monthly (quarterly) monetary policy shock series is 1.7 (3.6) basis points, which is an order of magnitude larger than the mean values reported above. For each firm, the monthly bond-level EBP is averaged across the firm's bonds in a given quarter to generate the quarterly firm-level series. The monthly bond-level EBP (spread) panel includes 10061 (11319) bonds issued by 1630 (1913) non-financial firms. The quarterly firm-level EBP (investment) series includes 1630 (1149) non-financial firms.

The second columns in Panels A.2a and A.2b report summary statistics for our dependent variables of interest, monthly bond-level credit spreads and quarterly firm-level investment, respectively. As with the EBP, the value of our mean bond-level credit spread—about 2 percentage points—is very similar to the corresponding mean value from Gilchrist and Zakrajšek (2012). Similarly, the average level of firms' investment in our sample—about 0.5 percent—is nearly identical to the corresponding mean value documented by Ottonello and Winberry (2020). The remainder of our summary statistics for firms' investment are also consistent with those documented by Ottonello and Winberry (2020), but with a moderately lower standard deviation and tighter tails.

As mentioned previously, our analysis focuses on publicly-listed U.S. firms who issue debt in corporate bond markets. While this tilts our sample towards large firms relative to

Ottonello and Winberry (2020)'s sample, data on both prices and quantities are crucial to inspect the transmission of monetary policy. Further, large firms have been shown to play an outsized role in driving the U.S. business cycles (e.g., Carvalho and Grassi, 2019). Still, relative to both the literatures on monetary policy's effects on firm-level investment (e.g., Ottonello and Winberry, 2020) and on bond-level credit spreads (e.g., Anderson and Cesa-Bianchi, 2024), our use of the Lehman-Warga database and a monetary policy shock series that spans periods of conventional and unconventional policy affords us a longer sample than most studies.[20]

This longer sample is made evident by the large number of observations we have for the monetary policy shock series, whose summary statistics at a monthly and quarterly frequency are tabulated in the third columns of Panels A.2a and A.2b, respectively. The quarterly monetary policy shock series is generated by summing the monthly series within each quarter. Of note, the mean *absolute* value of the monthly (quarterly) monetary policy shock series is 1.7 (3.6) basis points, which is an order of magnitude larger than the mean values reported in the table.

[20] Our time sample runs form 1985-2021. Relative to Anderson and Cesa-Bianchi (2024), for example, who also focus on publicly-listed U.S. firms that issue debt in corporate bond markets, our dataset includes about 2000 more bonds issued by about 800 more non-financial firms, since their sample runs only from 1999 to 2017. Cloyne et al. (2023), who focus on firm investment, leverage a relatively long time sample as well, from 1986 to 2016, although this is still about 6 years shorter than in our study. By contrast, Ottonello and Winberry (2020)'s time sample is shorter, running from 1990 to 2007.

B Additional Empirical Results and Robustness

In this section, we provide additional empirical results and robustness to complement our findings from the main text. In Section B.1, we provide robustness to our results from Section 2.4 linking firms' EBPs to the cyclicality of their default risk. We then turn to our main empirical results from Sections 3 and 4. Specifically, in Section B.2, we highlight that the heterogeneous responses we document are robust to controlling for heterogeneity according to other firm characteristics. In Section B.3, we show that our results are robust to using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{i(k)t-1}$. In Section B.4, we show that it is the EBP-component of firms' credit spreads that reacts heterogeneously to monetary policy and credit supply shocks. In Section B.5, we document the hetergeneous effects on firm debt issuance of both monetary policy and credit supply shocks. In Section B.6, we re-estimate our main specifications with alternative monetary policy shocks. Finally, in Section B.7, we showcase the robustness of our results from Section 6 linking the moments of the EBP distribution to the aggregate effectiveness of monetary policy.

B.1 Firm EBPs and Cyclicality of Default Risk

In Section 2.4, we showed empirically that low-EBP firms' default risk co-moves relatively less with aggregate risk, as proxied by the U.S. S&P500 index return. In this section, we highlight the robustness of this empirical result along three dimensions: (i) replacing the S&P500 return with the intermediary capital risk factor of He et al. (2017) as a measure of aggregate risk; (ii) interacting the S&P500 return simultaneously with other firm characteristics; and (iii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$.

The results from re-estimating regression (1) and (2) using as the measure of aggregate risk the intermediary capital risk factor of He et al. (2017) are presented in Table B.1. They are remarkably similar to the results using the S&P500 return from the main text. Both low-EBP and high-EBP firms' distance to defaults rise (default risks fall) when intermediary capital improves, but low-EBP firms' rises by about 50% less. This is shown explicitly in column (3), with sector-time fixed effects, which reflects the relative loading low-EBP firms'

Table B.1

Firms' Default Risk and Aggregate Risk, Measured as Intermediary Capital

$\Delta DD_{i,t}$	(1) Low-EBP	(2) High-EBP	(3) Relative Low-EBP
R_t^{Mkt}	.027***	.043***	
	(.007)	(.012)	
$R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$			-.013***
			(.004)

Note: Table B.1 reports the loadings of firms' default risk on the U.S. intermediary capital risk factor of He et al. (2017) as a measure of aggregate risk. The first row reports β^{Mkt} from regression (1), which is estimated separately for low-EBP firms (column (1))—firms in the bottom quintile of the cross-sectional EPB distribution—and high-EBP firms (column (2))—firms in the upper quintiles. The second row reports $\beta^{Mkt,Rel}$ from regression (2), which measures how low-EBP firms' ($\mathbf{1}EBP_{it-1}^{low} = 1$) default risk loads on aggregate risk relative to high-EBP firms' (column (3)). Standard errors are two-way clustered by firm and month. *** denotes statistical significance at the 1% level.

default risk on aggregate risk.

The results from estimating (2)—which measures the relative loading of low-EBP firms' default risk on aggregate risk (S&P500 return)—using 5 different threshold percentiles (the 15^{th}, 20^{th} [main text], 25^{th}, 33^{rd} and 50^{th}) of the EBP distribution to classify low-EBP firms (i.e., $\mathbf{1}EBP_{it-1}^{low} = 1$) are displayed in Figure B.3. The results are highly significant in all cases and are consistent with our headline result: low-EBP firms' default risk is less cyclically sensitive than high-EBP firms'.

Table B.2

Low- vs. High-EBP Firms' Default Risk Cyclicalities: Alternate Percentiles

	Dep. Var.: $\Delta DD_{i,t}$				
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}	15^{th}
$R_t^{Mkt} \times \mathbf{1}EBP_{i,t-1}^{Low}$	-0.15**	-0.23***	-0.25***	-0.29***	-0.33***
	(.06)	(.08)	(.09)	(.08)	(.09)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time-Sector FE	Yes	Yes	Yes	Yes	Yes

Note: Table B.2 reports $\beta^{Mkt,Rel}$ from regression (2), which measures how low-EBP firms' default risk loads on the market return relative to high-EBP firms' for different threshold percentiles for defining $\mathbf{1}EBP_{it-1}^{low}$. Specifically, it presents results for 5 different threshold percentiles: 50^{th}, 33^{rd}, 25^{th}, 20^{th} (our baseline) and the 15^{th}. Standard errors are two-way clustered by firm and month. *** (**) denotes statistical significance at the 1% (5%) level.

Finally, Table B.3 presents results from re-estimating regression (2) while also controlling for the loadings of other firm characteristics on aggregate risk. That is, we add to regression (2) the interactions $R_t^{Mkt} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. We define each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ in two ways: (1) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise; and (2) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. Columns (1) and (2) of Table B.3 present the estimated coefficients for $R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$ with $\mathbf{1Z}_{it-1}^{low}$ defined using the 20^{th} and 50^{th} percentiles, respectively. In both cases, the significant association between firms' EBPs and the cyclicality of firms' default risks remain after controlling for the loadings of other firm characteristics.

TABLE B.3
Low- vs. High-EBP Firms' Default Risk Cyclicalities: Controlling for Other Firm Characteristics

$\Delta DD_{i,t}$	(1) Control for 20^{th}	(2) Control for 50^{th}
$R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$	-0.20***	-0.17***
	(.06)	(.05)

Note: Table B.3 reports $\beta^{Mkt,Rel}$ from a modified regression (2) that controls for $R_t^{Mkt} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Column (1), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. In Column (2), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. *** denotes statistical significance at the 1% level.

B.2 Heterogeneous Effects by EBP vs. other Characteristics

In this section, we show that firms' EBPs matter for their responsiveness to monetary policy and credit supply shocks when also conditioning on other competing firm characteristics. To show this, we re-estimate our baseline regressions (4), (6) and (8), which contain the interaction term $\varepsilon_t^{shock} \times \mathbf{1}EBP_{i(k)t-1}^{low}$, when also including the interaction vector $\varepsilon_t^{shock} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q and where $shock = \{m\} \quad or \quad \{CS\}$.[21] We again define each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ in two ways: (1) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise; and (2) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise.

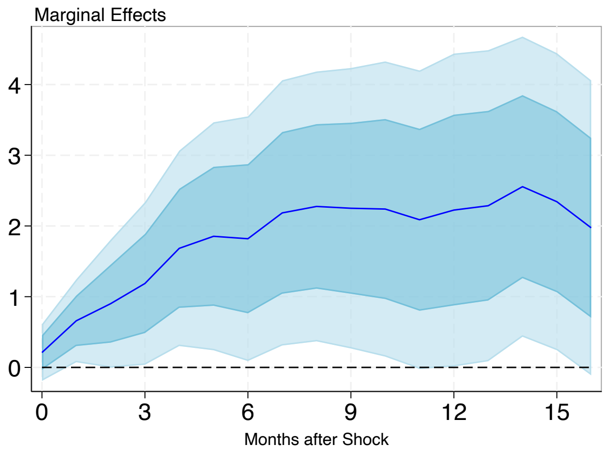
The results of these horserace regressions between firms' EBPs and other firm characteristics are displayed in Figures B.1, B.2, B.3 and B.4. The left panel in each figure displays low-EBP firms' response to the shock compared to high-EBP firms', controlling for the interaction $\varepsilon_t^{shock} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is defined based on the 20^{th} percentile of the cross-sectional distribution of firms' characteristics. The right panel in each figure displays the same, but with $\mathbf{1Z}_{it-1}^{low}$ defined based on the 50^{th} percentile of the cross-sectional distribution of firms' characteristics.

Across each figure and specification, we see that firms' EBPs continue to regulate the responsiveness of firms' credit spreads and investment to monetary policy and credit supply shocks. This highlights the economic relevance of firms' EBPs for explaining firms' heterogeneous reactions to monetary policy.

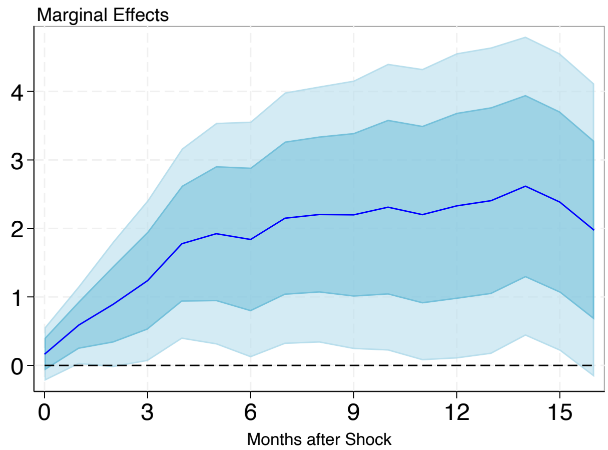
[21] We include these indicator variables of firm characteristics and their interactions with the shocks en lieu of firm characteristics in levels.

Figure B.1
Horserace Regressions: Relative Response of Low-EBP Firms' Spreads to Monetary Policy

(a) Horeserace with below 20^{th} Perc. Characteristics



(b) Horeserace with below 50^{th} Perc. Characteristics

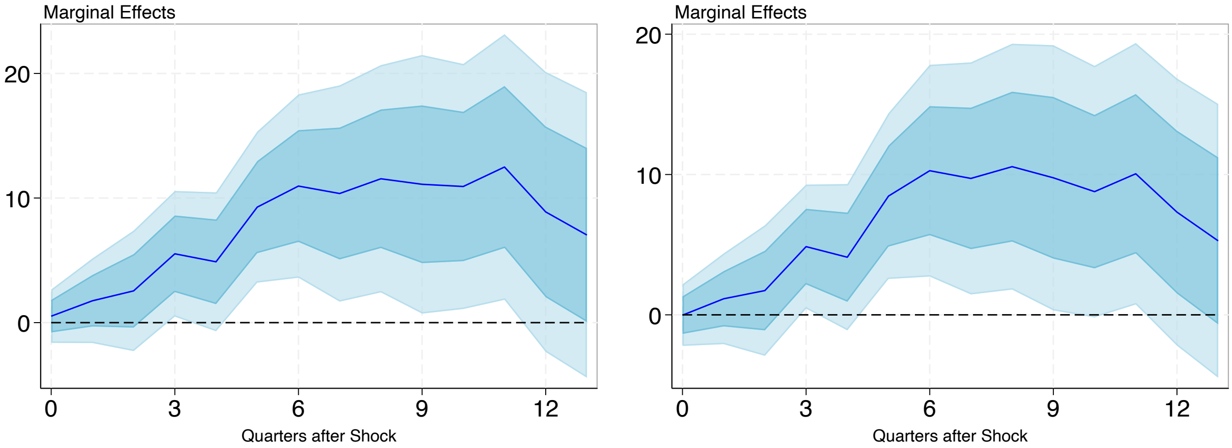


Note. Figure B.1 plots the credit spread response of low-EBP (sub 20^{th} percentile) firms' bonds to a monetary policy shock relative to high-EBP firms' using a modified regression (4) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Panel B.1a, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. In Panel B.1b, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

FIGURE B.2

Horserace Regressions: Relative Response of Low-EBP Firms' Investment to Monetary Policy

(A) Horeserace with below 20^{th} Perc. Characteristics (B) Horeserace with below 50^{th} Perc. Characteristics

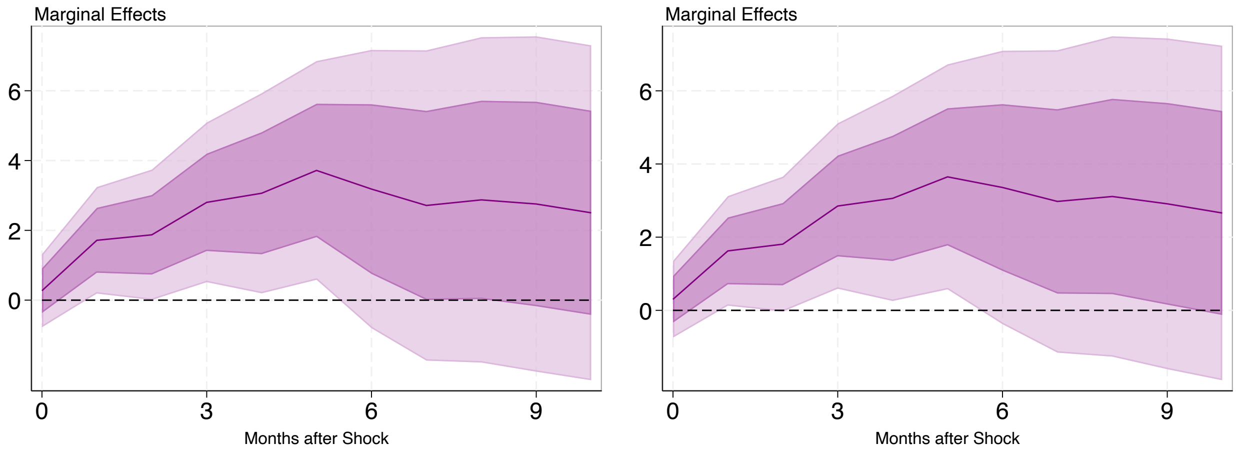


Note. Figure B.2 plots the investment response of low-EBP (sub 20^{th} percentile) firms to a monetary policy shock relative to high-EBP firms using a modified regression (6) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Panel B.2a, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. In Panel B.2b, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

Figure B.3

Horserace Regressions: Relative Response of Low-EBP Firms' Spreads to Credit Supply Shock

(A) Horeserace with below 20^{th} Perc. Characteristics (B) Horeserace with below 50^{th} Perc. Characteristics

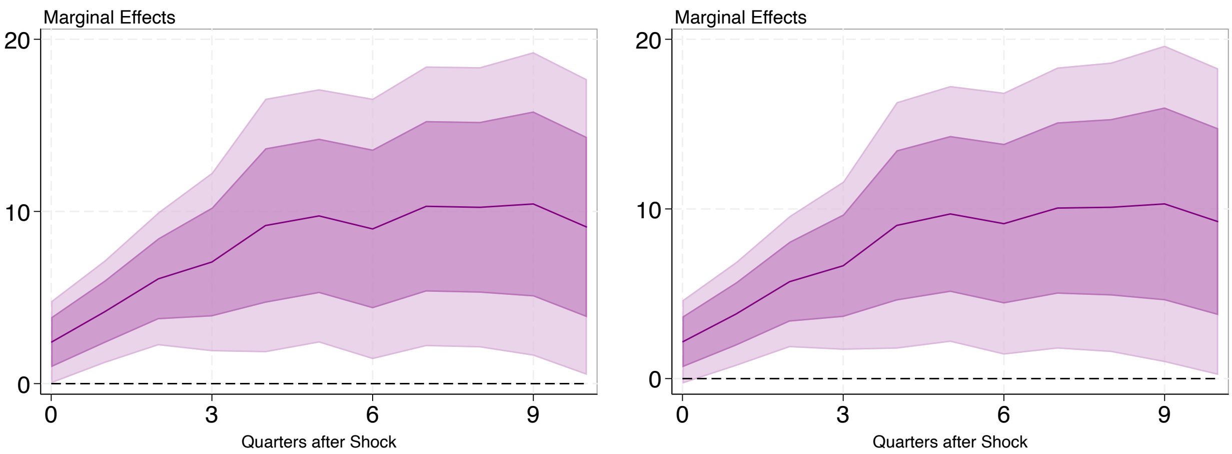


Note. Figure B.3 plots the credit spread response of low-EBP (sub 20^{th} percentile) firms' bonds to a credit supply shock relative to high-EBP firms' using a modified regression (8) that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Panel B.3a, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. In Panel B.3b, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

Figure B.4

Horserace Regressions: Relative Response of Low-EBP Firms' Investment to Credit Supply Shock

(a) Horeserace with below 20^{th} Perc. Characteristics (b) Horeserace with below 50^{th} Perc. Characteristics



Note. Figure B.4 plots the investment response of low-EBP (sub 20^{th} percentile) firms to a credit supply shock relative to high-EBP firms using a modified regression (8) that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Panel B.4a, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 20^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. In Panel B.4b, each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic Z_{it-1} is below the 50^{th} percentile of the firm-level distribution of Z_{it-1}, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

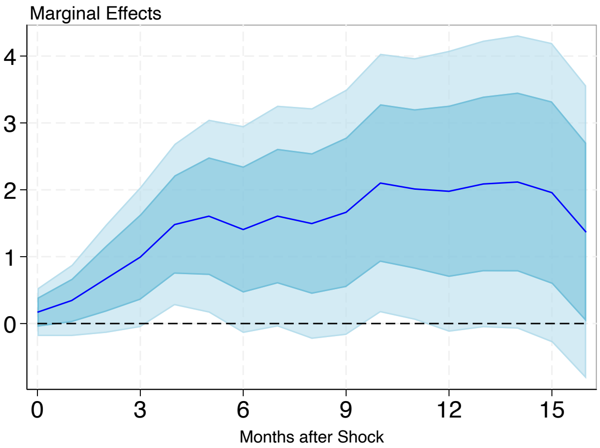
B.3 Heterogeneous Effects with Alternative EBP Percentiles

In this section, we show that our results from the main text are robust to using different threshold percentiles to define low-EBP firms, i.e., firms for which $\mathbf{1}EBP^{low}_{i(k)t-1} = 1$. In particular, we provide results for four other threshold percentiles to complement our baseline results using the 20^{th} percentile from the main text, namely, the 15^{th}, 25^{th}, 33^{rd} and 50^{th} (median) percentiles. The results for re-estimating regression (4)—monetary policy's effect on bond credit spreads—with these other percentiles are shown in B.5. The results for re-estimating regression (6)—monetary policy's effect on firm investment—with these other percentiles are shown in Figure B.6. The results for re-estimating regression (8)—credit supply's effect on bond credit spreads and firm investment—with these other percentiles are shown in Figures B.7 and B.8, respectively. In each case, we see similar heterogeneous responses for each of the thresholds, highlighting that our results from the main text are not tied to the 20^{th} percentile, but rather reflect a marked difference between low- and high-EBP firms.

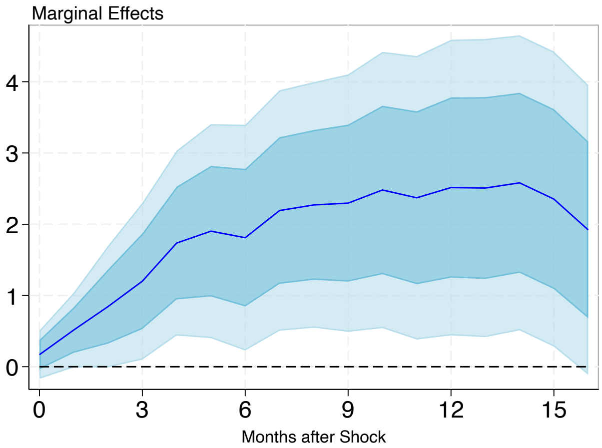
Figure B.5

Relative Response of Bond Credit Spreads to Monetary Policy by EBP Percentiles

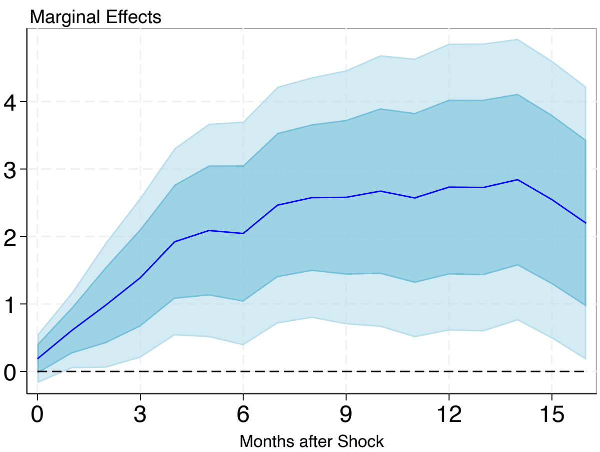
(A) Below 15^{th} EBP_{ikt-1} Percentile



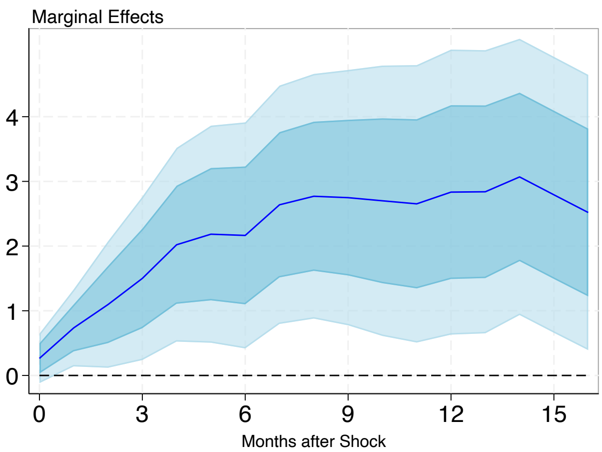
(B) Below 25^{th} EBP_{ikt-1} Percentile



(C) Below 33^{rd} EBP_{ikt-1} Percentile



(D) Below 50^{th} EBP_{ikt-1} Percentile

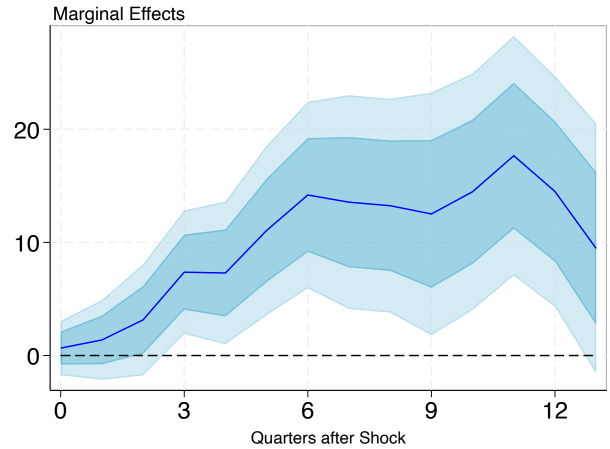


Note. Figure B.5 plots the β_1^hs from regression (4), which trace the credit spread response of low-EBP firms' bonds to a monetary policy shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (4). Panels B.5a, B.5b, B.5c, B.5d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a bond's EBP is below the 15^{th}, 25^{th}, 33^{rd} and 50^{th} percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

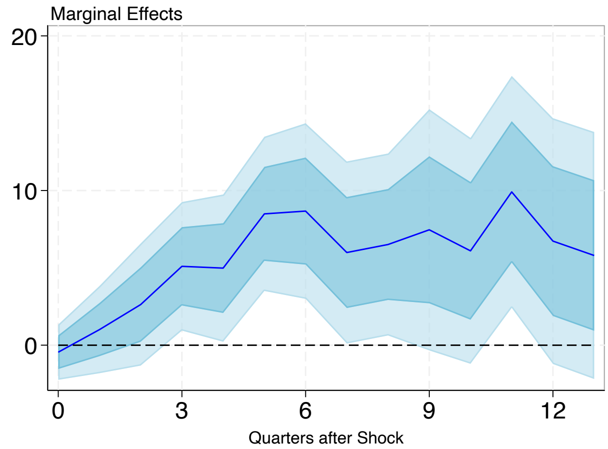
Figure B.6

Relative Response of Firm Investment to Monetary Policy by EBP Percentiles

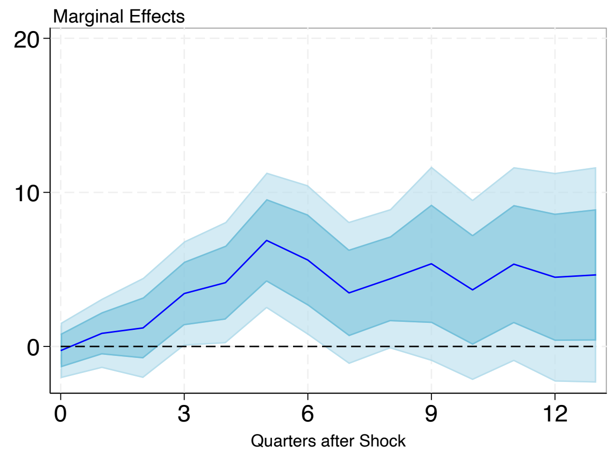
(A) Below 15^{th} EBP_{it-1} Percentile



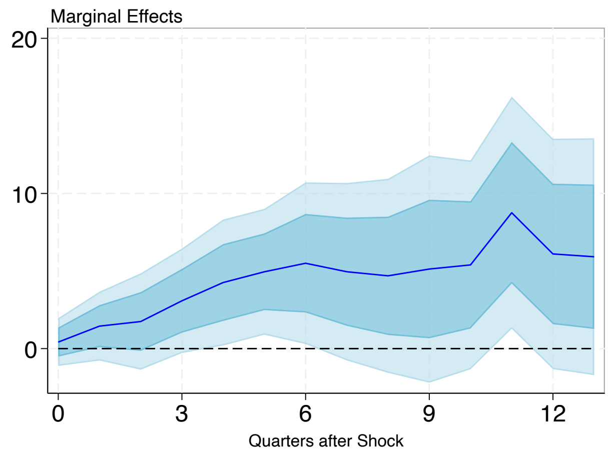
(B) Below 25^{th} EBP_{it-1} Percentile



(C) Below 33^{rd} EBP_{it-1} Percentile



(D) Below 50^{th} EBP_{it-1} Percentile

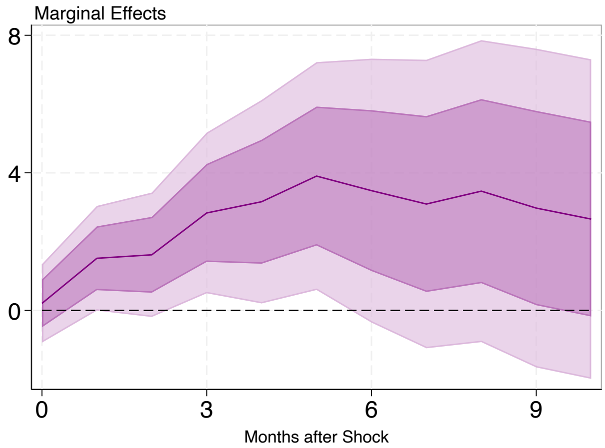


Note. Figure B.6 plots the β_1^hs from regression (6), which trace the investment response of low-EBP firms to a monetary policy shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (6). Panels B.6a, B.6b, B.6c, B.6d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the 15^{th}, 25^{th}, 33^{rd} and 50^{th} percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

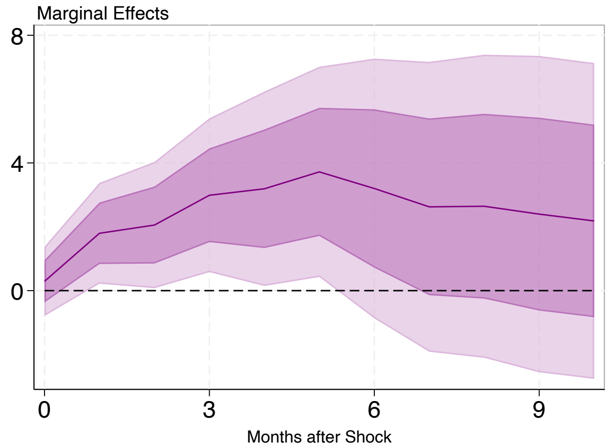
FIGURE B.7

Relative Response of Bond Credit Spreads to Credit Supply Shock by EBP Percentiles

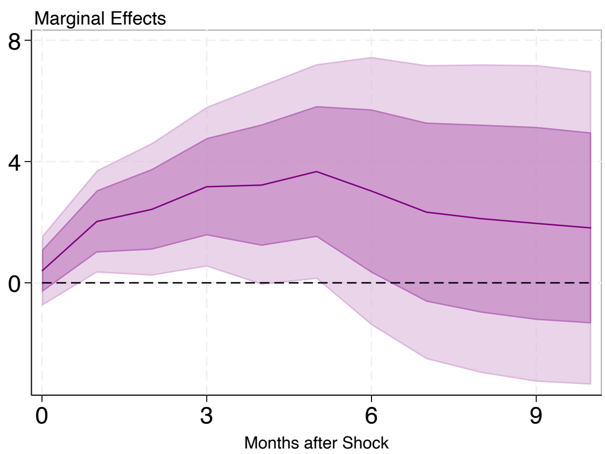
(A) Below 15^{th} EBP_{ikt-1} Percentile



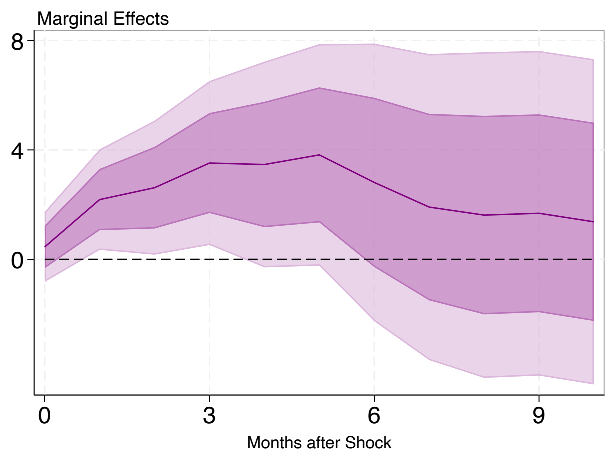
(B) Below 25^{th} EBP_{ikt-1} Percentile



(C) Below 33^{rd} EBP_{ikt-1} Percentile



(D) Below 50^{th} EBP_{ikt-1} Percentile

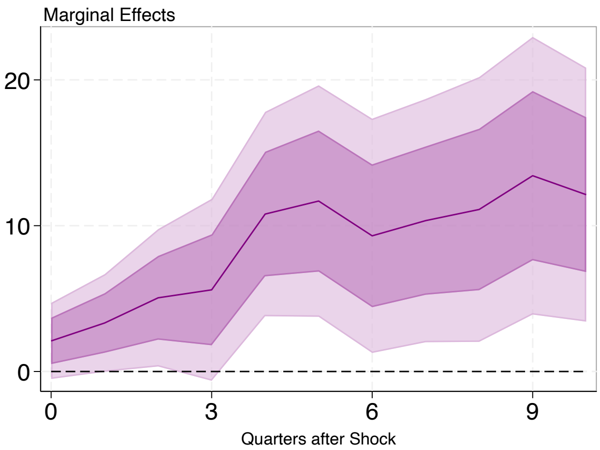


Note. Figure B.7 plots the β_1^hs from regression (8), which trace the credit spread response of low-EBP firms' bonds to a credit supply shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{ikt-1}$ in regression (8). Panels B.7a, B.7b, B.7c, B.7d set $\mathbf{1}EBP^{low}_{ikt-1} = 1$ if, respectively, a bond's EBP is below the 15^{th}, 25^{th}, 33^{rd} and 50^{th} percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

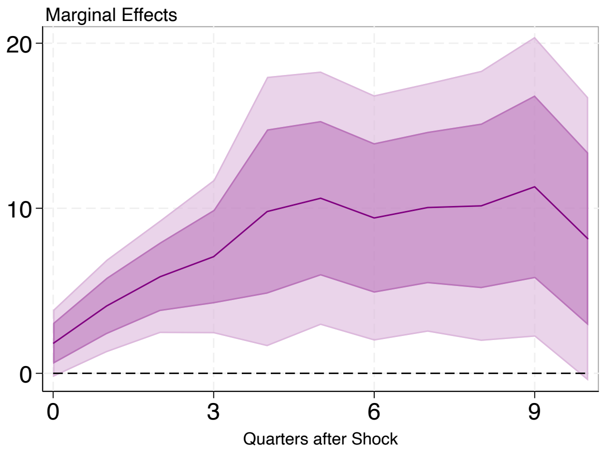
Figure B.8

Relative Response of Firm Investment to Credit Supply Shock by EBP Percentiles

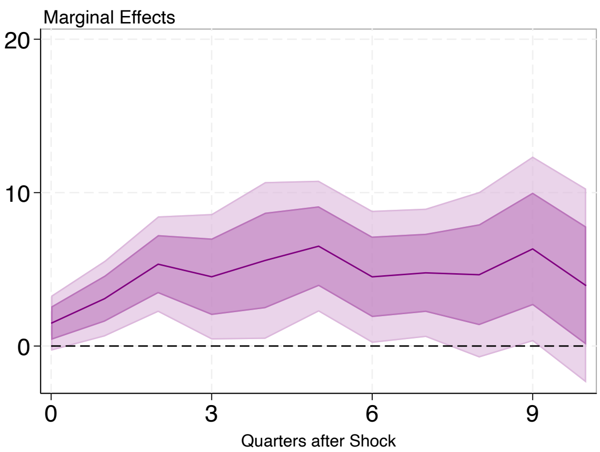
(a) Below 15^{th} EBP_{it-1} Percentile



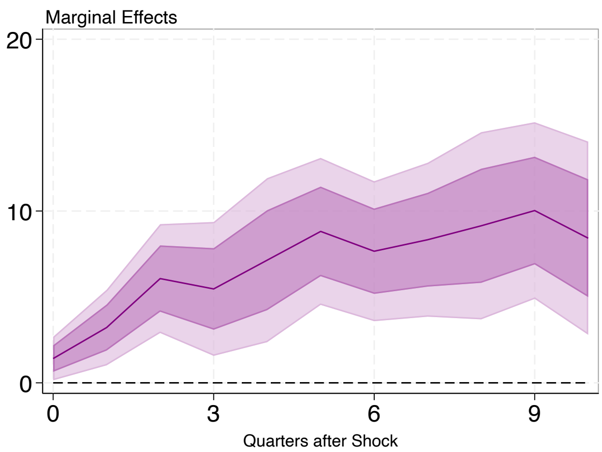
(b) Below 25^{th} EBP_{it-1} Percentile



(c) Below 33^{rd} EBP_{it-1} Percentile



(d) Below 50^{th} EBP_{it-1} Percentile



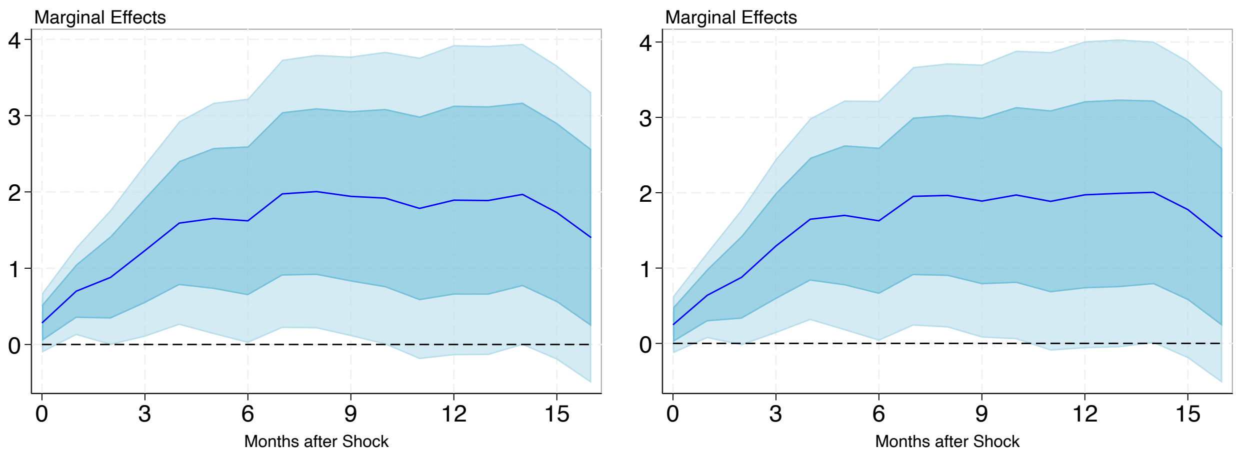
Note. Figure B.8 plots the β_1^hs from regression (8), which trace the investment response of low-EBP firms to a credit supply shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (8). Panels B.8a, B.8b, B.8c, B.8d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the 15^{th}, 25^{th}, 33^{rd} and 50^{th} percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

B.4 Heterogeneous Effects on Bond-Level EBPs

In this section, we re-estimate our baseline credit spread regressions (4) and (8) using as the dependent variable the h-period change in the EBP component of firms' credit spreads, $EBP_{ikt+h} - EBP_{ikt-1}$. These results are shown in Panel B.11a (monetary policy shock) and B.12a (credit supply shock), respectively. We also re-run the robustness exercises from Sections B.2 and B.3, i.e., running horse-race regressions between the EBP and other firm characteristics (Figures B.9 and B.10) and using other percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{ikt-1}$ (Figures B.11 and B.12), respectively. In all cases, the response of firms' EBPs tracks almost identically the response of firms' credit spreads, highlighting that it is the EBP-component of firms' credit spreads that reacts heterogeneously to monetary policy and credit supply shocks.

FIGURE B.9
Horserace Regressions: Relative Response of Low-EBP Firms' EBP to Monetary Policy

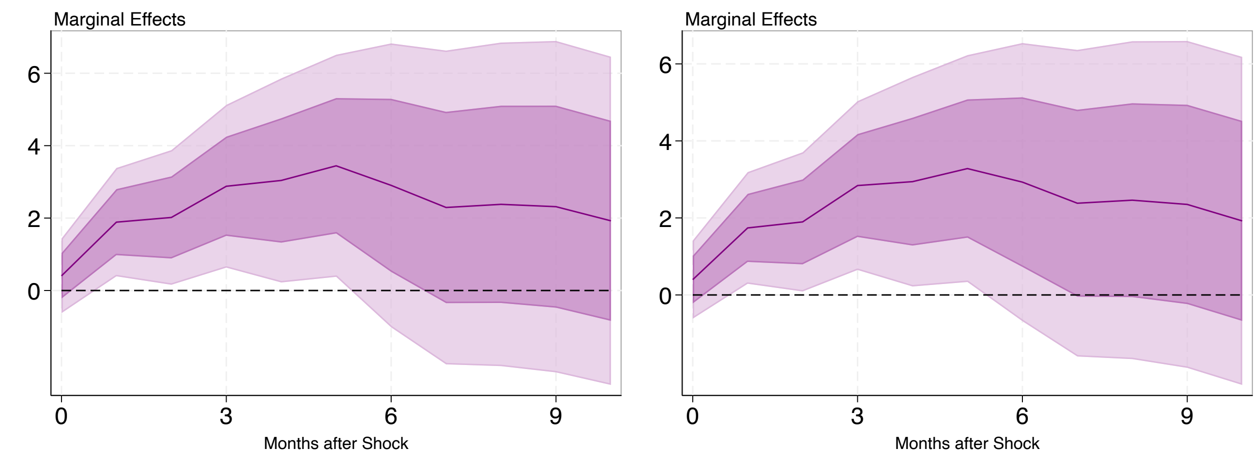
(A) Horeserace with below 20^{th} Perc. Characteristics (B) Horeserace with below 50^{th} Perc. Characteristics



Note. Figure B.9 plots the β_1^hs from a modified regression (4) that uses the change in bonds' EBPs rather than their credit spreads as the dependent variable and that controls for $\varepsilon_t^m \times \mathbf{1Z}^{low}_{it-1}$, where $\mathbf{1Z}^{low}_{it-1}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.1 apply.

Figure B.10
Horserace Regressions: Relative Response of Low-EBP Firms' EBP to Credit Supply Shock

(A) Horeserace with below 20^{th} Perc. Characteristics (B) Horeserace with below 50^{th} Perc. Characteristics

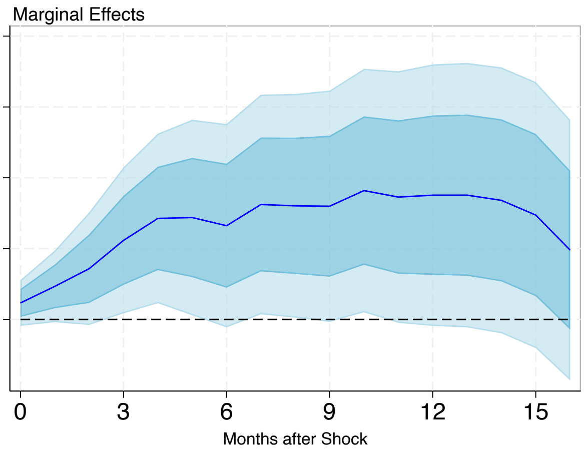


Note. Figure B.10 plots the β_1^hs from a modified regression (8) that uses the change in bonds' EBPs rather than their credit spreads as the dependent variable and that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.3 apply.

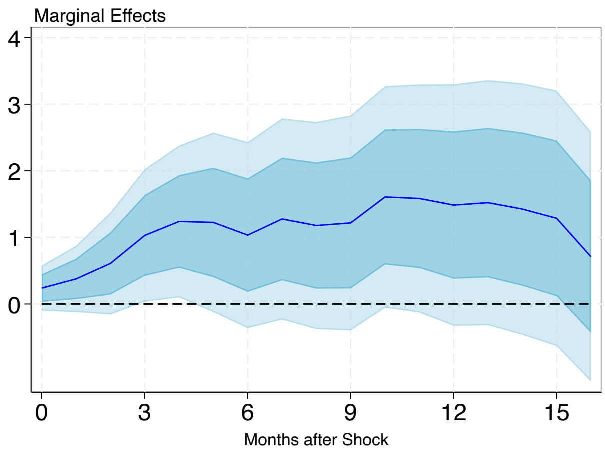
FIGURE B.11

Relative Response of Bond EBPs to Monetary Policy by EBP Percentiles

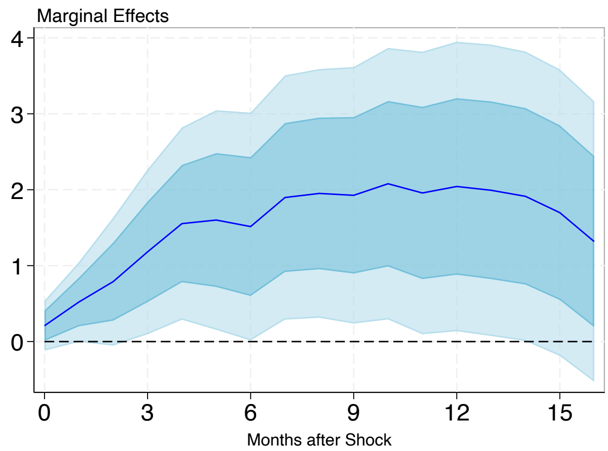
(A) Below 20^{th} EBP_{ikt-1} Percentile



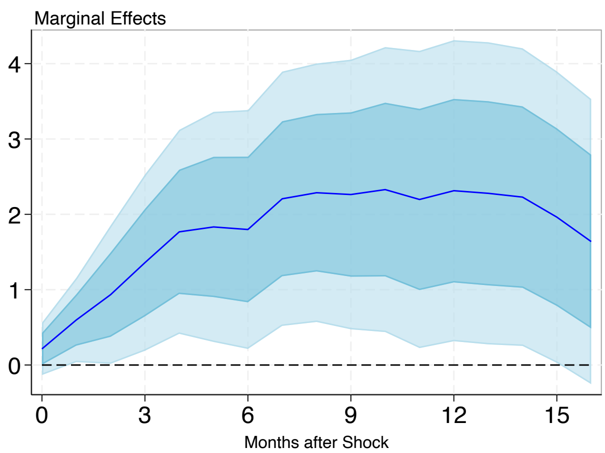
(B) Below 15^{th} EBP_{ikt-1} Percentile



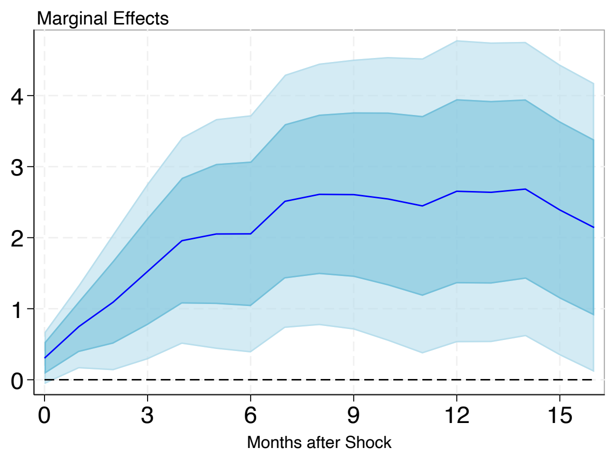
(C) Below 25^{th} EBP_{ikt-1} Percentile



(D) Below 33^{rd} EBP_{ikt-1} Percentile



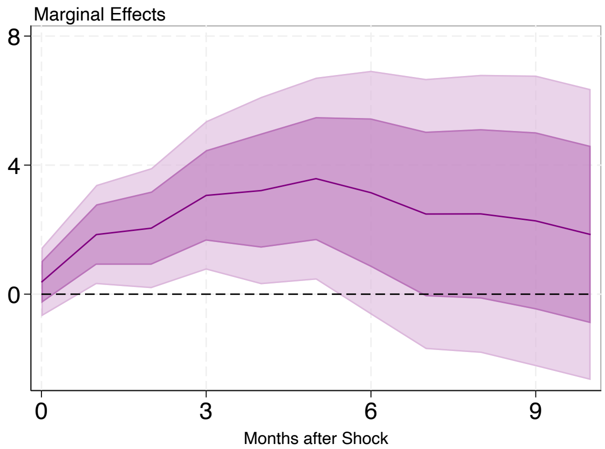
(E) Below 50^{th} EBP_{ikt-1} Percentile



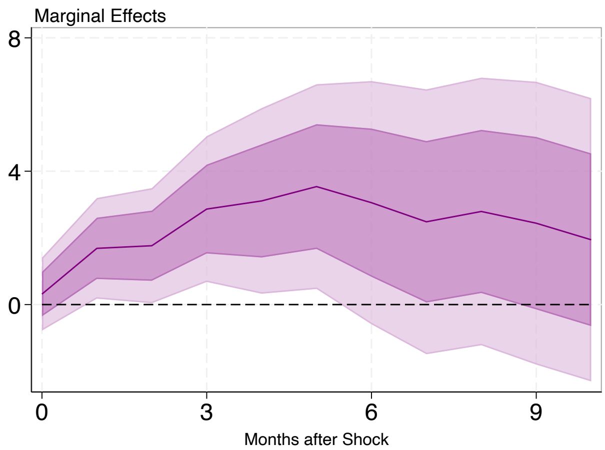
Note. Figure B.11 plots the β_1^hs from a modified regression (4) that uses changes in the EBP-component of firms' credit spreads as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$. The remaining notes from Figure B.5 apply.

Figure B.12
Relative Response of Bond EBPs to Credit Supply Shock by EBP Percentiles

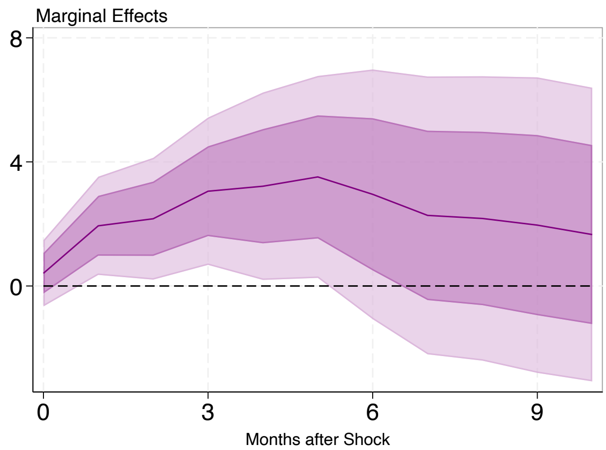
(a) Below 20^{th} EBP_{ikt-1} Percentile



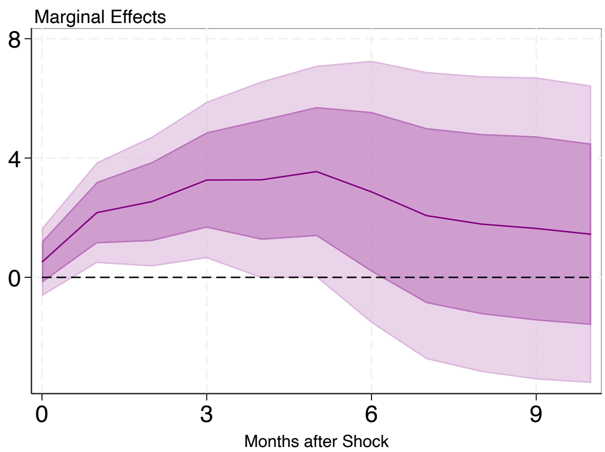
(b) Below 15^{th} EBP_{ikt-1} Percentile



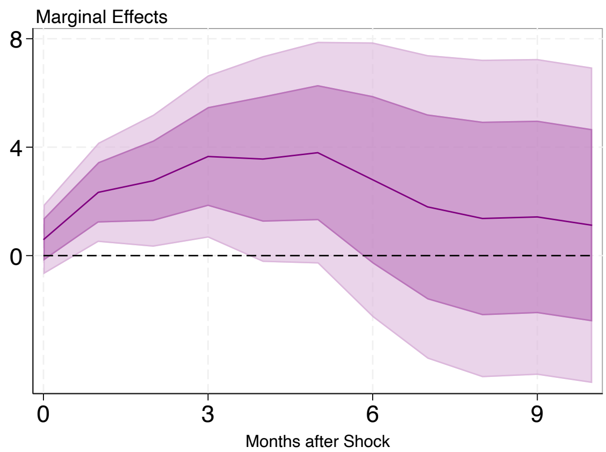
(c) Below 25^{th} EBP_{ikt-1} Percentile



(d) Below 33^{rd} EBP_{ikt-1} Percentile



(e) Below 50^{th} EBP_{ikt-1} Percentile



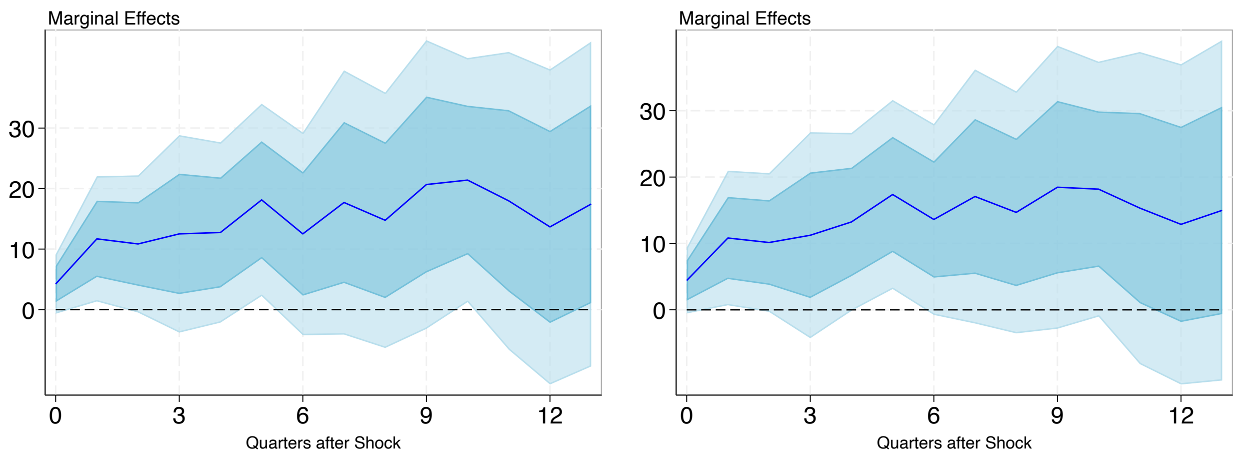
Note. Figure B.12 plots the β_1^hs from a modified regression (8) that uses changes in the EBP-component of firms' credit spreads as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$. The remaining notes from Figure B.7 apply.

B.5 Heterogeneous Effects on Firm-Level Debt Issuance

In this section, we re-estimate our baseline investment regressions (6) and (8) using as the dependent variable the h-period log change in firms' debt issuance, $\log D_{it+h} - \log D_{it-1}$. These results are shown in Panel B.15a (monetary policy shock) and B.16a (credit supply shock), respectively. We also re-run the robustness exercises from Sections B.2 and B.3, i.e., running horse-race regressions between the EBP and other firm characteristics (Figures B.13 and B.14) and using other percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$ (Figures B.15 and B.16), respectively. In all cases, the results are in line with the heterogeneous responses of investment: low-EBP firms increase debt issuance relative to high-EBP firms following expansionary monetary policy and credit supply shocks.

FIGURE B.13
Horserace Regressions: Relative Response of Low-EBP Firms' Debt Growth to Monetary Policy

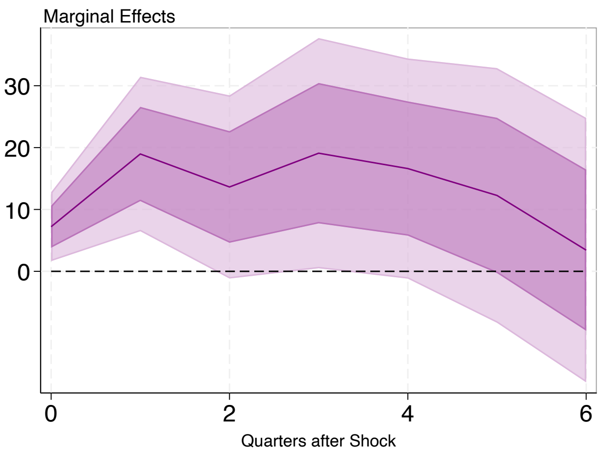
(A) Horeserace with below 20^{th} Perc. Characteristics (B) Horeserace with below 50^{th} Perc. Characteristics



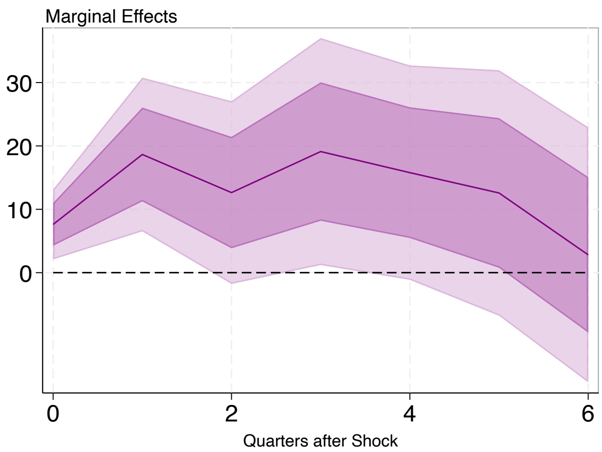
Note. Figure B.13 plots the β_1^hs from a modified regression (6) that uses the h-period log change in firms' debt issuance as the dependent variable and that controls for $\varepsilon_t^m \times \mathbf{1Z}^{low}_{it-1}$, where $\mathbf{1Z}^{low}_{it-1}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.2 apply.

Figure B.14
Horserace Regressions: Relative Response of Low-EBP Firms' Debt Growth to Credit Supply Shock

(A) Horeserace with below 20^{th} Perc. Characteristics



(B) Horeserace with below 50^{th} Perc. Characteristics

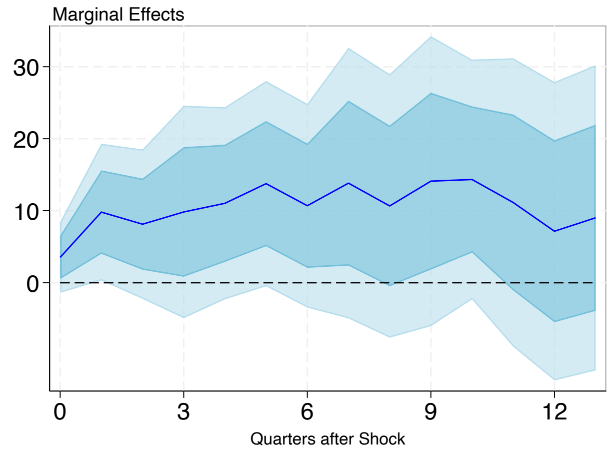


Note. Figure B.14 plots the β_1^hs from a modified regression (8) that uses the h-period log change in firms' debt issuance as the dependent variable and that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.4 apply.

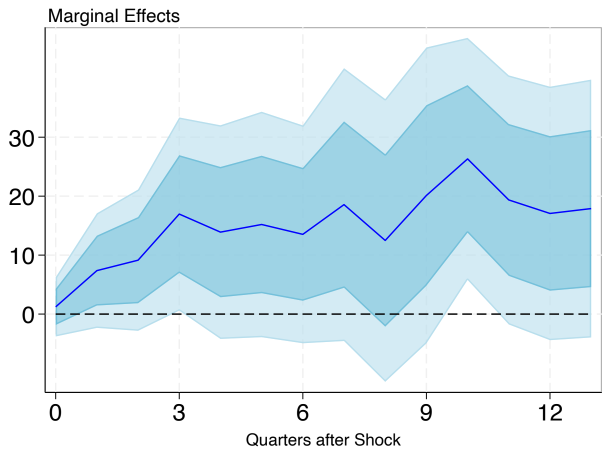
FIGURE B.15

Relative Response of Firm Debt to Monetary Policy Shock by EBP Percentiles

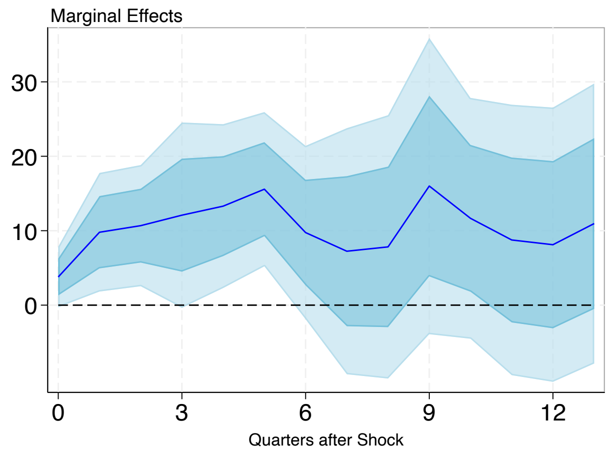
(A) Below 20^{th} EBP_{it-1} Percentile



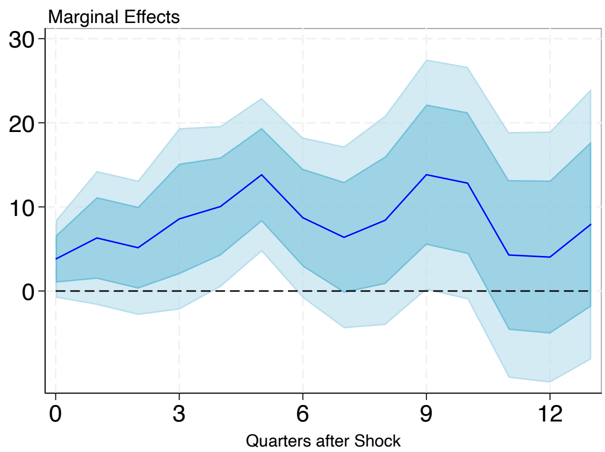
(B) Below 15^{th} EBP_{it-1} Percentile



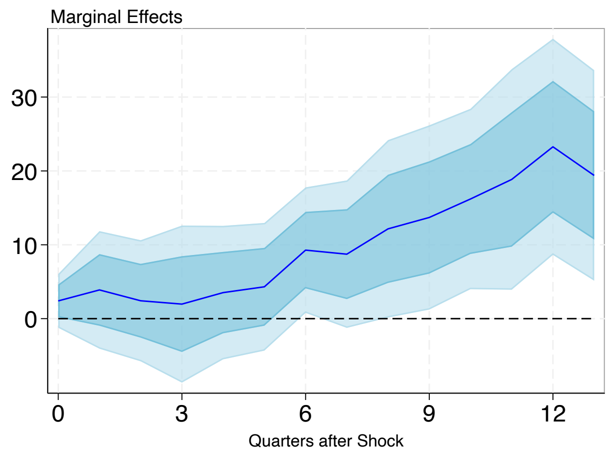
(C) Below 25^{th} EBP_{it-1} Percentile



(D) Below 33^{rd} EBP_{it-1} Percentile



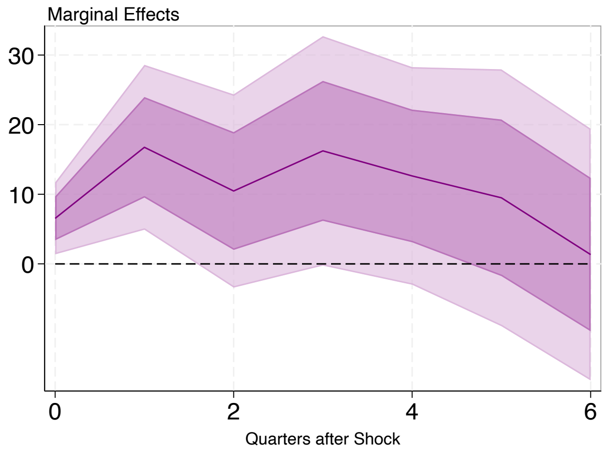
(E) Below 50^{th} EBP_{it-1} Percentile



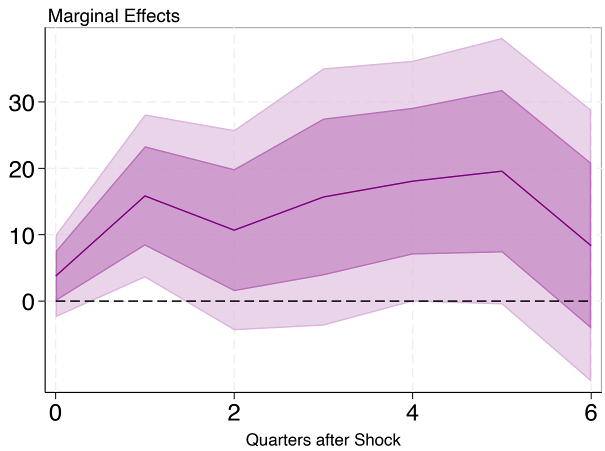
Note. Figure B.15 plots the β_1^hs from a modified regression (6) that uses the h-period log change in firms' debt issuance as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.6 apply.

FIGURE B.16
Relative Response of Firm Debt to Credit Supply Shock by EBP Percentiles

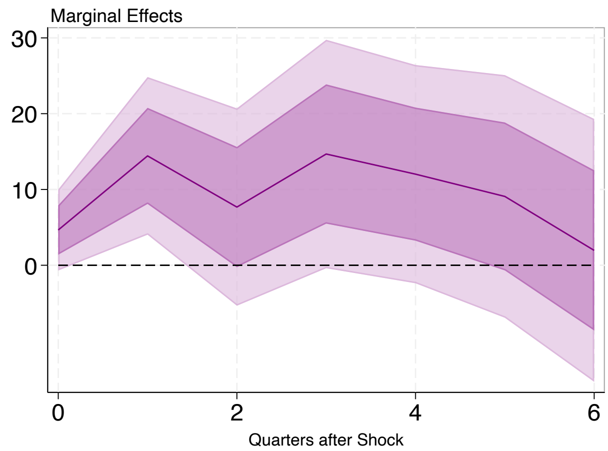
(A) Below 20^{th} EBP_{it-1} Percentile



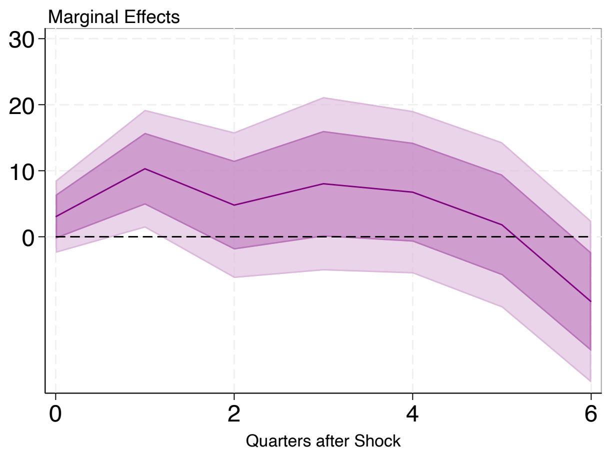
(B) Below 15^{th} EBP_{it-1} Percentile



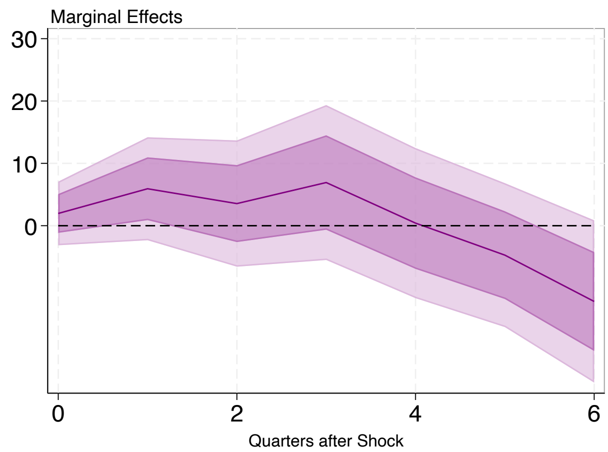
(C) Below 25^{th} EBP_{it-1} Percentile



(D) Below 33^{rd} EBP_{it-1} Percentile



(E) Below 50^{th} EBP_{it-1} Percentile



Note. Figure B.16 plots the β_1^hs from a modified regression (8) that uses the h-period log change in firms' debt issuance as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.8 apply.

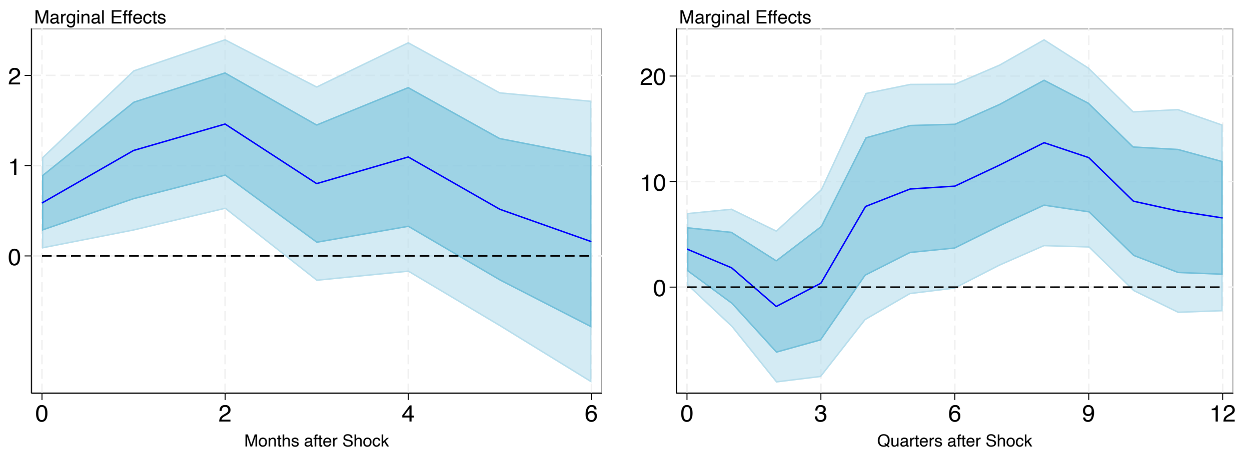
B.6 Heterogeneous Effects with Alternative Monetary Policy Shocks

In this section, we show our results for the heterogeneous responses of firms' investment and credit spreads are robust to using an alternative monetary policy shock series. For comparability with Ottonello and Winberry (2020), we re-estimate our results with high-frequency monetary policy shocks constructed from changes in the expected Federal Funds Rate around FOMC announcements, as implied by current-month Federal Funds future contracts (FF0). We take these shocks from Acosta and Saia (2020), who extend the shocks of Nakamura and Steinsson (2018) to cover the period from 2000 to 2019. We normalize the shock series to have the same variance as the Bu et al. (2021) series we use in our baseline.

The results for credit spreads—which come from re-estimating regression (4) with the FF0 shock—and for investment—which come from re-estimating regression (6) with the FF0 shock—are displayed in Figure B.17, respectively. In both cases, we document the same pattern as for the Bu et al. (2021) shock series in the main text. Specifically, low-EBP firms' credit spreads fall by less following an expansionary monetary policy shock (Panel B.17a), although these low-EBP firms invest relatively more than high-EBP firms (Panel B.17b). Further, as in the main text, the impulse responses are hump shaped and are of a comparable magnitude.

Figure B.17
High-Frequency FF0 Monetary Policy Shocks on Firms' Spreads and Investment

(a) Relative Response of Low-EBP Firms' Spreads (b) Relative Response of Low-EBP Firms' Investment



Note. Figure B.17 reports the dynamic responses of bond-level credit spreads and firm-level investment to high-frequency FF0 monetary policy shocks, as calculated by Acosta and Saia (2020) and Nakamura and Steinsson (2018). Panel B.17a plots the β_1^hs from regressions (4) with the FF0 shocks, which trace the credit spread $S_{ikt+h} - S_{ikt-1}$ response of low-EBP firms' bonds ($\mathbf{1}EBP_{ikt-1}^{low} = 1$) relative to high-EBP firms' bonds ($\mathbf{1}EBP_{ikt-1}^{low} = 0$). Panel B.17b plots the β_1^hs from regressions (6) with FF0 shocks, which trace the investment $\log(K_{it+h}/K_{it-1})$ response of low-EBP firms relative to high-EBP firms. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month/quarter.

B.7 Robustness of Aggregate Implications of EBP Heterogeneity

In this section, we show that our results from Section 6, where we documented that the cross-sectional EBP distribution is an important empirical driver of the aggregate effectiveness of monetary policy, are robust to horseraces between monetary policy's interaction with the moments of the EBP distribution and its interaction with various recession indicators.

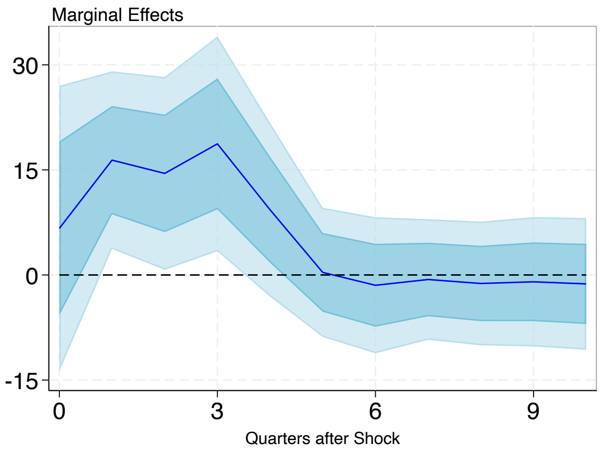
Specifically, we consider interactions between monetary policy shocks and two types of (lagged) recession indicators: (i) the smoothed U.S. recession probability measure from Chauvet (1998); (ii) a dummy variable for NBER-classified U.S. recessions. In particular, the Chauvet (1998) measure very closely tracks the recession measure used in Tenreyro and Thwaites (2016). We include these additional interaction terms in regression (13) from the main text.

The results are displayed in Figures B.18 and B.19, respectively. We find that the conditioning power of EBP skewness is unaffected by including the recession indicator interactions, with a right-skewing of the EBP distribution associated with a dampening of the effects of monetary policy shocks on aggregate investment growth. Interestingly, the results for the conditioning power of the median and dispersion of the EBP distribution are weakened when accounting for the well-documented weaker effects of monetary policy in recessions (Tenreyro and Thwaites (2016)), although they are still significant at some horizons. Overall, our findings highlight that the importance of the skewness of the EBP distribution for monetary policy's aggregate potency holds both in and out of recessions.

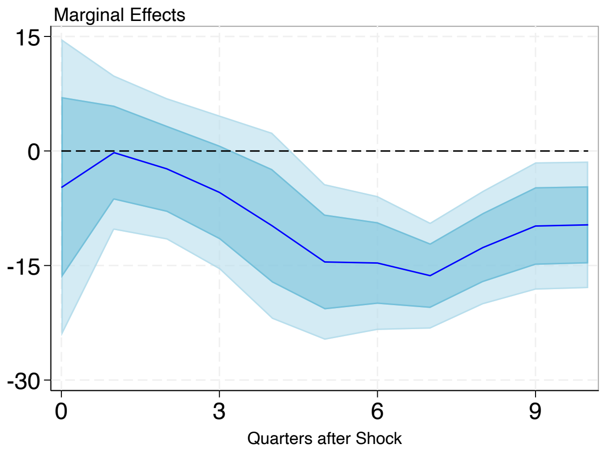
Figure B.18

Monetary Policy's Effect on Aggregate Investment Growth:
Horserace between EBP moments and Recession Probability Variable

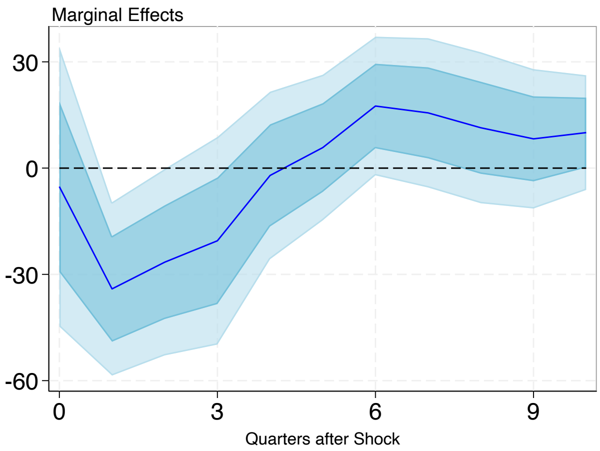
(a) Unconditional



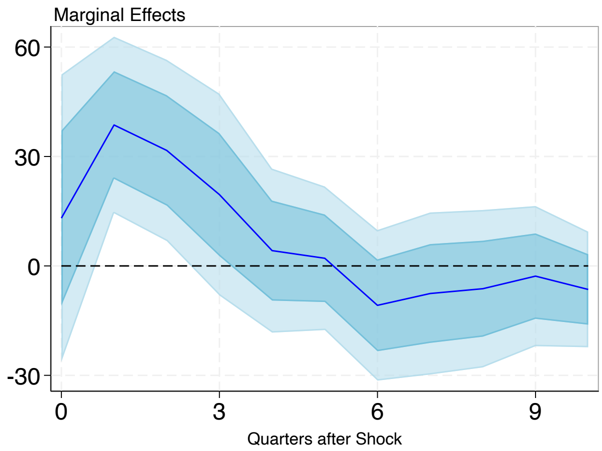
(b) Conditional on EBP Skewness



(c) Conditional on Median EBP



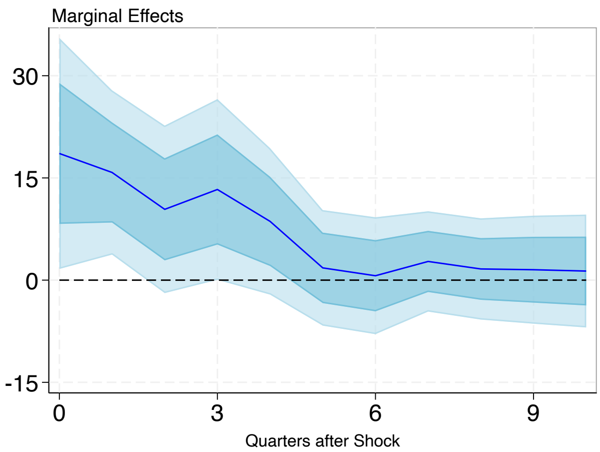
(d) Conditional on EBP Dispersion



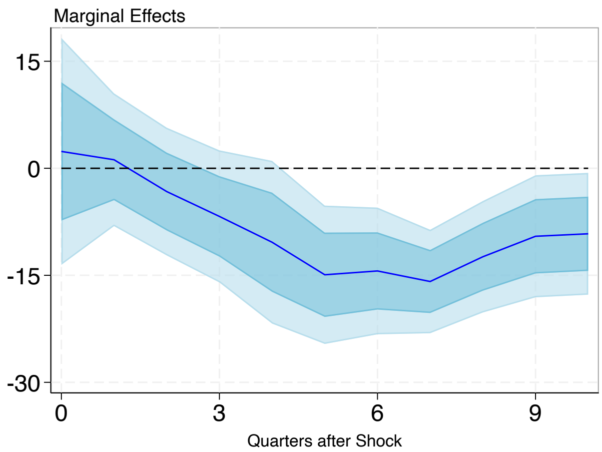
Note. Figure B.18 reports the regression results from estimating a modified regression (13) that includes the interaction between the monetary policy shock and the Chauvet (1998) recession probability variable. Panel B.18a shows unconditional effects, β_1^h. Panels B.18b, B.18c and B.18d show the effects conditional on the skewness, median and dispersion of the EBP distribution, measured in standard deviations, which are three of the elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

FIGURE B.19
Monetary Policy's Effect on Aggregate Investment Growth
Horserace between EBP moments and NBER Recession Indicator

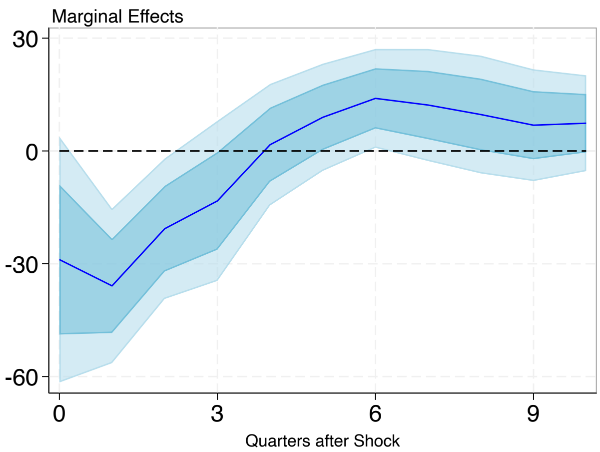
(A) Unconditional



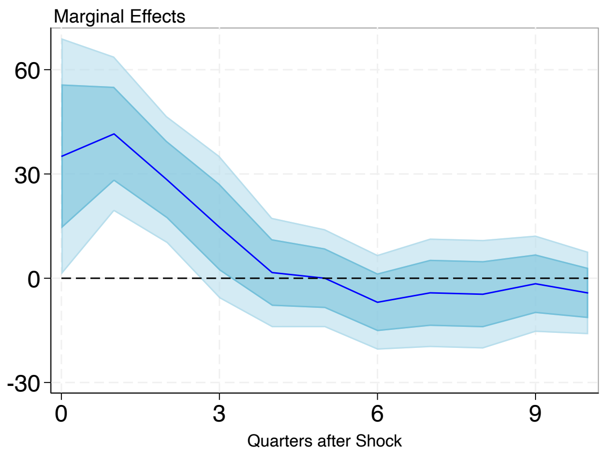
(B) Conditional on EBP Skewness



(C) Conditional on Median EBP



(D) Conditional on EBP Dispersion



Note. Figure B.19 reports the regression results from estimating a modified regression (13) that includes the interaction between the monetary policy shock and the NBER-recession indicator variable. Panel B.19a shows unconditional effects, β_1^h. Panels B.19b, B.19c and B.19d show the effects conditional on the skewness, median and dispersion of the EBP distribution, measured in standard deviations, which are three of the elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

C Model Appendix

In this section, we discuss the parameterization we use for the model in Section 5.

TABLE C.1
Model Parameterization

Parameter	Value	Description
$\overline{p}$	0.01	Expected Firm Probability of Default
$\overline{\mu}$	0.2	Expected Loss Share if Firm Defaults
ρ_L	0	Covariance between p and μ for Low-EBP firm
ρ_H	0.045	Covariance between p and μ for High-EBP firm
α	0.97	Firm Capital Elasticity
$\overline{z}$	1	Expected Productivity
θ	0.08	Intermediary Agency Friction Parameter
N_1	0.0003	Intermediary Net-Worth Pre-Shock
N_2	0.0008	Intermediary Net-Worth Post-Shock
R_1	1.06	Interest Rate Pre-Shock
R_2	1.05	Interest Rate Post-Shock

Table C.1 presents our model's parameterization. The first set of parameters are firms' expected default probability $\overline{p}$, which we set to 1%—in between the values found in Campbell et al., 2008 and Bernanke et al. (1999)—and firms' expected loss share when firms default $\overline{\mu}$, which we set to 20%—roughly the median loss share on senior-secured notes discussed in Altman et al., 2004 (Table 3). Next, we turn to the covariance between firms' probability of default and the default loss share ρ. We normalize this covariance to be 0 ($\rho_L = 0$) for the less cyclical firm and set the covariance to be 0.045 ($\rho_H = 0.045$) for the more cyclical firm. Given the other parameters of the model, this covariance differential allows us to match that low-EBP firms have on-average about a 1.5pp lower EBP than high-EBP firms do.

Turning to the production function parameters, we set $\alpha = 0.97$, which generates significant convexity of firms' MB curves around the equilibria, in line with the parameterization in Anderson and Cesa-Bianchi (2024). We normalize the expected productivity to unity ($\overline{z} = 1$). We set the fraction of intermediaries' revenue that they can abscond with to 8% ($\theta = 0.08$), similar to the value used in Anderson and Cesa-Bianchi (2024).

Finally, we turn to the parameters that we use for the comparative statics. On the demand side, we study a 1pp reduction in the risk-free benchmark rate from $R_1 = 1.06$ to $R_2 = 1.05$—which corresponds to the average 10Y U.S. Treasury yield over our sample (1985-2021). On the supply side, motivated by the financial accelerator mechanism of monetary policy transmission, we study an increase in intermediary net worth from $N_1 = 0.003$ to $N_2 = 0.008$, which are similar values to those used in Anderson and Cesa-Bianchi (2024). The increase in net worth is large enough relative to the reduction in the risk-free rate so that firms' credit spreads decline when changes in N and R are studied in the model together.

Overall, we stress that the model is not meant to provide quantitative predictions, but rather is meant to illustrate transmission mechanisms and provide conditions under which, given a reasonable parameterization, the model can qualitatively match the heterogeneous effects we document in the data.