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Thiago R T Ferreira, [1] Daniel A Ostry [2] and John Rogers[3]

Abstract

We re-examine how financial frictions shape the transmission of monetary policy using firms' excess bond premia (EBPs), the risk premium component of credit spreads. While monetary policy easing shocks compress credit spreads more for higher-EBP (riskier) firms, lower-EBP firms' investment responds more. Further, credit supply shocks replicate monetary policy's heterogeneous effects, whereas credit demand shocks elicit homogeneous firm responses. A model with financial frictions in which lower-EBP firms have flatter marginal benefit curves for capital rationalises firms' price and quantity reactions to these three shocks. In contrast, previously examined channels, while complementary, are inconsistent with our more comprehensive set of empirical moments.

Key words: Monetary policy, investment, credit spreads, excess bond premium, firm heterogeneity, credit supply, risk premium.

JEL classification: E22, E44, E50.

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(1) Federal Reserve Board. Email: thiago.r.teixeiraferreira@frb.gov
(2) Bank of England and Centre for Macroeconomics. Email: daniel.ostry@bankofengland.co.uk
(3) Fudan University. Email: johnrogers@fudan.edu.cn

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Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

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1 Introduction

How do firms' investment responses to monetary policy depend on their financial conditions? Most of the large literature addressing this question is informed by theories in which firms' access to external funds is subject to financial frictions (e.g., Bernanke and Gertler, 1989 and Kiyotaki and Moore, 1997). On the empirical front, the literature has proxied for the severity of firms' financial frictions using various firm characteristics, such as size (Gertler and Gilchrist, 1994), default risk (Ottonello and Winberry, 2020), age (Cloyne et al., 2023), and liability structure (Gürkaynak et al., 2022). The message of this research is that financial frictions, reflected in firms' marginal cost curves (Bernanke et al., 1999), play an important role in shaping their heterogeneous responses to monetary policy.

In this paper, we reconsider the role of financial frictions for the transmission of monetary policy by examining the responses of both firms' investment and credit spreads to monetary shocks. We show that while monetary policy easings compress credit spreads more for riskier firms, safer firms invest more. To inspect the mechanism, we examine firms' responses to both credit supply and credit demand shocks. We find that firms' heterogeneous reactions to credit supply and monetary policy shocks are similar, whereas credit demand shocks elicit largely homogeneous firm responses. Altogether, these results indicate that financial frictions affect firms' responsiveness to monetary policy primarily because they determine firms' positions along—and hence the slopes of—their marginal *benefit* curves for capital. From micro to macro, our results imply that the aggregate investment response to monetary policy is driven by firms with greater marginal propensities to invest out of changes in net worth, rather than by firms whose borrowing rates react more to policy. Consistent with this, we show empirically that the pass-through of monetary policy to aggregate investment varies over time with the distribution of firm financial conditions.

We begin by estimating how firms' responsiveness to monetary policy depends on their financial conditions. We do so using a data set that combines bond-level corporate yields and firm-level balance sheets for U.S. public non-financial firms from 1973 to 2021 with a monetary policy shock series that bridges periods of conventional and unconventional policy. To measure firms' financial conditions, we use their excess bond premia (EBPs)—the risk premium component of firms' credit spreads (Gilchrist and Zakrajšek, 2012)—which we show encode the cyclicality of firms' default risk.[1] Our first key empirical finding is that while monetary policy easing shocks compress credit spreads more for firms with higher ex-ante EBPs—that is, for firms whose default risk loads more on aggregate risk—it is firms with lower EBPs that invest more. In both cases, the heterogeneity we document is economically significant: the relative responses of low-EBP firms' investment and credit spreads are comparable to the average responses observed across all firms. Further, by including sector-time fixed effects in our baseline specifications, these responses measure the different reactions of low- and high-EBP firms in the same sector and time period. Finally, we show that, as a state variable, a firm's EBP is statistically distinct from other firm characteristics.

We rationalize these results with a model in which financial intermediaries, which differ in the extent of their financial frictions, lend capital to firms. Financial intermediaries' skin-in-the-game constraints (see Gertler and Kiyotaki, 2010, Gertler and Karadi, 2011 and Anderson and Cesa-Bianchi, 2021) imply that firms face upward-sloping marginal cost (MC) curves for capital. We calibrate the tightness financial intermediaries' constraints to match the empirical co-movement between low- and high-EBP firms' default risk and aggregate risk. As a result, when markets are segmented according to firm risk, firms with lower default-risk "betas" face flatter and more outward-shifted MC curves. Coupled with decreasing returns to scale in production, i.e., downward sloping marginal benefit (MB) curves for capital, these cyclically safer firms have lower EBPs in equilibrium, as they do in the data. Further, and crucially, due to the concavity of firms' production function, low-EBP firms' flatter and outward-shifted MC curves place them on flatter segments of their MB curves. These low-EBP firms therefore have greater marginal propensities to invest out of changes in intermediary net worth, a feature we highlight below.

Within this framework, monetary policy may alter capital market equilibrium by adjusting, potentially heterogeneously, both firms' MB and MC curves. Shifts and tilts of these curves then trace out firms' MC and MB curves, respectively. To assess whether

[1] Specifically, we show empirically that high-EBP firms' default risk, as measured by their distance to default, rises by about 50% more than low-EBP firms' when market returns fall.

monetary policy's heterogeneous effects arise primarily from movements in firms' MC or MB curves (or both), we use the credit supply and demand shocks of Ottonello and Song (2022), which are constructed by decomposing changes in intermediaries' net worth around earnings announcements using sign restrictions. Our second key empirical result is that credit supply shocks—which shift firms' MC curves—replicate monetary policy's heterogeneous effects, both in magnitude and direction. That is, 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. Conversely, credit demand shocks—which shift firms' MB curves—generate largely homogeneous firm responses. Thus, movements in firms' MC curves along their MB curves should be able to account for monetary policy's heterogeneous effects, which places a spotlight on the slope of firms' MB curves.

In light of these findings, we model a monetary policy easing as an increase in financial intermediaries' net worth, which leads to an outward shift and a flattening of firms' MC curves that traces along firms' MB curves. Since low-EBP firms operate on flatter segments of their MB curves, we find that a monetary policy easing engenders a relatively large increase in investment by lower-EBP firms despite a relatively mild fall in their credit spreads. Conversely, higher-EBP firms increase investment relatively little despite a larger fall in their credit spreads. These results match our empirical findings and highlight that low-EBP firms with greater marginal propensities to invest, due to their flatter MB curves, have an outsized role in the aggregate investment response to monetary policy.

Importantly, previous studies have emphasized that monetary policy can also induce heterogeneous firm responses from (asymmetric) shifts and tilts in firms' MB and MC curves as well as from differences in the slopes of firms' MC curves. By considering the responses of both firms' prices and quantities to monetary policy, credit supply and credit demand shocks, we show that these other channels, while complementary, are inconsistent with our findings. This is because: (i) firms' heterogeneous reactions to credit supply and monetary policy shocks are similar, whereas credit demand shocks elicit homogeneous firm responses; (ii) these channels, without differently-sloped MB curves, lead *both* the investment and credit spreads of either safe or risky firms to react more to monetary policy; and (iii) for asymmetric shifts in firms' MB curves, safe firms' product demand would need to be more cyclically sensitive even though their default risk is less cyclical.

Finally, consistent with our firm-level findings, we show that the cross-sectional distribution of firm 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 a more left-skewed EBP distribution, expansionary monetary policy shocks induce larger increases in aggregate investment growth. Through the lens of our model, this occurs because a larger mass of firms operate on flatter segments of their marginal benefit curves, and so have greater marginal propensities to invest. In all, these aggregate findings suggest a granular origin for monetary policy's time-varying effects.

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, 2021; 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).[2] We contribute to this literature by showing that a firm's EBP—the risk premium component of its credit spreads—is an important determinant of its responsiveness to monetary policy. Moreover, by considering the responses of both firms'

[2]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.

investment and credit spreads to monetary shocks, as well as to credit supply and demand shocks, we shed new light on why firms' risk profile affects their sensitivity to monetary policy. Specifically, we find that only shifts in firms' MC curves along differently sloped MB curves can explain monetary policy's heterogeneous effects conditional on firms' EBPs.

Second, our paper adds to the longstanding literature on the determinants of investment, especially the user cost of capital theory (Jorgenson, 1963) and the Q theory (Tobin, 1969).[3] 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.[4] 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 component of credit spreads in excess of firms' *expected* default risk (and bond characteristics)—the EBP—that best predicts aggregate economic activity. Our contribution to this literature is threefold: (i) we show that differences in EBPs across firms reflect differences in the covariance between firms' default risk and aggregate risk; (ii) we show that the sensitivity of firms' investment to changes in credit supply depend on their ex-ante EBP; and (iii) we provide evidence that firms' EBPs encode information on the slope of their MB curves for capital.

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 providing a new firm-level rationale for monetary policy's time-varying aggregate effects:

[3] 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).

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

variation over time in firms' positions along—and hence the slopes of—their MB curves.

2 Data and Descriptive Statistics

In this section, we describe our baseline monetary policy shock series (Section 2.1); briefly discuss the EBP calculation (Section 2.2); document how the cross-sectional EBP distribution evolves over time and relates to other firm characteristics (Section 2.3); and detail the common features of our regression specifications (Section 2.4).

2.1 Monetary Policy Shocks

As a baseline, we use the monetary policy shocks in Bu et al. (2021). These shocks combine three appealing features, which together distinguish them from other monetary policy shocks in the literature. 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.[5] 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.5 shows that our results are robust to using alternative monetary policy shocks.

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

2.2 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).

To calculate the excess bond premium, we follow an approach similar to Gilchrist and Zakrajšek (2012). 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). Then, we decompose each bond's credit spread S_{ikt} into two components. The first is driven by the firm's expected default risk—as measured by its distance to default (Merton, 1974)—as well as a vector of bond characteristics, and is termed the predicted spread $\hat{S}_{ikt}$. The second, and residual, component is the excess bond premium, EBP_{ikt}.[6]

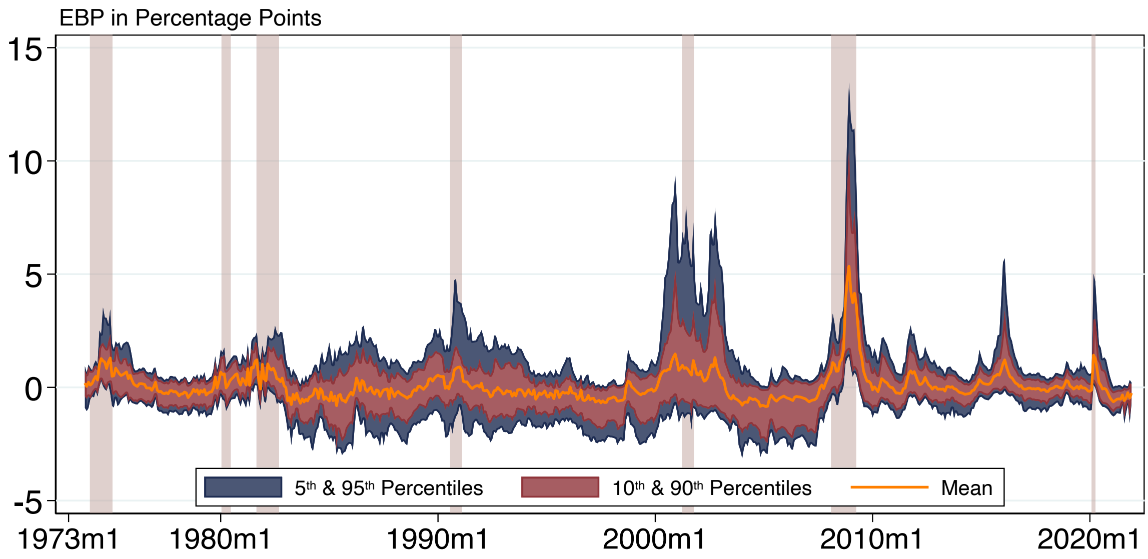
A higher EBP_{ikt} implies that, controlling for its expected default risk, the firm faces a higher marginal borrowing rate on its debt, and, thus, faces tighter financial conditions. In Section 5.2, we show that low-EBP firms' default risk loads economically and statistically less on aggregate risk than high-EBP firms'. This provides a novel explanation for differences in EBPs across firms, and is consistent with the risk premium interpretation of the average EBP across firms advocated by Gilchrist and Zakrajšek (2012).

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 11,913 bonds from

[6]Appendix A.3 provides more details on the EBP calculation. In addition, it 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.

1,872 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, which we show explicitly in Section 6. For more details about our dataset, including variable definitions, sample selection, cleaning of outliers, and summary statistics, see Appendix A.

2.3 The Cross-Sectional EBP Distribution

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

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

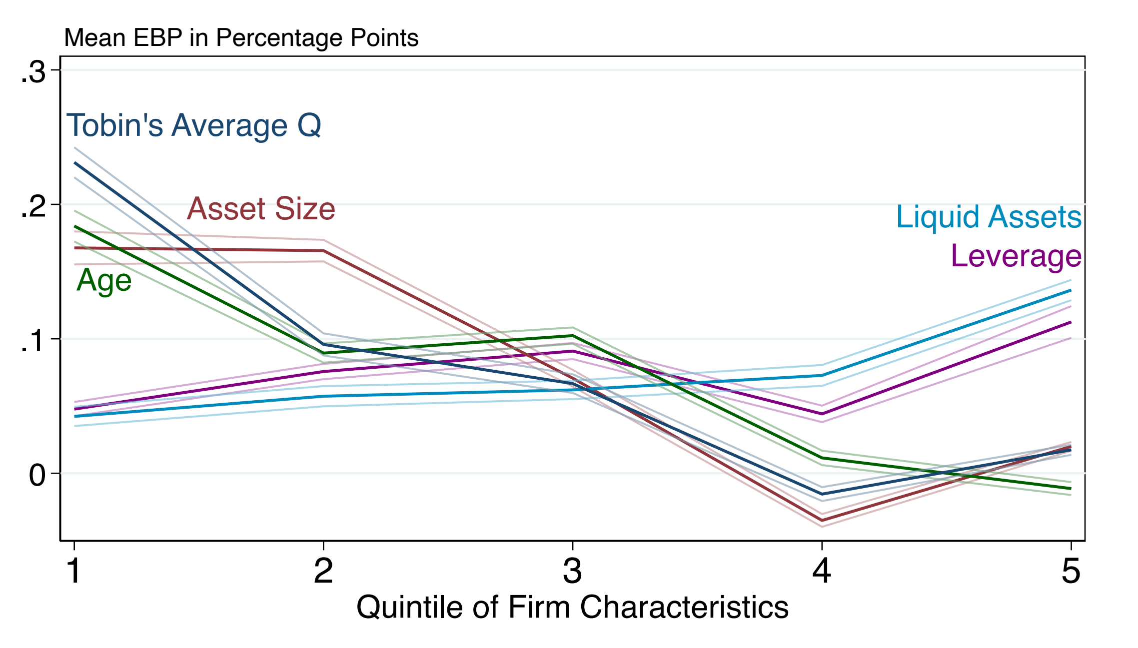
Note. Table 1 provides transition probabilities for monthly bond-level EBPs based on 5 states. Entry in row i and column j refers to the probability of transitioning from state (quintile) i to state (quintile) j in the subsequent month. Probabilities are calculated as an average over the sample.

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, a result we demonstrate formally in Section 5.2.

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 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),

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.

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.

2.4 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). As a baseline, we focus on the 20^{th} percentile of the cross-sectional distribution, such that $\mathbf{1}EBP_{ikt}^{low}$ 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.[7] Most importantly, we include in our regressions sector-time fixed effects to control for differences in sectoral sensitivities to time-varying factors, as well as firm fixed effects to control for permanent differences across firms. Inference is conducted using standard errors that are two-way clustered by firm and time period.

Throughout the paper, our specifications 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. Further, it also includes 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.

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.[8] 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; the economic policy uncertainty index of Baker et al. (2016); and the first three principal components of the U.S. Treasury yield curve.

3 Monetary Policy and Bond-Level Credit Spreads

In this section, we investigate the transmission of monetary policy to bond-level credit spreads both unconditionally and conditional on a bond's *ex-ante* EBP. We find that while expansionary monetary policy shocks decrease credit spreads on average, the decrease is

[7]Our conclusions, however, are not tied to this particular threshold. Appendix B.2 shows that our results are robust to using alternative percentiles for our indicator variable.

[8]We also include firms' EBPs and predicted spreads in levels in place of their interactions with the monetary policy shocks.

less pronounced for firms with low-EBP bonds compared to those with high-EBP bonds.

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

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

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 2.4. To measure the response conditional on bonds' ex-ante EBPs, we estimate the following regressions:

$$S_{ikt+h} - S_{ikt-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{ikt-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{2}$$

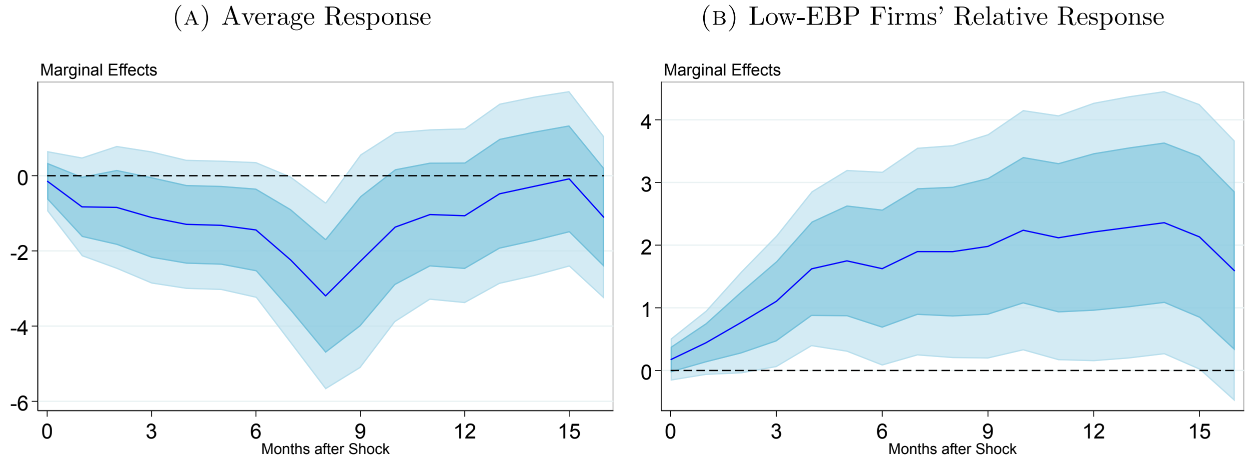
which include sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the monetary policy shock ε_t^m and $\mathbf{1}EBP_{ikt-1}^{low}$, an indicator variable that equals 1 if the EBP of firm i's bond k is in the bottom quintile of the cross-sectional EBP distribution in $t-1$, and 0 otherwise.[9] 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 (1), which trace the average response of bond-level credit spreads to a surprise monetary policy easing. Quantitatively, we find that a 1 percentage point easing shock induces a decline in the average bond's credit spread of over 3 percentage points, which occurs eight months after the shock. This result points to a delayed peak effect of monetary policy on firms' marginal borrowing rates, an issue overlooked by short-horizon studies.[10]

[9] Of note, $\mathbf{1}EBP_{ikt-1}^{low}$ is lagged one period, as are the controls in both specifications, to ensure they are not influenced by the contemporaneous monetary policy shock.

[10] 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 (1), which trace the unconditional (average) credit spread response. Panel 3b plots the β_1^hs from regression (2), 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.

Panel 3b reports the β_1^hs from regression (2), 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 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 the upper quintiles. Overall, monetary policy easings compress credit spreads meaningfully more for ex-ante riskier firms, that is, for firms with higher EBPs.

Robustness: We show that our results are robust to many variants of our empirical approach, including: (i) conditioning on 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.1); (ii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ (Appendix B.2); and (iii) using alternative monetary policy shocks (Appendix B.5).

4 Monetary Policy and Firm-Level Investment

In this section, we document that low-EBP firms increase investment relative to 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:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,q}^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + e_{ith}, \tag{3}$$

where K_{it} is the real book value of firm i's tangible capital stock (as in Ottonello and Winberry, 2020); 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 2.4. To assess the investment response conditional on firms' EBPs, we estimate the following regressions:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{4}$$

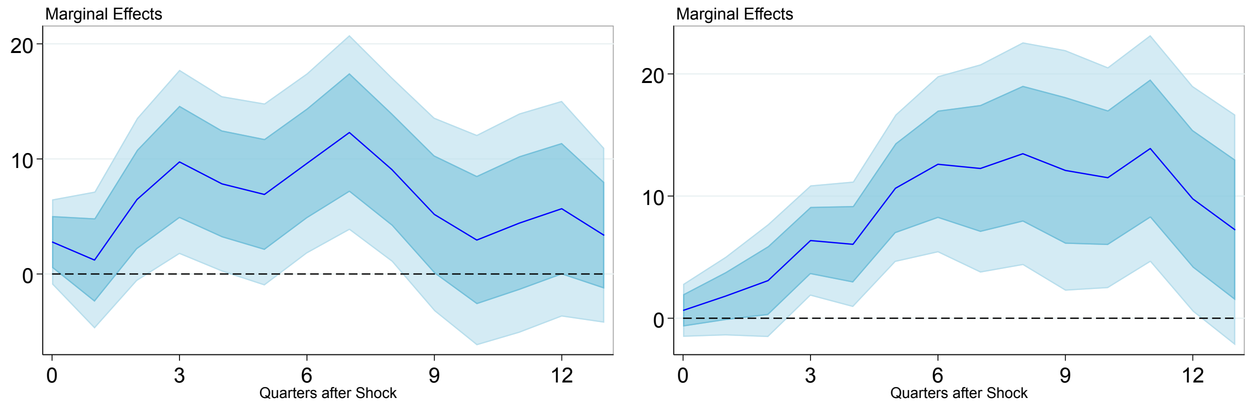
which include sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the monetary policy shock ε_t^m and $\mathbf{1}EBP_{it-1}^{low}$, an indicator variable that equals 1 if firm i's EBP is in the bottom quintile of the cross-sectional EBP distribution in $t-1$, and 0 otherwise.[11]

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, with a 1 percentage point monetary easing estimated to increase investment for the average firm

[11]The indicator variable is constructed based values of EBP_{it-1}, which corresponds to the average EBP_{ikt-1} on firm i's bonds within a given quarter.

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 (3), which trace the unconditional (average) investment response. Panel 4b plots the β_1^hs from regression (4), which trace 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.

by 12 percentage points at its peak, which occurs seven quarters after 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 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.4 provides evidence that low-EBP firms also increase debt issuance significantly more than high-EBP firms following a monetary easing.

When viewed through the lens of the financial accelerator channel presented in other models (e.g., Bernanke et al., 1999 and Ottonello and Winberry, 2020), our results from this section seem at odds with our findings from Section 3. Specifically, we have shown that while firms with ex-ante looser financial conditions—lower EBPs—experience milder declines in their credit spreads following a monetary easing, these less-risky firms increase investment

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

relatively more. Conversely, higher-EBP firms receive larger reductions in their marginal borrowing costs, but increase investment more modestly. The discrepancy between these results and the predictions of financial accelerator models owes to the latter's emphasis on heterogeneous shifts and changes in slope (i.e., "tilts") of firms' marginal cost curves for capital in response to monetary policy. Instead, in the next section, we show that to rationalize our empirical findings, one needs a model in which firms differ in the slopes of their marginal benefit curves for capital.

Robustness: We show that our results are robust to many variants of our empirical approach, including: (i) conditioning on 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.1); (ii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$ (Appendix B.2); and (iii) using alternative monetary policy shocks (Appendix B.5).

5 Interpretation of Empirical Results

In this section, we develop a stylized model and provide additional empirical evidence to interpret our headline results from Sections 3 and 4. Specifically, we first present a theoretical framework (Section 5.1), provide empirical evidence linking firms' EBPs to the cyclicality of their default risk (Section 5.2), and then show how this link implies low-EBP firms operate on flatter segments of their marginal benefit curves for capital in our model (Section 5.3). In Section 5.4, we show that firms' heterogeneous responses to credit supply shocks closely track their reactions to monetary surprises, while credit demand shocks produce homogeneous firm responses. This highlights that the slope of firms' marginal benefit curves, which are traced by changes in credit supply, are central to explain monetary policy's heterogeneous effects. And finally, in Section 5.5, we combine these ingredients to show that movements in firms' marginal cost curves along their differently-sloped marginal benefit curves rationalize our headline results.

5.1 Theoretical Setup

Our framework focuses on two types of agents: firms who demand capital for production and financial intermediaries who, subject to financial frictions similar to those proposed by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), supply capital to firms.

Financial intermediaries are endowed with net worth N and issue deposits D to households (not explicitly modeled here) at an exogenous gross interest rate R.[13] These intermediaries have access to a capital producing technology that transforms N and D on a one-to-one basis into capital K_S, which they supply to firms for a return R_K. As long as this return on capital exceeds the deposit rate ($R_K > R$), intermediaries have an incentive to leverage-up to increase the return on their equity. Motivated by real-world regulatory capital requirements and risk-management practices, we assume that intermediaries face a constraint that requires them to have sufficient skin in the game when lending to firms. This is modelled as an agency friction in which intermediaries can abscond with a fraction θ of their revenue $R_K K_S$. In turn, households only fund intermediaries that satisfy an incentive compatibility constraint: $R_K K_S - RD \geq \theta R_K K_S$. The optimization problem of the intermediaries is then:[14]

$$\max_{K_S} \; R_K K_S - RD \quad \text{s.t.} \quad R_K K_S - RD \geq \theta R_K K_S \quad \text{and} \quad K_S = D + N.$$

The solution to the problem above provides a schedule of how much capital intermediaries supply to firms for a given credit spread R_K/R. We focus on equilibria in which $R_K \geq R$. When $R_K > R$, intermediaries leverage-up until the point in which the skin-in-the-game constraint binds. Additionally, when $R_K = R$, financial intermediaries are indifferent between any level of deposits satisfying the skin-in-the-game constraint. Thus,

[13] For simplicity, we set $R = 1$.

[14] This financial intermediary problem has been used in other studies, such as Céspedes et al. (2017) and Anderson and Cesa-Bianchi (2021).

we obtain the following capital supply curve:

$$\frac{R_K}{R} = \begin{cases} \frac{K_S - N}{K_S(1-\theta)} & K_S \geq \frac{N}{\theta} \\ 1 & K_S < \frac{N}{\theta}, \end{cases} \tag{5}$$

where $K_S = N/\theta$ is the cutoff value of capital supply for which the intermediaries' constraint binds. Importantly, in the region where $K_S \geq N/\theta$, the capital supply curve is upward sloping in credit spreads. Of note, this capital supply curve is also the marginal cost (MC) of capital curve faced by firms.

The key fundamental shaping the marginal cost curve faced by firms is θ, which parameterizes intermediaries' shadow cost of leveraging-up to lend to firms. This shadow cost, or "lending premium", is a key determinant of firms' EBPs, consistent with Gilchrist and Zakrajšek (2012). A lower θ implies a decrease in the shadow cost of leverage, which decreases the premium that intermediaries require to lend to firms. This manifests, per equation (5), as both an outward shift and a flattening of firms' MC curves that decreases firms' marginal borrowing rate and increases their capital stock in equilibrium. While, for simplicity, we abstract from modelling firms' default risk, one interpretation for the lending premium parameter θ is that it measures the compensation that intermediaries require for the co-movement between firms' default risk and market-wide risk, i.e., a price of default risk.[15] In this case, risk-averse intermediaries would provide a lower price of default risk, a lower θ, to firms whose default risk is less correlated with aggregate risk.

Turning to capital demand, goods-producing firms use a decreasing returns to scale production technology K_D^α, with their profit maximization problem taking the form:

$$\max_{K_D} \; K_D^\alpha - R_K K_D,$$

where, as in Gertler and Karadi (2011), firms borrow at interest rate R_K because we assume, for simplicity, there are no frictions on their side that limit their access to intermediaries' funds. The first order condition of this problem yields the marginal benefit (MB) curve for

[15] Concretely, intermediaries would be willing to abscond with a larger fraction of their revenues from riskier investments.

capital:

$$\frac{R_K}{R} = \frac{1}{R}\alpha K_D^{\alpha-1}. \tag{6}$$

Due to decreasing returns to scale, $\alpha \in (0,1)$, firms' marginal benefit curves are downward sloping in credit spreads R_K/R. While the level of the curve traced in equation (6) measures firms' marginal product of capital, the slope is the rate at which this marginal product depletes as firms invest. Importantly, this rate is non-linear: firms with higher values of capital are on flatter portions of their marginal benefit curves. We refer to these firms as having greater "marginal propensities to invest" out of changes in their intermediaries' net worth, since shifts and tilts in firms' marginal cost curves will trace along flatter segments of their marginal benefit curves. Of note, higher values of α flatten firms' marginal benefit curves.

5.2 Firm EBPs and the Cyclicality of their Default Risk

We introduce EBP heterogeneity into the model by varying the lending premium parameters θs that intermediaries charge to firms. To this end, we estimate in this section how firms' default risk loads on aggregate risk and find that low-EBP firms' "distance to default" is economically and statistically less procyclical than high-EBP firms'. We use these estimates to calibrate the θs in our model. Since lower-θ firms in our model will have lower EBPs, we interpret θ as the price of firms' default risk. Differences in the cylicality of firms' default risks thus provide a new rationale for differences in EBPs across firms.

To measure default-risk loadings for low- and high-EBP firms, we estimate two types of regressions at a monthly frequency. First, we estimate separate regressions of the following form for firms in the bottom quintile (Low-EBP) and upper four quintiles (High-EBP) of the cross-sectional EBP distribution:[16]

$$\Delta DD_{i,t} = \alpha_i + \alpha_{s,m} + \beta^{Mkt} R_t^{Mkt} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + \varepsilon_{i,t}, \tag{7}$$

[16] For these regressions, we use EBP_{it-1}, which corresponds to the average EBP_{ikt-1} on firm i's bonds within a given month.

Table 2

Firms' Default Risk and Market 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 (7), 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 (8), 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.

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 firm-level and aggregate control variables described in Section 2.4.

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

$$\Delta DD_{i,t} = \alpha_i + \alpha_{s,t} + \beta^{Mkt,Rel}(R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \varepsilon_{i,t}, \tag{8}$$

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 (7)—indicate that when S&P500 index returns increase, firms' distance to defaults increase as well, that is, their default risk falls. However, comparing the point estimates reveals that high-EBP firms' distance to default rises by about 50% more than low-EBP firms'. That is, high-EBP firms' distance to default is significantly more procyclical than low-EBP firms' We see this also in column (3), which displays $\beta^{Mkt,Rel}$ from regression (8) 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.

The results in this section highlight that firms whose default risks load less on aggregate risk have lower EBPs. As shown in the next section, since firms with lower θs have lower EBPs, differences in θs across firms provide a reduced form way to model differences in the cyclicality of firms' default risk. Intuitively, risk-averse intermediaries would require less compensation, lower θs, to lend to firms whose default risk is less cyclically sensitive, thereby providing them a lower lending premium, that is, a lower EBP.

5.3 Firm EBPs and the Slopes of their Marginal Benefit Curves

In this section, we characterize capital market equilibrium in the model. We consider a series of financial intermediaries that lend to two types of firm, one type whose default risk co-moves strongly with market risk and the other whose default risk does not. For simplicity, we abstract from modeling firm default risk formally.[17] Instead, we model differences in the cyclicality of default risk across firms via reduced-form differences in firms' θs. Our main result is that, when markets are segmented according to firm risk (as in Chernenko and Sunderam, 2012), low-EBP firms with less-cyclical default risk, i.e., lower θs, operate on flatter segments of their marginal benefit curves.

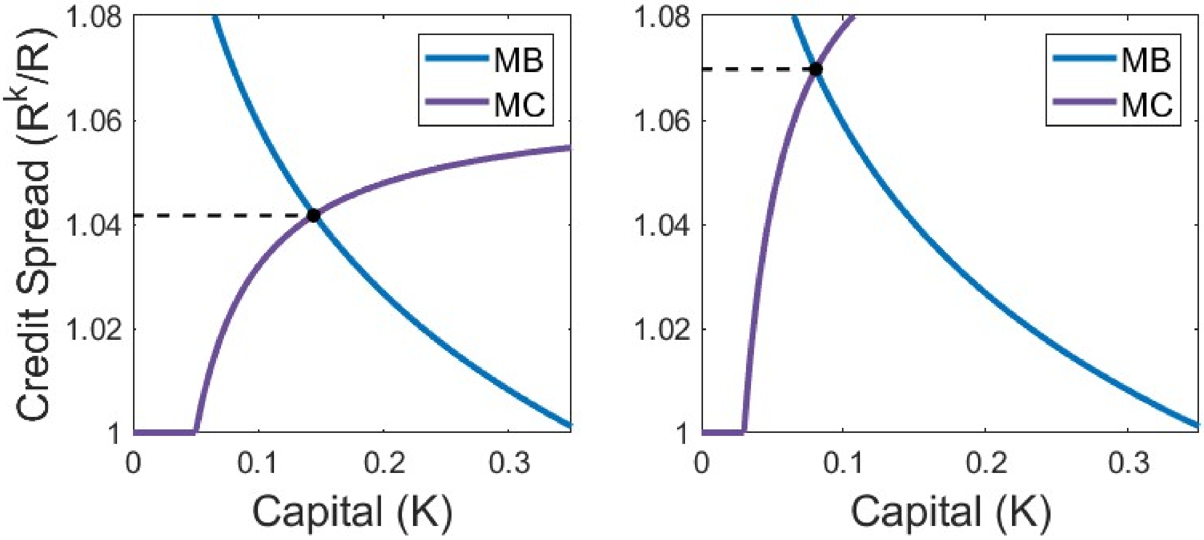
Specifically, Figure 5 displays the capital market equilibrium for the two types of firm, which occur at the intersection of the MB curves (in blue) and the MC curves (in purple) in each panel. While the MB curves are the same for the two types of firm, differences in the tightness of intermediaries' constraints, which we calibrate based on differences in the cyclicality of default risk across firms, imply that the low-θ (safer) firms in Panel 5a face more outward-shifted and flatter MC curves relative to the high-θ (riskier) firms in Panel 5b.[18] Since we abstract from firms' expected default risk in our framework, firms' equilibrium credit spreads in each panel may be interpreted as their EBPs. As a result, firms' with relatively low θs, i.e., safer firms, have lower EBPs in our framework.

[17] While we could model differences in the cyclicality of firms' default risk keeping expected default risk constant via a mean-preserving productivity process with differential loadings on aggregate risk, doing so would add little in terms of economic intuition.

[18] For details on the calibration, see Appendix C.1.

FIGURE 5
Capital Market Equilibrium

(A) Low-θ – Low-EBP Firm | (B) High-θ – High-EBP Firm



Note. Figure 5 presents the capital market equilibrium for two types of firm, which differ in how much their default risk co-moves with market risk. While both types of firm share the same marginal benefit (MB) curve, we model differences in the cyclicality of firms' default risk via differences in θs across firms, leading to differences in the marginal cost (MC) curve faced by firms. Specifically, the low-θ (less-cyclically sensitive) firms in Panel 5a have flatter and more outward shifted marginal cost (MC) curves compared to the high-θ firms in Panel 5b. When markets are segmented according to firm risk, equilibrium occurs at the intersection of the MB curve in blue and the MC curve in purple in each panel, which highlights that the low-θ firms in Panel 5a have lower equilibrium EBPs (credit spreads) and are on flatter segments of their MB curves in equilibrium than the high-θ firms in Panel 5b. Appendix C.1 provides details on the calibration.

While other papers in the literature have focused on the slopes of firms' MC curves for the transmission of monetary policy, we emphasize that the slopes of firms' MB curves play a crucial role. To this end, Figure 5 showcases our key result from this section: low-EBP firms (Panel 5a) are on flatter segments of their MB curves than high-EBP firms (Panel 5b) in equilibrium, due to their flatter and more outward shifted MC curves. As a consequence, low-EBP firms in our model have greater marginal propensities to invest out of shifts in their marginal cost curves, even though their credit spreads react relatively little. This result will be important to match the empirical responses of *both* credit spreads and investment to monetary policy shocks.

5.4 Monetary Policy and Credit Supply

Using this model of capital market equilibrium, we seek to understand how monetary policy transmits heterogeneously to firms' investment and credit spreads conditional on their EBPs. As shown in Ottonello and Winberry (2020), monetary policy affects capital markets by adjusting, potentially heterogeneously, both firms' credit demand (i.e., MB) and credit supply (i.e., MC) curves. The shifts and tilts of these curves then trace along firms' MC and MB curves.

To understand whether monetary policy's heterogeneous effects can be primarily attributed to movements in firms' MC or MB curves, we use the high-frequency financial 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. Most importantly, they decompose these shocks using sign restrictions into components capturing shocks to intermediaries' credit supply—which trace along firms' MB curves— and shocks to firms' credit demand—which trace along firms' MC curves.

Our strategy is to re-estimate our baseline regressions from Sections 3 and 4 using credit supply and credit demand shocks and then compare the resulting impulse responses to those from monetary policy shocks. This will help us to understand whether monetary policy's heterogeneous effects arise primarily from movements in firms' MC or MB curves and, by extension, whether it is the slope of firms' MC or MB curves that matter most for firms' heterogeneous responses. Specifically, we estimate:

$$S_{ikt+h} - S_{ikt-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h(\varepsilon_t^{fin} \times \mathbf{1}EBP_{ikt-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{9}$$

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h(\varepsilon_t^{fin} \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{10}$$

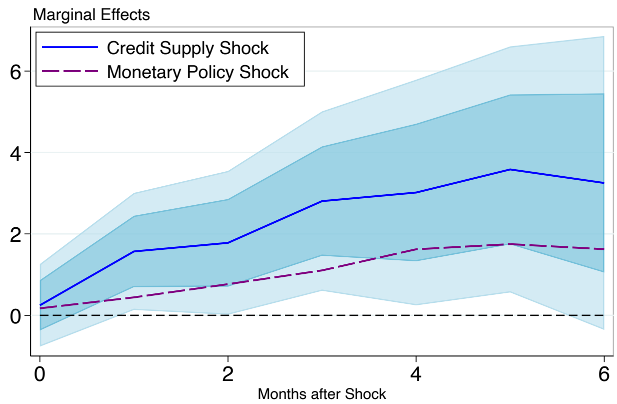
where ε_t^{fin} is either a credit supply shock ε_t^{CS} or a credit demand shock ε_t^{CD}, both of which we normalize to have the same variance as our monetary policy shock; and the remaining variables are the same as described previously.

FIGURE 6

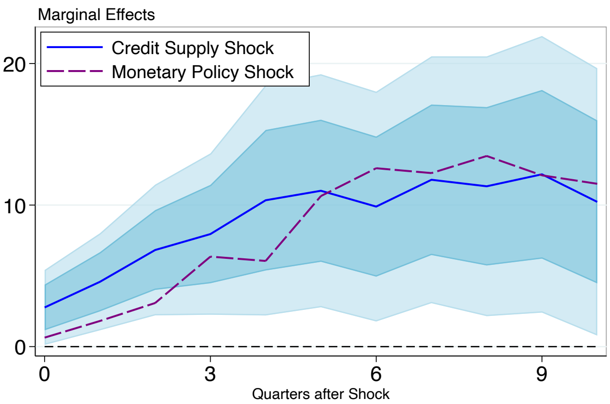
Credit Supply and Credit Demand Shocks on Firms' Spreads and Investment

(I) Credit Supply Shock Regressions

(A) Relative Response of Low-EBP Firms' Spreads

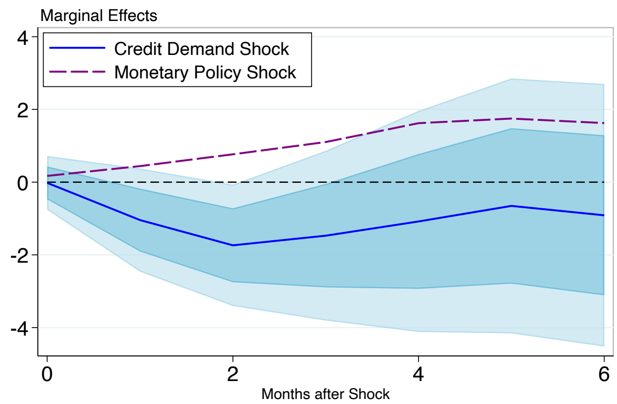


(B) Relative Response of Low-EBP Firms' Investment

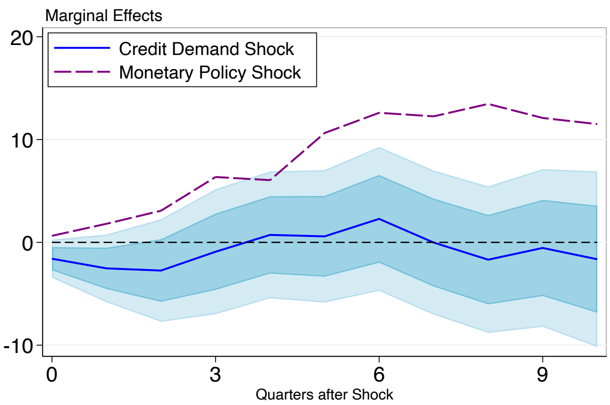


(II) Credit Demand Shock Regressions

(C) Relative Response of Low-EBP Firms' Spreads



(D) Relative Response of Low-EBP Firms' Investment



Note. Figure 6 reports the dynamic responses of bond-level credit spreads and firm-level investment to expansionary credit supply shocks ε_t^{CS} (Panels 6a and 6b) and credit demand shocks ε_t^{CD} (Panels 6c and 6d), as calculated by Ottonello and Song (2022). We normalize each shock series to have the same variance as our baseline monetary policy shocks (Bu et al. (2021)). Panel 6a plots in blue the β_1^hs from regression (9) with ε_t^{CS}, 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 6b plots in blue the β_1^hs from regression (10) with ε_t^{CS}, which trace the investment $\log(K_{it+h}/K_{it-1})$ response of low-EBP firms relative to high-EBP firms. Panels 6c and 6d plot in blue the same for credit demand shocks ε_t^{CD}. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month/quarter. For comparison, we also plot the (point estimate) responses of spreads and investment to monetary policy shocks in purple dashed lines, which are taken from Panels 3b and 4b, respectively.

Figure 6 presents the dynamic responses of bond-level credit spreads and firm-level investment to expansionary credit supply and credit demand shocks. For comparison, we also plot the point-estimate responses of spreads and investment to a monetary policy easing shock, which are taken from Panels 3b and 4b, respectively. The first key takeaway, as shown in Panels 6a and 6b, is the similarity between how firms respond to credit supply shocks and monetary policy shocks, both in terms of direction and magnitude. As is the case for monetary policy, while low-EBP firms' spreads decline relatively little in response to a surprise loosening of credit supply, they increase investment considerably more in comparison to high-EBP firms. By contrast, as shown in Panels 6c and 6d, low- and high-EBP firms respond similarly to credit demand shocks.

Altogether, these results highlight that monetary policy's heterogeneous effects, conditional on firms' EBPs, appear to operate predominantly through changes in credit supply, that is, through shifts and tilts in firms' MC curves. This result guides our choice to model monetary policy in the next section as acting via changes in intermediary net worth, which is also in line with a long literature on the balance-sheet channel of monetary policy (e.g., Bernanke and Gertler, 1995, Kashyap and Stein, 2000 and Adrian and Liang, 2018). As we will show explicitly, movements in firms' MC curves will place the slope of firms' MB curves, which they trace out, at the center of monetary policy's heterogeneous effects.

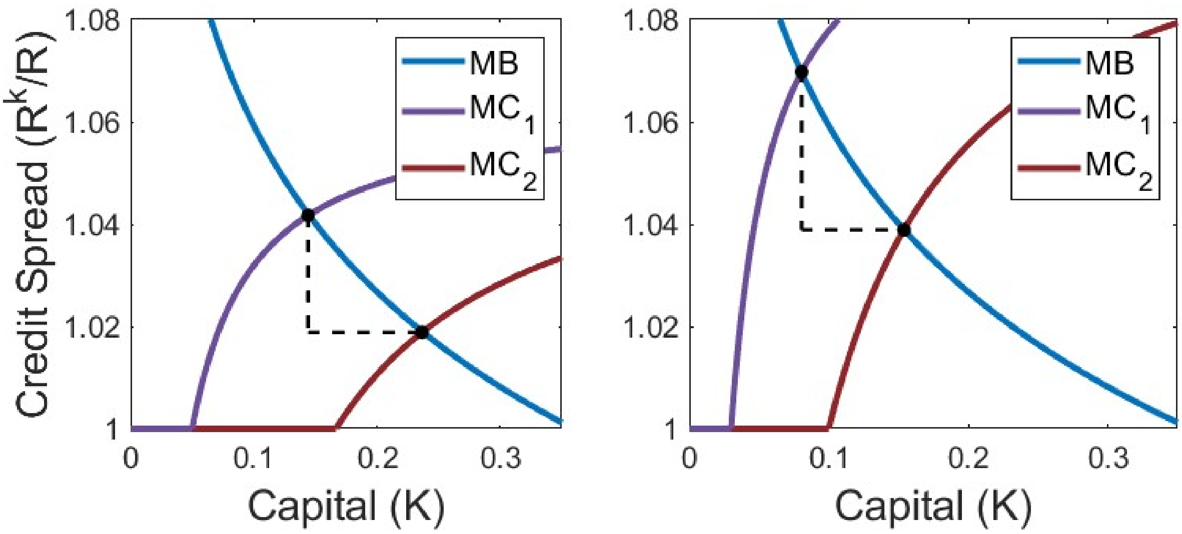
5.5 Monetary Policy Comparative Statics by Firm EBPs

In this section, we combine together the ingredients collected previously in Section 5 to rationalize monetary policy's heterogeneous effects on firms' credit spreads and investment, conditional on their EBPs. Motivated by the marked similarity between the transmission of credit supply shocks and monetary policy shocks in the data, we model a monetary policy easing as a uniform increase in financial intermediaries' net worth, which is common to both types of firms. This increase in intermediary net worth leads to a (non-uniform) rightward shift and flattening of intermediaries' credit supply curves—i.e., firms' MC curves—as seen in Figure 7.

The heterogeneous responses of firms' investment and credit spreads to the shift and

Figure 7
Monetary Policy's Effect on Credit Spreads and Investment by Firm EBP

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



Note. Figure 7 presents the comparative statics to a monetary policy easing, modelled as a uniform increase in financial intermediaries' net worth N, which is common to both types of firms. This shock shifts and flattens firms' MC (non-uniformly), from MC_1 to MC_2, tracing along firms' MB curves. Panel 7a shows the response of the low-θ – low-EBP firm, while Panel 7b shows the response of the high-θ – high-EBP firm. The low-EBP firms' investment increases relative to the high-EBP firms', although its credit spreads decline by relatively less. Appendix C.1 provides details on the calibration.

tilt of firms' MC curves depend principally on the slopes of their MB curves. Specifically, low-EBP firms on flatter segments of their MB curves invest considerably following a monetary easing, despite a relatively mild fall in their credit spreads (Panel 7a). This result is due to low-EBP firms' greater marginal propensities to invest of out changes in intermediary net worth, since their marginal products of capital deplete relatively slowly as they accumulate capital. Conversely, high-EBP firms on steeper segments of their MB curves are afforded a larger fall in their credit spreads, but invest relatively little (Panel 7b) due to the rapid depletion of their marginal product as they invest. In all, these comparative statics rationalize our empirical results for the sensitivity of firms' investment and credit spreads to monetary policy, conditional on their EBPs, by appealing to the slope of firms' MB curves for capital.[19]

[19]In Appendix C.3, we show empirically that low-EBP firms have higher capital intensities of production α than high-EBP firms. This acts to further flatten low-EBP firms' MB curves relative to high-EBP firms', amplifying the comparative statics shown here.

Although our analysis focuses on the slopes of firms' MB curves, which are traced out by shifts and tilts of firms' MC curves, monetary policy may generate heterogeneous affects through a number of channels. We discuss each of these channels below. We emphasize that while these other channels, all of which can be incorporated in our setup, are complementary to our economic narrative, they cannot rationalize our empirical results.

First, monetary policy may differentially shift and tilt firms' MC curves, as emphasized in Ottonello and Winberry (2020). Although we model a monetary easing as a uniform increase in intermediaries' net worth, this channel is present in our setup. Specifically, Figure 7 shows that low-EBP firms' MC curves shift right and flatten more than high-EBP firms' in response to the same increase in intermediary net worth, due to low-EBP firms' relatively low θs (see equation (5)). All else equal, however, greater shifts and tilts of low-EBP firms' MC curves induce *both* their investment *and* credit spreads to react more to monetary policy, which is inconsistent with our empirical results. Thus, without differences in the slope of firms' MB curves, asymmetric movements in firms' MC curves cannot explain our empirical results.

Second, monetary policy may shift firms' MB curves, due to changes in discounting and aggregate demand, which traces out firms' differently-sloped MC curves, as highlighted in Ottonello and Winberry (2020). While we abstract from shifts in firms' MB curves for simplicity, such shifts would induce heterogeneous responses in our framework since firms carry differently-sloped MC curves due to differences in θ. However, this channel is inconsistent with our empirical results for a number of reasons. First, rightward shifts in firms' MB curves from monetary easings increase credit spreads. Since we show in Figure 3a that credit spreads decline following a monetary easing, shifts in MB cannot be the main channel through which monetary policy operates. Second, we showed in Section 5.4 that the heterogeneous effects of monetary policy shocks and credit supply shocks are very similar, whereas credit demand shocks produce largely homogeneous effects conditional on firms' EBPs. Thus, shifts in MB cannot be the (main) driver of monetary policy's heterogeneous effects. And third, from a theoretical point of view, adding shifts in firms' MB curves to Figure 7 above would amplify the increase in low-EBP firms' investment, due to their flatter MC curves, but only mildly dampen the fall in their credit spreads. Thus, rightward shifts in MB predict low-EBP firms to experience both a larger fall in credit spreads and a larger increase in investment, which runs counter to our empirical results.[20]

Finally, monetary policy may induce heterogeneous shifts in firms' MB curves, due to differences in the responsiveness of firms' product demand, a channel discussed in Crouzet and Mehrotra (2020). If low-EBP firms' MB curves were more sensitive to monetary policy, due to a greater responsiveness in their product demand, this could in theory amplify both the relative responsiveness of low-EBP firms' investment and the unresponsiveness of low-EBP firms' credit spreads. However, since credit supply shocks alone generate heterogeneous effects similar to those of monetary policy, we view this channel as secondary. Furthermore, since low-EBP firms' default risk is less cyclically sensitive, it is difficult to conceptualize how their product demand could be more sensitive.

In all, we differ from previous studies by jointly considering the responses of credit spreads and investment to discipline our theoretical investigation into the transmission of monetary policy. In doing so, we find that differences in the slopes of firms' MB curves for capital, rather than their MC curves, play a central role in explaining firms' heterogeneous responses to monetary policy.

6 Firm EBPs & Monetary Policy's Aggregate Effects

In this section, we show that the cross-sectional EBP distribution is an important empirical driver of the aggregate effectiveness of monetary policy. This result indicates a granular origin for monetary policy's time-varying aggregate effects.

Based on the theoretical framework outlined in Section 5, the aggregate potency of monetary policy should depend on the distribution of firms' EBPs, since it encodes information on the slopes of firms' MB curves. Specifically, suppose there exists a continuum of firms and that the price of default risk, parameterized by θ, that intermediaries charge

[20]Figure 6c provides evidence of the inconsistency between shifts in firms' MB curves and our empirical findings. Specifically, although not statistically significant, the point-estimate response of low-EBP firms' credit spreads to credit demand shocks are the opposite sign to those from monetary policy shocks.

to firms is time varying. For example, as the economy enters a recession, intermediaries may require greater compensation from all firms for the covariance between their default risks and aggregate risk—which increases the mean of the firm-level θ distribution—or may require greater compensation particularly from high-risk firms—which right-skews the firm-level θ distribution.[21] Through the lens of our model, this implies an increase in the mass of firms in the economy with higher EBPs, i.e., the mass of firms on steeper segments of their MB curves. Thus, our model predicts that monetary policy is less effective at stimulating aggregate investment when a larger mass of firms have higher EBPs and more effective when a larger mass of firms have lower EBPs.

To evaluate this prediction, we use local projections of a similar form to those from previous sections, but with two modifications to exploit time-series variation: (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. Based on our earlier arguments, we expect that as the EBP distribution becomes more right skewed, all else equal, the transmission of monetary policy to aggregate investment becomes less potent. Similarly, all else equal, as the median EBP increases, the transmission of monetary policy to aggregate investment should also be less potent. While the effect of a more dispersed EBP distribution is ex-ante ambiguous, it provides an indication of whether firms in the left or right tail of the EBP distribution exert a greater influence over the aggregate effectiveness of monetary policy.

Specifically, we estimate the following local projections at a quarterly frequency for a series of horizons h:

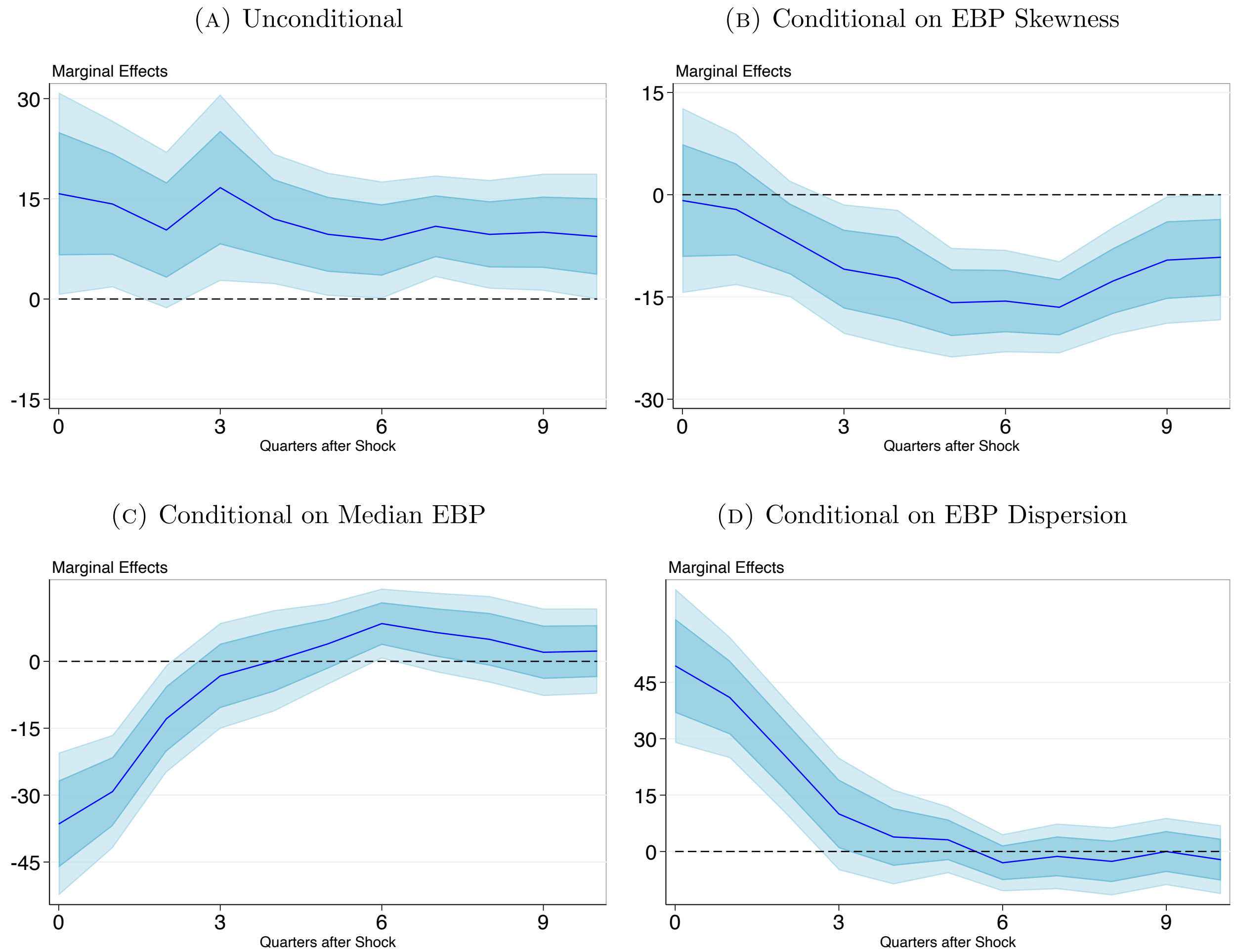
$$\frac{400}{h+1}\log\left(\frac{I_{t+h}}{I_{t-1}}\right) = \beta_0^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\beta}_2^h(\varepsilon_t^m \times \boldsymbol{M}_{t-1}) + \boldsymbol{\delta}_l^h \mathbf{Y}_{t-1} + e_{th}, \tag{11}$$

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; and $\mathbf{Y}_{t-1}$ includes the aggregate controls of Section 2.4 along with the vector $\boldsymbol{M}_{t-1}$.[22] We

[21]For evidence on the macroeconomic effects of time-varying cross-sectional financial skewness, see Ferreira (2024).

[22]For this regression, we substitute GDP growth for investment growth in the aggregate controls $\mathbf{Y}_{t-1}$ to

FIGURE 8
Monetary Policy's Effect on Aggregate Investment Growth



Note. Figure 8 reports the dynamic response of annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, to a 1 percentage point monetary policy easing shock ε_t^m, which we estimate using regression (11). 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.

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 the predictions of our model. First, Panel 8a shows that, on average, aggregate investment growth increases following a surprise monetary policy easing. Second, a more right-skewed

again align ourselves with the existing literature (e.g., Gilchrist and Zakrajšek, 2012). For the same reason, we use annualized aggregate investment growth as our dependent variable, although we find similar results if we use the level of aggregate investment.

EBP distribution is associated with a significantly weaker pass-through from monetary policy to aggregate investment (Panel 8b). Similarly, a higher median EBP also predicts a weaker transmission of monetary policy (Panel 8c), although the effects are relatively short-lived. And 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). This last result hints that low-EBP firms—those with the greatest marginal propensities to invest and flattest MB curves—drive a meaningful share of monetary policy's aggregate effects. 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, while this section leverages time-series variation, we show in Appendix B.6 that monetary policy's aggregate effects conditional on 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 conditioning effects of the EBP distribution are not driven solely by 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 three main parts. First, 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. Second, we find that monetary policy and credit supply shocks elicit similar firm responses, whereas firms respond homogeneously to credit demand shocks. Guided by this, we build a model in which the tightness of intermediaries' constraints are tied to the cyclicality of firms' default risk. This implies that safer firms face more-outward shifted and flatter MC curves, and so have lower EBPs and operate on flatter segments of their MB curves. Monetary policy induced shifts in firms' MC curves then trace out low-EBP firms' relatively flat MB curves, which yields our results. Third, we show that the cross-sectional EBP distribution is an important empirical driver of the pass-through of monetary policy to aggregate investment. Our results suggest that low-EBP firms with greater marginal propensities to invest drive the aggregate effectiveness of monetary policy.

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 contributes to these three aspects. On the distributional front, we show that monetary policy is less effective at stimulating the investment of firms with higher EBPs, due to their steeper marginal benefit curves. On the aggregate front, our paper not only provides a theoretical argument for monetary policy's time-varying effects, but also offers a specific observable—the cross-sectional EBP distribution—to monitor them. On the channels front, our paper provides new evidence on the salience of the slope of firms' marginal benefit curves to feed the construction of richer models of the macroeconomy.

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Internet Appendix

(Intended for online publication only)

Firm Financial Conditions and the Transmission of Monetary Policy

by T. Ferreira, D. Ostry, J. Rogers

August 16, 2024

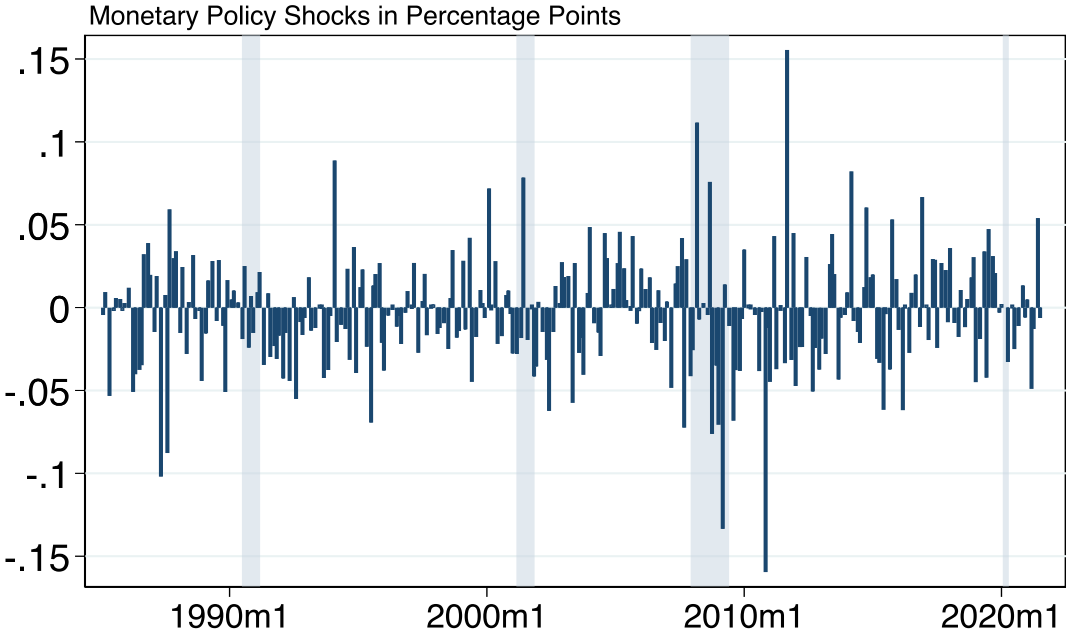
A Data Summary

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.5, 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.

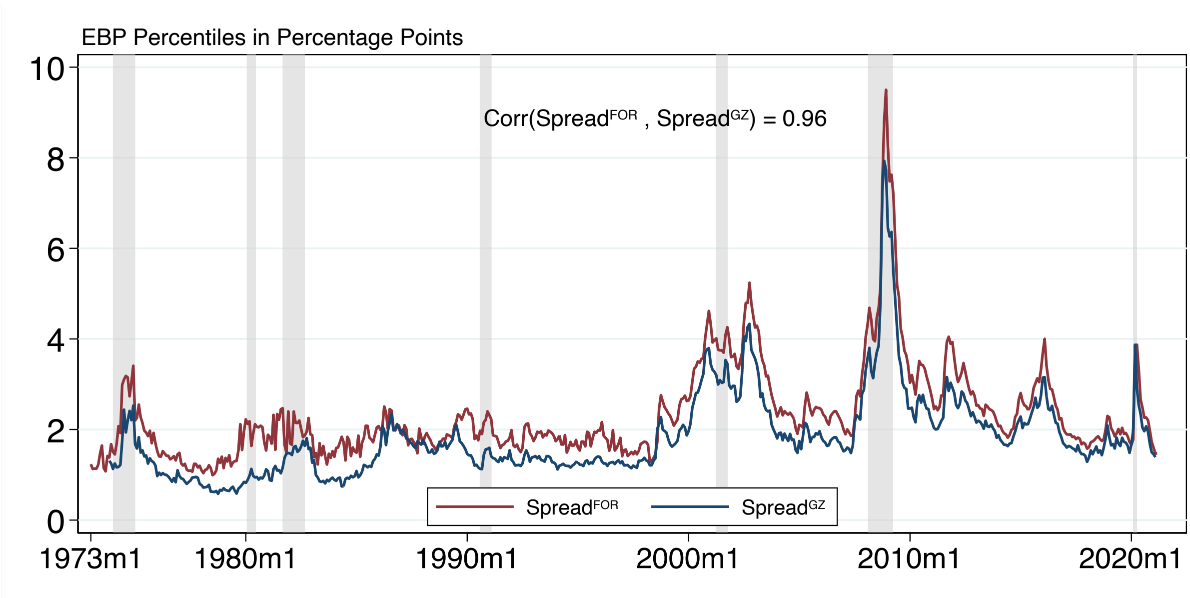
11. *Short-Term Assets*: defined as the ratio of current assets (actq in Compustat) to total assets (atq in Compustat).

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 and CPI*: measured as real chained gross domestic product (GDPC1 in FRED), real chained investment (RINV in FRED) and consumer price index for cities (CPIAUCSL 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 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.

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.

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, which we calculate in a similar fashion to Gilchrist and Zakrajšek (2012). 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:

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

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) 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

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	

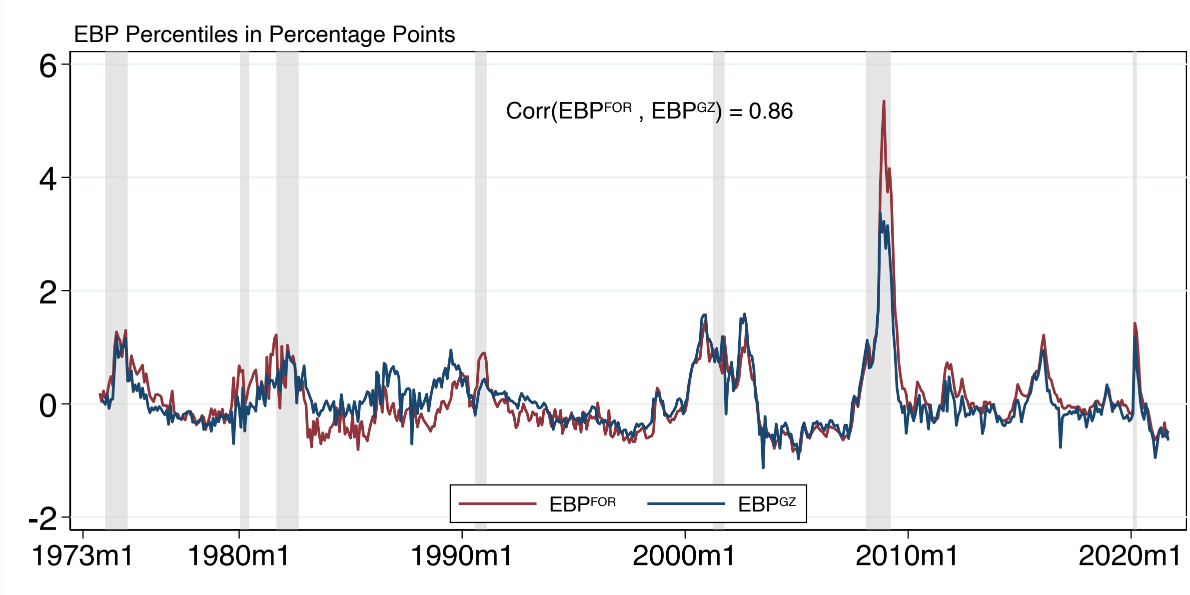
Note. Table A.1 present the estimated coefficients, standard errors and T-statistics from estimating regression (A.1) by OLS. The sample period is October 1973 to December 2021 and includes 682,316 observations. LEV_t, SLP_t, CRV_t refer to the level, slope and curvature (first three principal components) 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.

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.

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

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

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.

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 11,913 bonds from 1,872 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.[23] Due to the issues raised in Vassalou and Xing (2004), we follow Gilchrist and Zakrajšek (2012) by implementing the two-step

[23] 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.

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.[24] 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.[25] 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).

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

[25] 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, 2021), 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.[26]

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.

[26]Our time sample runs form 1985-2021. Relative to Anderson and Cesa-Bianchi (2021), 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 highlight that the heterogeneous responses we document are robust to controlling for heterogeneity according to other firm characteristics. In Section B.2, 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.3, we show that firms' homgoeneous responses to credit demand shocks are robust to considering alternative percentiles and to horseraces with other firm characteristics. In Section B.4, we document the hetergeneous effects on firm debt issuance of both monetary policy and credit supply shocks. In Section B.5, we re-estimate our main specifications with alternative monetary policy shocks. Finally, in Section B.6, we showcase the robustness of our results linking the EBP distribution to the aggregate effectiveness of monetary policy.

B.1 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 (2) ,(4), (9) and (10), which contain the interaction term $\varepsilon^{shock}_t \times \mathbf{1}EBP^{low}_{i(k)t-1}$, when also including the interaction vector $\varepsilon^{shock}_t \times \mathbf{1Z}^{low}_{it-1}$, 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 and where $shock = \{m\} \quad or \quad \{CS\}$.[27] We define each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}^{low}_{it-1}$ in two ways: (1) $\mathbf{1}Z^{low}_{it-1} = 1$ 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) $\mathbf{1}Z^{low}_{it-1} = 1$ 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.

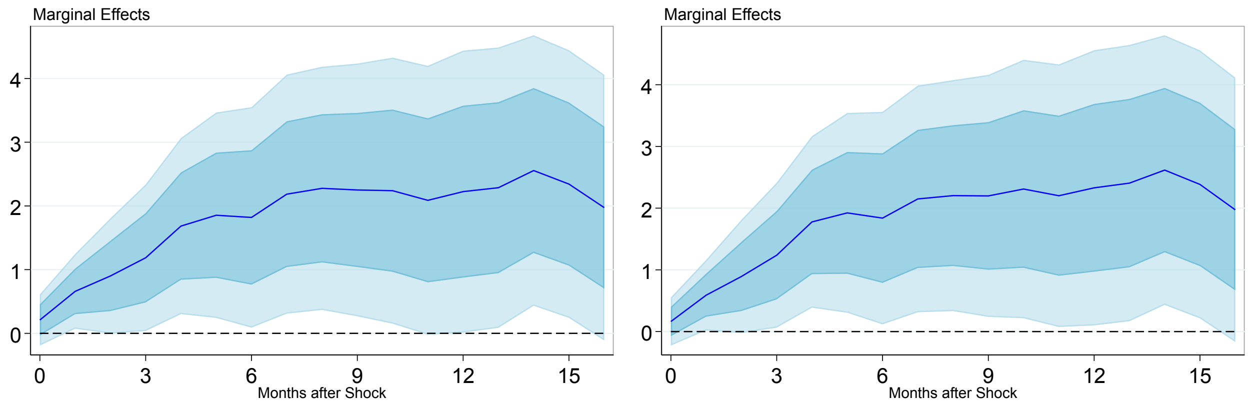
The results of these horserace regressions between firms' EBPs and other firm char-

[27]We include these indicator variables of firm characteristics and their interactions with the shocks en lieu of firm characteristics in levels. We consider credit demand shocks in the next section.

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



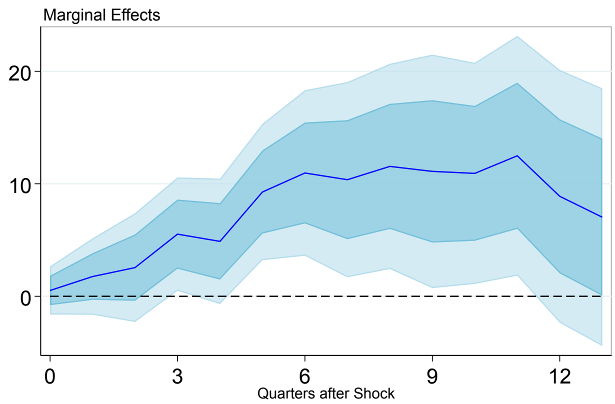
Note. Figure B.1 plots the credit spread response of low-EBP (sub 20^{th} percentile) firms' bonds to a monetary policy shock relative to high-EBP firms' using a modified regression (2) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of 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.

acteristics are displayed in Figures B.1, B.2, B.3 and B.4. The left panel in each figure displays the response of low-EBP firms' outcome variable 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.

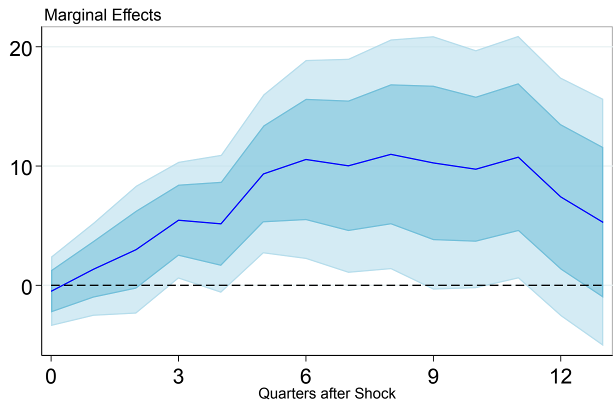
Across each figure and specification, we see that firms' EBPs continue to regulate the responsiveness of firms' credit spreads and investment to monetary policy and credit supply shocks. This highlights the economic relevance of firms' EBPs for explaining firms' heterogeneous reactions to monetary policy.

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

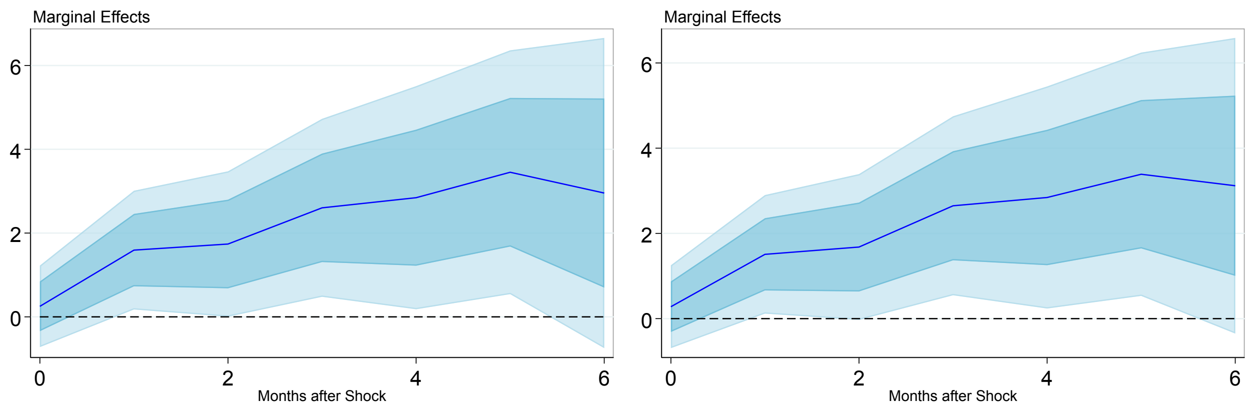


Note. Figure B.2 plots the investment response of low-EBP (sub 20^{th} percentile) firms to a monetary policy shock relative to high-EBP firms using a modified regression (4) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator 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.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

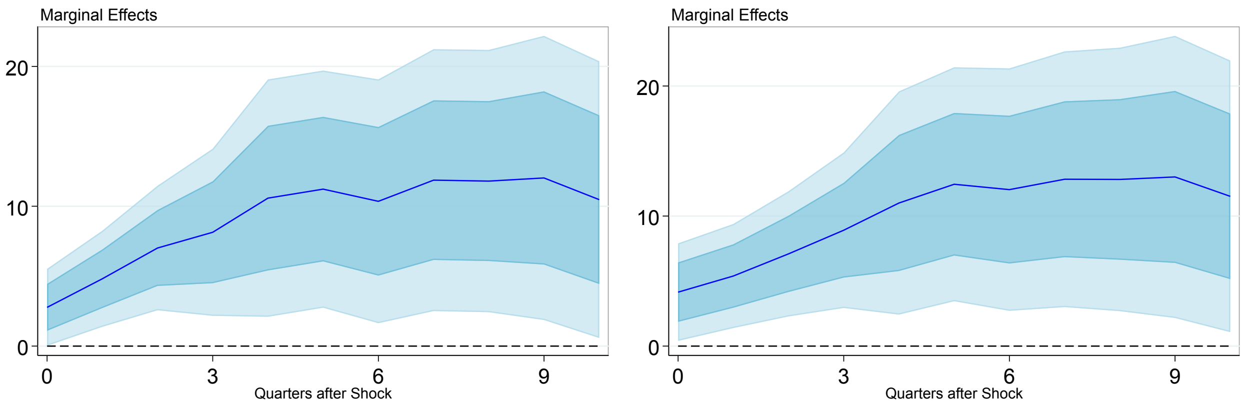


Note. Figure B.3 plots the credit spread response of low-EBP (sub 20^{th} percentile) firms' bonds to a credit supply shock relative to high-EBP firms' using a modified regression (9) that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector 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 (10) that controls for $\varepsilon_t^{CD} \times \mathbf{1Z}_{it-1}^{low}$, 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.

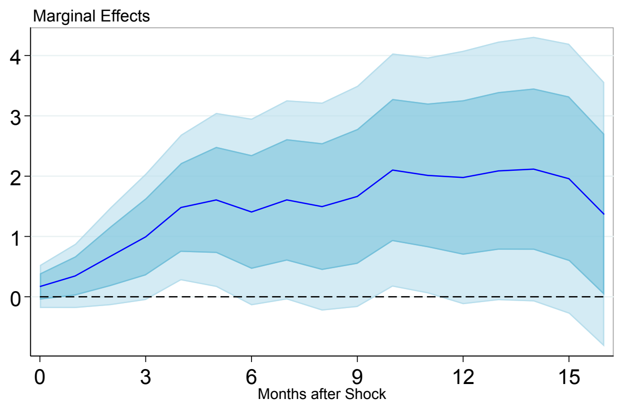
B.2 Heterogeneous Effects with Alternative EBP Percentiles

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 three other threshold percentiles in addition to our baseline 20^{th} percentile used in the main text, namely, the 15^{th}, 25^{th} and 33^{rd} percentiles. The results for re-estimating regression (2)—monetary policy's effect on bond credit spreads—with these other percentiles are shown in B.5. The results for re-estimating regression (4)—monetary policy's effect on firm investment—with these other percentiles are shown in Figure B.6. The results for re-estimating regression (9)—credit supply's effect on bond credit spreads—with these other percentiles are shown in B.7. The results for re-estimating regression (10)—credit supply's effect on firm investment—with these other percentiles are shown in Figure B.8. 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.

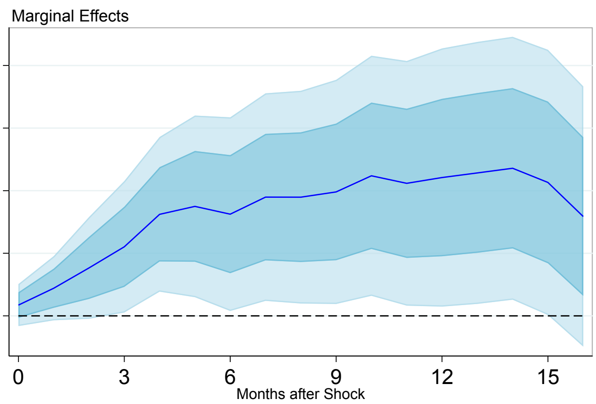
FIGURE B.5

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

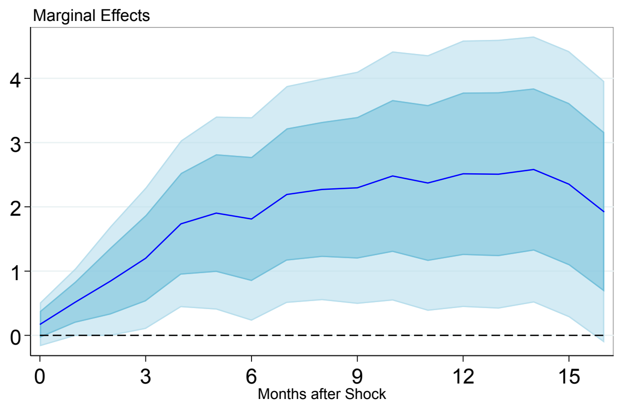
(A) Below 15^{th} EBP_{ikt-1} Percentile



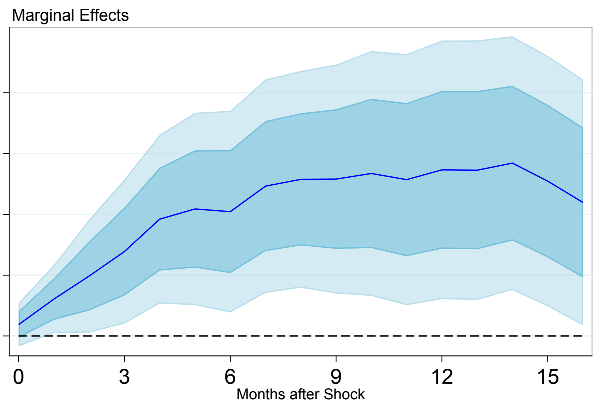
(B) Below 20^{th} EBP_{ikt-1} Percentile



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



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

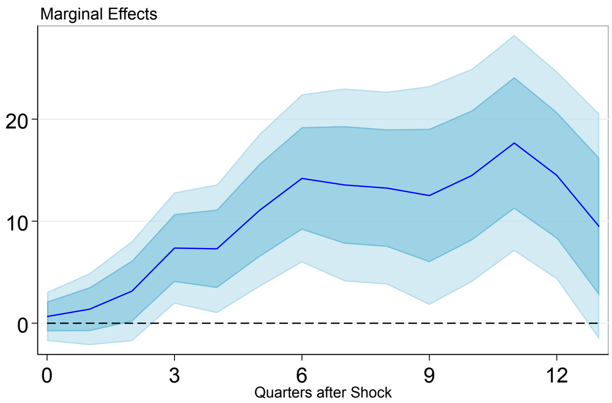


Note. Figure B.5 plots the β_1^hs from regression (2), which trace the credit spread response of low-EBP firms' bonds to a monetary policy shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (2). Panels B.5a, B.5b, B.5c, B.5d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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.

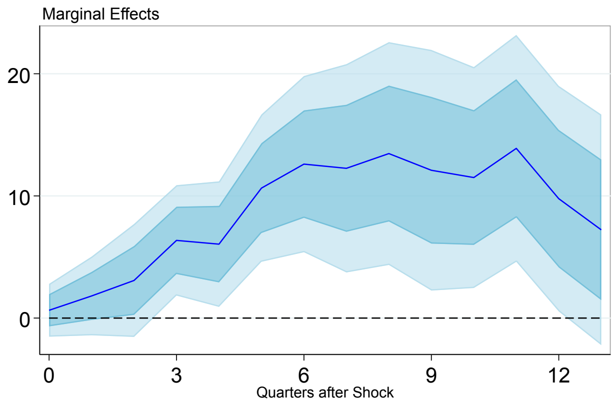
FIGURE B.6

Relative Response of Firm Investment to Monetary Policy by EBP Percentiles

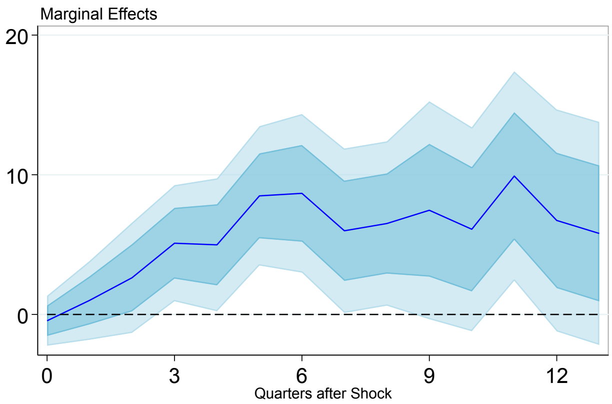
(A) Below 15^{th} EBP_{it-1} Percentile



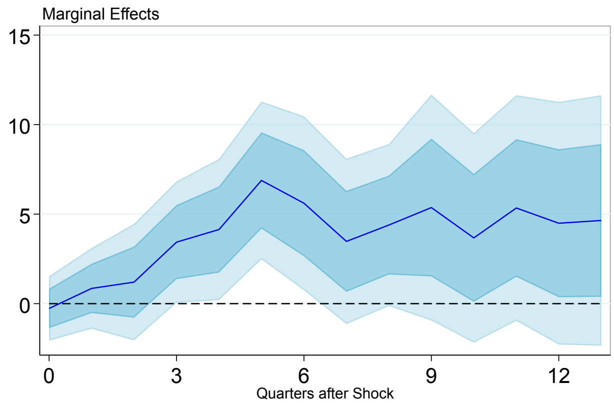
(B) Below 20^{th} EBP_{it-1} Percentile



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



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

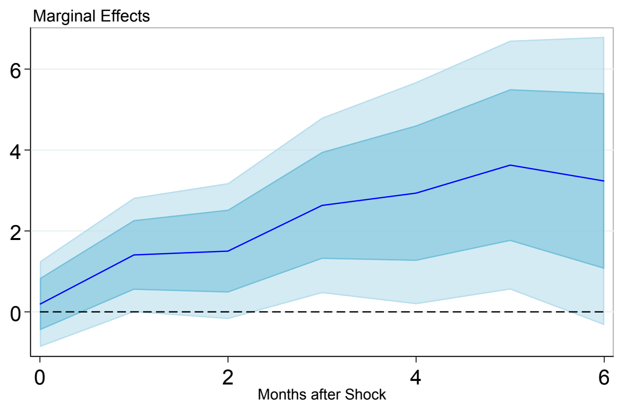


Note. Figure B.6 plots the β_1^hs from regression (4), which trace the investment response of low-EBP firms to a monetary policy shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (4). Panels B.6a, B.6b, B.6c, B.6d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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.

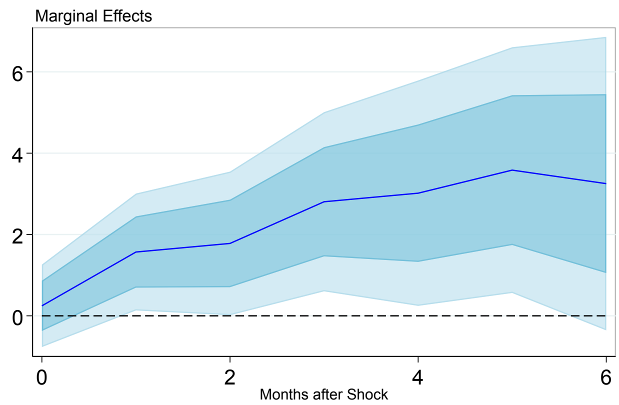
Figure B.7

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

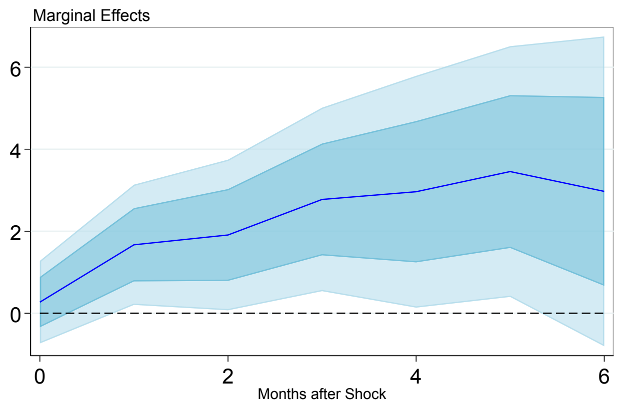
(a) Below 15^{th} EBP_{ikt-1} Percentile



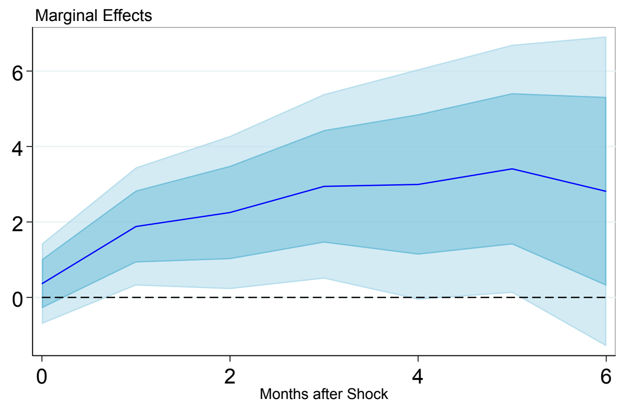
(b) Below 20^{th} EBP_{ikt-1} Percentile



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



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

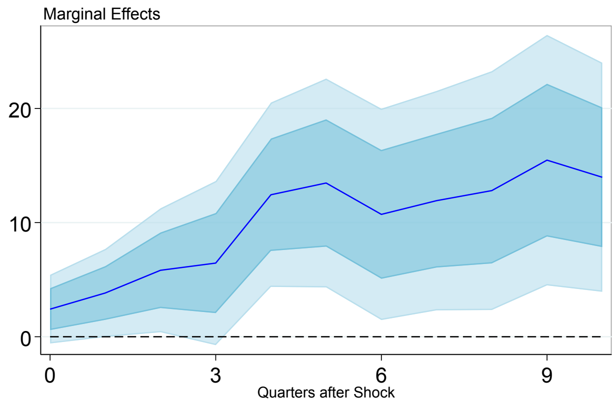


Note. Figure B.7 plots the β_1^hs from regression (9), which trace the credit spread response of low-EBP firms' bonds to a credit supply shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (9). Panels B.7a, B.7b, B.7c, B.7d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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.

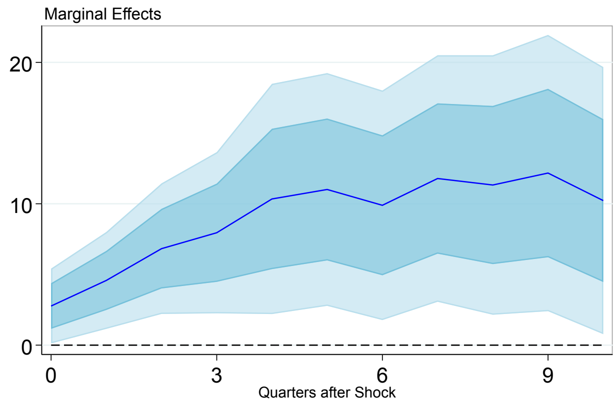
Figure B.8

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

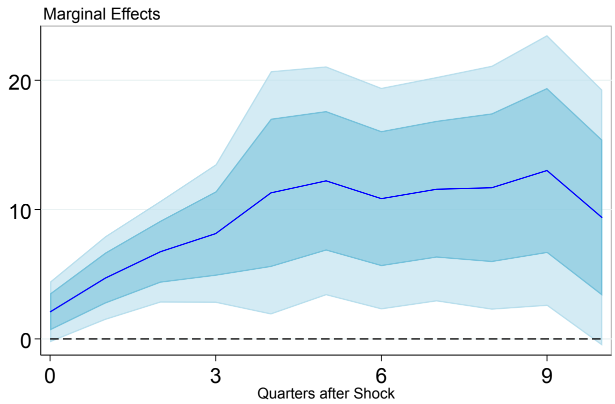
(A) Below 15^{th} EBP_{it-1} Percentile



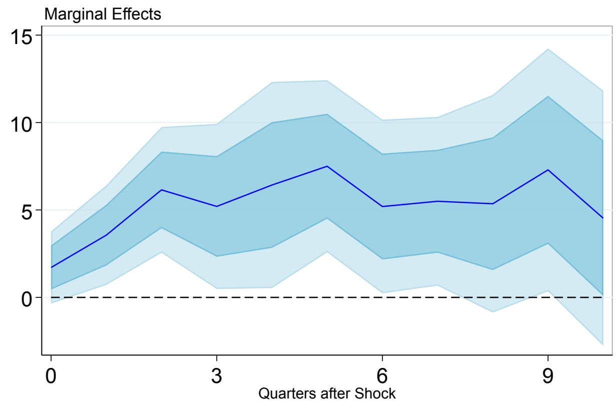
(B) Below 20^{th} EBP_{it-1} Percentile



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



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



Note. Figure B.8 plots the β_1^hs from regression (10), 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 (10). Panels B.8a, B.8b, B.8c, B.8d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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.3 Homogeneous Effects from Credit Demand Shocks

In this section, we perform the same robustness exercises from Sections B.1 and B.2 for credit demand shocks. Overall, our findings confirm our results from the main text: low- and high-EBP firms' investment and credit spreads respond similarly to credit demand shocks. This stands in marked contrast to credit supply shocks, which, like monetary policy shocks, induce significant heterogeneous responses across firms.

Specifically, we begin by running horse regressions between firms' EBPs and other firm characteristics of a similar form to those in Section B.1. The results for credit spreads are displayed in Figure B.9 and for investment are displayed in Figure B.10. The left panel in each figure displays the response of low-EBP firms' outcome variable to the credit demand shock compared to high-EBP firms', controlling for the interaction $\varepsilon_t^{CD} \times \mathbf{1Z}_{it-1}^{low}$, 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.

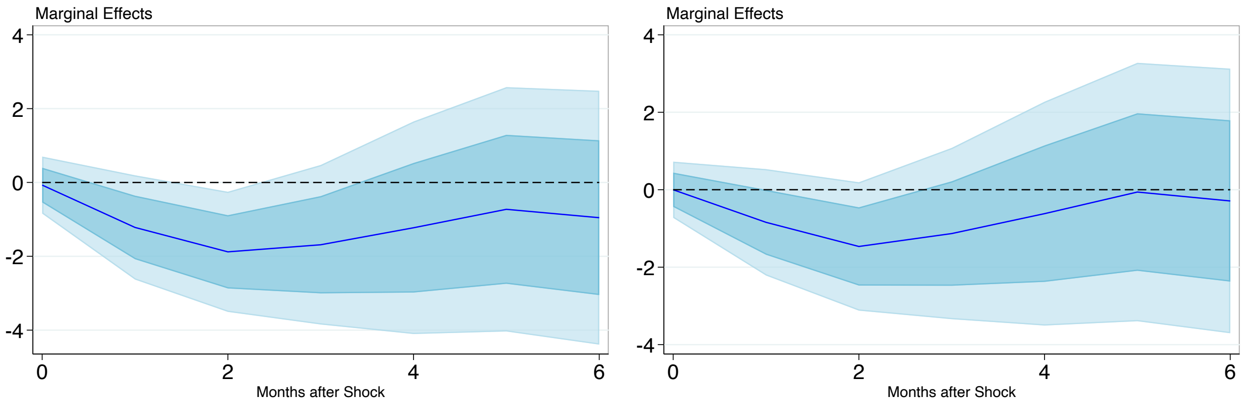
Across these figures, we see that, even when controlling for the conditioning effects of other firm characteristics, low-EBP and high-EBP firms' investment and credit spreads continue to respond similarly to credit demand shocks, as in the main text.

Next, as in Section B.2, we re-estimate the responses of firms' investment and credit spreads conditional on firms' EBPs for three other threshold percentiles in addition to our baseline 20^{th} percentile used in the main text, namely, the 15^{th}, 25^{th} and 33^{rd} percentiles. The results for credit spreads are displayed in Figure B.11 and for investment are displayed in Figure B.12. In terms of investment, across the three alternative percentiles, the response of low-EBP firms relative to high-EBP firms to a credit demand shock is statistically indistinguishable from zero. For credit spreads, while there is some evidence of mild heterogeneity at the 25^{th} and 33^{rd} percentiles, this occurs only for 1 or 2 months. Furthermore, the direction of this heterogeneity runs counter to what we observe for monetary policy.

Overall, given that monetary policy can in principle lead to heterogeneous firm re-

Figure B.9
Horserace Regressions: Relative Response of Low-EBP Firms' Spreads to Credit Demand Shock

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

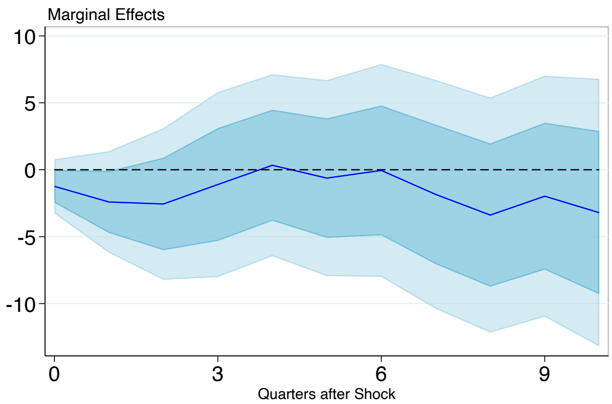


Note. Figure B.9 plots the credit spread response of low-EBP (sub 20^{th} percentile) firms' bonds to a credit demand shock relative to high-EBP firms' using a modified regression (9) that controls for $\varepsilon_t^{CD} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector 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.9a, 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.9b, 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.

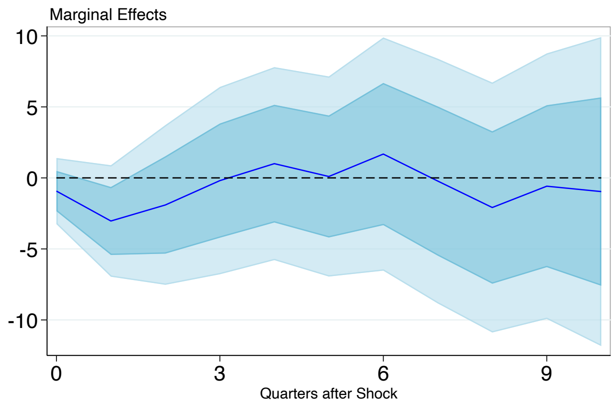
sponses by both adjusting firms' marginal benefit and marginal cost curves, that credit demand surprises generate largely homogeneous reactions while we have shown that credit supply shocks replicate the heterogeneous effects of monetary policy highlights the centrality of movements in firms' marginal cost curve along differently-sloped marginal benefit curves for the transmission of monetary policy in capital markets.

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

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



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

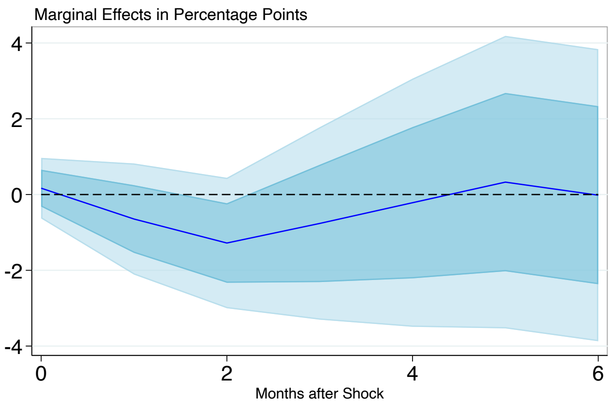


Note. Figure B.10 plots the investment response of low-EBP (sub 20^{th} percentile) firms to a credit demand shock relative to high-EBP firms using a modified regression (10) that controls for $\varepsilon_t^{CD} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator 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.10a, 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.10b, 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.

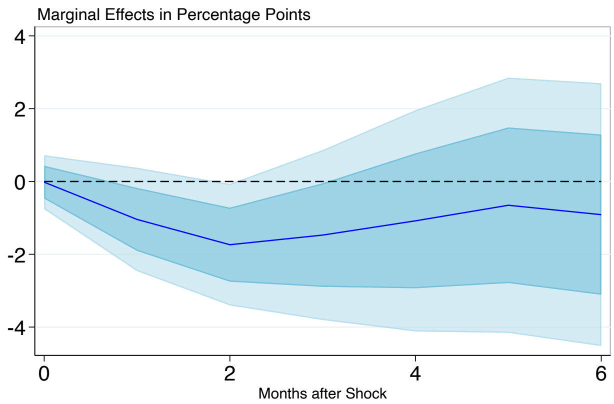
FIGURE B.11

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

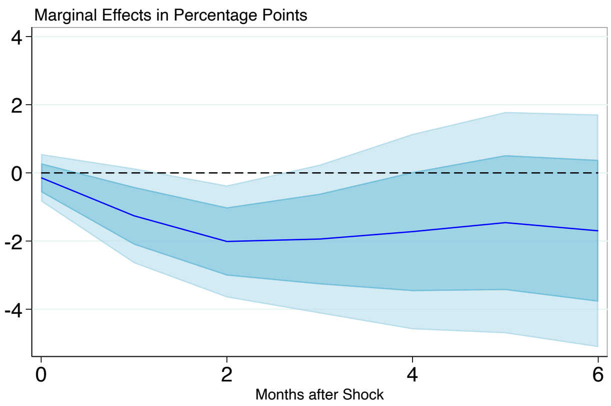
(A) Below 15^{th} EBP_{ikt-1} Percentile



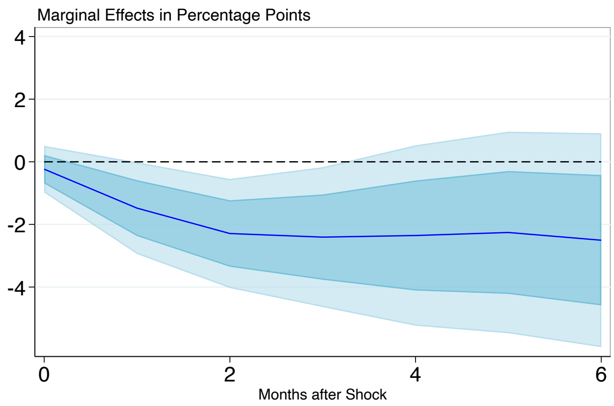
(B) Below 20^{th} EBP_{ikt-1} Percentile



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



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

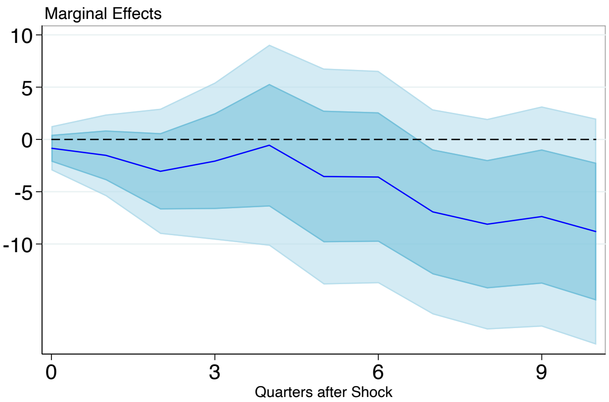


Note. Figure B.11 plots the β_1^hs from regression (9), which trace the credit spread response of low-EBP firms' bonds to a credit demand shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (9). Panels B.11a, B.11b, B.11c, B.11d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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.

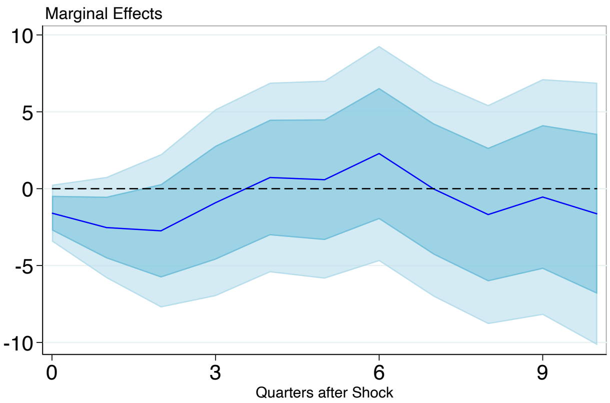
FIGURE B.12

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

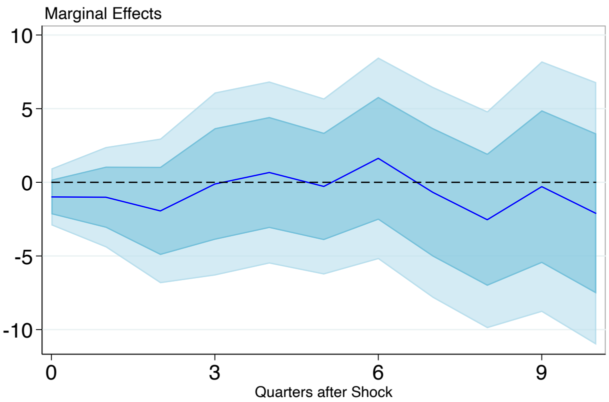
(A) Below 15^{th} EBP_{it-1} Percentile



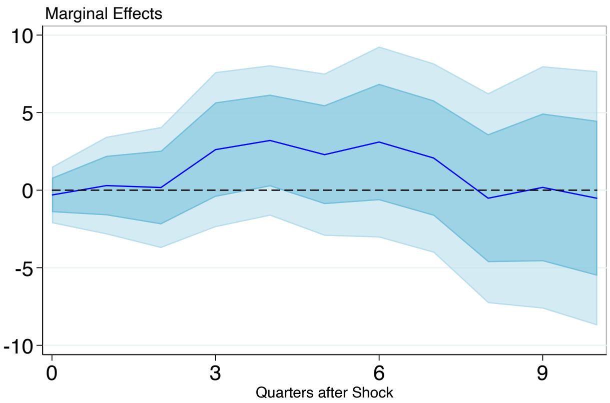
(B) Below 20^{th} EBP_{it-1} Percentile



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



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



Note. Figure B.12 plots the β_1^hs from regression (10), which trace the investment response of low-EBP firms to a credit demand shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (10). Panels B.12a, B.12b, B.12c, B.12d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's bond's EBP is below the 15^{th}, 20^{th} (our baseline from the main text), 25^{th} and 33^{rd} 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 Firm-Level Debt Issuance

In this section, we perform the same exercises from Sections B.1 and B.2 for firms' debt issuance. We provide evidence that, similar to firm investment, low-EBP firms increase debt issuance relative to high-EBP firms following a monetary policy easing and an increase in credit supply.

First, analogous to Section B.1, we estimate:

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

where $D_{i,t}$ is firm i's real outstanding debt (short- plus long-term) in period t, $\varepsilon_t^{m\ or\ CS}$ is either a monetary policy shock or a credit supply shock, and $\varepsilon_t^{m\ or\ CS} \times \mathbf{1Z}_{it-1}^{low}$ is an interaction between the shock and a vector of indicator variables for other firm characteristics, namely, firms' distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q.[28] As before, we consider two threshold percentiles to define $\mathbf{1Z}_{it-1}^{low}$, the 20^{th} and 50^{th} percentiles, while $\mathbf{1EBP}_{it-1}^{low}$ is defined based on the 20^{th} as in our baseline results in the main text.

The results for monetary policy shocks are displayed in Figure B.13 while the results for the credit supply shocks are displayed in Figure B.14. The left panel in each figure defines $\mathbf{1Z}_{it-1}^{low}$ based on the 20^{th} percentile while the right panel defines it based on the median.

Second, analogous to Section B.2, we estimate:

$$\log\left(\frac{D_{it+h}}{D_{it-1}}\right) = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h(\varepsilon_t^{m\ or\ CS} \times \mathbf{1}EBP_{it-1}^{low}) + e_{ith}, \tag{B.2}$$

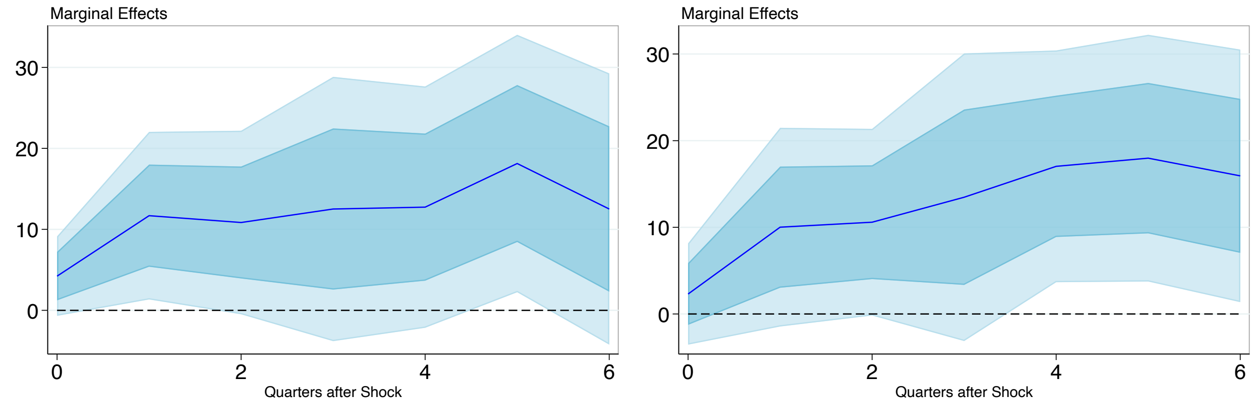
using 4 different threshold percentiles to define low-EBP firms, i.e., firms for which $\mathbf{1}EBP_{i(k)t-1}^{low} = 1$: the 15^{th}, 20^{th}, 25^{th} and 33^{rd} percentiles. The results are displayed in Figures and .

Across these figures and specifications, we see that low-EBP firms increase debt is-

[28] We of course also include $\mathbf{1}EBP_{it-1}^{low}$ and $\mathbf{1Z}_{it-1}^{low}$ in the specification.

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

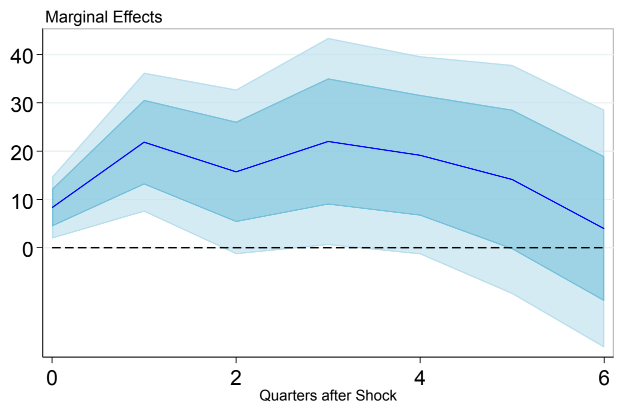


Note. Figure B.13 plots the β_1^hs from regression (B.1), which trace the debt issuance response of low-EBP (sub 20^{th} percentile) firms to a monetary policy shock relative to high-EBP firms, controlling for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector 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.13a, 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.13b, 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.

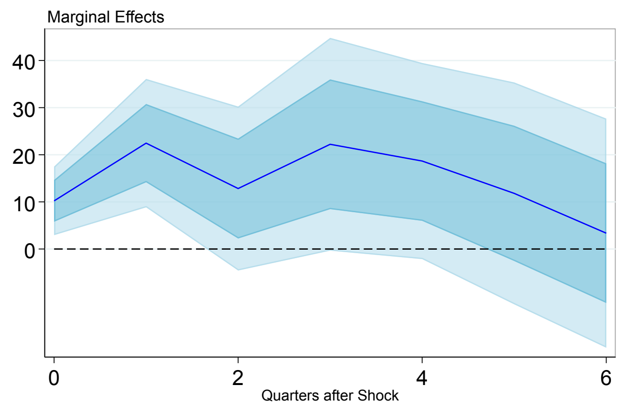
suance relative to high-EBP firms following expansionary monetary policy and credit supply shocks. Combined with our findings in the main text, we have that expansionary monetary policy and credit supply shocks lower credit spreads relatively little for low-EBP firms, but they respond by both borrowing more and investing more. This further highlights the importance of the slope of firms' marginal benefit curve for understanding the reactions of firms to monetary shocks.

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



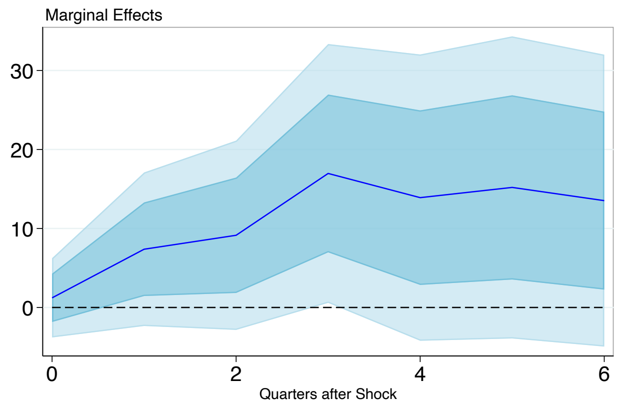
(b) Horeserace with below 50^{th} Perc. Characteristics



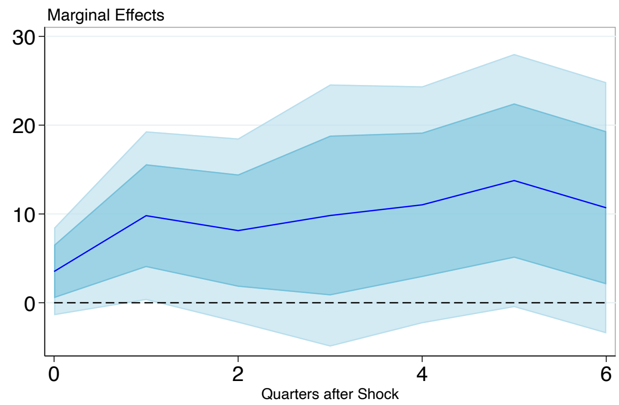
Note. Figure B.14 plots the β_1^hs from regression (B.1), which trace the debt issuance response of low-EBP (sub 20^{th} percentile) firms to a credit supply shock relative to high-EBP firms, controlling for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector 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.14a, 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.14b, 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.15
Relative Response of Firm Debt to Monetary Policy by EBP Percentiles

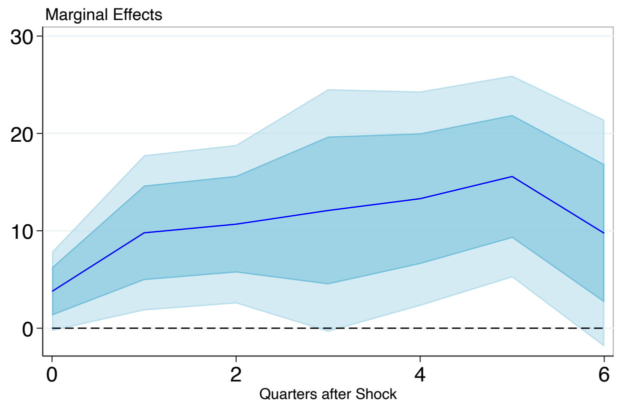
(A) Below 15^{th} EBP_{it-1} Percentile



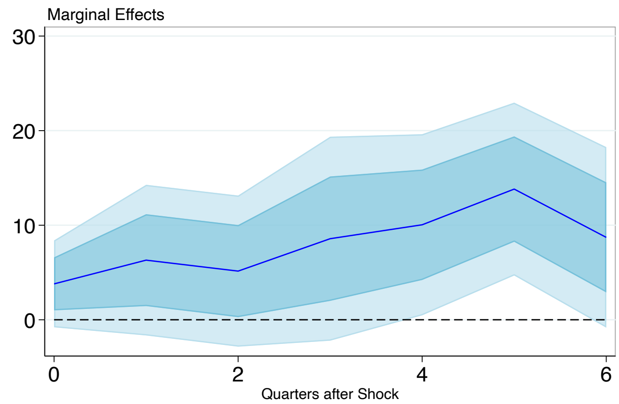
(B) Below 20^{th} EBP_{it-1} Percentile



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



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

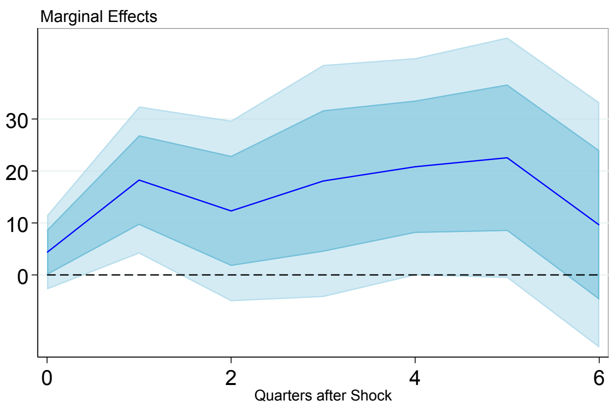


Note. Figure B.15 plots the β_1^hs from regression (B.2), which trace the response of low-EBP firms' debt issuance to a monetary policy easing shock relative to high-EBP firms', using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (B.2). Panels B.15a, B.15b, B.15c, B.15d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the 15^{th}, 20^{th}, 25^{th} and 33^{rd} 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.

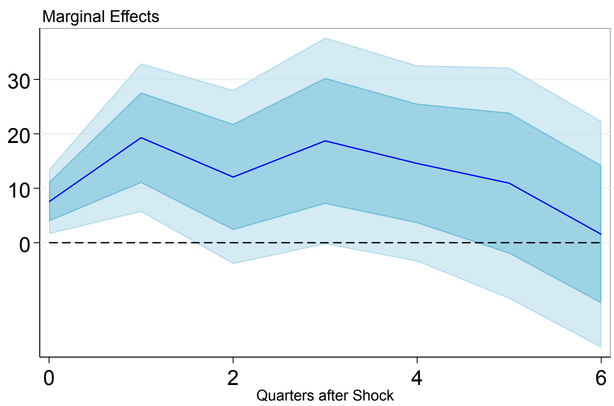
FIGURE B.16

Relative Response of Firm Debt to Credit Supply by EBP Percentiles

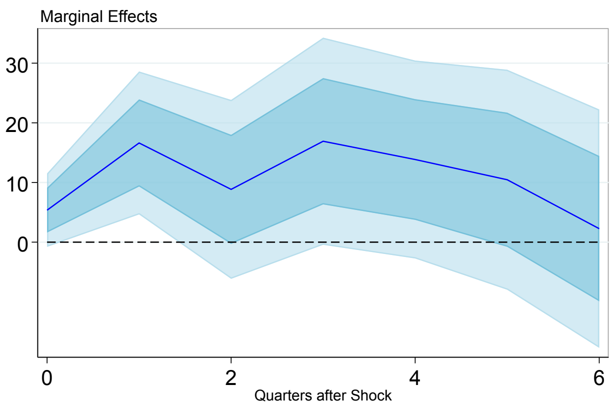
(A) Below 15^{th} EBP_{it-1} Percentile



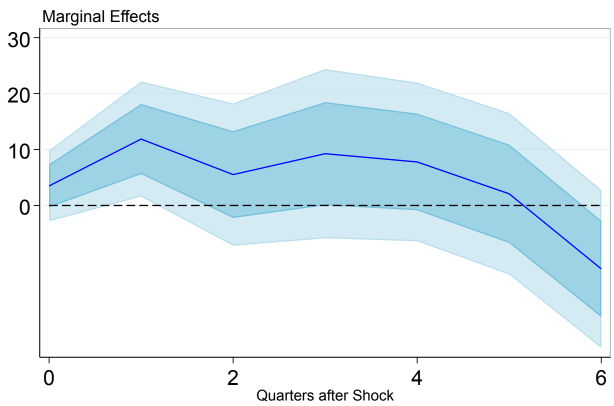
(B) Below 20^{th} EBP_{it-1} Percentile



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



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



Note. Figure B.16 plots the β_1^hs from regression (B.2), which trace the response of low-EBP firms' debt issuance to an expansionary 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 (B.2). Panels B.16a, B.16b, B.16c, B.16d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the 15^{th}, 20^{th}, 25^{th} and 33^{rd} 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.

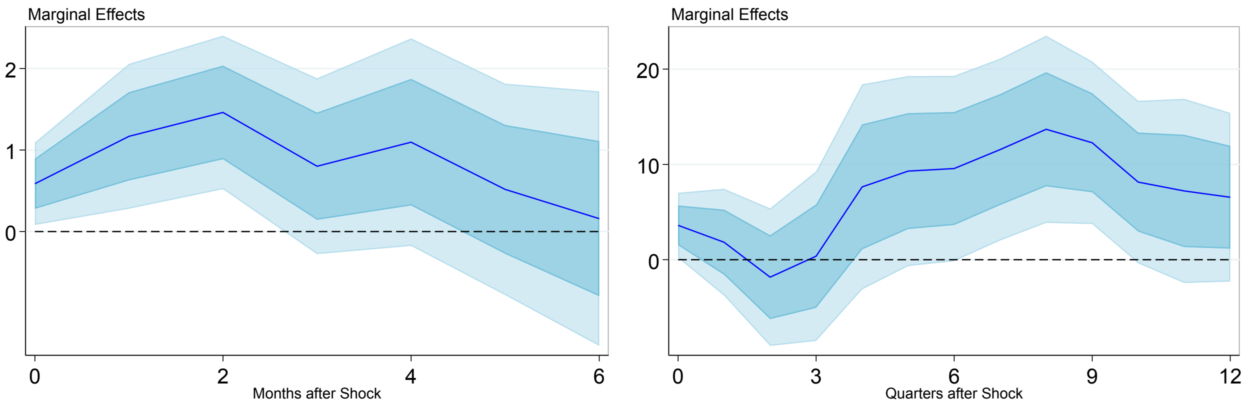
B.5 Heterogeneous Effects with Alternative Monetary Policy Shocks

In this section, we show our results for the heterogeneous responses of firms' investment and credit spreads are robust to using alternative 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.

The results for credit spreads—which come from re-estimating regression (2) with the FF0 shock—and for investment—which come from re-estimating regression (4) 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), and yet, these low-EBP firms still 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 (9) 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 (10) 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.6 Robustness of Aggregate Implications of EBP Heterogeneity

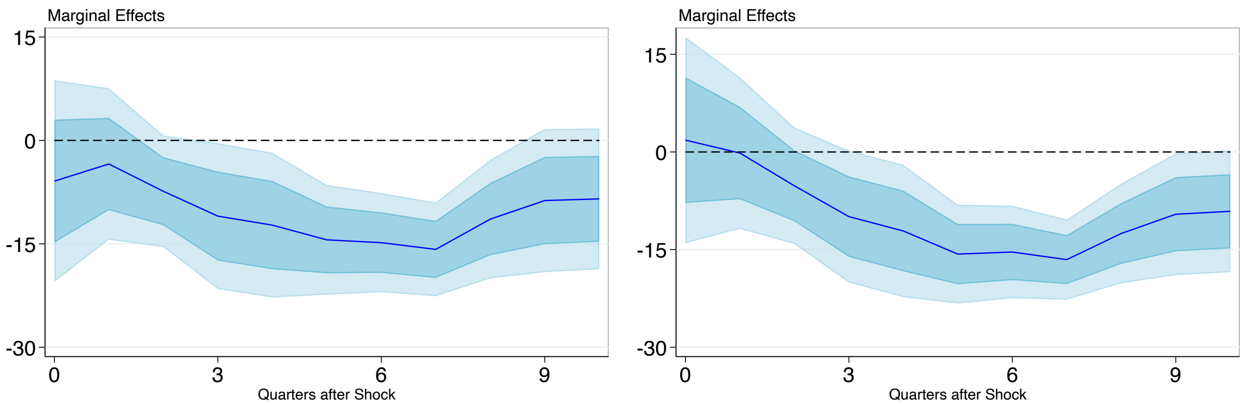
In this section, we show that our results from Section 6, where we documented that the cross-sectional EBP distribution is an important empirical driver of the aggregate effectiveness of monetary policy, are robust to horseraces between monetary policy's interaction with the moments of the EBP distribution 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 (11) from the main text.

The results are displayed in Figure B.18, focusing on the skewness of the EBP distribution. As in the main text, we see that a right-skewing of the EBP distribution is associated with a dampening of the effect of expansionary monetary policy shocks on aggregate investment growth. This suggests that the conditioning power of the moments of the cross-sectional EBP distribution—and the importance of the slope of firms' marginal benefit curves for the aggregate effectiveness of monetary policy—are more general than the well-documented weaker potency of monetary policy in recessions (Tenreyro and Thwaites (2016)).

FIGURE B.18
EBP Skewness and Monetary Policy's Effect on Aggregate Investment Growth: Controlling for Recession Indicators

(A) Control for Recession Probability Interaction (B) Control for NBER-Classified Recession Interaction



Note. Figure B.18 reports the dynamic response of annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, to a 1 percentage point monetary policy easing shock conditional on the skewness of the cross-sectional EBP distribution, which we estimate using regression (11) augmented with interactions between monetary policy shocks and various recession indicators. In Panel B.18a, the recession indicator is the smoothed U.S. recession probability measure of Chauvet (1998); in Panel B.18b, it is the NBER-classified recession indicator variable. 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 provide further information related to our model. In particular, we present the model's calibration (Section C.1); provide empirical robustness for the link between the cyclicality of firms' default risk and their EBPs (Section C.2); and detail a link between the slope of firms' marginal benefit curves and their EBPs in the data, which reinforces our theoretical results from the main text (Section C.3).

C.1 Model Calibration

TABLE C.1
Benchmark Model Calibration

Parameter	**Value**	**Description**
N_1	0.003	Intermediary Net-Worth Pre-Shock
N_2	0.01	Intermediary Net-Worth Post-Shock
R	1	Opportunity Cost
θ_H	0.1	Agency Friction of High-EBP Firm
θ_L	0.06	Agency Friction of Low-EBP Firm
α	0.955	Firm Capital Elasticity

Table C.1 presents our model's calibration. Among the parameters are the net-worth of intermediaries before and after the shock, which we select such that intermediaries' constraints bind for both firms. The safe interest rate, R, is set to 1 in the model for simplicity. α, the intensity of capital in firms' production functions as well as firms' returns to scale, is set close to 1 (0.955). This decreases the concavity of firms' production function, thereby flattening out firms' marginal benefit curves for capital especially at higher values of capital.

Finally, as discussed in the main text, we posit that intermediaries charge firms different θs—which parameterize the tightness of intermediaries constraints—as a reduced form way of capturing differences in the cylicality of firms' default risk. We calibrate the low-EBP firms' θ_L and high-EBP firms' θ_H to approximately match the cyclicality of low- and high-EBP firms' default risk, as estimated in regression (7) in Section 5.2.[29]

[29]To map into our model, we divide the cyclicality estimates in Table 2 by 10.

C.2 Firm EBPs and Marginal Cost Curves in the Data

In Section 5.2, we showed empirically that low-EBP firms' default risk co-moves relatively less with the market factor, proxied by the U.S. S&P500 index return. We then used these differences in default risk cyclicality to calibrate the θs in our model. In this section, we highlight the robustness of these empirical results by varying the threshold percentile used to define the low-EBP firm. In particular, we provide results for three alternative threshold percentiles in addition to our baseline 20^{th} percentile used in the main text, namely, the 15^{th}, 25^{th} and 33^{rd} percentiles.

Table C.2
Differences in Low- and High-EBP Firms' Default Risk Cyclicalities: Alternate Percentiles

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

Note: Table C.2 reports $\beta^{Mkt,Rel}$ from regression (8), 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 4 different threshold percentiles: 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% level.

The results from re-estimating regression (8)—which measures the relative loading on the S&P500 return of low-EBP firms' default risk relative to high-EBP firms'—with these alternative percentiles is displayed in Figure C.2. 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'.

C.3 Firm EBPs and Marginal Benefit Curves in the Data

Finally, while we emphasize in the main text that firms' positions along—and hence the *local* slopes of—their marginal benefit curves for capital are central to explain monetary policy's heterogeneous effects by firm EBP, *global* differences in firms' marginal benefit curves can matter as well. Specifically, differences in the capital intensity (α) of firms' production functions varies the elasticity of their marginal benefit curves, with higher-α firms having globally flatter marginal benefit curves.

In this section, we document that low-EBP firms also have higher αs—i.e., globally flatter marginal benefit curves—which amplifies our theoretical results from the main text. That is, through the lens of our model, lower-EBP firms with higher αs would experience an even small decline in credit spreads in response to a monetary easing, while investing even more.

To compare the capital elasticity of low- and high-EBP firms, we estimate two panel specifications: (i) with capital as the single input (as in our model); and (ii) which additionally controls for inputs that can be frictionlessly adjusted (Hall, 1986, 1988) as well as firms' unobservable idiosyncratic productivity (Olley and Pakes, 1996):

$$\begin{aligned}
\log Y_{i,t} &= \beta_i + \alpha \log K_{i,t} + \alpha^{Rel}(\log K_{i,t} \times \mathbf{1}EBP^{low}_{it-1}) + \sigma \mathbf{1}EBP^{low}_{it-1} + \varepsilon_{i,t}, \qquad \text{(C.1)} \\
\log Y_{i,t} &= \beta_i + \alpha \log K_{i,t} + \alpha^{Rel}(\log K_{i,t} \times \mathbf{1}EBP^{low}_{it-1}) + \sigma \mathbf{1}EBP^{low}_{it-1} + \omega_{i,t} \\
&\qquad + \gamma \log M_{i,t} + \delta \log O_{i,t} + \varepsilon_{i,t}, \qquad \text{(C.2)}
\end{aligned}$$

where output $Y_{i,t}$ is real sales; β_i is a firm fixed effect; $M_{i,t}$ and $O_{i,t}$ are real variable inputs—intermediate goods (e.g., materials) and other operating expenses (including salaries), respectively—which may be correlated with productivity $\omega_{i,t}$.

The results from estimating these two specifications are presented in Table C.3. While we estimate the single-input specification (C.1) using OLS, we achieve consistent estimates of the factor elasticities in specification (C.2) by (i) instrumenting the variable inputs with their lags; and (ii) using a variable input as a proxy variable for unobserved productivity

Table C.3
Production Function Estimation and the Relative Capital Intensity of Low-EBP Firms

$\log Y_{i,t}$	(1) Model Specification	(2) Full Specification
$\log K_{i,t}$	0.77^{***}	0.11^{***}
	(.26)	(.01)
$\log K_{i,t} \times \mathbf{1}EBP^{Low}_{i,t-1}$	0.01^{*}	0.02^{***}
	(.01)	(.00)
$\log M_{i,t}$		0.60^{***}
		(.01)
$\log O_{i,t}$		0.28^{***}
		(0.02)

Note: Table C.3 provides firm production functions estimates and, in particular, presents the capital intensity of low-EBP firms' production relative to high-EBP firms' (α^{Rel}) using regressions (C.1) and (C.2). Column 1 reports estimates from the model specification (C.1), where capital is the single factor input, while column 2 reports estimates from the full specification (C.2), which accounts for frictionless inputs and unobserved productivity. Standard errors are two-way clustered by firm and quarter in column 1 and bootstrapped in column 2. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

(see Levinsohn and Petrin, 2003 and Ackerberg et al., 2015).[30]

Across both production function specifications, Table C.3 showcases that low-EBP firms have statistically significantly larger capital elasticities than do high-EBP firms.[31] This implies that low-EBP firms' marginal benefit curves are flatter than high-EBP firms', in a global sense. While these differences may appear small, any differences in α will further amplify the responsiveness of low-EBP firms' investment and dampen the reaction of low-EBP firms' spreads coming from the differences in θ.

[30] $M_{i,t}$ and $O_{i,t}$ are measured as real cost of goods sold and selling, general and administrative expenses from Compustat, respectively. We use $M_{i,t}$ as the proxy variable.

[31] Estimated capital elasticities are known to be smaller when including other inputs (Petrin et al., 2004).