# Firm Risk Premia and Monetary Policy Transmission*

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September 11, 2026

**Abstract**

We study how firms' financial conditions shape the transmission of monetary policy, measuring those conditions using firms' excess bond premia (EBPs)—what investors price into credit spreads beyond expected default risk. We show this includes firms' default-risk cyclicality: low-EBP firms' default risk co-moves less with aggregate risk. We find that monetary easings compress low-EBP firms' credit spreads by less while raising their investment by more. Credit supply shocks produce the same contrast. In a stylized model, matching these results requires monetary policy to adjust firms' capital supply curves more than their demand curves, and that low-EBP firms sit on flatter portions of their convex demand curves. As the model implies, the cross-sectional EBP distribution predicts the aggregate potency of monetary policy.

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

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*This paper builds on the previously circulated paper "*Firm Financial Conditions and the Transmission of Monetary Policy*" co-authored with John Rogers. We are grateful to Carolyn Davin and Caitlin Dutta for outstanding research assistance. We also thank anonymous referees, Andrea Ajello, Boragan Aruoba, Florin Bilbiie, Vasco Carvalho, Ambrogio Cesa-Bianchi, Giancarlo Corsetti, Carlos Vianna de Carvalho, Maarten De Ridder, Janice Eberly, Luca Fornaro, Maren Froemel, Etienne Gagnon, Nils Gornemann, Matteo Iacoviello, Priit Jeenas, Pablo Ottonello, Nic Kozeniauskas, Aeimit Lakdawala, Deborah Lucas, Simon Lloyd, Ali Ozdagli, Hélène Rey, Michael Smolyansky, Alejandro Vicondoa, Tim Willems, Thomas Winberry, Christian Wolf and presentation attendees at the University of Cambridge, Federal Reserve Board, RCEA 2022, SNDE 2022, CEMLA 2022, Barcelona School of Economics Summer Forum 2022, IAAE 2022, CICF 2022, Banque de France–CEPR–Sciences Po–OFCE EME Workshop 2022, Wake Forest Empirical Macroeconomics Workshop 2023, Queen Mary University of London Workshop in Quantitative Macroeconomics 2023, NBER Summer Institute 2023, Banco Central de Chile, and the SED Winter Meeting 2024. The views expressed in this paper are solely those of the authors and should not be interpreted as reflecting the views of the Vanguard Group, nor the Bank of England or its committees.

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# 1 Introduction

How do firms' financial conditions shape the transmission of monetary policy? A large literature grounds this question in theories of financial frictions (e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997), with the severity of these frictions proxied empirically by firm characteristics such as size (Gertler and Gilchrist, 1994), liquid assets (Jeenas, 2019), and age (Cloyne et al., 2023). This existing literature has focused on either quantities or prices: Ottonello and Winberry (2020) find that less-constrained firms—those with low leverage and high distance-to-default—invest more after a monetary policy easing, while Anderson and Cesa-Bianchi (2024) find that their credit spreads fall by less. We study price and quantity responses jointly, for two shocks—monetary policy and credit supply—and with a new proxy for the frictions firms face when borrowing to invest: their excess bond premia (EBPs), which measure what investors price into firms' credit spreads beyond expected default risk (Gilchrist and Zakrajšek, 2012).

Together, these ingredients discipline the channels through which financial conditions shape monetary policy transmission. Unconditional credit spread and investment responses reveal whether monetary policy shifts capital supply or demand curves more on average, while conditional responses restrict cross-firm differences in these curves' slopes and any asymmetries in their shifts. Shocks to financial intermediary net worth isolate the credit supply channel. And EBPs price frictions that balance-sheet characteristics miss, such as premia for firms' default-risk cyclicality. We find that monetary and credit supply easings compress spreads and raise investment on average, with low-EBP firms' spreads falling by less even as their investment rises by more. Matching these moments in a stylized supply-and-demand framework requires supply to shift more than demand, and points to low-EBP firms' lower supply curves intersecting flatter portions of their convex demand curves. Thus, a given supply shift raises their investment by more while compressing their spreads by less.

We first look for risk premia in firms' EBPs. These EBPs are constructed by stripping firms' expected default risk from their credit spreads using a single price of risk across firms and over time. Any firm-specific or time-varying pricing of default risk is therefore embedded in firms' EBPs.[1] Averaging EBPs across firms isolates the common component, which Gilchrist and Zakrajšek (2012) link to the financial sector's risk-bearing capacity. We instead look for firm-specific pricing of risk by estimating how firms' distance-to-default loads on aggregate risk factors, including the S&P500 return and the intermediary capital risk factor of He et al. (2017). For both factors, low-EBP firms' default risk co-moves less with aggregate risk: their distance-to-default falls by up to 20 percent less than high-EBP firms' when aggregate risk rises. The same holds within firm, so this pricing also varies over time as firms' EBPs move. Thus, firms' default risk cyclicality is one premium priced into firms' EBPs. Since EBPs embed other premia and convenience yields as well, we interpret firms' EBPs as multidimensional premia that shape their access to external funds.

We then study how firms' EBPs condition their responses to monetary policy. Our sample combines bond-level credit spreads and firm-level balance sheets for U.S. public non-financial firms from 1985 to 2021. We find that surprise monetary easings compress credit spreads less for lower-EBP firms, yet their investment increases by more. Quantitatively, in response to a 1 percentage point (pp) easing, the spreads of low-EBP firms—those in the bottom quintile of the EBP distribution—fall by 2pp less than high-EBP firms' at their peak, while their investment rises by 12pp more. These differential responses are large—comparable to the average responses observed across all firms—pointing to the relevance of firms' EBPs as state variables for monetary transmission. These results incorporate sector-time fixed effects, and hold controlling for other firm characteristics, for alternative definitions of "low-EBP firms", with alternative monetary policy shocks, and excluding the zero-lower-bound period.

To evaluate credit supply's role in shaping monetary transmission across firms, we repeat the analysis using credit supply shocks. We use the high-frequency shocks of Ottonello and Song (2025), which are measured as changes in financial intermediaries' net worth around their earnings announcements, purged of information related to non-financial firms. These shocks' heterogeneous effects mimic those from monetary policy shocks. Since monetary policy transmits, at least in part, by adjusting credit supply (Bernanke and Gertler,

[1]The Merton (1974) model used to construct firms' expected default risk—i.e., their distance-to-default—assumes zero covariance between a firm's default risk and aggregate risk, so any pricing of that covariance would enter the EBP component of credit spreads.

1995; Kashyap and Stein, 2000), credit supply shocks—which move intermediaries' net worth without adjusting the risk-free rate on-impact—isolate this channel. Thus, monetary policy's heterogeneous effects can be generated by changes in credit supply alone.

To understand the economic channels required to match these results, we build a stylized model of capital markets. Homogeneous financial intermediaries, subject to skin-in-the-game balance sheet constraints (Gertler and Kiyotaki, 2010 and Gertler and Karadi, 2011), lend capital to firms that differ in how their default risk covaries with aggregate risk. Intermediaries' constraints imply that firms face upward sloping capital supply (marginal cost) curves, and firms with lower default-risk cyclicality tighten those constraints less, thus facing lower (and flatter) curves. In extensions, we show that other firm-specific premia and convenience yields similarly alter these capital supply curves. All firms share the same convex capital demand curve. In equilibrium, EBPs arise endogenously: intermediaries' balance-sheet capacity drives the average EBP, as in Gilchrist and Zakrajšek (2012), while firms with lower default-risk cyclicality have lower EBPs, as in the data. Crucially, low-EBP firms with lower supply curves sit on flatter portions of their convex demand curves.

The data tightly constrain how these supply and demand curves can move. Monetary policy easings, as in Ottonello and Winberry (2020), can shift both curves: an increase in intermediary net worth shifts firms' capital supply curves outward, and a fall in the risk-free rate shifts their demand curves outward. That spreads fall and investment rises on average requires capital supply to move more than demand. That low-EBP firms' investment rises by more while their spreads fall by less requires either that they sit on flatter segments of their convex demand curves or that demand shifts more for these firms. Two findings favor the first: (i) low-EBP firms' sales rise only marginally relative to high-EBP firms' when policy eases; and (ii) sizable asymmetric shifts produce counterfactual spread responses. Heterogeneity therefore follows from where each firm's capital supply curve intersects the common convex demand curve, with low-EBP firms positioned on flatter demand segments.

Finally, the EBP distribution conditions how much monetary policy affects aggregate investment. As our framework implies, monetary easings raise aggregate investment by more when the EBP distribution has a lower median or is more left-skewed. Importantly, these effects hold controlling for monetary policy's weaker transmission in recessions.

**Literature Review:** Our paper relates to three strands in the literature. The first studies firm financial heterogeneity and monetary transmission. This literature builds on theories in which firms' access to external funds is subject to financial frictions, such as agency costs (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, greater frictions raise and steepen firms' marginal cost curves (Ottonello and Winberry, 2020). On the empirical front, the literature has used many firm characteristics to measure these frictions, such as liability structure (Ippolito et al., 2018; Gürkaynak et al., 2022), age (Bahaj et al., 2022; Durante et al., 2022), size (Crouzet and Mehrotra, 2020), leverage (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] David and Zeke (2024) study how monetary policy affects long-run dynamics of TFP via firms' exposure to aggregate risk. We contribute to this literature by showing that firms' EBPs sort their investment and credit spread responses in opposite directions for both monetary policy and credit supply shocks. We also show that EBPs are distinct from the characteristics above; they embed default-risk cyclicality and other premia those measures miss. Moreover, studying prices and quantities together, for two shocks, isolates the contributions of credit supply from those of demand, which studies of a single outcome or shock cannot do.

Second, we relate to the literature on the determinants of investment, especially user cost of capital (Jorgenson, 1963) and Q theory (Tobin, 1969).[3] To address Q theory's empirical weakness based on equity prices, Philippon (2009) builds a model in which a "bond market's Q", captured by firm credit spreads, predicts U.S. aggregate investment. Relatedly,

[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.

[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).

Gilchrist and Zakrajšek (2007) and Gilchrist et al. (2014) find similar results for firm-level credit spreads, which are the main source of variation in firms' user-cost of capital. Gilchrist and Zakrajšek (2012) clarify that it is the EBP component of credit spreads—which they link to financial intermediaries' risk-bearing capacity—that best predicts aggregate economic activity. Our contribution is to focus on this component's cross-section, where we document that default risk cyclicality is one premium that investors price into firms' EBPs. In a stylized model, we also show how EBPs can embed an array of premia and convenience yields. Further, since the model's average EBP reflects intermediaries' balance-sheet capacity while the cross-section reflects the frictions individual firms face, this helps connect financial-sector and firm-centered theories of investment.

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

# 2 Data and Descriptive Statistics

## 2.1 Data Sources and EBP Calculation

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

Using this data, we first compute the credit spread $S_{ikt}$ on the bond $k$ issued by firm $i$ at time $t$ as the difference between the bond's yield and the yield on a U.S. Treasury that shares the same maturity, with the latter calculated by Gürkaynak et al. (2007). Following Gilchrist and Zakrajšek (2012), we then calculate the excess bond premium by decomposing each bond's credit spread $S_{ikt}$ into two components. The first is the predicted spread $\hat{S}_{ikt}$, computed from the fitted values of the following panel regression of bond-level credit spreads on firm-level expected default risk—as measured by firms' distance to default $DD_{it}$ (Merton, 1974)—and a vector of bond characteristics $\mathbf{X}_{ikt}$ that includes, e.g., the bonds' duration, age, par value, coupon rate, and whether it is callable:

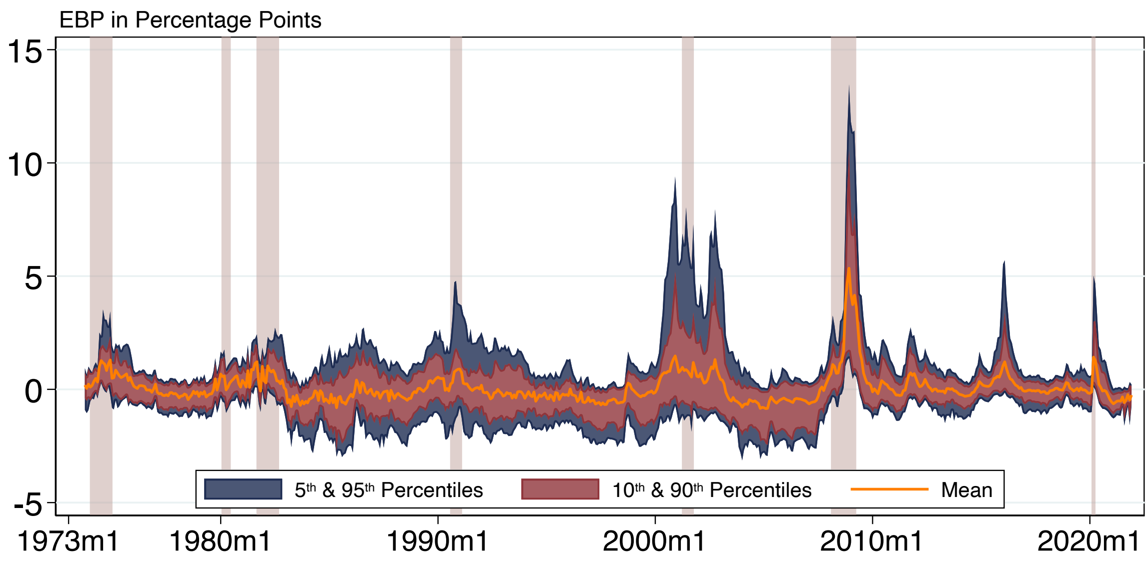
$$\log S_{ikt} = \beta DD_{it} + \boldsymbol{\gamma}'\mathbf{X}_{ikt} + \upsilon_{ikt}. \tag{1}$$

The second component is the excess bond premium, $EBP_{ikt}$, calculated from the bond-level residuals in regression (1) (Appendix A.3). We define a firm's $EBP_{it}$ as the equal-weighted average of $EBP_{ikt}$ across its outstanding bonds. EBPs summarize the premia and convenience yields investors price in beyond firms' expected default risk and the bonds' characteristics.[4] Section 3 provides an example of one such priced risk premium—the cyclicality of firms' default risk—showing that EBPs behave as risk premia should. Altogether, the risk premia and convenience yields in EBPs act as financial frictions that shape the marginal cost curves firms face when borrowing to invest (Section 6). Just as the average EBP is a widely used gauge of aggregate financial conditions, we expect firm-specific EBPs to be informative measures of firm-level financial conditions. This motivates our investigation of firms' EBPs as state variables driving their sensitivity to monetary policy.

We calculate EBPs for all the bonds in the Lehman-Warga (1973–1998) and ICE (1997–

[4]The distance-to-default term in regression (1) may not fully purge credit spreads of firms' expected default risk. We therefore re-estimate (1) controlling for non-linear $DD_{it}$ terms and construct a modified EBP, $EBP\_exDD_{ikt}$. Although the $2^{nd}$, $3^{rd}$ and $4^{th}$ powers of $DD_{it}$ are significant, using $EBP\_exDD_{ikt}$ does not affect our results (Appendix B.8).

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




*Note*. Figure 1 shows the mean and selected percentiles (5th, 10th, 90th, and 95th) 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.

2021) databases whose firm's balance sheet information and equity prices are available in Compustat and CRSP, respectively.[5] This yields an EBP dataset with 10,061 bonds issued by 1,630 firms at a monthly frequency from 1973 to 2021.[6] Appendix A provides variable definitions, sample selection, outlier cleaning, and summary statistics.

## 2.2 The Cross-Sectional EBP Distribution

Figure 1 plots the bond-level cross-sectional EBP distribution, which displays considerable heterogeneity. For most of the sample, left-tail percentiles lie below zero: an appreciable segment of bonds receive a discount relative to what their expected default risk and bond's characteristics predict. These percentiles also fluctuate less cyclically than the mean EBP, rising above zero only during the 2008 crisis. Right-tail percentiles, in contrast, are more

[5] Appendix A.3 details the EBP calculation and shows that our mean credit spread and mean EBP correlate with those of Gilchrist and Zakrajšek (2012) at 96% and 86%, respectively.

[6] Focusing on bond-financed firms tilts our sample toward large firms, but data on both spreads and investment are essential to our analysis. Since large firms play an outsized role in driving U.S. business cycles (Carvalho and Grassi, 2019), our firm-level results should also be relevant for monetary policy's aggregate effects, as we show in Section 7.

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.

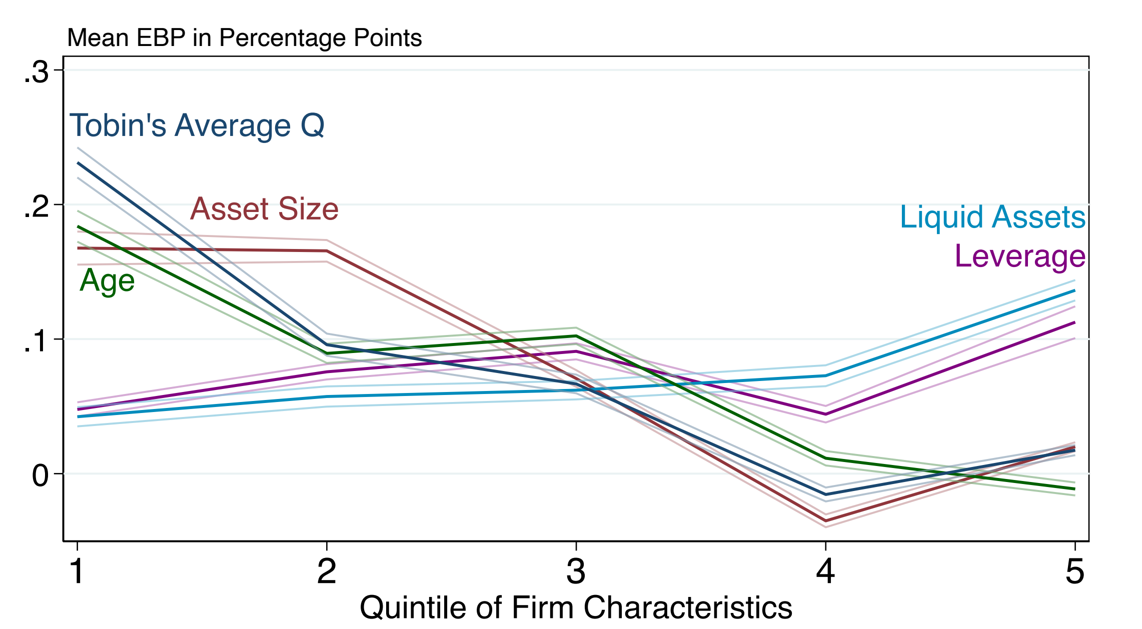
volatile than the mean and generally positive, so these firms usually pay a premium on their borrowing costs, especially in recessions.

Although the percentiles of the EBP distribution vary considerably over time, a bond's place within it is reasonably persistent. The Markov transition matrix in Table 1 shows that a bond's EBP is far more likely to stay in its quintile in the next month (diagonal entries) than to move to any other, particularly in the lowest and highest quintiles. Such persistence is necessary if EBPs are to reflect durable frictions rather than transitory noise.

Figure 2 reports firms' average EBP across quintiles of five other firm characteristics: leverage, liquid assets, age, size, and Tobin's average Q. There is limited association between firms' EBPs and their leverage or liquid asset share, two prominent measures of financial constraints. In contrast, older and larger firms, and firms with higher Tobin's Qs, tend to have lower EBPs. Despite these correlations, the conditioning power of firms' EBPs for monetary policy transmission is not driven by these characteristics.[7]

[7] We show this in two ways, both of which yield results similar to our baseline: (1) a modified EBP that purges credit spreads of these characteristics, $EBP\_exChar_{ikt}$ (Appendix B.8); and (2) a horserace between monetary policy's interaction with firms' EBPs and its interactions with these characteristics (Appendix B.2).

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.

## 2.3 Common Features of Regression Specifications

This section outlines common features of our regression. Although we present them in the context of evaluating monetary policy's effects, they apply throughout the paper.

To estimate monetary policy's effects conditional on firms' EBPs, we follow Gertler and Gilchrist (1994) and Cloyne et al. (2023) in constructing indicator variables for whether an EBP lies below a given threshold of the cross-sectional distribution, which we interact with monetary policy shocks in panel local projections à la Jordà (2005).[8] In our baseline, $\mathbf{1}EBP^{low}_{ikt}$ equals 1 if the EBP of firm $i$'s bond $k$ is in the bottom quintile of the time-$t$ distribution, and 0 otherwise. For firm-level regressions, we use its firm-level counterpart, $\mathbf{1}EBP^{low}_{it}$. We focus on the bottom tail since these firms' investment is particularly responsive to monetary policy, which matters for aggregate effects (Section 7). Our conclusions

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

are robust to other thresholds, such as the median (Appendix B.3), and to specifications with linear interactions or within-firm variation (Appendix B.8).

In our baseline specifications, we use the monetary policy shocks of Bu et al. (2021), which combine three appealing features. 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 largely free of the central bank information effect, whereby policy announcements may also reveal the central bank's views on the macroeconomy. Third, these shocks are not predictable by ex-ante available information, such as Blue Chip forecasts, "big data" measures of economic activity, news releases, and consumer sentiment.[9] We calculate the shocks from January 1985 to July 2021, summing them within the month (quarter) for monthly (quarterly) regressions. We also normalize the shocks so that positive values denote easings. Appendix A.1 provides further details; Appendices B.9 and B.10 show that our results are robust to alternative monetary policy shocks and to excluding the zero-lower-bound periods, respectively.

Throughout the paper, we include sector-time fixed effects to control for differences in sectoral sensitivities to time-varying factors, and firm fixed effects for permanent differences across firms. Our specifications also include firm-level controls $\mathbf{Z}_{it}$: leverage, (log) size, sales growth, age, share of liquid assets, short-term asset share (current over total assets), Tobin's (average) Q, and the indicator variables used in the interaction terms (i.e., $\mathbf{1}EBP^{low}_{ikt}$). We further include the interaction between the monetary policy shock and $\mathbf{1}\hat{S}^{low}_{ikt}$, defined as $\mathbf{1}EBP^{low}_{ikt}$ but using predicted spreads, thus controlling for the role of the expected default-risk component of credit spreads. Our inference uses standard errors that are two-way clustered by firm and time period.

To measure the average response of spreads and investment to monetary policy, we include aggregate controls $\mathbf{Y}_{t-1}$ in lieu of sector-time fixed effects. These controls include three lags of the Chicago Fed's national activity index (GDP growth in quarterly regressions), CPI inflation, the unemployment rate, the economic policy uncertainty index (Baker et al., 2016), and the first three principal components of the U.S. Treasury yield curve.

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

# 3 Firm EBPs, Default Risk and Aggregate Risk

In this section, we show that the cyclicality of firms' default risk is priced into firms' EBPs: firms with lower EBPs have default risk that co-moves significantly less with aggregate risk factors. This is one of many premia and convenience yields EBPs are likely to embed.

The credit spread equation (1) assumes a uniform pricing of expected default risk ($\beta$) over time and across firms. Thus, any time-variation and firm-specific pricing of default risk is embedded in $EBP_{ikt}$. Gilchrist and Zakrajšek (2012) average EBPs across firms and therefore capture time-variation in the *average* price of expected default risk, which they relate to the financial sector's aggregate risk-bearing capacity and risk aversion. We instead use the full panel variation in EBPs to test whether firms' EBPs price default risk in a *firm-specific* and time-varying way. As the residual from equation (1), $EBP_{ikt}$ is orthogonal to firms' distances-to-default by construction, so any residual dependence is non-linear.

We estimate how low- and high-EBP firms' default risk loads on aggregate risk factors. We use two factors, which are informative in complementary ways: (1) the return to the S&P500 index $R_t^{Mkt}$, to proxy for the market return à la CAPM (Sharpe, 1964); and (2) the intermediary capital risk factor $\eta_t^{\Delta}$, which captures innovations to US intermediaries' capital and which He et al. (2017) show prices the cross-section of expected returns across many asset classes. The market return is the natural benchmark, but firms' distances-to-default are constructed from their equity prices and volatilities, so loadings on it could partly reflect firms' equity betas.[10] Intermediary capital, by contrast, is not an input to firms' distances-to-default; moreover, as marginal investors in corporate bonds, intermediaries' risk-bearing capacity helps price default-risk covariance in the framework we develop in Section 6.

We estimate two firm-level panel regressions at a monthly frequency, separately for each risk factor. The first measures the average loading of firms' default risk on aggregate

[10] Still, as default means firm equity goes to zero, a loading on equity beta can in part reflect priced default risk beta.

TABLE 2

Firm Default Risk and Aggregate Risk Factors: Low- vs. High-EBP Firms

| $\Delta \log DD_{i,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_t^{Mkt}$ | .613*** | | | |
| | (.103) | | | |
| $R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$ | | -.067*** | | |
| | | (.022) | | |
| $\eta_t^{\Delta}$ | | | .024*** | |
| | | | (.005) | |
| $\eta_t^{\Delta} \times \mathbf{1}EBP_{it-1}^{low}$ | | | | -.004*** |
| | | | | (.001) |
| N | 145,604 | 154,179 | 145,604 | 154,179 |
| Adj. $R^2$ | .16 | .38 | .14 | .38 |
| Macro-Financial Controls | Yes | No | Yes | No |
| Firm FE | Yes | Yes | Yes | Yes |
| Sector×Month FE | Yes | No | Yes | No |
| Sector×Time FE | No | Yes | No | Yes |

*Note*: Table 2 reports the loadings of log-change in firms' default risk on the U.S. S&P500 index return ($R_t^{Mkt}$) and the intermediary capital risk factor ($\eta_t^{\Delta}$). Columns (1) and (3) report $\beta^{Agg}$ from regression (2) using $R_t^{Mkt}$ and $\eta_t^{\Delta}$, respectively, as the aggregate risk factor. Columns (2) and (4) report $\beta^{Agg,Rel}$ from regression (3), which measures how low-EBP firms' ($\mathbf{1}EBP_{it-1}^{low} = 1$) default risk loads on a given aggregate risk factor relative to high-EBP firms', using $R_t^{Mkt}$ and $\eta_t^{\Delta}$, respectively, as the aggregate risk factor. We drop 1% of firm-month observations with $DD_{it} \leq 0$, where the log-change is undefined. Standard errors are two-way clustered by firm and month. *** denotes statistical significance at the 1% level.

risk factors; the second measures how that loading differs for low- versus high-EBP firms:

$$\Delta \log DD_{i,t} = \alpha_i + \alpha_{s,m} + \beta^{Agg} Risk\_Factor_t^{Agg} + \boldsymbol{\gamma}\, \mathbf{Z}_{it-1} + \boldsymbol{\delta}\, \mathbf{Y}_{t-1} + \varepsilon_{i,t}, \tag{2}$$

$$\Delta \log DD_{i,t} = \alpha_i + \alpha_{s,t} + \beta^{Agg,Rel} (Risk\_Factor_t^{Agg} \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}\, \mathbf{Z}_{it-1} + \varepsilon_{i,t}, \tag{3}$$

where $\Delta \log DD_{i,t}$ is the log-change in firm $i$'s distance to default, which captures proportional movements in default risk and is therefore comparable across firms; $\alpha_i$, $\alpha_{s,m}$ and $\alpha_{s,t}$ are firm, sector-by-calendar-month and sector-time fixed effects; $\mathbf{Z}_{it-1}$ and $\mathbf{Y}_{t-1}$ are the firm-level and aggregate controls described in Section 2.3; and $\mathbf{1}EBP_{it-1}^{low}$ is the low-EBP indicator defined in Section 2.3. Since the set of low-EBP firms rotates over time, regression (3) allows for *time-variation* in firm-specific pricing of default risk.

Table 2 shows that firms' default risk rises with aggregate risk, and that it does so significantly less for low-EBP firms. The positive coefficients in columns (1) and (3)—$\beta^{Agg}$ from regression (2)—indicate that when S&P500 index returns or intermediary capital decline, firms' distances-to-default decline as well, that is, their default risk rises. Columns (2) and (4), which display $\beta^{Agg,Rel}$ from regression (3), show that this rise is non-uniform: low-EBP firms' default risk loads significantly less on aggregate risk than high-EBP firms', even within the same sector-time. Quantitatively, low-EBP firms' distances-to-default fall 10 to 20 percent less than high-EBP firms' when aggregate risk rises.[11]

These results mean that two firms with the same distance-to-default can face different credit spreads because they have different default-risk cyclicalities.[12] This is the sense in which firms' EBPs price the *cyclicality* of default risk rather than its *level*, which equation (1) absorbs through $DD_{it}$. Moreover, the relationship holds within firm: when a firm's EBP is above its own historical average, its default risk loads more on aggregate risk (see Appendix B.1). Firm-specific pricing of default risk therefore varies over time—variation that would be lost by conditioning on a time-invariant default-risk beta estimated over the full sample.

Two exercises indicate that firms' EBPs carry information about default-risk cyclicality beyond what is in other firm characteristics. First, sorting firms on EBPs purged of leverage, size, sales growth, age, current asset share and Tobin's Q, as well as of polynomial distance-to-default terms, leaves the differential unchanged. Second, the differential survives a horserace in which the aggregate risk factors are interacted simultaneously with these other characteristics. Appendix B.1 reports both exercises, and further shows that our results are robust to alternative percentile cutoffs for $\mathbf{1}EBP^{low}_{it-1}$, a linear rather than indicator interaction, and level- rather than log-changes in firms' distances-to-default.

Firms' EBPs therefore price the covariance between their default risk and aggregate risk, and do so in a way that varies over time and across firms. They also embed other premia

[11] The differential loading of low-EBP firms' distance-to-default on aggregate risk rises to $30\% - 40\%$ when using a level-change rather than log-change to construct the dependent variable (see Appendix B.1).

[12] In the Merton (1974) model, firms' default risk is driven by their equity values and volatilities, so differences in default-risk cyclicality will in part reflect differences in the sensitivity of firms' equity prices and volatility to aggregate risk. Our point is that this sensitivity is priced in the EBP—net of expected default risk—and not only in equity returns.

and convenience yields, which is why we treat EBPs as multi-dimensional borrowing premia. Whatever their composition, these premia shape the marginal cost curve for external finance faced by firms, which we model in Section 6.

# 4 Monetary Policy Shocks, Spreads and Investment

In this section, we study the response of firms' credit spreads and investment to monetary policy shocks, both on average and conditional on firms' *ex-ante* EBPs. We find a contrast between prices and quantities: monetary policy easings compress credit spreads more for higher-EBP firms, yet raise investment more for lower-EBP firms.

## 4.1 Monetary Policy and Bond-Level Credit Spreads

To measure the unconditional response of credit spreads to monetary policy, we estimate the following regressions at a monthly frequency for a series of horizons $h$:[13]

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

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

$$S_{ikt+h} - S_{ikt-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{ikt-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{5}$$

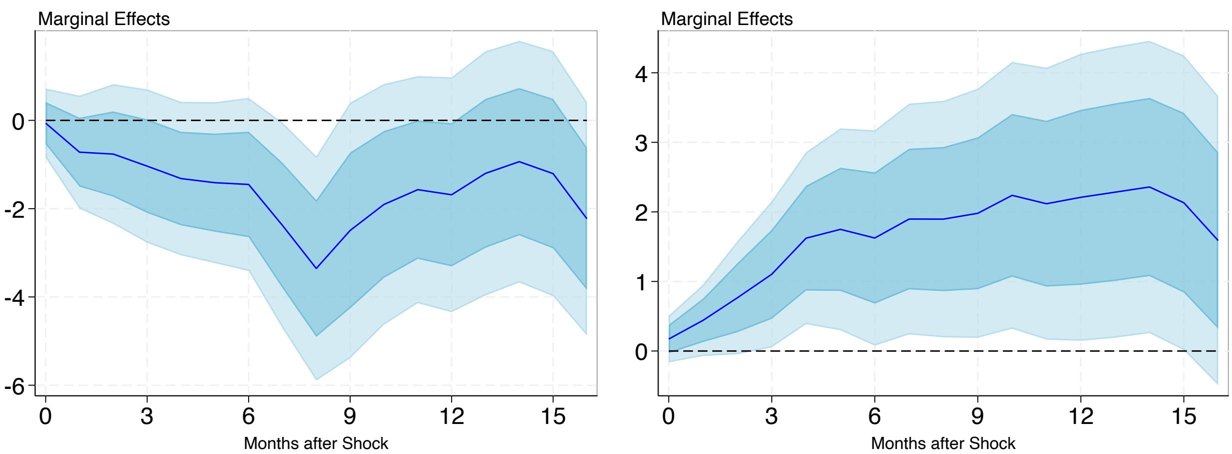
which include sector-time fixed effects $\alpha_{s,t}^h$ and the interaction between the monetary policy shock $\varepsilon_t^m$ and $\mathbf{1}EBP_{ikt-1}^{low}$, the low-EBP indicator from Section 2.3.[14] With sector-time fixed effects, $\beta_1^h$ measures the response of credit spreads to monetary policy for low-EBP bonds

[13] The specifications in this subsection are based on Anderson and Cesa-Bianchi (2024).

[14] Appendix B.7 shows our results hold when conditioning on firm-level rather than bond-level EBPs.

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

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




*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, $\varepsilon_t^m$. Panel 3a plots the $\beta_1^h$s from regression (4), which trace the unconditional (average) credit spread response. Panel 3b plots the $\beta_1^h$s from regression (5), which trace the credit spread response of low-EBP 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 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.

*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 $\beta_1^h$s from regression (4), which trace the average response of bond-level credit spreads to a surprise monetary policy easing. We find that a 1 percentage point easing shock induces a decline in the average bond's credit spread of over 3 percentage points 8 months after the shock, albeit with wide confidence bands. This result suggests a delayed peak effect of monetary policy on firms' marginal borrowing rates, an issue overlooked by short-horizon studies.[15]

Panel 3b reports the $\beta_1^h$s from regression (5), 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'

[15]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).

following a monetary policy easing. Quantitatively, 8 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 in upper quintiles—roughly two-thirds of the average response at the same horizon. The same pattern holds when spreads are measured in proportional (i.e., log-changes) rather than absolute changes (Appendix B.7), and it is the EBP component of credit spreads itself that adjusts (Appendix B.4). Overall, monetary policy easings compress credit spreads meaningfully more for higher-EBP bonds, that is, for bonds of firms facing greater borrowing premia.

## 4.2 Monetary Policy and Firm-Level Investment

Turning to quantities, we document that low-EBP firms' investment increases more than that of high-EBP firms' following a monetary policy easing.

Following a similar structure to the previous subsection, 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 $h$:[16]

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

where $K_{it}$ is the real book value of firm $i$'s tangible capital stock, $\alpha_{s,q}^h$ is a sector-quarter seasonal fixed effect, and the remaining variables are as defined in Section 4.1.[17] To assess the investment response conditional on firms' EBPs, we estimate the following regressions:

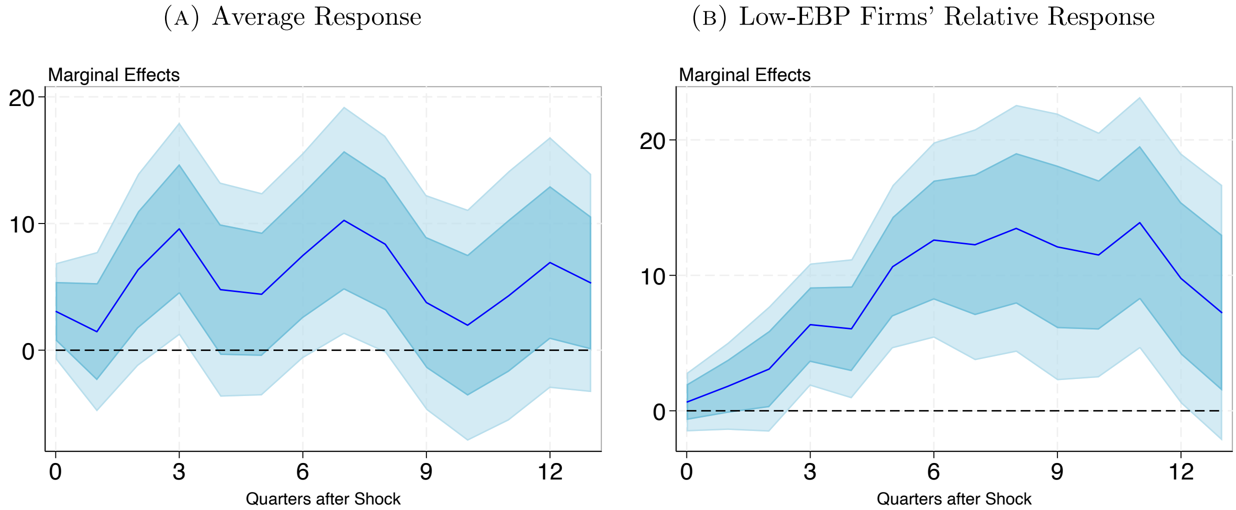
$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^m \times \mathbf{1}EBP_{it-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{7}$$

where $\mathbf{1}EBP_{it-1}^{low}$ is the firm-level low-EBP indicator from Section 2.3.

Analogous to Section 4.1, Figure 4 highlights that monetary policy exerts a sizable, but heterogeneous, effect on firms' investment. The average investment response to mon-

[16] The specifications in this subsection are based on Ottonello and Winberry (2020).
[17] We also include one lag of firm-level EBPs and predicted spreads as controls.

Figure 4
Firm-Level Investment Response to Monetary Policy




*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, $\varepsilon_t^m$. Panel 4a plots the $\beta_1^h$s from regression (6), which trace the unconditional investment response. Panel 4b plots the $\beta_1^h$s from regression (7), which traces the investment response of low-EBP firms, defined as firms with EBPs in the bottom quintile of the cross-sectional EBP distribution at $t-1$ ($\mathbf{1}EBP_{it-1}^{low} = 1$), relative to high-EBP firms, i.e., firms not in the bottom quintile. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

etary policy across firms is traced in Panel 4a. The response is hump-shaped and carries wide confidence bands, with a 1 percentage point monetary easing estimated to increase investment for the average firm by 10 percent at its peak, which occurs 7 quarters after the shock.[18] This average effect, however, masks considerable heterogeneity based on firms' ex-ante EBPs, as shown in Panel 4b. The positive marginal effects, in this case, indicate that low-EBP firms, i.e., those facing lower borrowing premia, increase investment considerably more than high-EBP firms following a monetary easing. Quantitatively, 7 quarters after the shock, low-EBP firms' investment is estimated to have increased by 12 percentage points more than high-EBP firms'—a differential as large as the average response across all firms. Consistent with these results, Appendix B.5 provides evidence that low-EBP firms' debt also increases significantly more than high-EBP firms' following a monetary easing.

Two exercises indicate that firms' EBPs carry information for monetary policy trans-

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

mission to credit spreads and investment beyond that contained in other firm characteristics. First, sorting firms on EBPs purged of characteristics $\mathbf{Z}_{it-1}$, as well as of polynomial distance-to-default terms, leaves the heterogeneity unchanged (Appendix B.8). Second, the heterogeneity survives a horserace in which monetary policy shocks are interacted simultaneously with $\mathbf{Z}_{it-1}$, distance-to-default, and firms' credit ratings (Appendix B.2). The results also hold within firm, using deviations of firms' EBPs from their own historical averages à la Ottonello and Winberry (2020), so they are not driven by permanent differences across firms (Appendix B.8). Our results are further robust to alternative percentiles of the EBP distribution, a linear rather than indicator interaction, alternative monetary policy shocks, and excluding the zero-lower-bound period (Appendices B.3, B.8, B.9 and B.10).

# 5 Credit Supply Shocks, Spreads and Investment

This section shows that the effects of credit supply shocks conditional on firms' EBPs mimic those from monetary policy. Since these shocks move intermediaries' net worth but not the risk-free rate on impact, monetary policy's heterogeneous effects can arise from changes in credit supply alone.

To measure credit supply shocks, we use the high-frequency shocks identified by Ottonello and Song (2025). These shocks are constructed, over the period 2002 to 2020, by measuring changes in the market value of intermediaries' net worth in narrow windows around their earnings announcements. Using sign restrictions, the shocks are then purged of information related to non-financial firms (e.g., credit demand), with the residual purged shocks reflecting pure changes in credit supply.

We then re-estimate our baseline regressions from Sections 4.1 and 4.2 using the credit supply shocks. Specifically, we estimate:

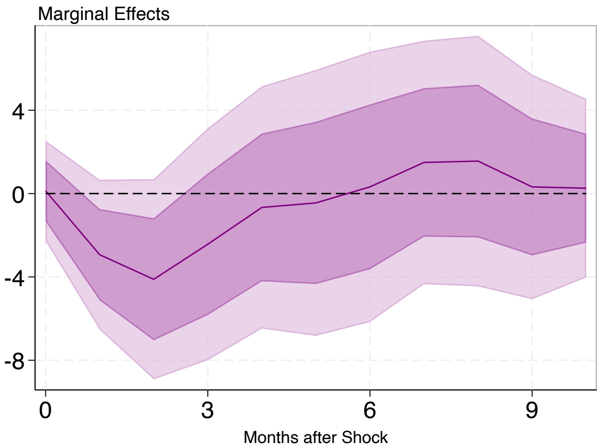
$$Y_{i(k)t+h} - Y_{i(k)t-1} = \alpha_i^h + \alpha_{s,m/q}^h + \beta_1^h \varepsilon_t^{CS} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + \boldsymbol{\delta}^h \mathbf{Y}_{t-1} + e_{i(k)th}, \tag{8}$$

$$Y_{i(k)t+h} - Y_{i(k)t-1} = \alpha_i^h + \alpha_{s,t}^h + \beta_1^h (\varepsilon_t^{CS} \times \mathbf{1} EBP_{i(k)t-1}^{low}) + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{i(k)th}, \tag{9}$$

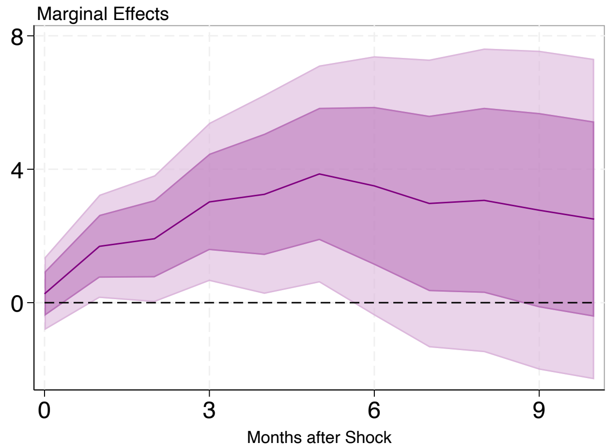
FIGURE 5

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

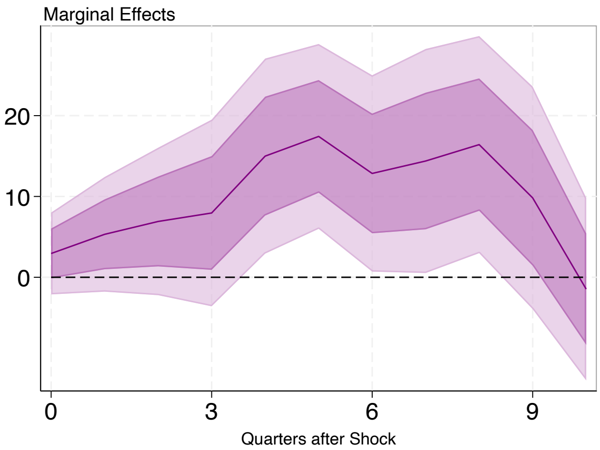
(A) Average Spread Response



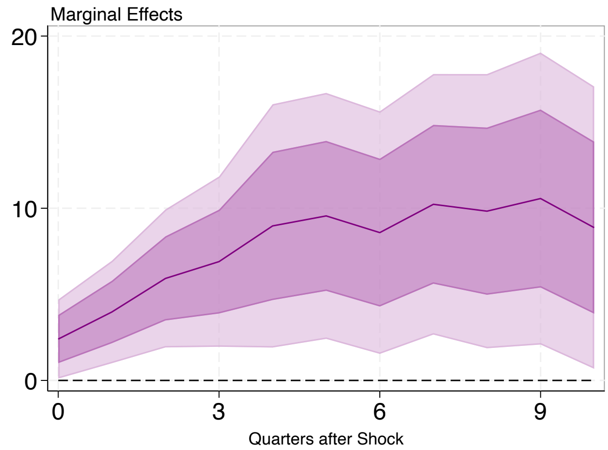

(B) Low-EBP Bonds' Relative Spread Response




(C) Average Investment Response




(D) Low-EBP Firms' Relative Investment Response




*Note.* Figure 5 reports the dynamic responses of bond-level credit spreads and firm-level investment to an expansionary credit supply shock $\varepsilon_t^{CS}$, as calculated by Ottonello and Song (2025). Panels 5a and 5c plot the $\beta_1^h$s from regression (8), tracing the average credit spread $S_{ikt+h} - S_{ikt-1}$ and investment $\log(K_{it+h}/K_{it-1})$ response, respectively. Panels 5b and 5d plot the $\beta_1^h$s from regression (9), tracing the credit spread and investment response of low-EBP bonds and firms, respectively, relative to high-EBP ones. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and time.

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

Figure 5 presents the dynamic responses of bond-level credit spreads and firm-level investment to an expansionary credit supply shock. On average, credit supply expansions significantly raise firms' investment, while their effect on credit spreads, though negative, is imprecisely estimated (Panels 5a and 5c). The key takeaway is that there is a clear similarity between how firms respond to credit supply shocks and monetary policy shocks conditional on their EBPs. Specifically, while low-EBP bonds' credit spreads decline relatively little in response to a surprise easing of credit supply (Panel 5b), low-EBP firms increase investment considerably more than high-EBP firms (Panel 5d); at their peaks, these relative effects reach 4 and 10 percentage points, respectively. As for monetary policy, this pattern holds when spreads are measured in proportional rather than absolute changes (Appendix B.7). Here too, it is the EBP component of credit spreads that reacts (Appendix B.4), and low-EBP firms increase their debt by more (Appendix B.5).

Once again, these results survive a horserace against other firm characteristics used in Section 4 (Appendix B.2), and are unchanged when sorting firms based on EBPs purged of $\mathbf{Z}_{it-1}$ and polynomial distance-to-default terms (Appendix B.8). Although low-EBP bonds' relative spread response is less precisely estimated under linear and within-firm EBP interactions, the results are further robust to alternative EBP percentiles (Appendix B.3).

# 6 Interpretation of Empirical Results

In this section, we develop a stylized model of capital markets that shows how differences in the financial frictions firms face, combined with convex capital demand, can generate the price-quantity contrast documented in Sections 4 and 5. We present here the case of default-risk cyclicality priced by financially constrained intermediaries, although Appendix C.2 shows the mechanism does not depend on this particular premium.

## 6.1 Theoretical Framework

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

The economy features both idiosyncratic and aggregate risk. Idiosyncratic risk takes the form of island-specific firm default risk: with some probability $p_j$, a random variable, firms on island $j$ draw the low productivity state $Z_j = Z^{low}$, which leads them to default on their loans. Default probabilities are therefore exogenous to firms' borrowing decisions. Aggregate risk comes from a random loss share $\mu \in (0, 1)$ for intermediaries on defaulted loans that is common to both islands, in line with empirical evidence linking recovery values with aggregate conditions (e.g., Altman et al., 2004). Crucially, $p_j$ and $\mu$ are drawn from a joint probability distribution $F_j(p_j, \mu)$ and may be correlated, with island-specific covariance $\rho_j$. Firms and intermediaries know $F_j$ but borrow and lend, respectively, before these variables realize. Appendix C.2 generalizes this framework to risk-averse intermediaries and to EBPs that embed risk premia beyond default-risk cyclicality, as well as convenience yields, and shows the mechanism is unchanged—though convenience yields vertically shift firms' marginal cost curves without tilting them.

We assume that all firms carry the same expected default risk, $\mathbb{E}[p_j] \equiv \overline{p}$, so that firms on the two islands only differ in the covariance $\rho_j$ between their default risk and aggregate risk. A higher $\rho_j$ implies that island-$j$ firms' default risk is more *countercyclical*, since it increases more in worse aggregate states, i.e., when the loss share on defaulted loans is higher. This isolates the heterogeneity we document in Section 3: firms with the same distance-to-default can differ in how their default risk co-moves with aggregate risk.

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

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

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

where $R_j^K$ denotes the borrowing rate on capital.[19] The first order condition of this problem yields firms' marginal benefit (MB), i.e. demand, curve for capital:

$$\frac{R_j^K}{R} = \frac{1}{R} \alpha \overline{Z} K_j^{\alpha-1}, \tag{10}$$

where $R$ denotes the gross risk-free interest rate and $R_j^K/R$ is island-$j$ firms' credit spread. Since $\alpha \in (0,1)$, firms' MB curves in equation (10)—which trace their marginal products of capital—are downward sloping and convex, so their slope flattens at higher levels of capital. Thus, firms with more capital operate on locally flatter portions of their MB curves, where their credit spreads decline relatively little as capital increases.[20]

**Financial intermediaries** on both islands are endowed with the same net worth $N$. They also issue deposits $D$ to households (not explicitly modeled here) at the risk-free rate $R$. These intermediaries have access to a capital producing technology that transforms $N$ and $D$ on a one-to-one basis into capital $K_j$, which they supply to firms for a return $R_j^K$. In the event of firm default, intermediaries on both islands lose the same fraction $\mu$ of their promised return on capital $R_j^K K_j$, where $\mu$ is drawn from probability distribution $F_j$.[21]

We assume, as in Anderson and Cesa-Bianchi (2024), that intermediaries only lend to firms on their own island, in line with empirical evidence on segmentation in corporate bond markets based on firm risk (see, e.g., Chernenko and Sunderam, 2012; Manconi et al., 2012). Motivated by regulatory capital requirements and internal risk-management

[19] This setup assumes firms internalize repayment in all states. Under limited liability, firms instead solve $\max_{K_j} (1-\mathbb{E}[p_j]) \left[Z^{high} K_j^{\alpha} - R_j^K K_j\right]$, which has the same functional form. Since $Z^{high}$ is common to both islands, firms on both islands face the same MB curve under either setup.

[20] The relationship between credit spreads $\frac{R^K}{R}$ and log capital $x = \log(K)$ is also (i) downward sloping and (ii) convex. This can be verified by rewriting equation (10) as $\frac{R_j^K}{R} = f(x) = \frac{\alpha \overline{Z}}{R} \exp\left[(\alpha-1)x\right]$, and showing that $f'(x) < 0$ and $f''(x) > 0$.

[21] We specify the recovery rate given default as a fraction of the promised return. Appendix C.3 shows that specifying it as a fraction of the principal, as in Bernanke et al., 1999, leaves the level of firms' marginal cost curves dependent on $\rho_j$ but not their slope. The mechanism, though, is unchanged, since lower-$\rho_j$ firms still reach equilibrium on flatter segments of their marginal benefit curves.

practices, intermediaries face a constraint that requires them to have sufficient skin in the game when lending to firms. This is modeled as an agency friction in which intermediaries may abscond with a fraction $\theta$ of their revenue; since the decision to abscond occurs prior to the realization of shocks, the constraint involves expected revenue. In turn, households only fund intermediaries that satisfy this incentive compatibility constraint.

The optimization problem of the risk-neutral intermediaries is the following:

$$\max_{K_j} \ (1-\mathbb{E}[p_j])R_j^K K_j + \mathbb{E}[p_j(1-\mu)]R_j^K K_j - R(K_j - N) \quad \text{s.t.} \tag{11}$$

$$(1-\mathbb{E}[p_j] + \mathbb{E}[p_j(1-\mu)])R_j^K K_j - R(K_j - N) \geq \theta(1-\mathbb{E}[p_j] + \mathbb{E}[p_j(1-\mu)])R_j^K K_j. \tag{12}$$

Our framework shares its capital supply and demand setup with Ottonello and Winberry (2020) and its constrained-intermediary structure with Anderson and Cesa-Bianchi (2024). In these papers, firms differ in the *level* of their default risk or leverage. Here firms differ in the compensation intermediaries require to lend to them: in our baseline model, these differences arise from default-risk cyclicality, but could come from other premia and convenience yields. Relatedly, firms' marginal cost curves slope upward because intermediaries' constraints tighten with lending, not because firms' own default risk rises with borrowing.

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

$$\frac{R_j^K}{R} = \begin{cases} \frac{1}{1-\overline{p}\cdot\overline{\mu}-\rho_j} & K_j < \frac{N}{\theta} \\ \frac{1}{1-\overline{p}\cdot\overline{\mu}-\rho_j}\frac{K_j-N}{K_j(1-\theta)} & K_j \geq \frac{N}{\theta}, \end{cases} \tag{13}$$

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

To isolate the EBP component of credit spreads, we equalize all other parameters across islands, so that differences in default-risk cyclicality $\rho_j$ are the key fundamental shaping differences in firms' MC curves. Per equation (13), a lower $\rho_j$ (less cyclical default risk) reduces the compensation intermediaries need to lend to firms: (i) it lowers the intercept of their MC curve and (ii), in this setup, also flattens its slope, due to the relaxation of intermediaries' incentive compatibility constraint. While cross-sectional differences in the frictions firms face—in our model, default-risk cyclicality—generate a distribution of firm-level EBPs, the average EBP is tied to intermediaries' aggregate net worth ($N$) and the tightness of their financial constraint ($\theta$). Our framework is therefore in line with the original interpretation of the average EBP as a measure of the financial sector's aggregate risk-bearing capacity (Gilchrist and Zakrajšek, 2012), and adds a cross-sectional dimension.

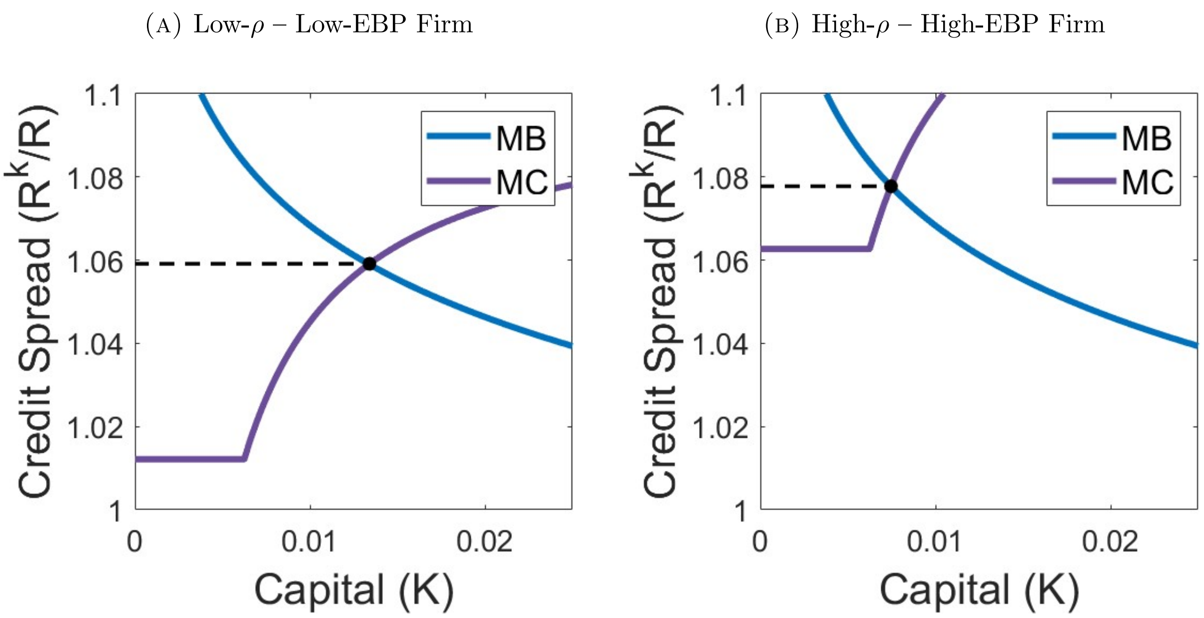
## 6.2 Capital Market Equilibrium and Firm EBPs

Figure 6 displays capital market equilibrium on the two islands, which occurs at the intersection of the MB curves (in blue) and the MC curves (in purple) in each panel. While the MB curves are the same for the two types of firm, the low-$\rho_j$ firms in Panel 6a face lower—and, in this specification, flatter—MC curves compared to those faced by high-$\rho_j$ firms in Panel 6b, and hence have lower credit spreads in equilibrium. We normalize $\rho_j = 0$ (i.e., acyclical default risk) on the low-$\rho_j$ island and set the value on the high-$\rho_j$ island to match the average EBP differential between low- and high-EBP firms in the data (1.8pp). Details on the rest of the model parameterization are in Appendix C.1.

Since all firms carry the same expected default risk $\mathbb{E}[p_j] \equiv \overline{p}$, differences in equilibrium credit spreads across Panels 6a and 6b arise from differences in the cyclicality of firms' default risk $\rho_j$. These differences in credit spreads should therefore be interpreted as differences in firms' EBPs.[22] Thus, firms with relatively low $\rho_j$s, i.e., cyclically safer firms,

[22]The Merton (1974) model, used to construct firms' expected default risks, their predicted credit spreads and their EBPs, assumes a zero covariance between firms' default risk and aggregate risk ($\rho_j = 0$). Thus,

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




*Note.* Figure 6 presents the capital market equilibrium for two types of firm, which differ in how much their default risk co-moves with aggregate risk. While both types of firm share the same marginal benefit (MB) curve, since they carry the same expected default risk ($\overline{p}$), differences in the cyclicality of firms' default risk ($\rho_j$) lead low-$\rho_j$ (less-cyclically sensitive) firms in Panel 6a to face lower and flatter marginal cost (MC) curves compared to the high-$\rho_j$ firms in Panel 6b. When markets are segmented according to firm risk, equilibrium occurs at the intersection of the MB curve and the MC curve in each panel. Low-$\rho_j$ firms in Panel 6a have lower equilibrium credit spreads (EBPs) and are on flatter segments of both their MB and MC curves in equilibrium compared with the high-$\rho_j$ firms in Panel 6b. Appendix C.1 provides full details on the parameterization.

have lower EBPs in our framework, reproducing the motivating evidence from Section 3.

Because low-EBP firms face lower MC curves, they reach equilibrium at higher capital and, given convex MB curves, on locally flatter segments of their MB curves than high-EBP firms. This difference in local MB slopes is what allows the model to reproduce the contrast between credit spread and investment responses documented in Sections 4 and 5.

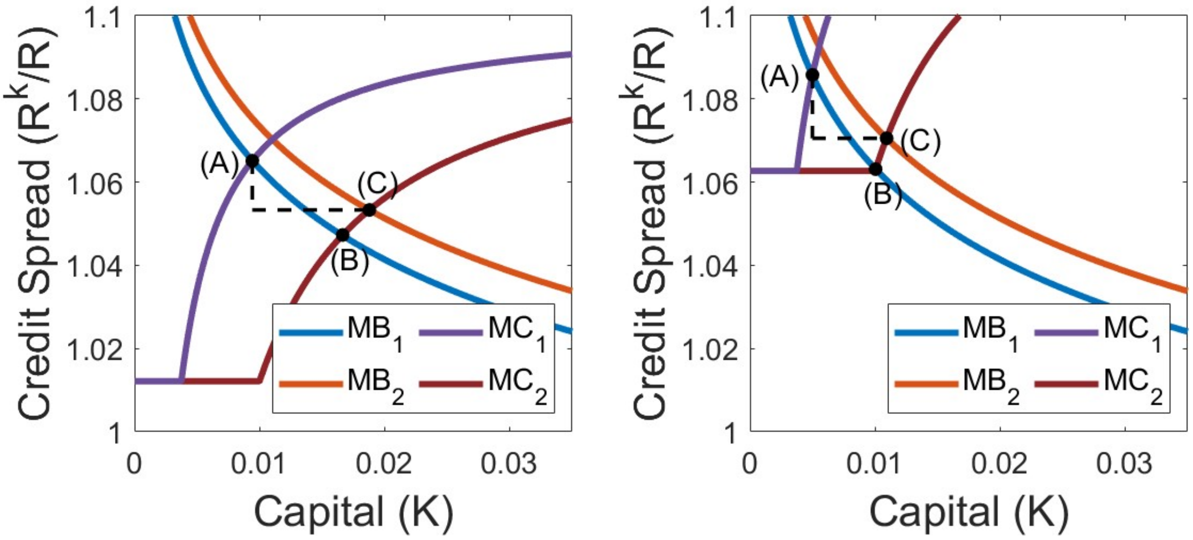
### 6.3 Monetary Policy Comparative Statics by Firm EBPs

Within our stylized setup, we use comparative statics to interpret our empirical results from Sections 4 and 5. In the spirit of Ottonello and Winberry (2020), we consider monetary

differences in default-risk cyclicality would be captured in the EBP component of firms' credit spreads.

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

(A) Low-$\rho$ – Low-EBP Firm (B) High-$\rho$ – High-EBP Firm




*Note.* Figure 7 presents the comparative statics to a monetary policy easing, modeled as a uniform increase in financial intermediaries' net worth $N$ and a decline in the risk-free interest rate $R$ across both islands. These shocks (i) shift and flatten firms' MC curves, from $\mathrm{MC}_1$ to $\mathrm{MC}_2$, and (ii) shift firms' MB curves, from $\mathrm{MB}_1$ to $\mathrm{MB}_2$, respectively. We set the relative size of these shifts so that credit spreads decline and investment increases on both islands, as in the data. Panel 7a shows the response of the low-$\rho$ – low-EBP firm, while Panel 7b shows the response of the high-$\rho$ – high-EBP firm. Appendix C.1 provides details on the parameterization.

policy easings as both (i) a rightward shift and flattening of firms' MC curves, due to an increase in intermediaries' net worth $N$; and (ii) an outward shift in firms' MB curves, due to a reduction in the risk-free rate $R$. We consider the two economic channels in turn, with changes in $R$ and $N$ common across islands in our baseline, and then discuss heterogeneous movements in firms' curves, which might result from general equilibrium price effects that we do not explicitly model. The exercise asks which movements in firms' capital supply and demand curves are consistent with the contrast we document: easings compress credit spreads more for higher-EBP firms, yet raise investment more for lower-EBP firms.

We first consider the effects of movements in firms' MC curves. In response to an expansionary monetary policy shock that increases intermediary net worth ($N$) uniformly across islands, firms' MC curves shift rightward and flatten.[23] Crucially, because low-EBP

[23]Firms' MC curves flatten in the sense that, at any given spread, the slope of the MC curve falls in proportion to the increase in $N$.

firms are on flatter portions of their convex MB curves at their initial equilibrium (A), movements in MC curves alone generate larger investment increases and smaller spread reductions for low-EBP firms compared to high-EBP firms. This result is consistent with the empirical evidence from Section 4, and is illustrated by comparing the transition from equilibrium (A) to (B) in Panels 7a and 7b.

We then consider shifts in firms' MB curves. For low-EBP firms, MB-curve shifts trace along flatter MC curves, inducing a larger increase in investment but a smaller increase in credit spreads relative to high-EBP firms—the transition from equilibrium (B) to (C) in Panels 7a and 7b. MB-curve shifts therefore reinforce the investment heterogeneity produced by MC-curve shifts but work against the heterogeneity in spreads. Observing both patterns in the data thus requires monetary policy to move firms' MC curves more than their MB curves, as in the transition from (A) to (C) in Figure 7.

The average response of firms in the data points to the same requirement, and does so without using the cross-section: monetary easings lower credit spreads and raise investment. These responses are possible only if MC curves react more than MB curves. Changes in capital supply are therefore key to monetary policy's heterogeneous effects, consistent with their role in its overall transmission (e.g., Bernanke and Gertler, 1995).[24]

Credit supply shocks discipline the role of MB convexity. Through the lens of our model, they correspond to a uniform increase in intermediaries' net worth $N$, which shifts and flattens firms' MC curves while leaving their MB curves unchanged. The contrast between spread and investment responses documented in Section 5 must therefore arise from movements in capital supply alone in our setup, which requires low-EBP firms to sit on locally flatter portions of convex MB curves. To the extent that MB curves may also shift—for instance, due to general equilibrium effects we do not model—such shifts must again be smaller than the movements in firms' MC curves.

The data also restrict how much firms' MC curves can move asymmetrically. Starting from equilibrium (C), a further rightward shift or flattening of one firm's MC curve—due,

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

for instance, to a larger increase in its intermediaries' net worth—lowers that firm's credit spread *and* raises its investment. Sizable asymmetries would therefore undo either low-EBP firms' smaller spread reduction or high-EBP firms' smaller investment increase. Observing both patterns thus requires asymmetric MC movements to be small.

Finally, the data speak to whether monetary policy shifts low-EBP firms' MB curves by more than high-EBP firms'—due, for instance, to greater exposure to unmodeled changes in demand. Such asymmetric shifts raise low-EBP firms' investment further while dampening the decline in their credit spreads, and can therefore account for part of our results. Appendix B.6 finds little support for this using sales growth to proxy for such demand effects: low-EBP firms' sales increase only marginally relative to high-EBP firms' following a monetary easing. The contrast between spread and investment responses therefore reflects primarily movements in their MC curves along locally differently-sloped MB curves.

Taken together, our empirical moments discipline the model along three margins: the average response of spreads and investment requires capital supply to move more than demand; the price-quantity contrast requires firms to sit on differently sloped portions of their convex demand curves; and the muted sales response argues against capital demand shifting disproportionately for low-EBP firms. None of these requires asymmetric curve movements. The heterogeneity instead follows from where firms' capital supply curves sit, with low-EBP firms sitting on flatter segments of their convex demand curves.

# 7 Firm EBPs & Monetary Policy's Aggregate Effects

In this section, we provide evidence that firms' EBPs may also shape monetary policy's aggregate effects. Our firm-level results of Section 4 and the framework of Section 6 imply that when firms in the economy have lower EBPs—as proxied by a lower median or a left-skewing of the cross-sectional EBP distribution—monetary policy should have larger effects on aggregate investment.

To test these predictions, we run time-series local projections of a similar form to regression (6) from Section 4, but with two main modifications: (i) we use U.S. aggregate investment as our dependent variable, and (ii) we use the first three cross-sectional moments of the EBP distribution as state variables. Specifically, we estimate the following local projections at a quarterly frequency for a series of horizons $h$:

$$\frac{400}{h+1}\log\left(\frac{I_{t+h}}{I_{t-1}}\right) = \beta_0^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\beta}_2^h(\varepsilon_t^m \times \boldsymbol{M}_{t-1}) + \boldsymbol{\delta}_l^h \mathbf{Y}_{t-1} + e_{th}, \tag{14}$$

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 distribution, normalized to have zero mean and unit variance; and $\mathbf{Y}_{t-1}$ includes the aggregate controls of Section 2.3 along with the vector $\boldsymbol{M}_{t-1}$.[25] We measure dispersion and skewness using the 20th and 80th percentiles and use Newey-West standard errors with 12 lags for inference.

Figure 8 shows the results from these regressions. First, Panel 8a shows that, on average, a surprise 1pp monetary policy easing raises aggregate investment growth by around 15pp within 3 quarters of the shock. Second, a more right-skewed EBP distribution is associated with weaker pass-through from monetary policy to aggregate investment (Panel 8b), with a 1-standard-deviation increase in skewness predicted to reduce this response by roughly 15pp after 6 quarters. A higher median EBP also predicts a significantly weaker transmission of monetary policy (Panel 8c), although the effects are short-lived. Finally, a more dispersed EBP distribution predicts a stronger pass-through (Panel 8d), a moment for which our framework offers no clear prediction. These conditioning effects—particularly those of skewness—are robust to controlling for interactions between monetary policy shocks and recession indicators similar to those of Tenreyro and Thwaites (2016), and to using the mean rather than the median EBP (Appendix B.11).

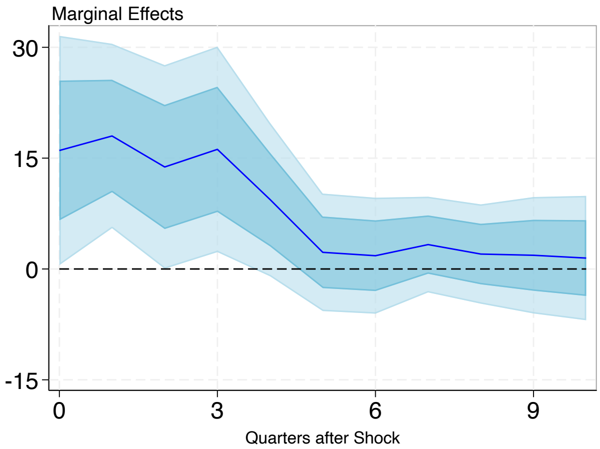
Overall, the findings of this section indicate that the same conditioning variable that sorts firm-level responses also predicts the aggregate potency of monetary policy. As shown in Section 6.1 our framework reproduces Gilchrist and Zakrajšek (2012)'s interpretation of the average EBP as the financial sector's aggregate risk-bearing capacity, and adds a

[25]For consistency, we include interactions between monetary policy and the moments of the cross-sectional predicted spread distribution in $\mathbf{Y}_{t-1}$. We also substitute GDP growth for investment growth in the aggregate controls to align ourselves with the existing forecasting literature (e.g., Ferreira, 2024).

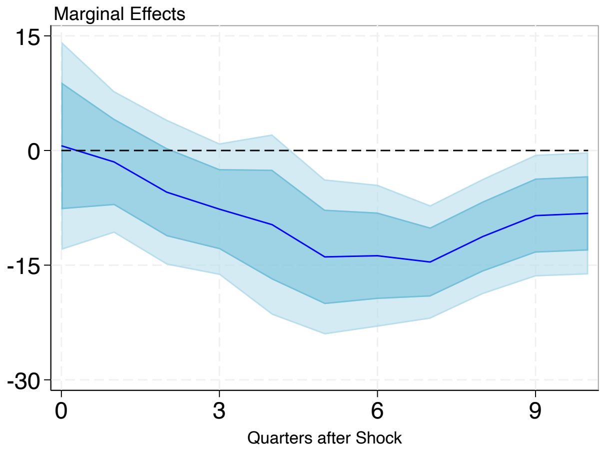
FIGURE 8

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

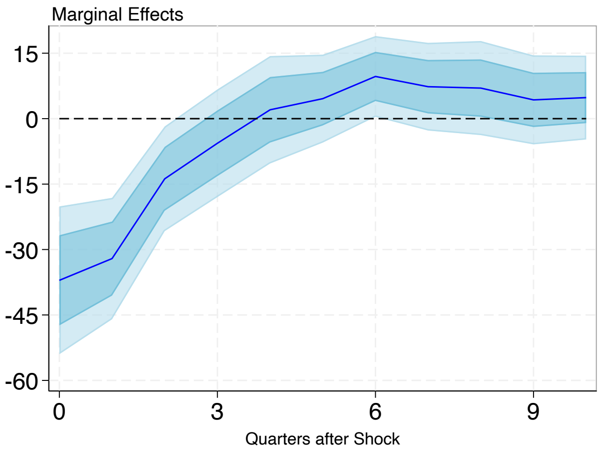
(A) Unconditional



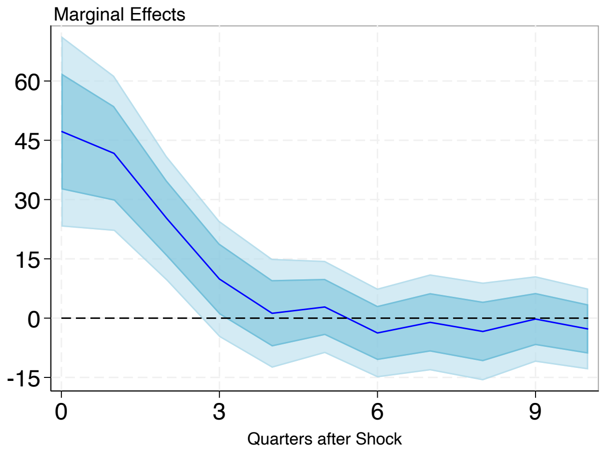

(B) Conditional on EBP Skewness




(C) Conditional on Median EBP




(D) Conditional on EBP Dispersion




*Note.* Figure 8 reports the dynamic response of annualized aggregate investment growth to a 1 percentage point monetary policy easing shock $\varepsilon_t^m$, which we estimate using regression (14). Panel 8a shows unconditional effects, $\beta_1^h$. 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.

cross-sectional dimension. Our results are consistent with that distinction: the skewness of the EBP distribution conditions monetary policy's effects beyond the average EBP alone.

# 8 Conclusion

This paper studies how firms' financial conditions shape the transmission of monetary policy, measuring those conditions with firms' excess bond premia (EBPs). Firms' EBPs price the frictions they face when borrowing to invest: firms with lower EBPs have default risk that co-moves less with aggregate risk, though this is one of several frictions EBPs embed. Sorting firms on this measure, we find that monetary easings compress low-EBP firms' credit spreads by less while raising their investment by more—differentials comparable to the average responses, and robust to controlling for other firm characteristics. Credit supply shocks produce the same contrast. Matching these moments requires monetary policy to move firms' capital supply curves more than their demand curves, with low-EBP firms sitting on flatter portions of convex demand. We also show that the cross-sectional distribution of EBPs conditions how much monetary policy moves aggregate investment.

Policymakers and researchers often discuss three key aspects of the transmission of monetary policy: its distributional effects, its aggregate potency, and the channels through which it operates. Our paper touches on these three aspects. On the distributional front, we show that monetary policy is more effective at stimulating the investment of firms with lower EBPs. On the aggregate front, our paper offers a specific observable—the moments of the cross-sectional EBP distribution—to monitor monetary policy's time-varying aggregate effects. On the channels front, the combination of our empirical results and stylized model restricts how monetary policy moves firms' capital supply and demand curves—restrictions that should guide the construction of richer models of capital markets.

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Internet Appendix (for online publication only)

# Firm Risk Premia and Monetary Policy Transmission

by T. Ferreira and D. Ostry

September 11, 2026

# C Model Appendix

# A Data Summary

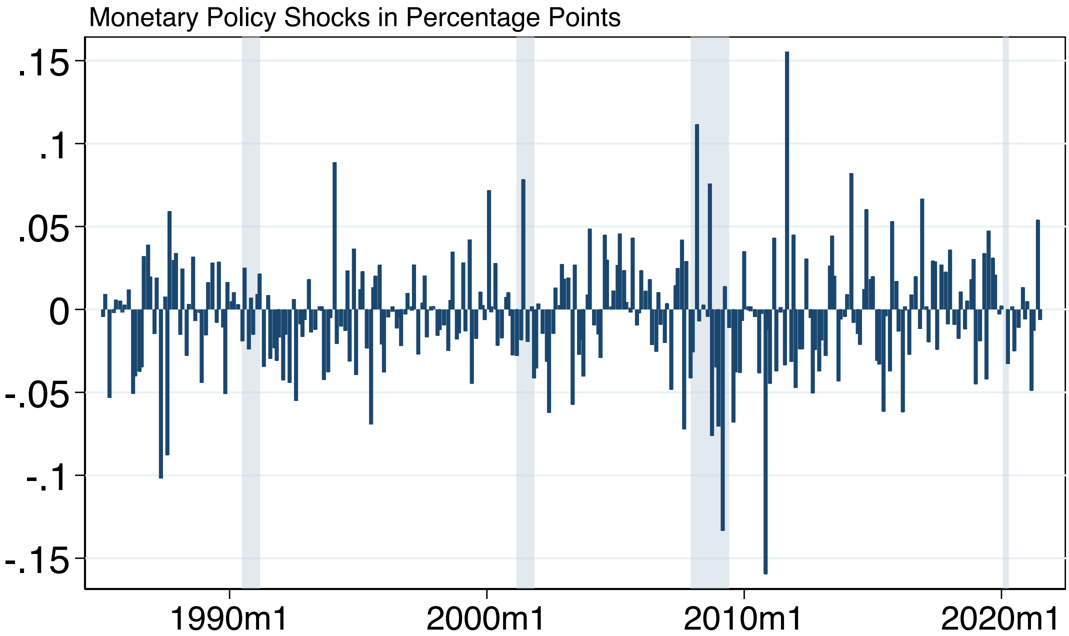
In this section, we present further details on our baseline monetary policy shock series (Appendix A.1), provide variable definitions and outline our sample (Appendix A.2), discuss in more detail the EBP and distance to default calculations (Appendix A.3), and provide summary statistics for our main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

## A.1 Monetary Policy Shocks

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

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.9, 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.

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; for regressions, we then normalize positive values to represent easings. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.

## A.2 Variable Definitions and Sample Selection

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

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

in Compustat. From this period onwards, we compute the evolution of the capital stock using the changes of net plant, property, and equipment (ppentq in Compustat), which is a measure of net of depreciation investment with significantly more observations than ppegtq. If a firm has a missing observation of ppentq located between two periods with non-missing observations we estimate its value by linear interpolation. We consider only investment spells of 15 quarters or more and we winsorize the top and bottom 0.5% of investment observations per period to remove outliers.

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

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

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

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

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

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

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

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

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

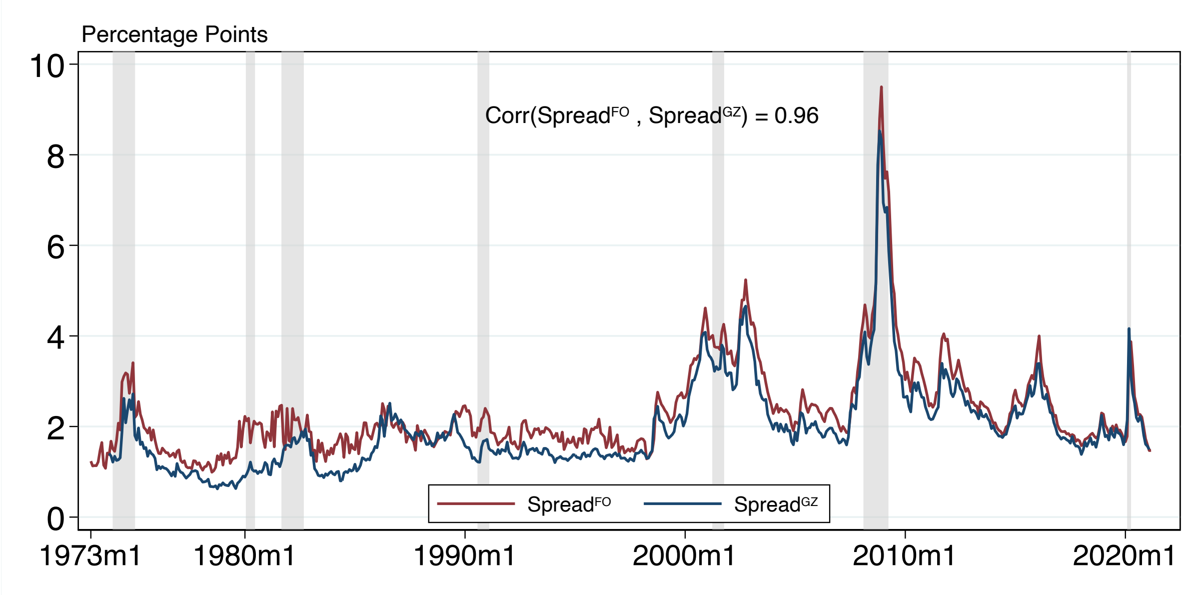
11. *Short-Term Assets*: defined as the ratio of current assets (actq in Compustat) to total assets (atq in Compustat).

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

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

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

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.

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.

## A.3 Calculating Distance to Default and the EBP

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

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

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

where $DD_{it}$ is firm $i$'s distance to default (Merton, 1974), and $\mathbf{X}_{ikt}$ 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 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:

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

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

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

Implementing this procedure for the bonds in ICE and Lehman-Warga whose firm's balance sheet data and equity prices are available from Compustat and CRSP, respectively, yields, after data cleaning as described in Appendix A.2, a sample of monthly EBPs for 10,061 bonds from 1,630 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 $\mu_V$ is the expected growth rate of $V$, $\sigma_V$ is the volatility of $V$, and $Z_t$ denotes the

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 | |

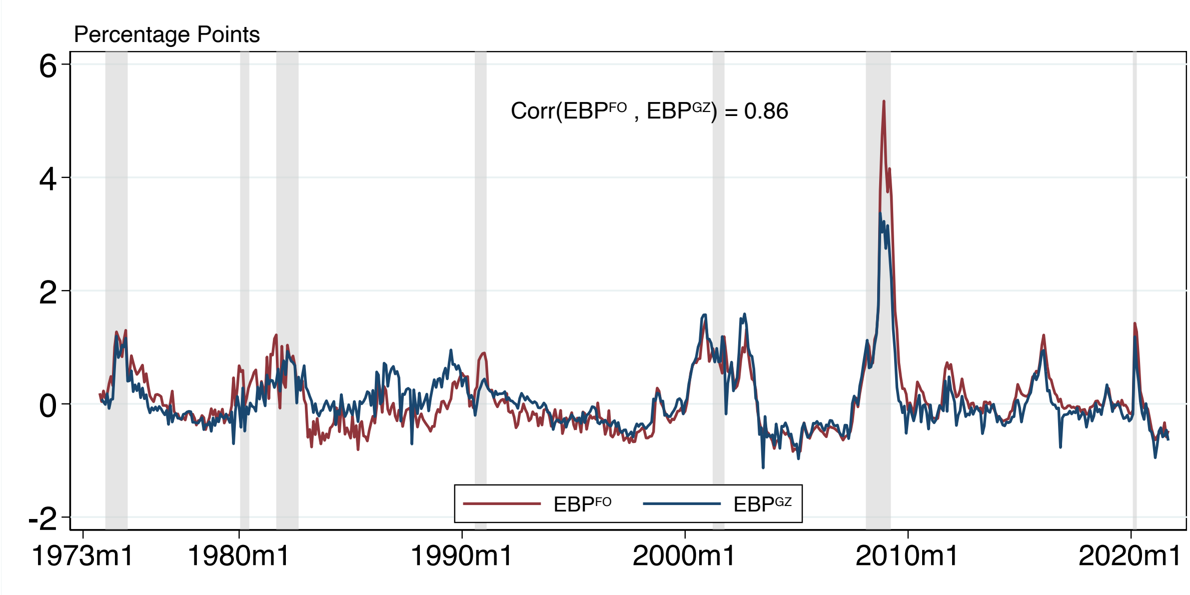
*Note.* Table A.1 present the estimated coefficients, standard errors and T-statistics from estimating regression (A.1) by OLS. The sample period is October 1973 to December 2021 and includes 682,316 observations. $LEV_t$, $SLP_t$, $CRV_t$ refer to the level, slope and curvature (first three principal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

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

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.

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

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

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 $\sigma_E$, equations (A.5) and (A.6) provide a two equation system that can be used to solve for the two unknowns $V$ and $\sigma_V$.[26] Due to the issues raised in Vassalou and Xing (2004), we follow Gilchrist and Zakrajšek (2012) by implementing the two-step iterative procedure of Bharath and Shumway (2008). First, we set $\sigma_V = \sigma_E$ for each day in a one-year rolling window and then substitute $\sigma_V$ 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 $\sigma_V$ as well as for $\mu_V$.[27] We then iterate on $\sigma_V$ until convergence.

Given solutions $(V, \sigma_V, \mu_V)$ 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 $\mu_V$ and volatility $\sigma_V$ 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.[28] The summary statistics for the monthly bond-level and quarterly firm-level EBPs

[26] Daily data for $E$ is from CRSP ($prc * shrout$) and is used to calculate a daily 252-day historical rolling-window equity volatility $\sigma_E$. 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.

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

[28] The difference in the number of observations between the quarterly firm-level EBP series and the

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

(A) Monthly Variables

| | $EBP_{ikt}$ | $S_{ikt}$ | $\varepsilon_t^m$ |
|---|---|---|---|
| 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

| | $EBP_{it}$ | $\Delta log(K_{it})$ | $\varepsilon_t^m$ |
|---|---|---|---|
| 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.

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).

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

monthly bond-level EBP series reflects these two levels of averaging.

also consistent with those documented by Ottonello and Winberry (2020), but with a moderately lower standard deviation and tighter tails.

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

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.

# B Additional Empirical Results and Robustness

In this section, we provide additional empirical results and robustness to complement our findings from the main text. In Section B.1, we provide robustness to our results from Section 3 linking firms' EBPs to the cyclicality of their default risk. We then turn to the empirical results from Sections 4 and 5. Specifically, in Section B.2, we highlight that the heterogeneous responses we document are robust to controlling for heterogeneity according to other firm characteristics. In Section B.3, we show that our results are robust to using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{i(k)t-1}$. In Section B.4, we show that it is the EBP-component of firms' credit spreads that reacts heterogeneously to monetary policy and credit supply shocks. In Section B.5, we document the heterogeneous effects on firm debt growth of both monetary policy and credit supply shocks. Section B.6 does the same for firms' sales growth. In Section B.7, we consider alternative forms for our credit spread regressions. In Section B.8, we show that our results are robust to using alternative functional forms to define the EBP interactions. In Section B.9, we re-estimate our main specifications with alternative monetary policy shocks, while Section B.10 re-estimates our monetary policy shock regressions excluding the zero-lower-bound period. Finally, in Section B.11, we showcase the robustness of our results from Section 7 linking the moments of the EBP distribution to the aggregate effectiveness of monetary policy.

## B.1 Firm EBPs and Cyclicality of Default Risk

In Section 3, we showed empirically that low-EBP firms' default risk co-moves less with aggregate risk, as proxied by the U.S. S&P500 index return and the intermediary capital risk factor of He et al. (2017). In this section, we highlight the robustness of this empirical result along four dimensions: (i) using the level-change in distance-to-default rather than log-change as the dependent variable; (ii) interacting the aggregate risk factors simultaneously with other firm characteristics in a horserace with the EBP; (iii) using alternative percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$; and (iv) using alternative functional forms to construct the interaction terms.

TABLE B.1
Firm Default Risk and Aggregate Risk Factors: Low- vs. High-EBP Firms

| $\Delta DD_{i,t}$ | (1) Low-EBP | (2) High-EBP | (3) Relative | (4) Low-EBP | (5) High-EBP | (6) Relative |
|---|---|---|---|---|---|---|
| $R_t^{Mkt}$ | .677*** | 1.04*** | | | | |
| | (.127) | (.222) | | | | |
| $R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$ | | | -.245*** | | | |
| | | | (.066) | | | |
| $\eta_t^{\Delta}$ | | | | .026*** | .042*** | |
| | | | | (.007) | (.012) | |
| $\eta_t^{\Delta} \times \mathbf{1}EBP_{it-1}^{low}$ | | | | | | -.011*** |
| | | | | | | (.004) |
| N | 28,529 | 112,578 | 155,939 | 28,529 | 112,578 | 155,939 |
| Adj. $R^2$ | .13 | .11 | .29 | .12 | .11 | .29 |
| Macro-Financial Controls | Yes | Yes | No | Yes | Yes | No |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector×Month FE | Yes | Yes | No | Yes | Yes | No |
| Sector×Time FE | No | No | Yes | No | No | Yes |

*Note*: Table B.1 reports the loadings of level-changes in firms' default risk on the U.S. S&P500 index return ($R_t^{Mkt}$) and the intermediary capital risk factor ($\eta_t^{\Delta}$). Columns (1), (2), and (4), (5) report $\beta^{Agg}$ from estimating regression (2) separately for low- and high-EBP firms, using $R_t^{Mkt}$ and $\eta_t^{\Delta}$, respectively, as the aggregate risk factor. Columns (3) and (6) report $\beta^{Agg,Rel}$ from regression (3), which measures how low-EBP firms' ($\mathbf{1}EBP_{it-1}^{low} = 1$) default risk loads on a given aggregate risk factor relative to high-EBP firms', using $R_t^{Mkt}$ and $\eta_t^{\Delta}$, respectively, as the aggregate risk factor. Standard errors are two-way clustered by firm and month. *** denotes statistical significance at the 1% level.

Table B.1 present results from re-estimate our baseline regressions using $\Delta DD_{it}$ rather than $\Delta \log DD_{it}$ as the dependent variable. Columns (1) and (4) present results from estimating regression (2) separately for low-EBP firms, using the U.S. S&P500 index return ($R_t^{Mkt}$) and intermediary capital risk factor ($\eta_t^{\Delta}$) as the aggregate risk factor, respectively. Columns (2) and (5) do the same for high-EBP firms. Columns (3) and (6) estimate regression (3), which measures the relative loading of low-EBP firms, using the two risk factors, respectively. The results are qualitatively consistent with our baseline, and, quantitatively larger, with changes low-EBP firms' distance to default loading up to 40% less on aggregate risk than high-EBP firms'.

Tables B.2 and B.3 present results from re-estimating regression (3) while also controlling for how other firm characteristics may explain default-risk loadings on aggregate risk. That is, we add to regression (3) the interactions $Risk\_Factor_t^{Agg} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. We define each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low(high)}$ in three ways: (1) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is below the $20^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise; (2) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is below the $50^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise; and (3) $\mathbf{1}Z_{it-1}^{high} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. Columns (1), (2) and (3) of Table B.2 present the estimated coefficients for $R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$ with $\mathbf{1Z}_{it-1}^{low(high)}$ defined using the $20^{th}$, $50^{th}$ and $80^{th}$ percentiles, respectively, while Table B.3 does the same for $\eta_t^{\Delta Mkt} \times \mathbf{1}EBP_{it-1}^{low}$. The results highlight that, across percentiles and risk factors, the significant association between firms' EBPs and the cyclicality of their default risks remains.

Table B.2
Firm's EBP, Default Risk and Market Risk Factor: Controlling for Firm Characteristics

| $\Delta \log DD_{i,t}$ | Control for $< 20^{th}$ Perc. Characteristics | Control for $< 50^{th}$ Perc. Characteristics | Control for $> 80^{th}$ Perc. Characteristics |
|---|---|---|---|
| $R_t^{Mkt} \times \mathbf{1}EBP_{it-1}^{low}$ | -.090*** | -.100*** | -.089*** |
| | (.022) | (.021) | (.022) |
| N | 157,647 | 157,647 | 157,647 |
| Adj. $R^2$ | .39 | .39 | .38 |
| Firm FE | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes |

*Note*: Table B.2 reports $\beta^{Mkt,Rel}$ from a modified regression (3) that controls for $R_t^{Mkt} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Column (1), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is below the $20^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. In Column (2), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is below the $50^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. In Column (3), 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 above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. *** denotes statistical significance at the 1% level.

Next, Tables B.4 and B.5 present results from re-estimating (3)—which measures the relative loading of low-EBP firms' default risk on aggregate risk factors (S&P500 return and

Table B.3

Firm's EBP, Default Risk & Intermediary Capital Risk Factor: Controlling for Firm Characteristics

| $\Delta \log DD_{i,t}$ | Control for $< 20^{th}$ Perc. Characteristics | Control for $< 50^{th}$ Perc. Characteristics | Control for $> 80^{th}$ Perc. Characteristics |
|---|---|---|---|
| $\eta_t^{\Delta} \times \mathbf{1}EBP_{it-1}^{low}$ | -.005*** | -.005*** | -.005*** |
| | (.001) | (.001) | (.001) |
| N | 157,647 | 157,647 | 157,647 |
| Adj. $R^2$ | .38 | .38 | .38 |
| Firm FE | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes |

*Note*: Table B.3 reports $\beta^{Mkt,Rel}$ from a modified regression (3) that controls for $\eta_t^{\Delta Mkt} \times \mathbf{1Z}_{it-1}^{low}$, where $\mathbf{1Z}_{it-1}^{low}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. In Column (1), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is below the $20^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. In Column (2), each indicator variable $\mathbf{1}Z_{it-1} \in \mathbf{1Z}_{it-1}^{low}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is below the $50^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. In Column (3), 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 above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. *** denotes statistical significance at the 1% level.

intermediary capital risk factor, respectively)—using 5 different threshold percentiles (the $15^{th}$, $20^{th}$ [main text], $25^{th}$, $33^{rd}$ and $50^{th}$) of the EBP distribution to classify low-EBP firms (i.e., $\mathbf{1}EBP_{it-1}^{low} = 1$). 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'.

Finally, Tables B.6 and B.7 re-estimate (3) using alternative functional forms to define the EBP interaction with aggregate risk factors. In particular, it presents four alternative functional forms: (i) a linear interaction; (ii) an interaction that isolates for within-firm variation in EBPs à la Ottonello and Winberry (2020); (iii) and (iv) interactions with alternative EBPs that are purged of dependence on other firm characteristics and non-linear distance-to-default terms, respectively. Across these functional forms and risk factors, the findings are strongly consistent with our baseline. In particular, the linear interaction shows that the distances-to-default of higher-EBP firms loads more on aggregate risk than lower ones. Next, focusing on the within-firm variation specification, we see that firms whose EBPs are higher than their historical average see their default risk rise more when aggregate

Table B.4
Firm's EBP, Default Risk and Market Risk Factor: Alternate Percentiles

| | Dep. Var.: $\Delta \log DD_{i,t}$ | | | | |
|---|---|---|---|---|---|
| Low Percentile | $15^{th}$ | $20^{th}$ | $25^{th}$ | $33^{rd}$ | $50^{th}$ |
| $R_t^{Mkt} \times \mathbf{1}EBP_{i,t-1}^{Low}$ | -.064*** | -.067*** | -.071*** | -.085*** | -.097*** |
| | (.024) | (.022) | (.024) | (.019) | (.017) |
| N | 154,179 | 154,179 | 154,179 | 154,179 | 154,179 |
| Adj. $R^2$ | .38 | .38 | .38 | .38 | .38 |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes | Yes | Yes |

*Note*: Table B.4 reports $\beta^{Mkt,Rel}$ from regression (3), which measures how low-EBP firms' default risk loads on the S&P500 return relative to high-EBP firms' for different threshold percentiles for defining $\mathbf{1}EBP_{it-1}^{low}$. Specifically, it presents results for 5 different threshold percentiles: $50^{th}$, $33^{rd}$, $25^{th}$, $20^{th}$ (our baseline) and the $15^{th}$. Standard errors are two-way clustered by firm and month. *** (**) denotes statistical significance at the 1% (5%) level.

Table B.5
Firm's EBP, Default Risk & Intermediary Capital Risk Factor: Alternate Percentiles

| | Dep. Var.: $\Delta \log DD_{i,t}$ | | | | |
|---|---|---|---|---|---|
| Low Percentile | $15^{th}$ | $20^{th}$ | $25^{th}$ | $33^{rd}$ | $50^{th}$ |
| $\eta_t^{\Delta} \times \mathbf{1}EBP_{i,t-1}^{Low}$ | -.004*** | -.004*** | -.004*** | -.005*** | -.005*** |
| | (.001) | (.001) | (.001) | (.001) | (.001) |
| N | 154,179 | 154,179 | 154,179 | 154,179 | 154,179 |
| Adj. $R^2$ | .38 | .38 | .38 | .38 | .38 |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes | Yes | Yes |

*Note*: Table B.5 reports $\beta^{Mkt,Rel}$ from regression (3), which measures how low-EBP firms' default risk loads on the He et al. (2017) intermediary capital risk factor relative to high-EBP firms' for different threshold percentiles for defining $\mathbf{1}EBP_{it-1}^{low}$. Specifically, it presents results for 5 different threshold percentiles: $50^{th}$, $33^{rd}$, $25^{th}$, $20^{th}$ (our baseline) and the $15^{th}$. Standard errors are two-way clustered by firm and month. *** (**) denotes statistical significance at the 1% (5%) level.

risk rises. This highlights that firm-specific pricing of default risk can vary over time and is captured in firms' EBPs. Finally, constructing $\mathbf{1}EBP_{it-1}^{low}$ using alternative EBPs that purge credit spreads explicitly of other firm characteristics (leverage, size, sales growth, age, current asset share, and Tobin's average Q) and non-linear distance-to-default terms ($DD^2$, $DD^3$, $DD^4$) produces similar results to our baseline, showing that it is not these components of the EBP that drive our results.

Table B.6

Firm's EBP, Default Risk and Market Risk Factor: Alternate EBP Functional Forms

| $\Delta \log DD_{i,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $R_t^{Mkt} \times EBP_{it-1}$ | .047*** | | | |
| | (.008) | | | |
| $R_t^{Mkt} \times (EBP_{it-1} - \overline{EBP}_i)$ | | .051*** | | |
| | | (.009) | | |
| $R_t^{Mkt} \times \mathbf{1}\widetilde{EBP\_exChar}_{it-1}^{low}$ | | | -.067*** | |
| | | | (.021) | |
| $R_t^{Mkt} \times \mathbf{1}\widetilde{EBP\_exDD}_{it-1}^{low}$ | | | | -.057** |
| | | | | (.024) |
| N | 154,179 | 154,179 | 154,179 | 154,179 |
| Adj. $R^2$ | .39 | .38 | .38 | .38 |
| Firm FE | Yes | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes | Yes |

*Note*: Table B.6 reports $\beta^{Agg,Rel}$ from regression (3), which measures how low-EBP firms' default risk loads on the market return relative to high-EBP firms' using different functional forms to define the interaction. Column (1) uses a linear interaction; Column (2) uses a within-firm linear interaction as in Ottonello and Winberry (2020); Column (3) presents the relative loading of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Column (4) uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. Standard errors are two-way clustered by firm and month. *** (**) denotes statistical significance at the 1% (5%) level.

Table B.7
Firm's EBP, Default Risk & Intermediary Capital Risk Factor: Alternate EBP Functional Forms

| $\Delta \log DD_{i,t}$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $\eta_t^{\Delta} \times EBP_{it-1}$ | .002*** | | | |
| | (.0003) | | | |
| $\eta_t^{\Delta} \times (EBP_{it-1} - \overline{EBP}_i)$ | | .002*** | | |
| | | (.0003) | | |
| $\eta_t^{\Delta} \times \mathbf{1}\widetilde{EBP\_exChar}_{it-1}^{low}$ | | | -.003*** | |
| | | | (.001) | |
| $\eta_t^{\Delta} \times \mathbf{1}\widetilde{EBP\_exDD}_{it-1}^{low}$ | | | | -.004** |
| | | | | (.001) |
| N | 154,179 | 154,179 | 154,179 | 154,179 |
| Adj. $R^2$ | .38 | .38 | .38 | .38 |
| Firm FE | Yes | Yes | Yes | Yes |
| Sector×Time FE | Yes | Yes | Yes | Yes |

*Note*: Table B.7 reports $\beta^{Agg,Rel}$ from regression (3), which measures how low-EBP firms' default risk loads on the He et al. (2017) intermediary capital risk factor relative to high-EBP firms' using different functional forms to define the interaction. Column (1) uses a linear interaction; Column (2) uses a within-firm linear interaction as in Ottonello and Winberry (2020); Column (3) presents the relative loading of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Column (4) uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. Standard errors are two-way clustered by firm and month. *** (**) denotes statistical significance at the 1% (5%) level.

## B.2 Heterogeneous Effects by EBP vs. other Characteristics

In this section, we show that firms' EBPs matter for their responsiveness to monetary policy and credit supply shocks when also conditioning on other competing firm characteristics. To show this, we re-estimate our baseline regressions (5), (7) and (9), which contain the interaction term $\varepsilon_t^{shock} \times \mathbf{1}EBP_{i(k)t-1}^{low}$, when also including the interaction vector $\varepsilon_t^{shock} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ 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 $shock = \{m\} \quad or \quad \{CS\}$.[29] We again define each indicator variable $\mathbf{1}Z_{it-1}^{low(high)} \in \mathbf{1Z}_{it-1}^{low(high)}$ in three ways: (1) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is below the $20^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise; (2) $\mathbf{1}Z_{it-1}^{low} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is below the $50^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise; and (3) $\mathbf{1}Z_{it-1}^{high} = 1$ if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise.

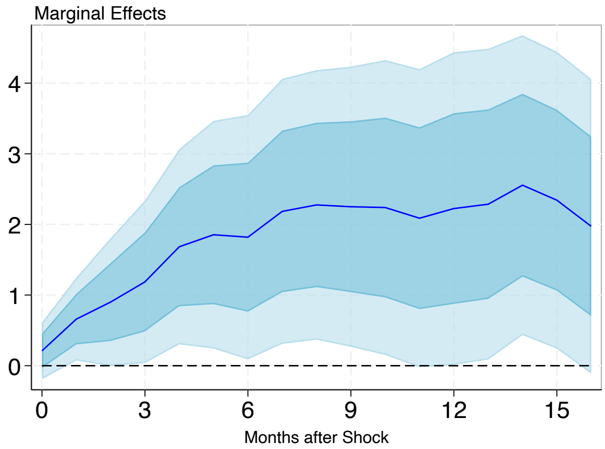
The results of these horserace regressions between firms' EBPs and other firm characteristics are displayed in Figures B.1, B.2, B.3 and B.4. Panel (a) in each figure displays the response of low-EBP firms—or bonds in the credit spread figures—to the shock compared to high-EBP ones, controlling for the 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. Panel (b) 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, while Panel (c) in each figure displays our response of interest, but with $\mathbf{1Z}_{it-1}^{high}$ defined based on the $80^{th}$ 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.

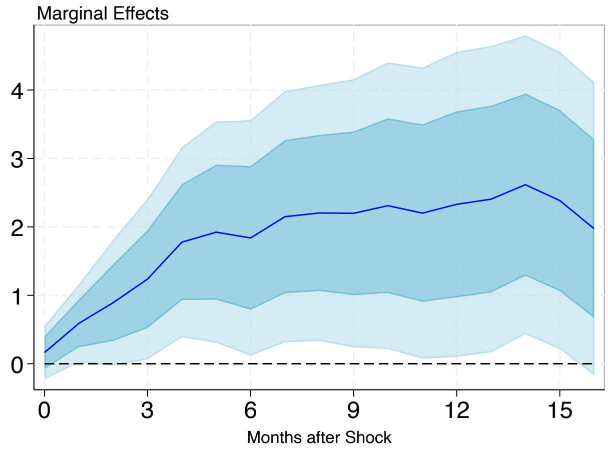
[29]We include these indicator variables of firm characteristics and their interactions with the shocks en lieu of firm characteristics in levels.

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

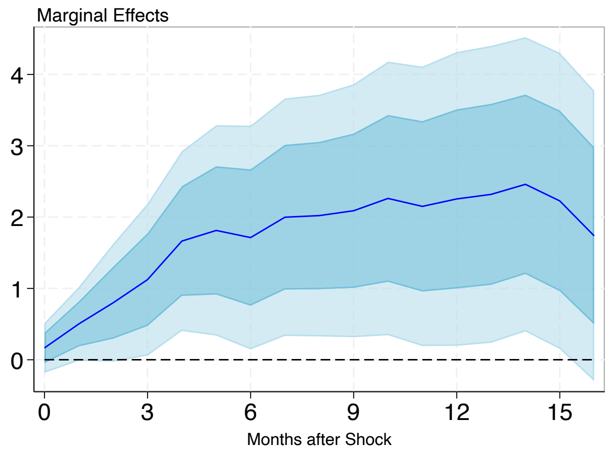
(A) Horserace with below $20^{th}$ Perc. Characteristics




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




(C) Horserace with above $80^{th}$ Perc. Characteristics

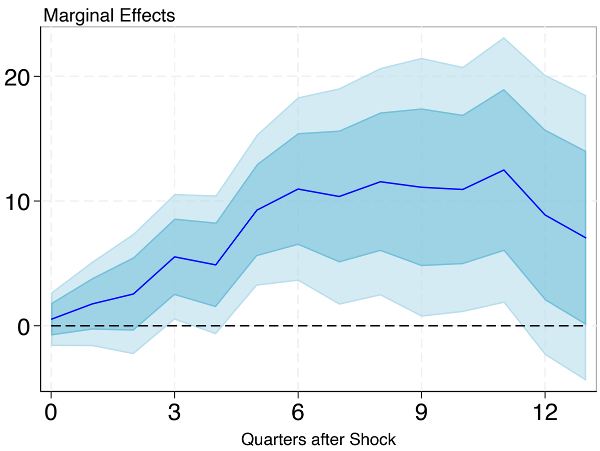



*Note.* Figure B.1 plots the credit spread response of low-EBP (sub $20^{th}$ percentile) firms' bonds to a monetary policy shock relative to high-EBP firms' using a modified regression (5) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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. In Panel B.1c, each indicator variable $\mathbf{1}Z_{it-1}^{high} \in \mathbf{1Z}_{it-1}^{high}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

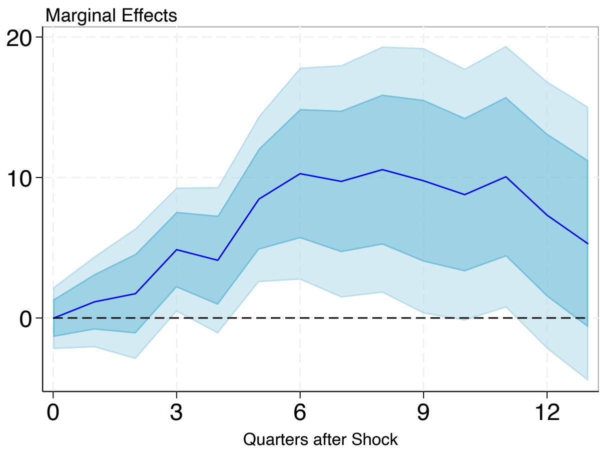
FIGURE B.2

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

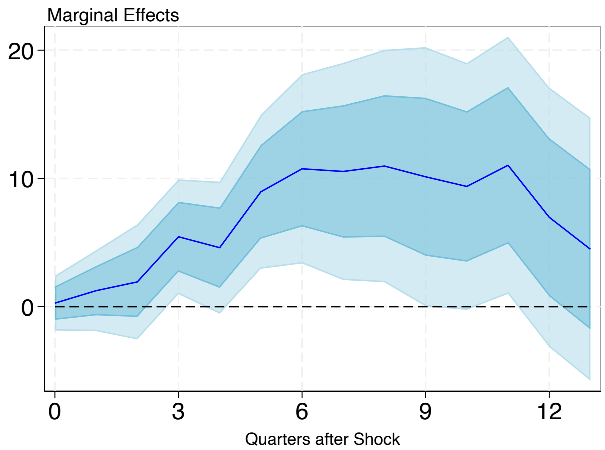
(A) Horserace with below $20^{th}$ Perc. Characteristics




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



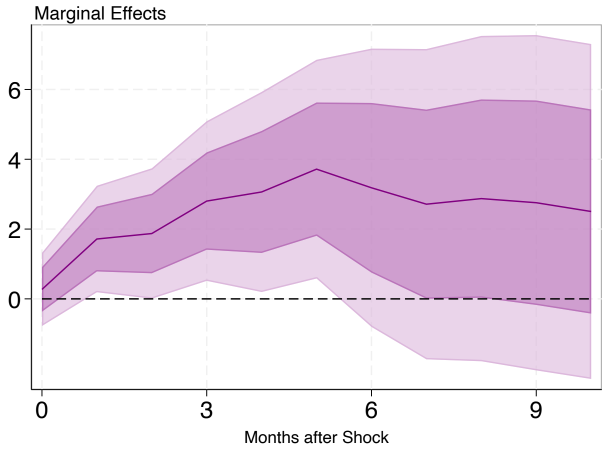

(C) Horserace with above $80^{th}$ Perc. Characteristics



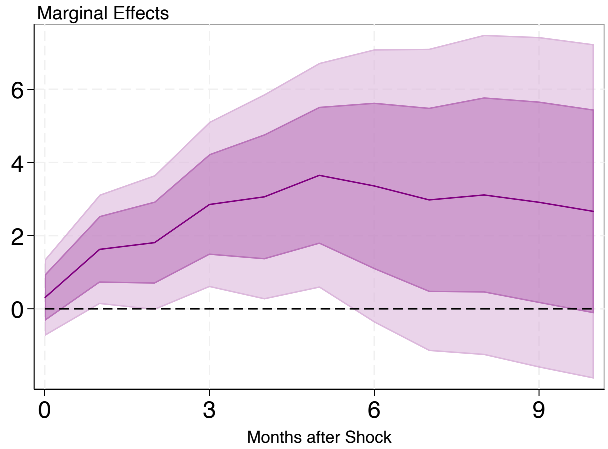

*Note.* Figure B.2 plots the investment response of low-EBP (sub $20^{th}$ percentile) firms to a monetary policy shock relative to high-EBP firms using a modified regression (7) that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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. In Panel B.2c, each indicator variable $\mathbf{1}Z_{it-1}^{high} \in \mathbf{1Z}_{it-1}^{high}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ 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

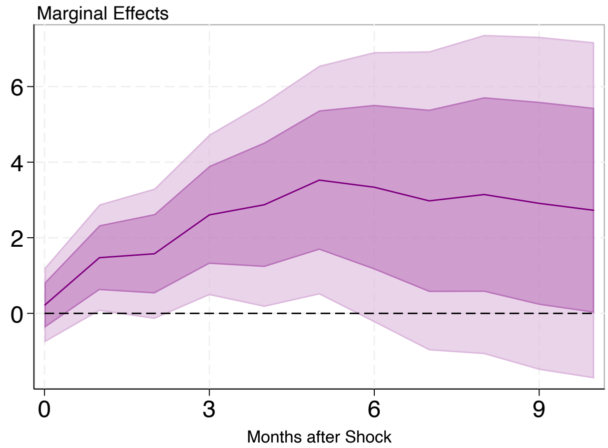
(a) Horserace with below $20^{th}$ Perc. Characteristics




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




(c) Horserace with above $80^{th}$ Perc. Characteristics

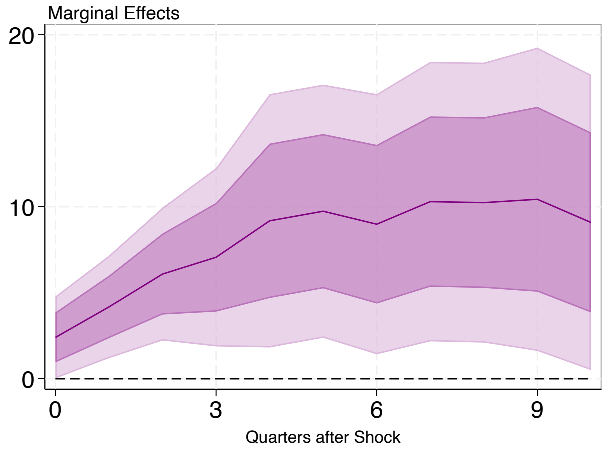



*Note.* Figure B.3 plots the credit spread response of low-EBP (sub $20^{th}$ percentile) firms' bonds to a credit supply shock relative to high-EBP firms' using a modified regression (9) that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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. In Panel B.3c, each indicator variable $\mathbf{1}Z_{it-1}^{high} \in \mathbf{1Z}_{it-1}^{high}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ 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.

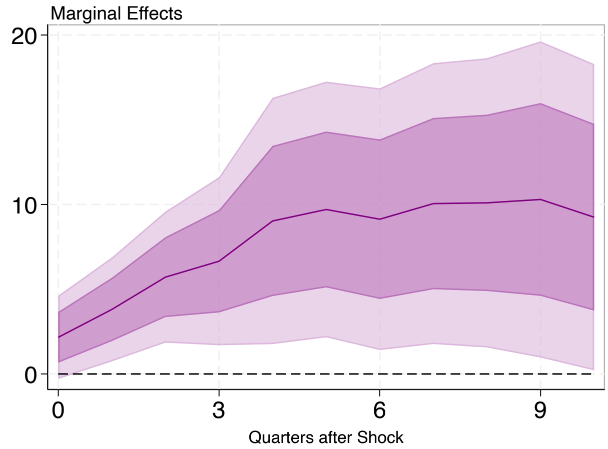
Figure B.4

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

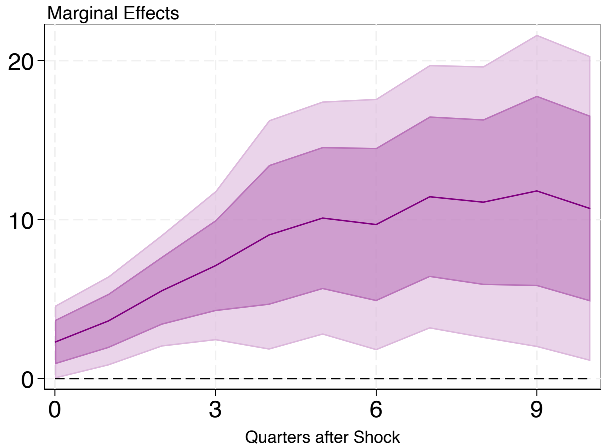
(a) Horserace with below $20^{th}$ Perc. Characteristics




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




(c) Horserace with above $80^{th}$ Perc. Characteristics



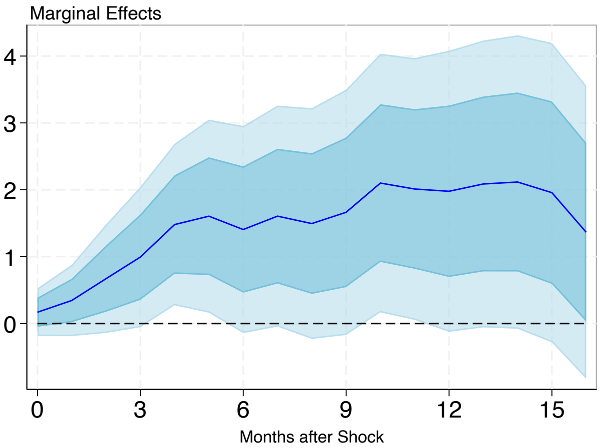

*Note.* Figure B.4 plots the investment response of low-EBP (sub $20^{th}$ percentile) firms to a credit supply shock relative to high-EBP firms using a modified regression (9) that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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 $\mathbf{1}Z_{it-1}^{low} \in \mathbf{1Z}_{it-1}^{low}$ 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. In Panel B.4c, each indicator variable $\mathbf{1}Z_{it-1}^{high} \in \mathbf{1Z}_{it-1}^{high}$ is equal to 1 if the value of a firm's characteristic $Z_{it-1}$ is above the $80^{th}$ percentile of the firm-level distribution of $Z_{it-1}$, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

## B.3 Heterogeneous Effects with Alternative EBP Percentiles

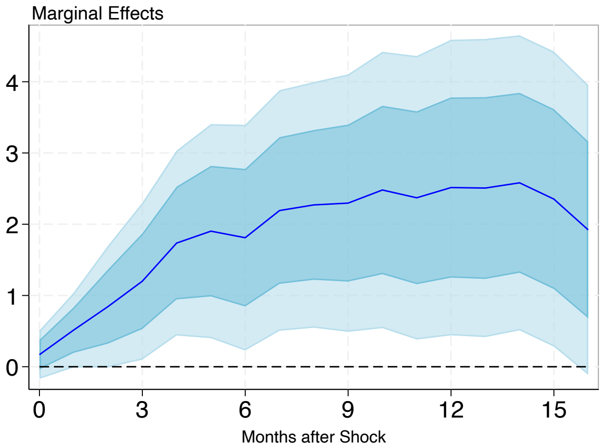
In this section, we show that our results from the main text are robust to using different threshold percentiles to define low-EBP firms, i.e., firms for which $\mathbf{1}EBP^{low}_{i(k)t-1} = 1$. In particular, we provide results for four other threshold percentiles to complement our baseline results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

FIGURE B.5
Relative Response of Bond Credit Spreads to Monetary Policy by EBP Percentiles

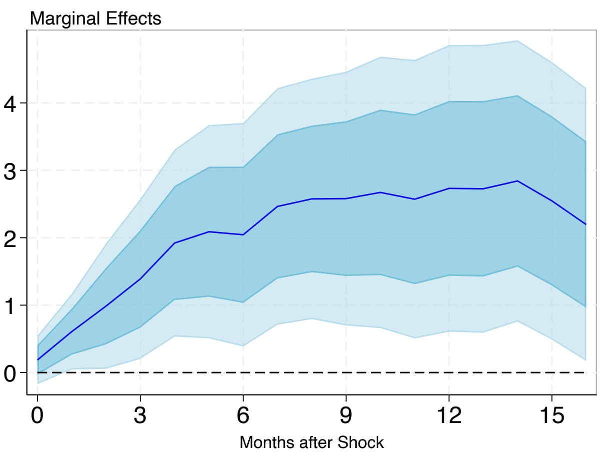
(A) Below $15^{th}$ $EBP_{ikt-1}$ Percentile



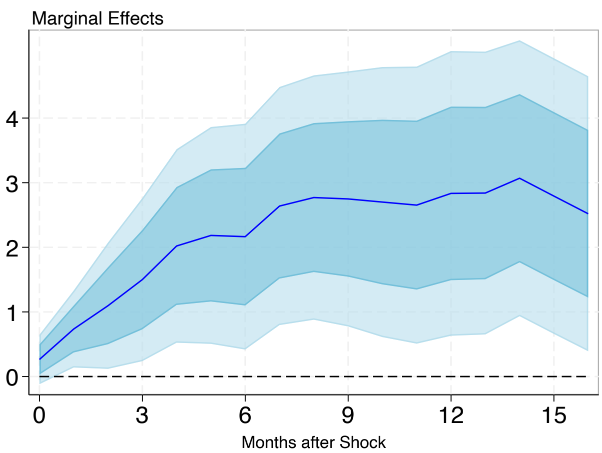

(B) Below $25^{th}$ $EBP_{ikt-1}$ Percentile




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




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

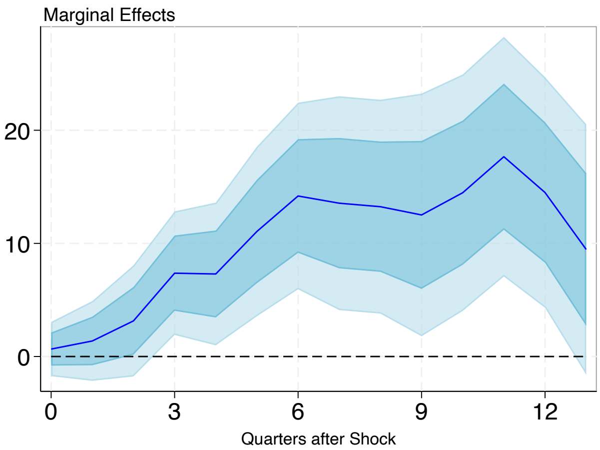



*Note.* Figure B.5 plots the $\beta_1^h$s from regression (5), which trace the credit spread response of low-EBP firms' bonds to a monetary policy shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (5). Panels B.5a, B.5b, B.5c, B.5d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a bond's EBP is below the $15^{th}$, $25^{th}$, $33^{rd}$ and $50^{th}$ percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

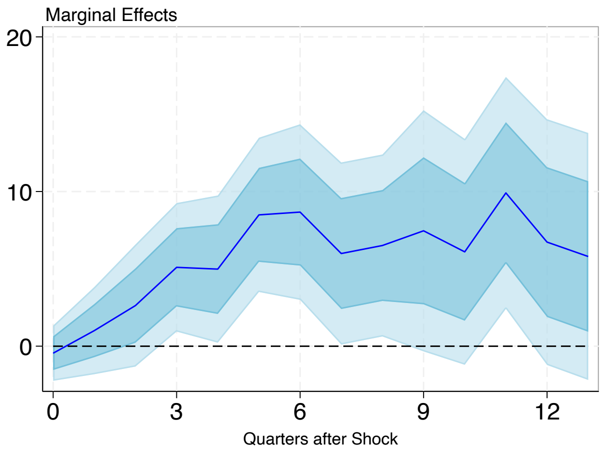
FIGURE B.6

Relative Response of Firm Investment to Monetary Policy by EBP Percentiles

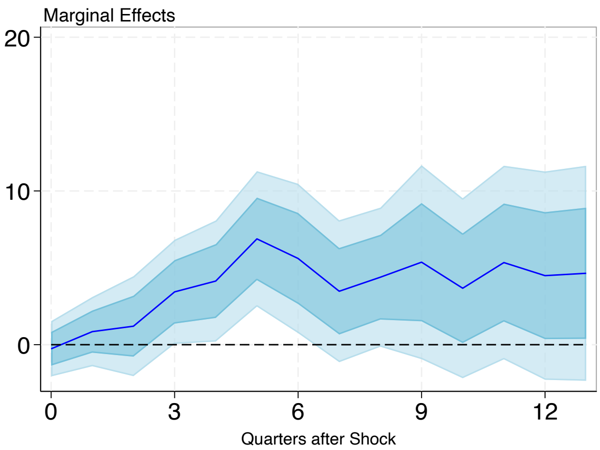
(A) Below $15^{th}$ $EBP_{it-1}$ Percentile



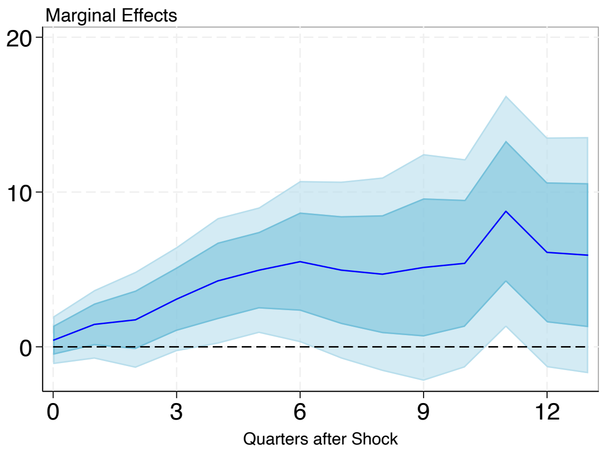

(B) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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

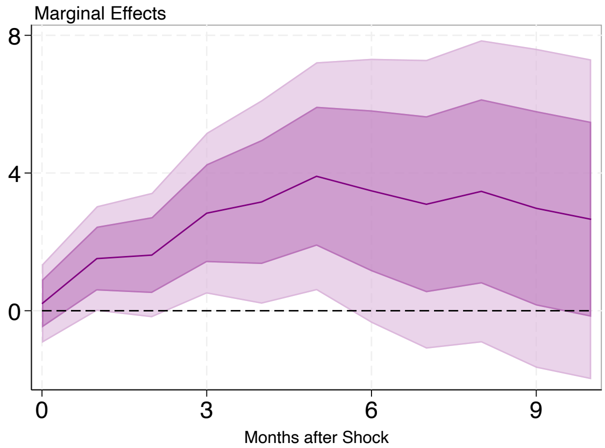



*Note.* Figure B.6 plots the $\beta_1^h$s from regression (7), which trace the investment response of low-EBP firms to a monetary policy shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (7). Panels B.6a, B.6b, B.6c, B.6d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the $15^{th}$, $25^{th}$, $33^{rd}$ and $50^{th}$ percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

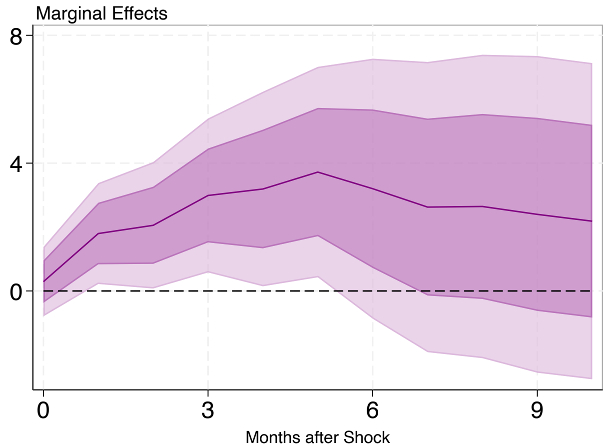
Figure B.7

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

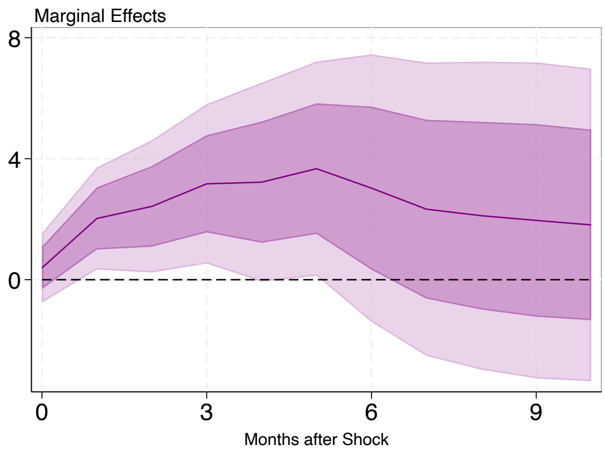
(a) Below $15^{th}$ $EBP_{ikt-1}$ Percentile



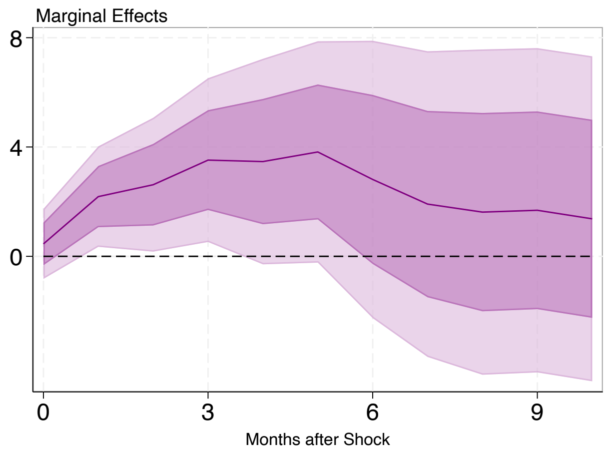

(b) Below $25^{th}$ $EBP_{ikt-1}$ Percentile




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




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

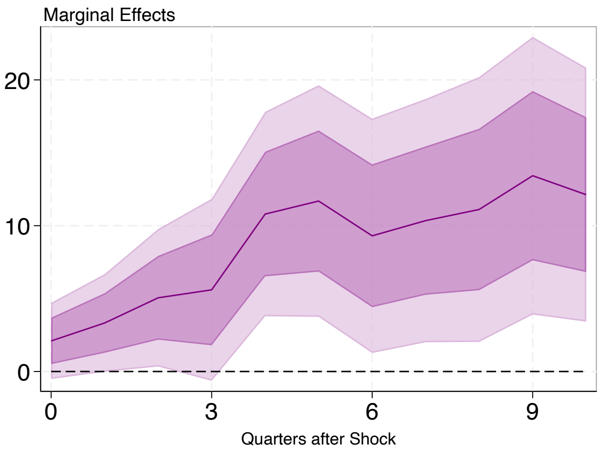



*Note.* Figure B.7 plots the $\beta_1^h$s from regression (9), which trace the credit spread response of low-EBP firms' bonds to a credit supply shock relative to high-EBP firms' bonds, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$ in regression (9). Panels B.7a, B.7b, B.7c, B.7d set $\mathbf{1}EBP_{ikt-1}^{low} = 1$ if, respectively, a bond's EBP is below the $15^{th}$, $25^{th}$, $33^{rd}$ and $50^{th}$ percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

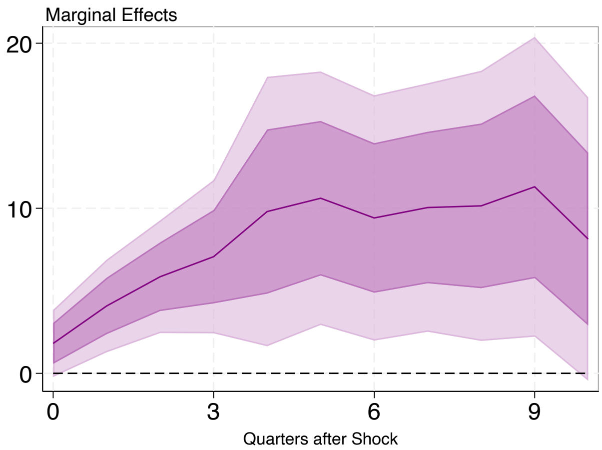
Figure B.8

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

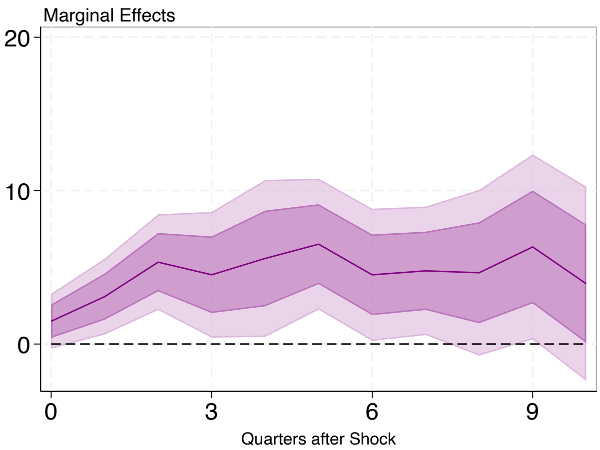
(A) Below $15^{th}$ $EBP_{it-1}$ Percentile



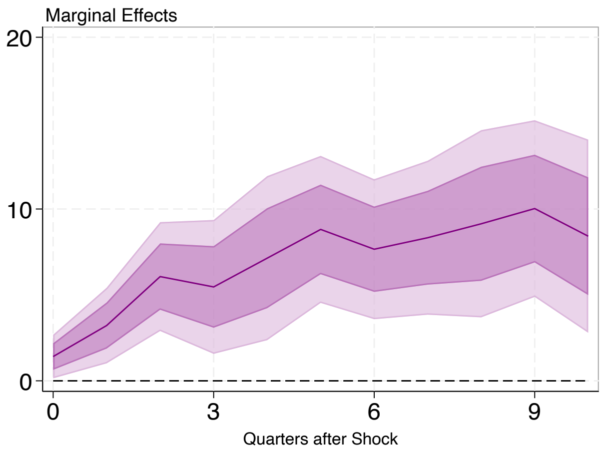

(B) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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



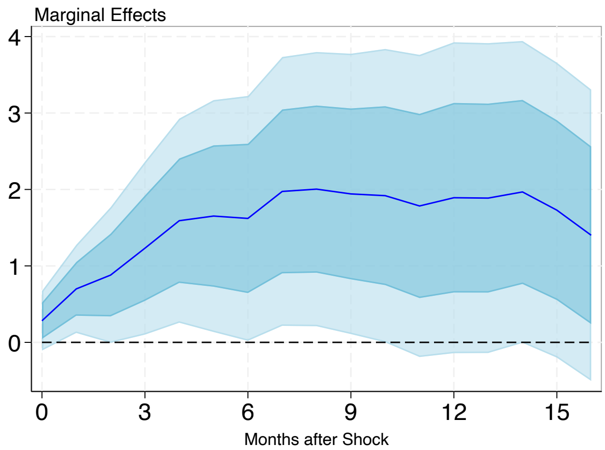

*Note.* Figure B.8 plots the $\beta_1^h$s from regression (9), which trace the investment response of low-EBP firms to a credit supply shock relative to high-EBP firms, using different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$ in regression (9). Panels B.8a, B.8b, B.8c, B.8d set $\mathbf{1}EBP_{it-1}^{low} = 1$ if, respectively, a firm's EBP is below the $15^{th}$, $25^{th}$, $33^{rd}$ and $50^{th}$ percentiles of the EBP distribution, and 0 otherwise. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

## B.4 Heterogeneous Effects on Bond-Level EBPs

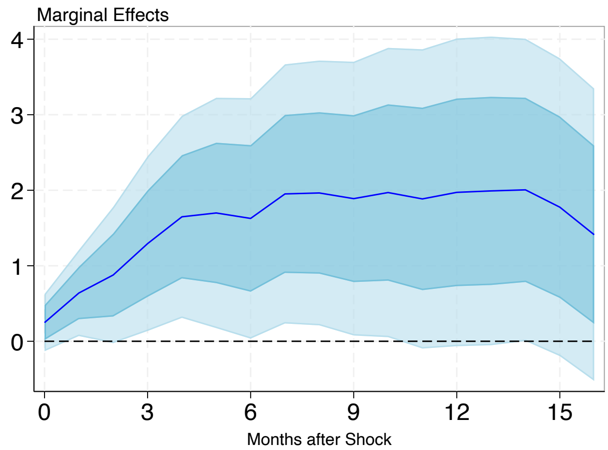
In this section, we re-estimate our baseline credit spread regressions (5) and (9) using as the dependent variable the h-period change in the EBP component of firms' credit spreads, $EBP_{ikt+h} - EBP_{ikt-1}$. These results are shown in Panel B.11a (monetary policy shock) and B.12a (credit supply shock), respectively. We also re-run the robustness exercises from Sections B.2 and B.3, i.e., running horse-race regressions between the EBP and other firm characteristics (Figures B.9 and B.10) and using other percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{ikt-1}$ (Figures B.11 and B.12), respectively. In all cases, the response of firms' EBPs tracks almost identically the response of firms' credit spreads, highlighting that it is the EBP-component of firms' credit spreads that reacts heterogeneously to monetary policy and credit supply shocks.

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

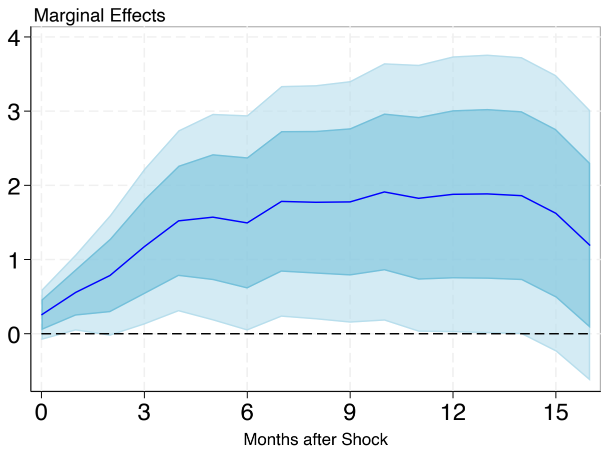
(A) Horserace with below $20^{th}$ Perc. Characteristics




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



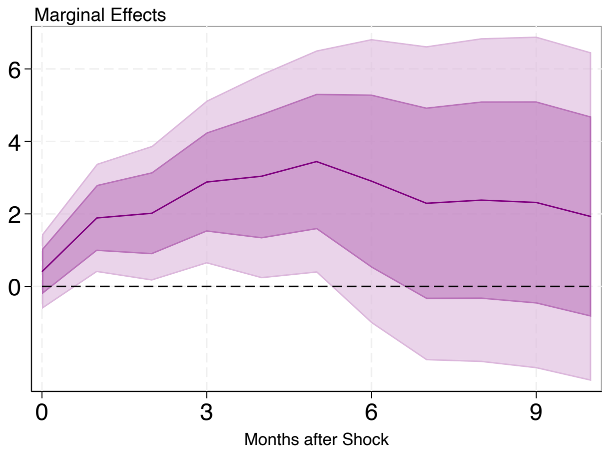

(C) Horserace with above $80^{th}$ Perc. Characteristics



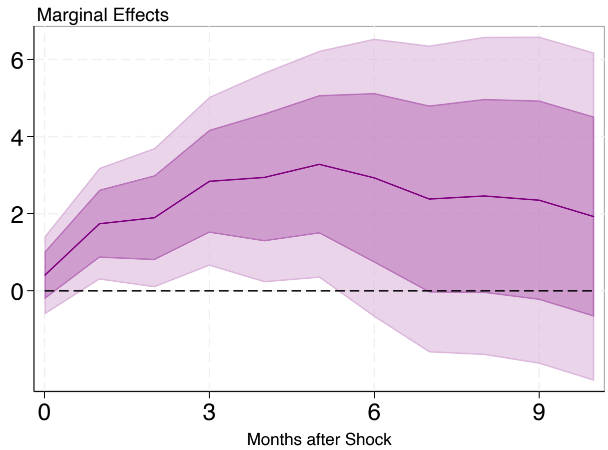

*Note.* Figure B.9 plots the $\beta_1^h$s from a modified regression (5) that uses the change in bonds' EBPs rather than their credit spreads as the dependent variable and that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.1 apply.

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

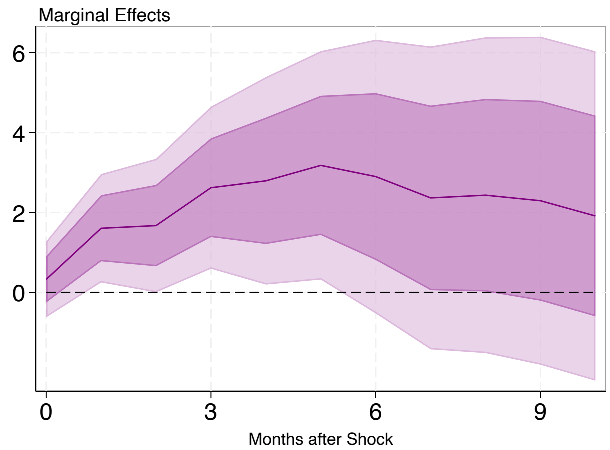
(A) Horserace with below $20^{th}$ Perc. Characteristics




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




(C) Horserace with above $80^{th}$ Perc. Characteristics

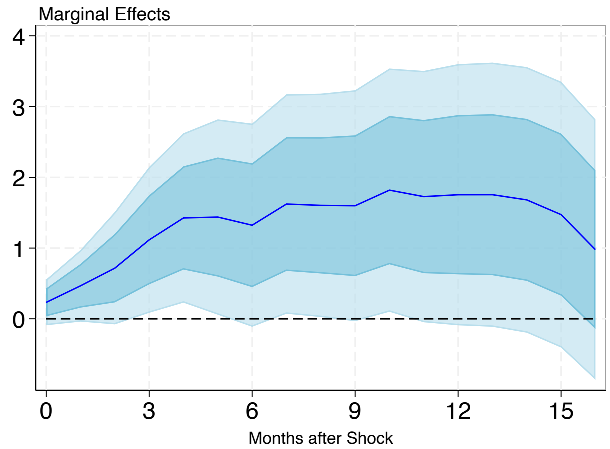



*Note.* Figure B.10 plots the $\beta_1^h$s from a modified regression (9) that uses the change in bonds' EBPs rather than their credit spreads as the dependent variable and that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.3 apply.

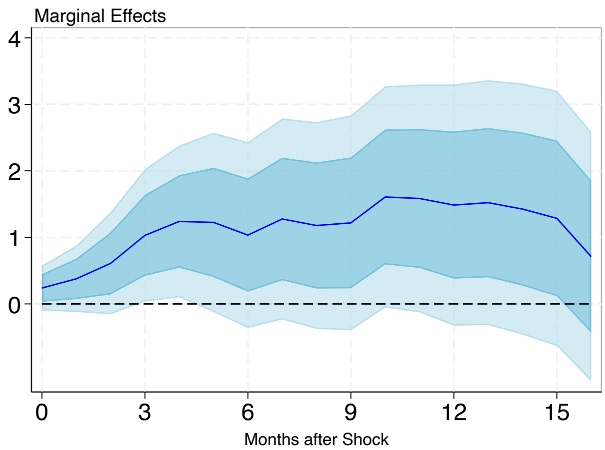
Figure B.11

Relative Response of Bond EBPs to Monetary Policy by EBP Percentiles

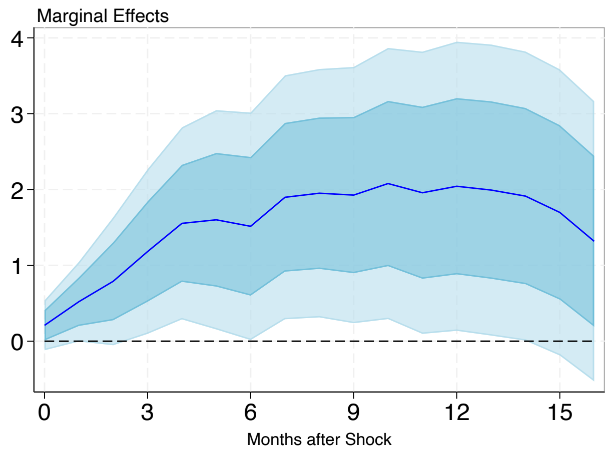
(a) Below $20^{th}$ $EBP_{ikt-1}$ Percentile



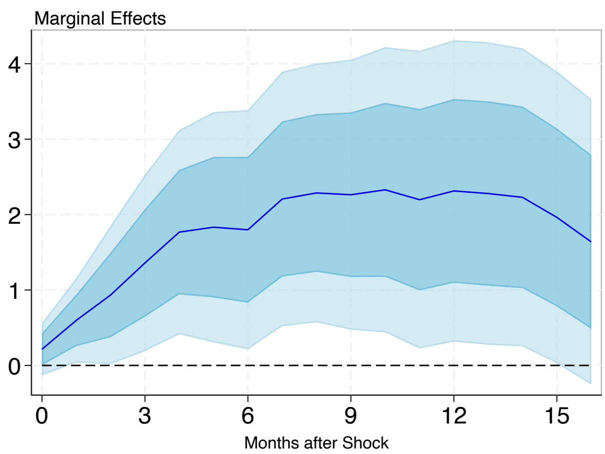

(b) Below $15^{th}$ $EBP_{ikt-1}$ Percentile



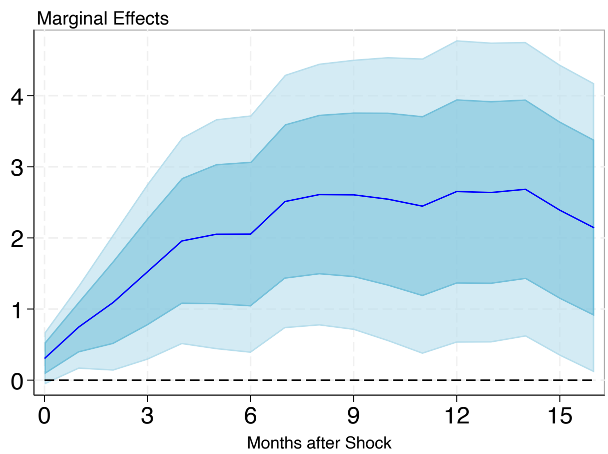

(c) Below $25^{th}$ $EBP_{ikt-1}$ Percentile




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




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

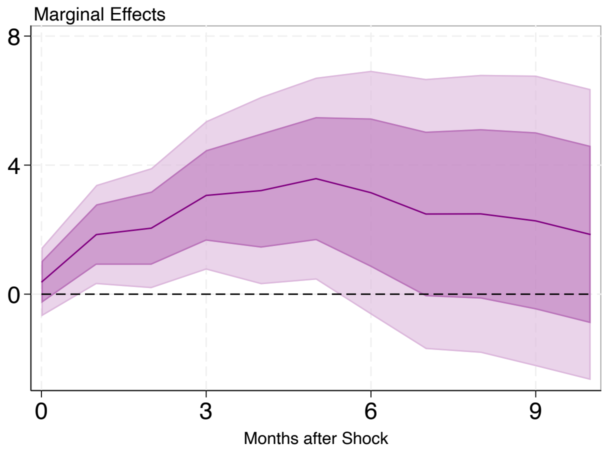



*Note.* Figure B.11 plots the $\beta_1^h$s from a modified regression (5) that uses changes in the EBP-component of firms' credit spreads as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$. The remaining notes from Figure B.5 apply.

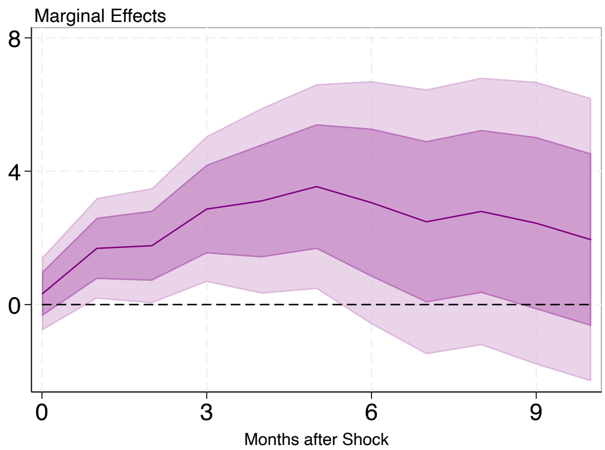
FIGURE B.12

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

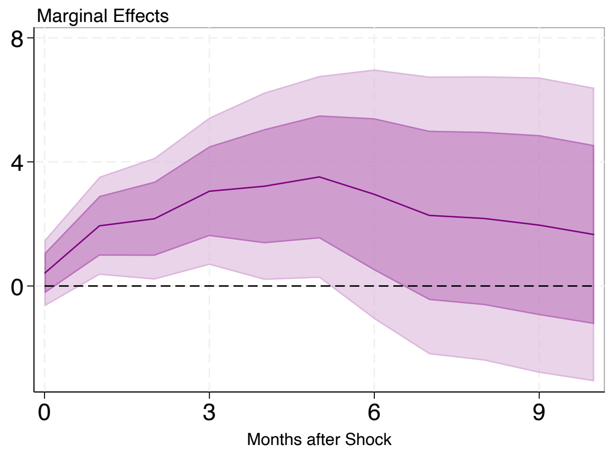
(A) Below $20^{th}$ $EBP_{ikt-1}$ Percentile



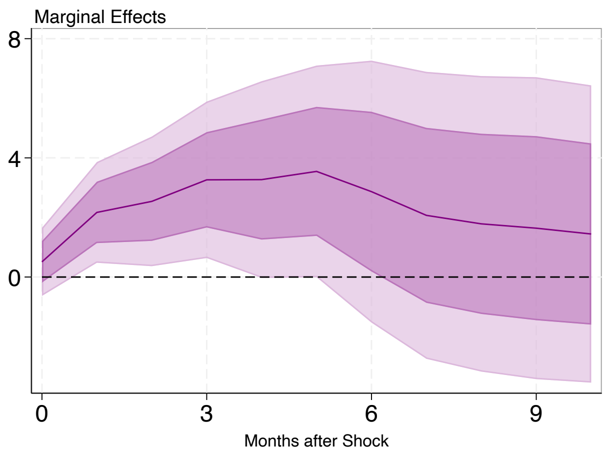

(B) Below $15^{th}$ $EBP_{ikt-1}$ Percentile



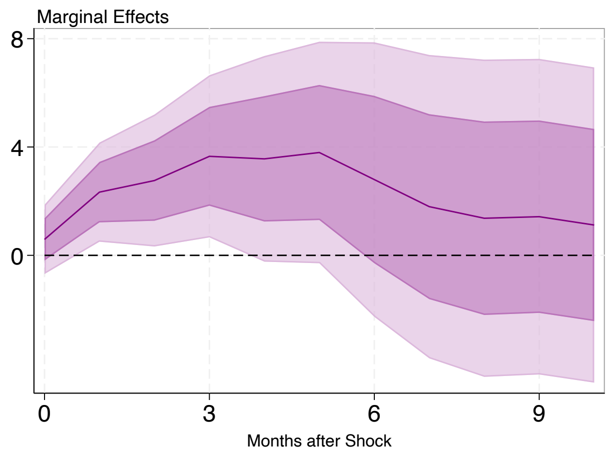

(C) Below $25^{th}$ $EBP_{ikt-1}$ Percentile




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




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



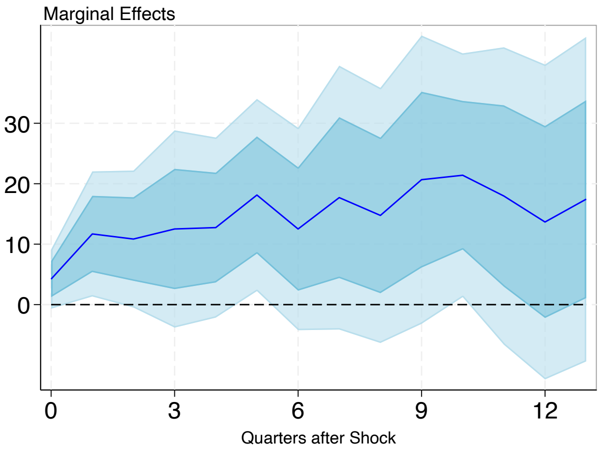

*Note.* Figure B.12 plots the $\beta_1^h$s from a modified regression (9) that uses changes in the EBP-component of firms' credit spreads as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{ikt-1}^{low}$. The remaining notes from Figure B.7 apply.

## B.5 Heterogeneous Effects on Firm-Level Debt Growth

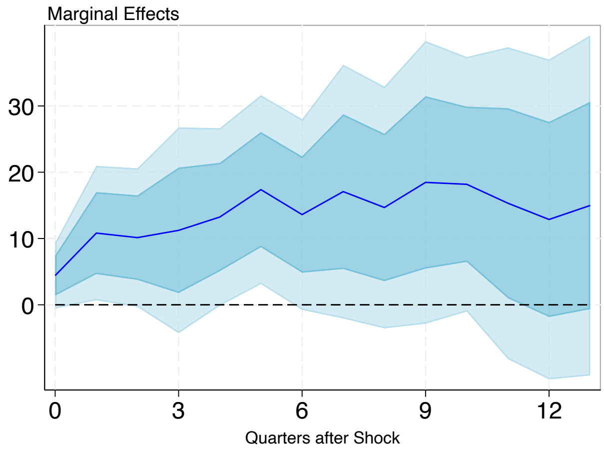
In this section, we re-estimate our baseline investment regressions (7) and (9) using as the dependent variable the h-period log change in firms' debt, $\log D_{it+h} - \log D_{it-1}$. These results are shown in Panel B.15a (monetary policy shock) and B.16a (credit supply shock), respectively. We also re-run the robustness exercises from Sections B.2 and B.3, i.e., running horse-race regressions between the EBP and other firm characteristics (Figures B.13 and B.14) and using other percentiles of the EBP distribution to define $\mathbf{1}EBP^{low}_{it-1}$ (Figures B.15 and B.16), respectively. In all cases, the results are in line with the heterogeneous responses of investment: low-EBP firms increase debt relative to high-EBP firms following expansionary monetary policy and credit supply shocks.

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

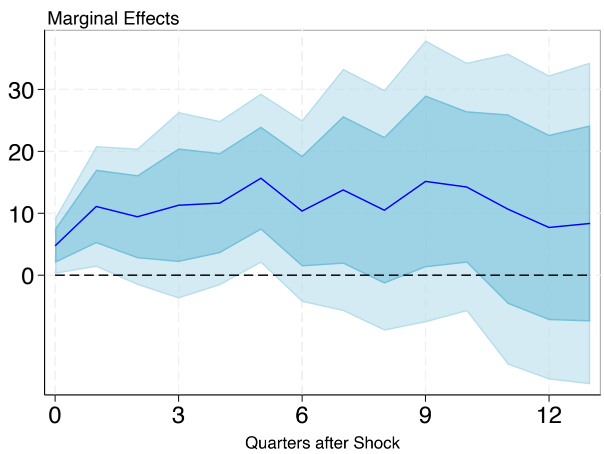
(a) Horserace with below $20^{th}$ Perc. Characteristics




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




(c) Horserace with above $80^{th}$ Perc. Characteristics

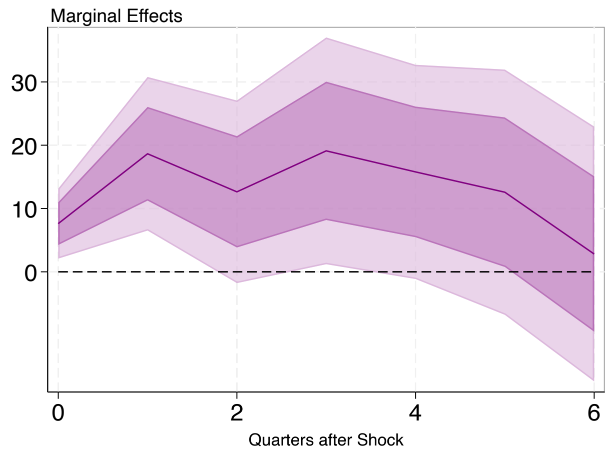



*Note.* Figure B.13 plots the $\beta_1^h$s from a modified regression (7) that uses the h-period log change in firms' debt as the dependent variable and that controls for $\varepsilon_t^m \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.2 apply.

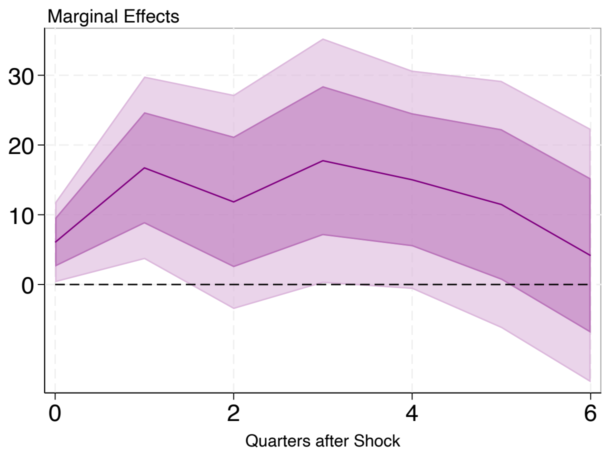
Figure B.14
Horserace Regressions: Relative Response of Low-EBP Firms' Debt Growth to Credit Supply Shock

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


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




(c) Horserace with above $80^{th}$ Perc. Characteristics

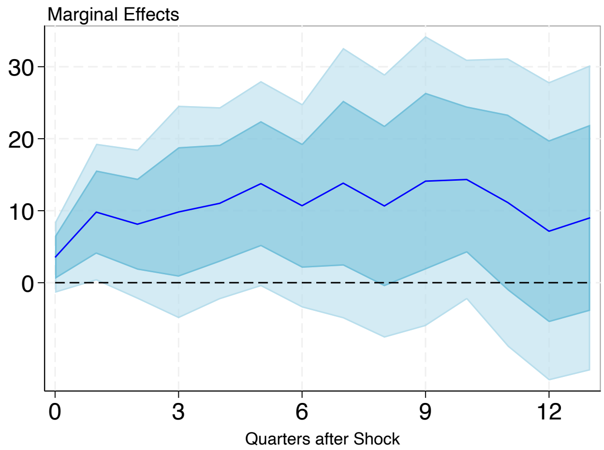



*Note.* Figure B.14 plots the $\beta_1^h$s from a modified regression (9) that uses the h-period log change in firms' debt as the dependent variable and that controls for $\varepsilon_t^{CS} \times \mathbf{1Z}_{it-1}^{low(high)}$, where $\mathbf{1Z}_{it-1}^{low(high)}$ is a vector of indicator variables based on other firm characteristics, namely, distance to default, leverage, credit rating, age, size, sales growth, share of liquid assets, and Tobin's Q. The remaining notes from Figure B.4 apply.

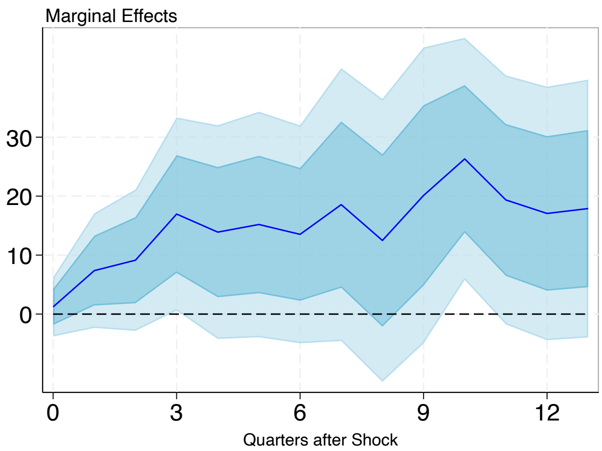
FIGURE B.15

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

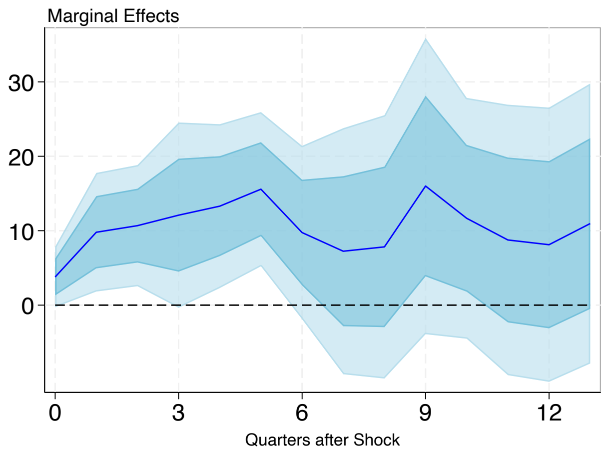
(A) Below $20^{th}$ $EBP_{it-1}$ Percentile



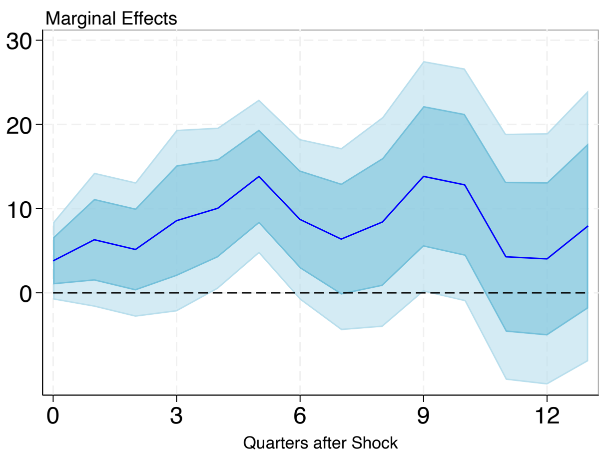

(B) Below $15^{th}$ $EBP_{it-1}$ Percentile



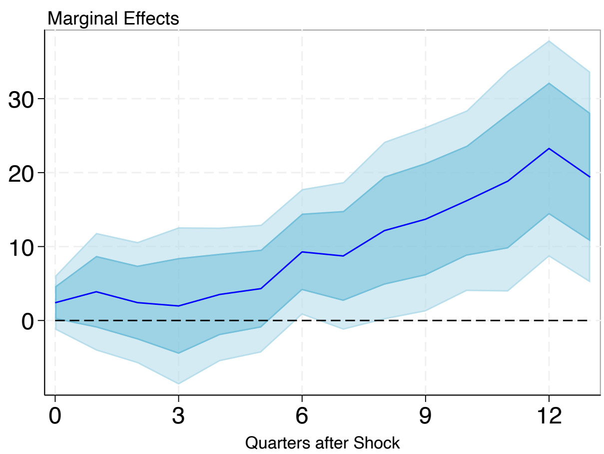

(C) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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

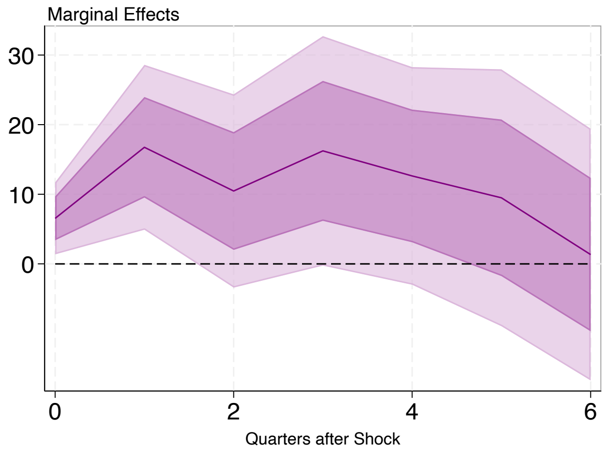



*Note.* Figure B.15 plots the $\beta_1^h$s from a modified regression (7) that uses the h-period log change in firms' debt as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.6 apply.

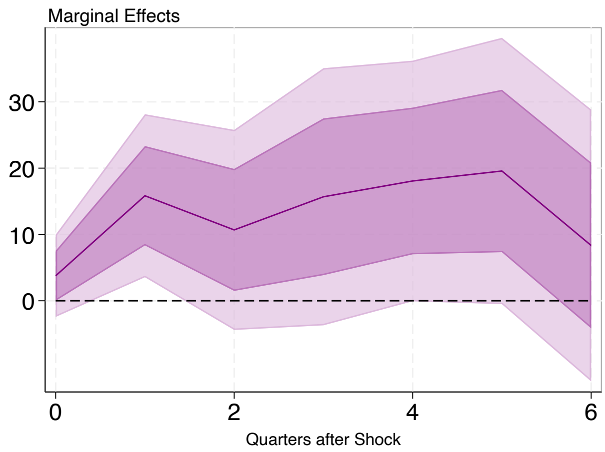
FIGURE B.16

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

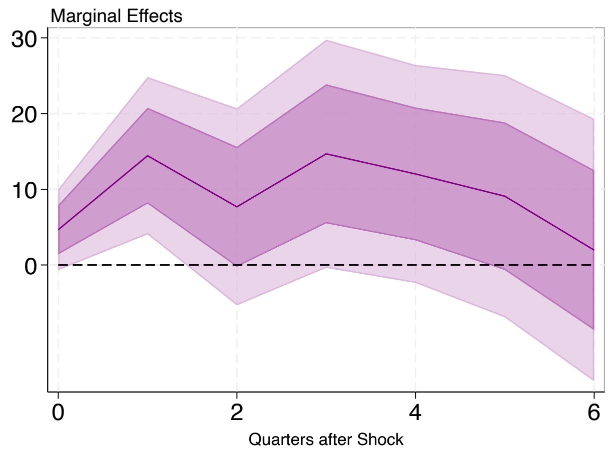
(A) Below $20^{th}$ $EBP_{it-1}$ Percentile



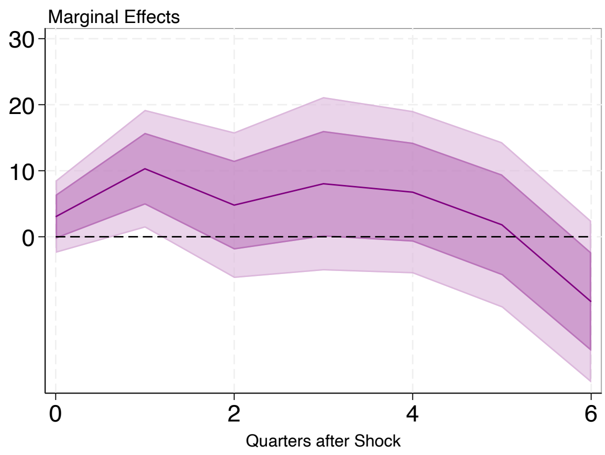

(B) Below $15^{th}$ $EBP_{it-1}$ Percentile



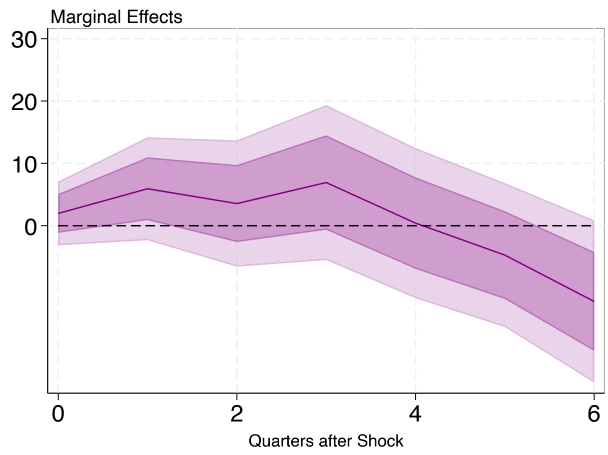

(C) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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




*Note.* Figure B.16 plots the $\beta_1^h$s from a modified regression (9) that uses the h-period log change in firms' debt as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.8 apply.

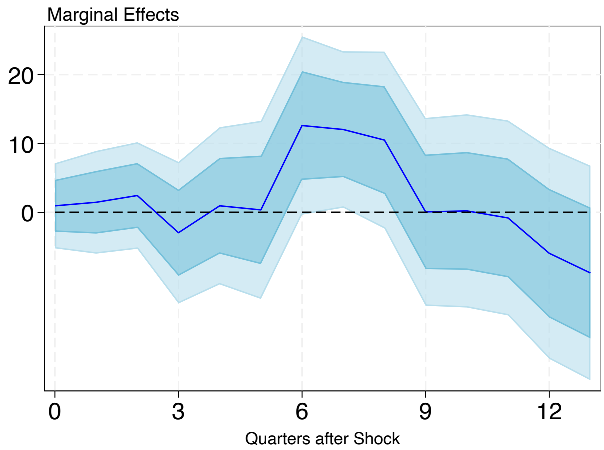
## B.6 Heterogeneous Effects on Firm-Level Sales Growth

In this section, we re-estimate our baseline investment regressions (7) and (9) using as the dependent variable the h-period log change in firms' sales, $\log Sale_{it+h} - \log Sale_{it-1}$. These results are shown in Panel B.17 (monetary policy shock) and B.18 (credit supply shock), respectively, for a variety of percentiles. While there is some evidence that low-EBP firms' sales increase relative to high-EBP firms' following expansionary monetary policy shocks, these effects are significantly smaller in magnitude and much less significant than the results for firms' investment or debt. The results are even weaker for credit supply shocks.

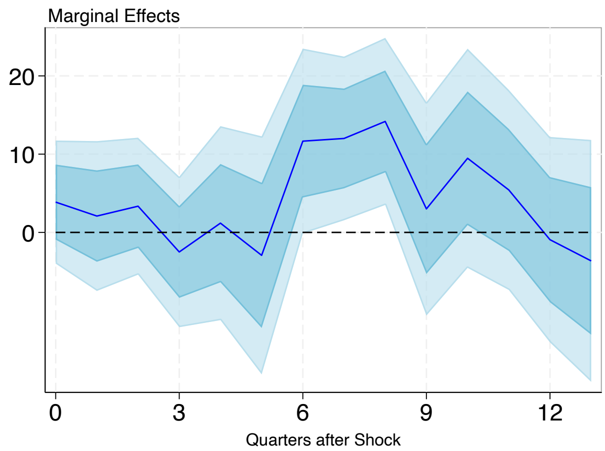
Overall, these findings suggest that the differential transmission of monetary policy to firms' investment conditional on their EBPs does not primarily operate via a differential increase in their sales and cash flows. Through the lens of our model, this suggests that larger shifts in low-EBP firms' marginal benefit curves may play a lesser role than differences in the slopes of their marginal benefit curves around equilibrium in rationalizing our headline empirical results. Specifically, if monetary policy easings significantly increased the demand of low-EBP firms' products–and hence their sales–compared to high-EBP firms', this would differentially increase low-EBP firms' marginal benefit to accumulating capital, which could explain our findings. While these results show there is some evidence of this channel, it cannot explain the majority of our results.

FIGURE B.17
Relative Response of Firm Sales Growth to Monetary Policy Shock by EBP Percentiles

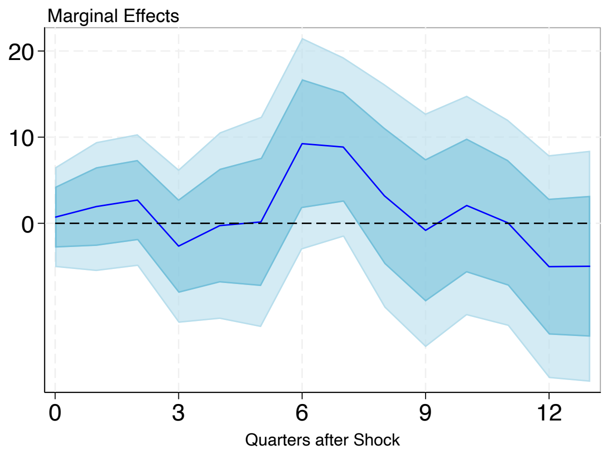
(A) Below $20^{th}$ $EBP_{it-1}$ Percentile



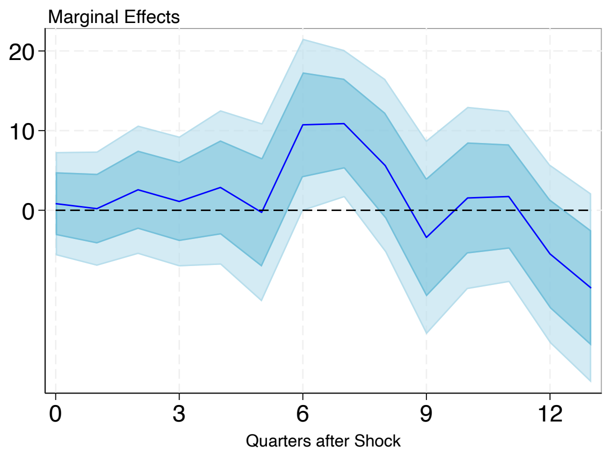

(B) Below $15^{th}$ $EBP_{it-1}$ Percentile



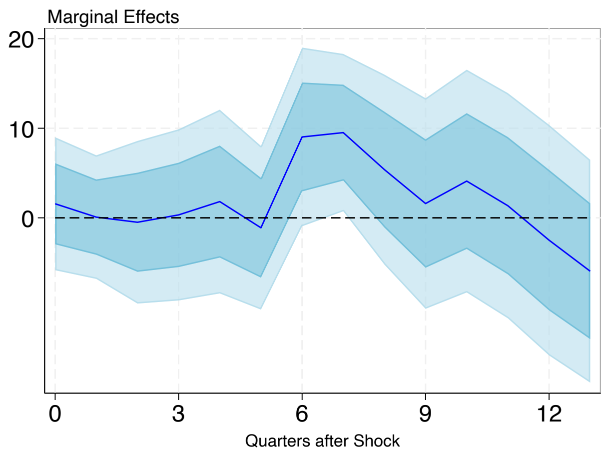

(C) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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

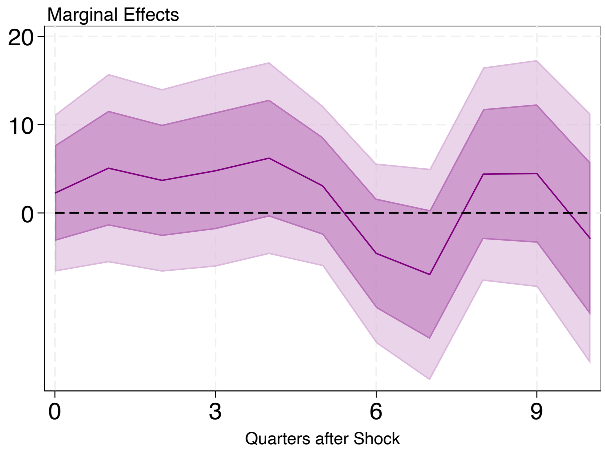



*Note.* Figure B.17 plots the $\beta_1^h$s from a modified regression (7) that uses the h-period log change in firms' sales as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.6 apply.

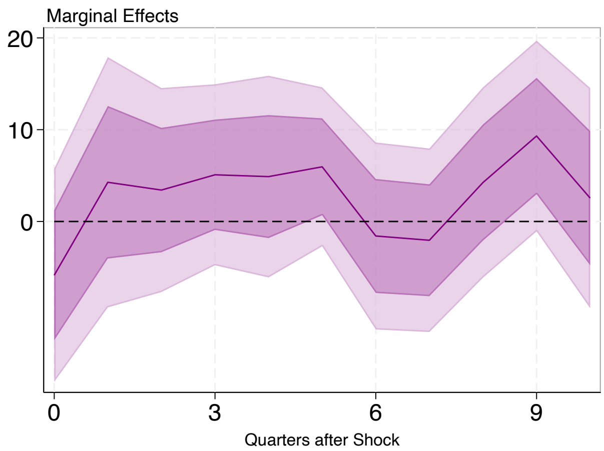
Figure B.18

Relative Response of Firm Sales Growth to Credit Supply Shock by EBP Percentiles

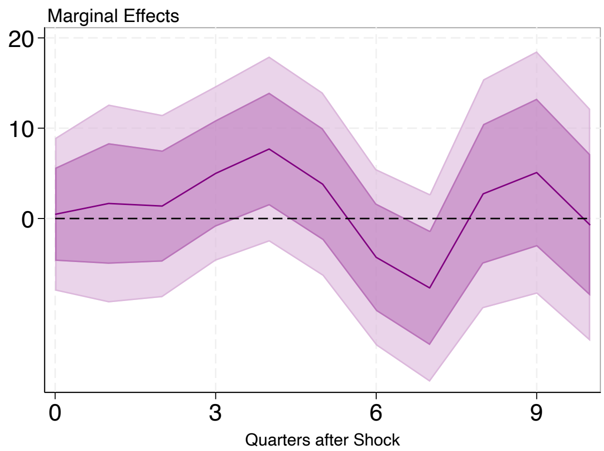
(a) Below $20^{th}$ $EBP_{it-1}$ Percentile



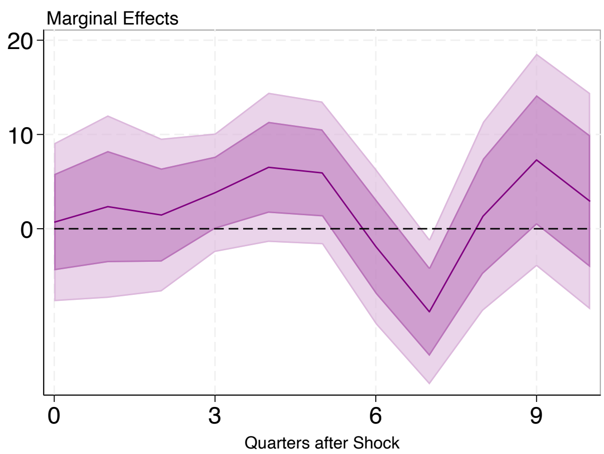

(b) Below $15^{th}$ $EBP_{it-1}$ Percentile



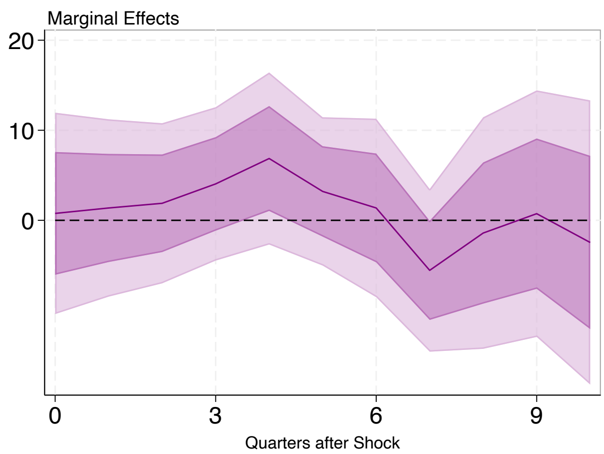

(c) Below $25^{th}$ $EBP_{it-1}$ Percentile




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




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



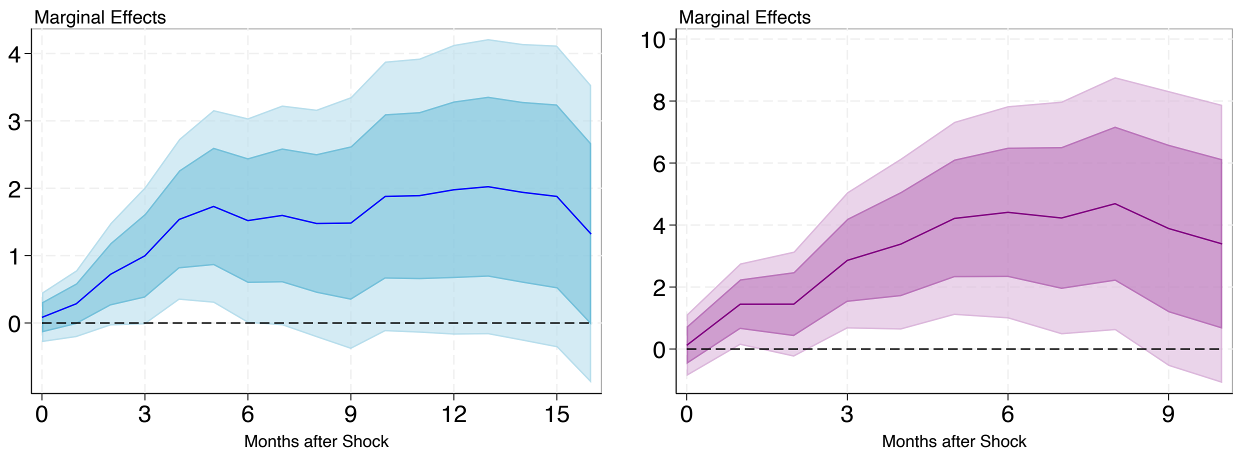

*Note.* Figure B.18 plots the $\beta_1^h$s from a modified regression (9) that uses the h-period log change in firms' sales as dependent variable and uses different percentiles of the EBP distribution to define $\mathbf{1}EBP_{it-1}^{low}$. The remaining notes from Figure B.8 apply.

## B.7 Alternative Credit Spread Specifications

In this section, we present results to 2 adjustments to our baseline credit spread regressions. First, Figure B.19 presents results based on using firm-level average EBPs rather than bond-level EBPs to construct the indicator variable in regressions (5) and (9)—specifically: $\varepsilon_t \times \mathbf{1}EBP^{low}_{it-1}$. This draws a parallel between our investment specification. Figure B.20 instead uses h-period log-change in credit spreads, rather than the raw change, to define the dependent variable—specifically: $log(1+S_{ikt+h}) - log(1+S_{ikt-1})$. This specification, if anything, should dampen our results, since high-EBP firms tend to have higher credit spreads. In both cases, however, the results are similar to those from our baseline specification.

FIGURE B.19
Heterogeneous Effects by EBP on Firm-Level Spreads

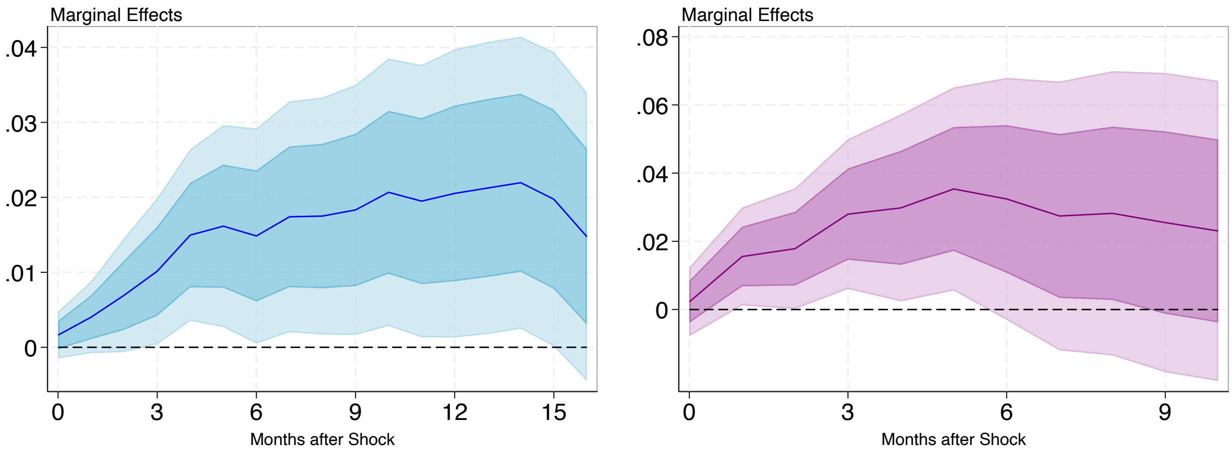
(A) Monetary Policy Shocks (B) Credit Supply Shocks




*Note.* Figure B.19 plots the $\beta_1^h$s from modified regressions (5) and (9), respectively, that use firm-level (average) EBP rather than bond-level EBPs to construct the indicator variable: $\varepsilon_t \times \mathbf{1}EBP^{low}_{it-1}$. The remaining notes from Figures 3 and 5 apply.

Figure B.20
Heterogeneous Effects by EBP on Log(Spreads)

(a) Monetary Policy Shocks (b) Credit Supply Shocks




*Note.* Figure B.20 plots the $\beta_1^h$s from modified regressions (5) and (9), respectively, that uses the log-change in gross credit spreads, rather than the raw change, to define the outcome variable. The remaining notes from Figures 3 and 5 apply.

## B.8 Heterogeneous Effects with Alternative EBP Functional Forms

In this section, we re-estimate our baseline regressions (5), (7) and (9) using alternative functional forms to estimate the heterogeneous effects of monetary policy and credit supply shocks conditional on firms' EBPs. Specifically, we consider 4 functional forms, where $s = \{m, CS\}$: (1) linear interaction between the shock and firms' lagged EBPs ($\varepsilon_t^s \times EBP_{i(k)t-1}$); (2) a linear interaction that isolates for within-firm variation in EBPs à la Ottonello and Winberry (2020) ($\varepsilon_t^s \times (EBP_{i(k)t-1} - \overline{EBP}_{i(k)})$); (3) a modified low-EBP indicator that equals 1 if a firm's EBP, purged of the firm characteristics in $\mathbf{Z}_{it-1}$, is in the bottom quintile of this 'new' EBP distribution, and zero otherwise ($\varepsilon_t^s \times \mathbf{1}\widetilde{EBP\_exChar}^{low}_{i(k)t-1}$) ; and (4) a second modified low-EBP indicator that equals 1 if a firm's EBP, purged of higher-order distance-to-default terms ($DD^2$, $DD^3$ and $DD^4$), is in the bottom quintile of this 'new' EBP distribution, and zero otherwise ($\varepsilon_t^s \times \mathbf{1}\widetilde{EBP\_exDD}^{low}_{i(k)t-1}$).

The results are presented in Figures B.21 and B.22 (monetary policy shock) and Figures B.23 and B.24 (credit supply shock), alongside our baseline interaction coefficients (in Panel (a) of each Figure). Panel (b) in each figure showcases that firms with higher ex-ante EBPs see a greater reduction in their credit spreads and increase investment more following expansionary monetary policy or credit supply shocks.[30] This highlights that our results are generally robust to considering a linear interaction functional form, as opposed to the indicator variable approach we use in our baseline. Panel (c) in each figure shows that our results are significantly driven by within-firm variation, consistent with Ottonello and Winberry (2020). Panel (d) in each figure shows that our results are robust to sorting firms based on an alternative EBP purged of firm characteristics. The similarity of these results to our baseline highlights that the information in firms' EBPs that is relevant for firms' heterogeneous effects of monetary policy and credit supply shocks is distinct from these other firm characteristics. Finally, panel (e) showcases the relative response of low-EBP firms based on EBPs that have additionally been purged of higher-order dependence on firms' distances-to-default. Again, the similarity with our baseline specification shows that our results are not driven by these potential non-linearities, with this alternative EBP

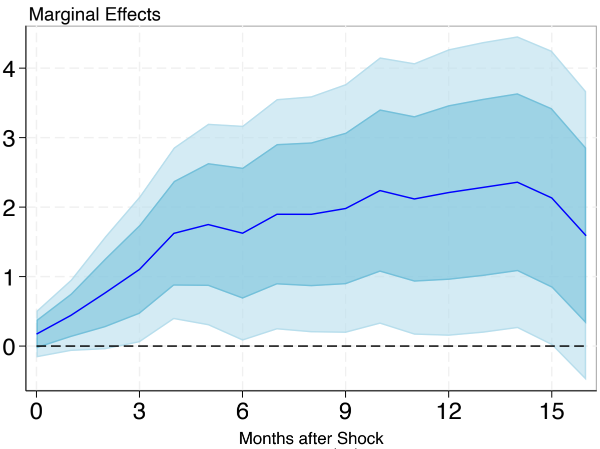
[30] The results in panels (b) and (c) are not statistically significant for the effects of credit supply shocks on credit spreads, although the point estimates are persistently in the right direction.

construction potentially helping to better isolate for the risk-premium component of credit spreads.

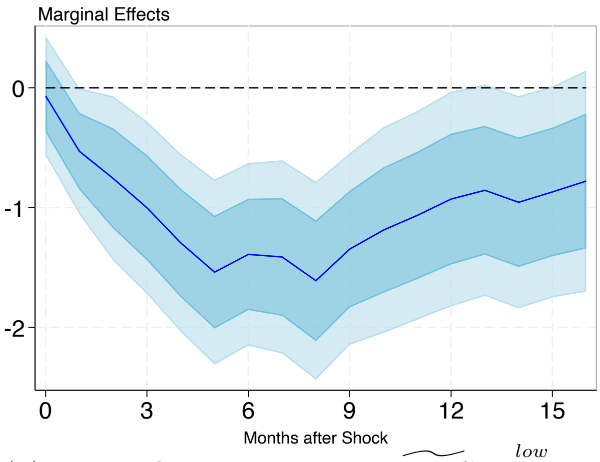
FIGURE B.21

Monetary Policy and Credit Spreads: Alternative EBP Functional Forms

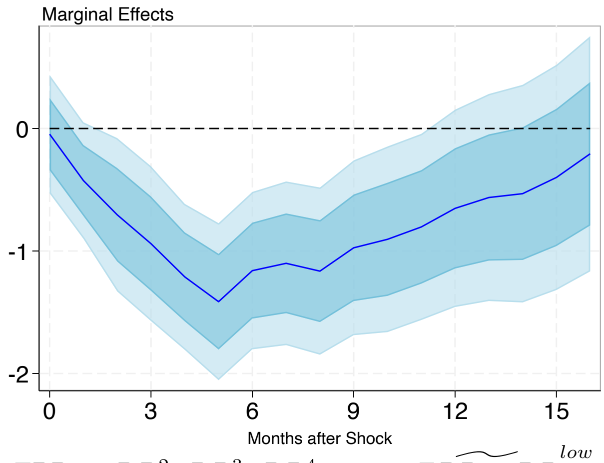
(A) Baseline: $\varepsilon_t^m \times \mathbf{1}EBP_{ikt-1}^{low}$



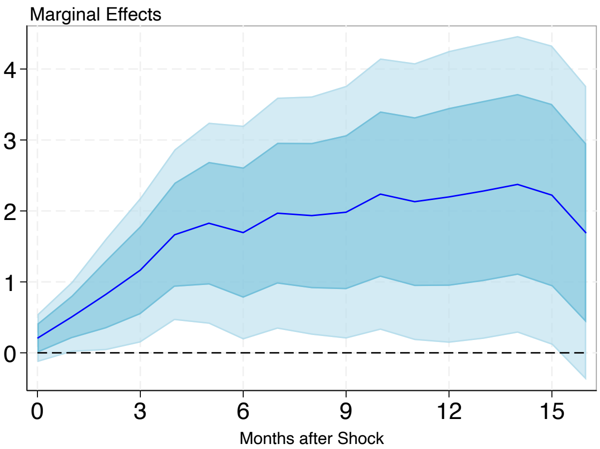

(B) Linear: $\varepsilon_t^m \times EBP_{ikt-1}$



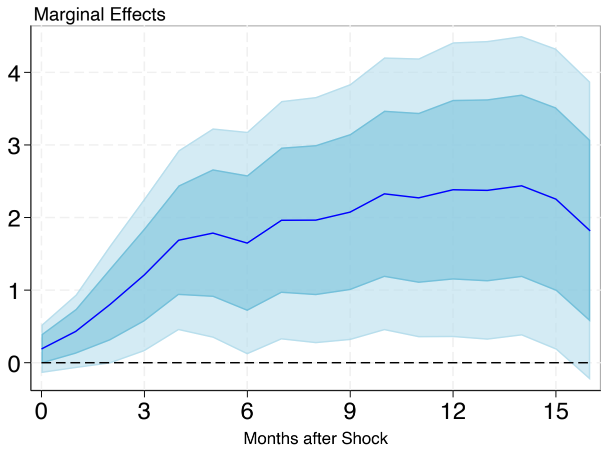

(C) Within-Firm: $\varepsilon_t^m \times (EBP_{ikt-1} - \overline{EBP}_{ik})$




(D) EBP ex-firm char.:$\varepsilon_t^m \times \mathbf{1}\widetilde{EBP\_exChar}_{ikt-1}^{low}$




(E) EBP ex-$DD^2$, $DD^3$, $DD^4$: $\varepsilon_t^m \times \mathbf{1}\widetilde{EBP\_exDD}_{ikt-1}^{low}$

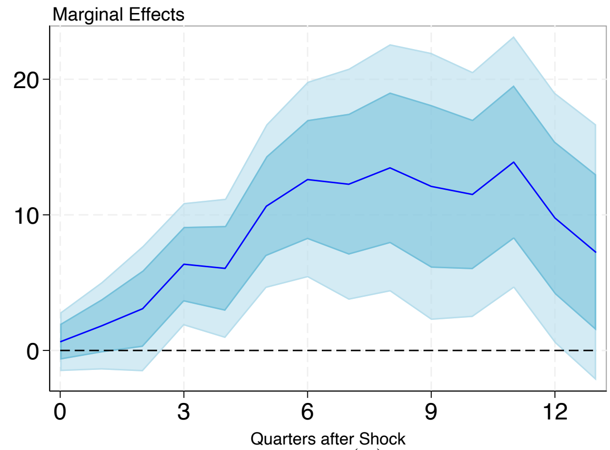



*Note.* Figure B.21 plots the $\beta_1$s from a modified regression (5) that uses different functional forms for the EBP interaction term. Panel B.21a presents the baseline result (from Figure 3b). Panel B.21b uses a linear interaction; panel B.21c uses a within-firm linear interaction as in Ottonello and Winberry (2020); Panel B.21d presents the relative response of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Panel B.21e uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. The remaining notes from Figure 3 apply.

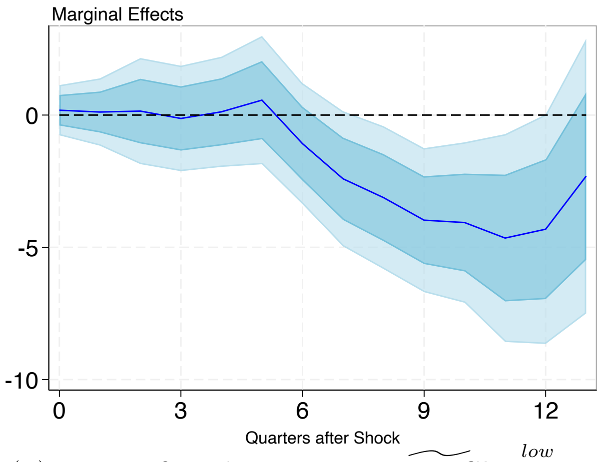
Figure B.22

Monetary Policy and Investment: Alternative EBP Functional Forms

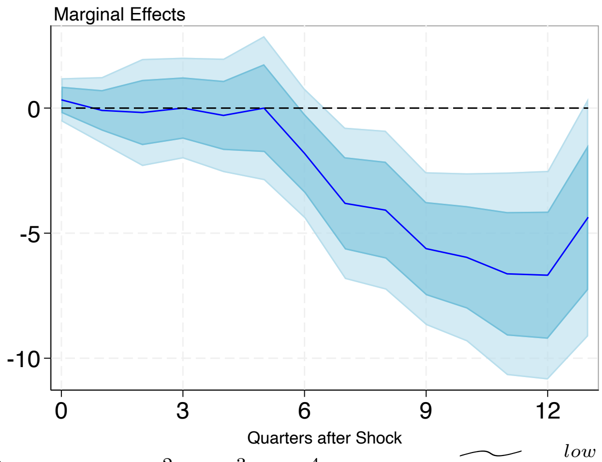
(a) Baseline: $\varepsilon_t^m \times \mathbf{1}EBP_{it-1}^{low}$



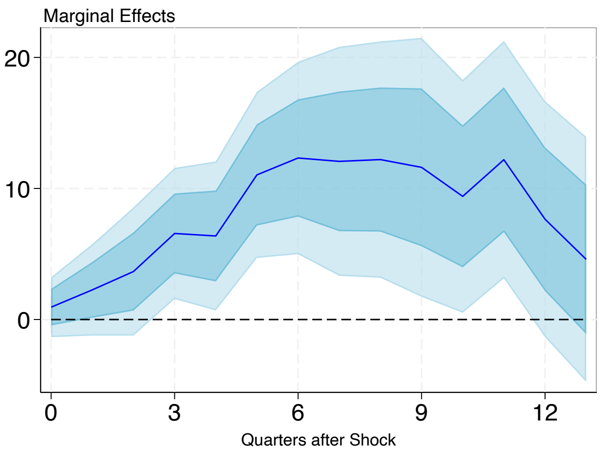

(b) Linear: $\varepsilon_t^m \times EBP_{it-1}$



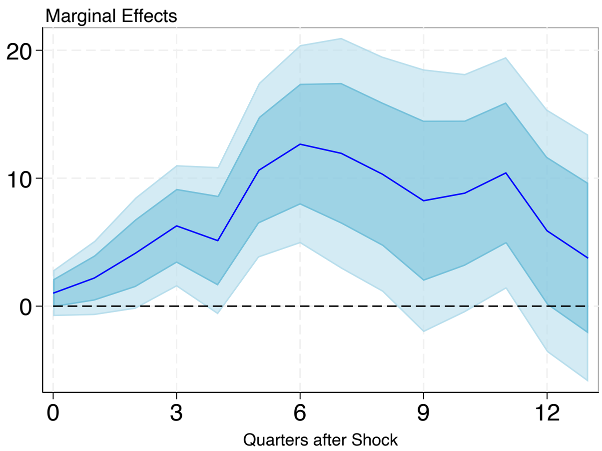

(c) Within-Firm: $\varepsilon_t^m \times (EBP_{it-1} - \overline{EBP}_i)$




(d) EBP ex-firm char.:$\varepsilon_t^m \times \mathbf{1}\widetilde{EBP\_exChar}_{it-1}^{low}$




(e) EBP ex-$DD^2$, $DD^3$, $DD^4$: $\varepsilon_t^m \times \mathbf{1}\widetilde{EBP\_exDD}_{it-1}^{low}$

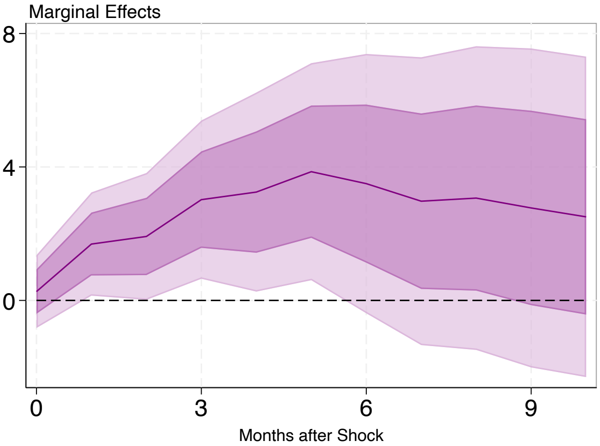



*Note.* Figure B.22 plots the $\beta_1$s from a modified regression (7) that uses different functional forms for the EBP interaction term. Panel B.22a presents the baseline result (from Figure 4b). Panel B.22b uses a linear interaction; panel B.22c uses a within-firm linear interaction as in Ottonello and Winberry (2020); Panel B.22d presents the relative response of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Panel B.22e uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. The remaining notes from Figure 4 apply.

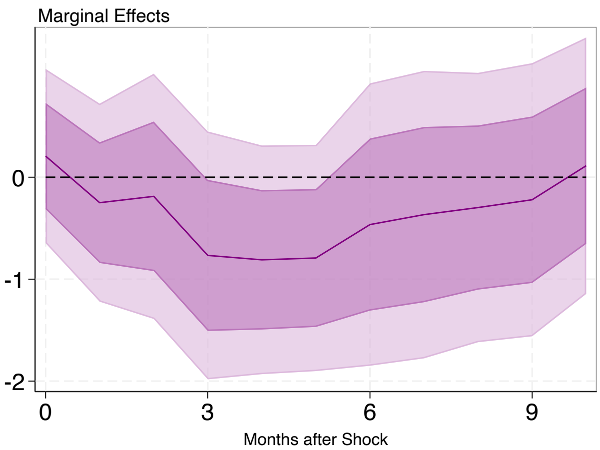
Figure B.23

Credit Supply Shocks and Credit Spreads: Alternative EBP Functional Forms

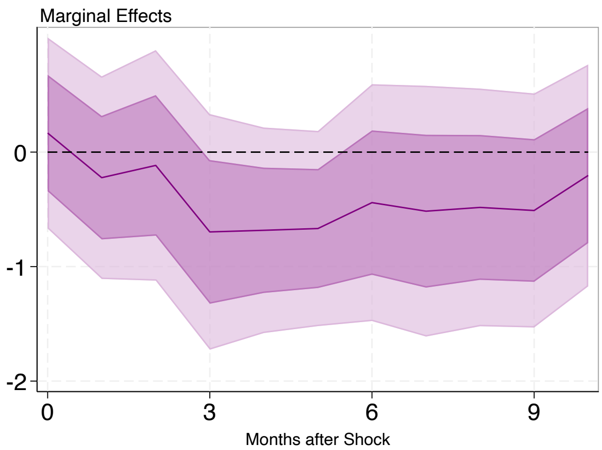
(a) Baseline: $\varepsilon_t^{CS} \times \mathbf{1}EBP_{ikt-1}^{low}$



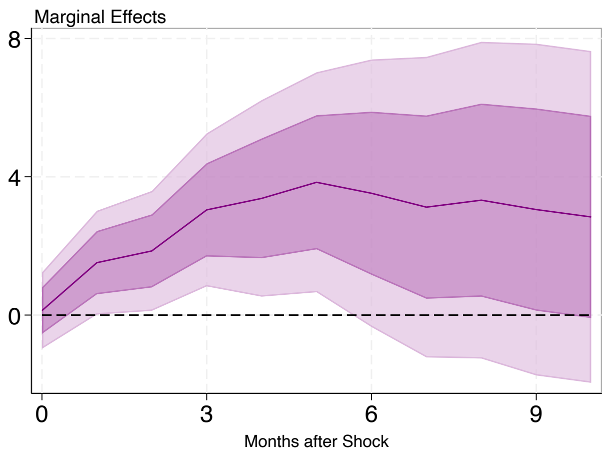

(b) Linear: $\varepsilon_t^{CS} \times EBP_{ikt-1}$



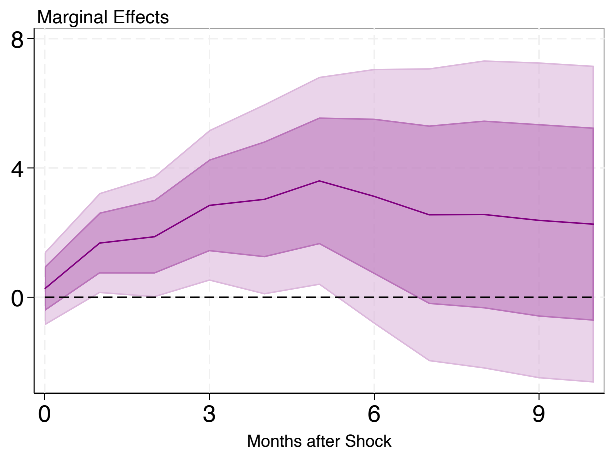

(c) Within-Firm: $\varepsilon_t^{CS} \times (EBP_{ikt-1} - \overline{EBP}_{ik})$




(d) EBP ex-firm char.: $\varepsilon_t^{CS} \times \mathbf{1}\widetilde{EBP\_exChar}_{ikt-1}^{low}$




(e) EBP ex-$DD^2$, $DD^3$, $DD^4$: $\varepsilon_t^{CS} \times \mathbf{1}\widetilde{EBP\_exDD}_{ikt-1}^{low}$

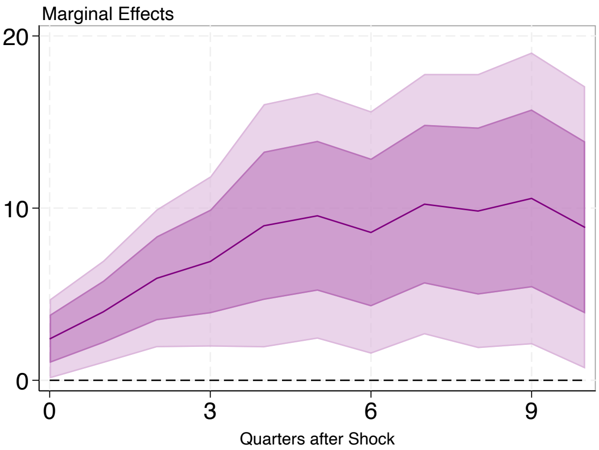



*Note.* Figure B.23 plots the $\beta_1$s from a modified regression (9) that uses different functional forms for the EBP interaction term. Panel B.23a presents the baseline result (from Figure 5). Panel B.23b uses a linear interaction; panel B.23c uses a within-firm linear interaction as in Ottonello and Winberry (2020); Panel B.23d presents the relative response of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Panel B.23e uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. The remaining notes from Figure 5 apply.

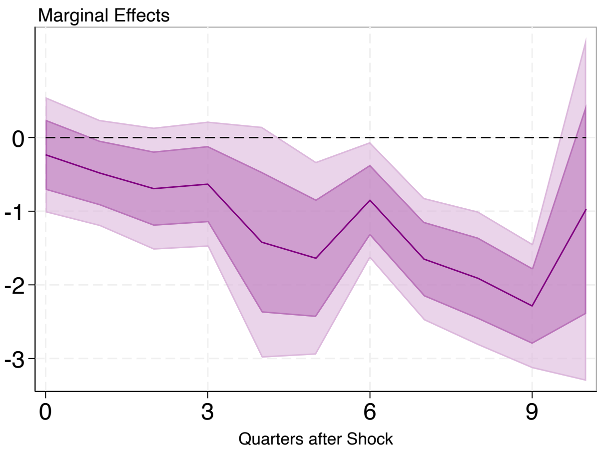
FIGURE B.24

Credit Supply Shocks and Investment: Alternative EBP Functional Forms

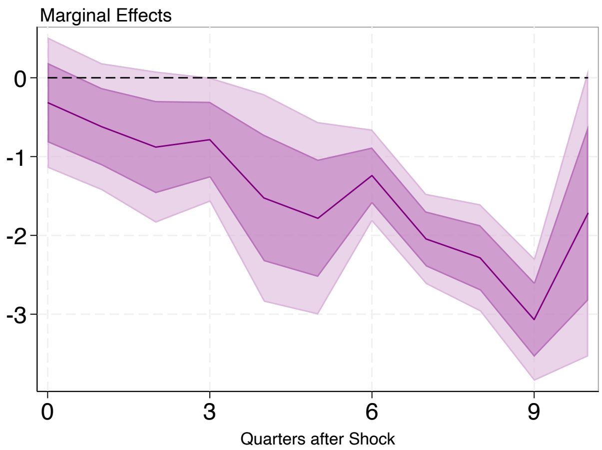
(A) Baseline: $\varepsilon_t^{CS} \times \mathbf{1}EBP_{it-1}^{low}$



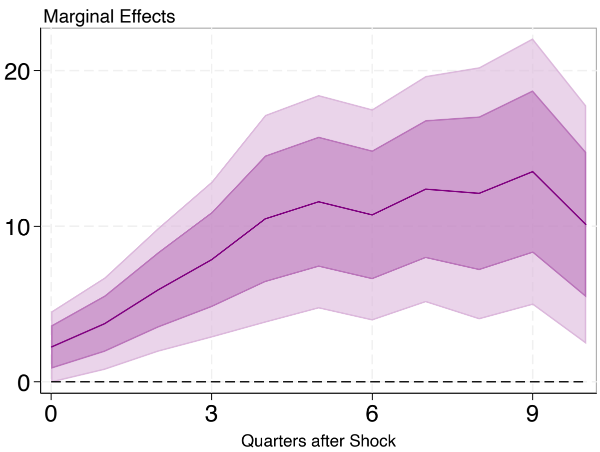

(B) Linear: $\varepsilon_t^{CS} \times EBP_{it-1}$



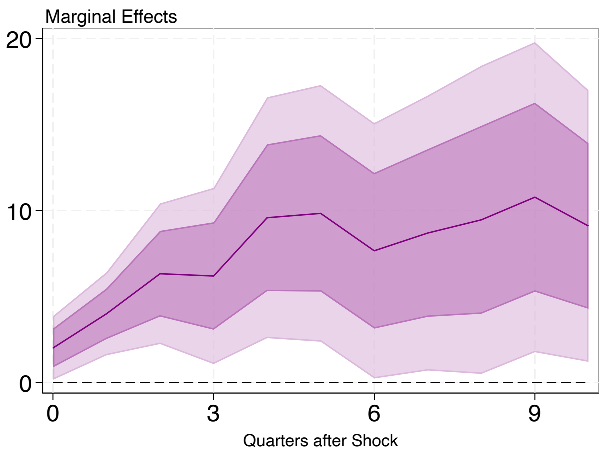

(C) Within-Firm: $\varepsilon_t^{CS} \times (EBP_{it-1} - \overline{EBP}_i)$




(D) EBP ex-firm char.: $\varepsilon_t^{CS} \times \mathbf{1}\widetilde{EBP\_exChar}_{it-1}^{low}$




(E) EBP ex-$DD^2$, $DD^3$, $DD^4$: $\varepsilon_t^{CS} \times \mathbf{1}\widetilde{EBP\_exDD}_{it-1}^{low}$




*Note.* Figure B.24 plots the $\beta_1$s from a modified regression (9) that uses different functional forms for the EBP interaction term. Panel B.24a presents the baseline result (from Figure 5). Panel B.24b uses a linear interaction; panel B.24c uses a within-firm linear interaction as in Ottonello and Winberry (2020); Panel B.24d presents the relative response of firms whose EBPs purged of the firm characteristics in $\mathbf{Z}_{it-1}$ are in the bottom quintile of the distribution; and Panel B.24e uses an alternative EBP that has purged spreads of non-linear distance-to-default terms to construct the low-EBP indicator. The remaining notes from Figure 5 apply.

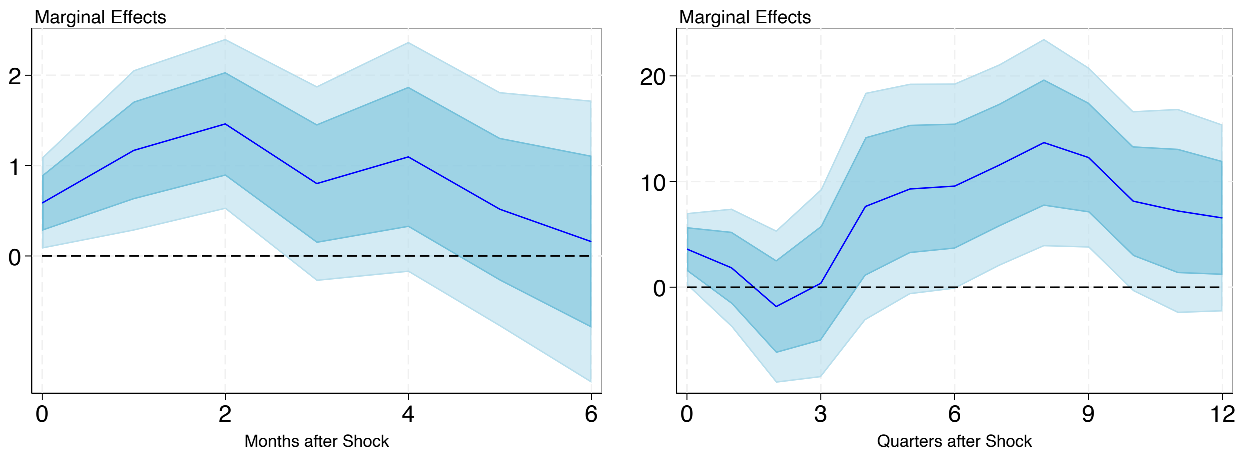
## B.9 Heterogeneous Effects with Alternative Monetary Policy Shocks

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

The results for credit spreads—which come from re-estimating regression (5) with the FF0 shock—and for investment—which come from re-estimating regression (7) with the FF0 shock—are displayed in Figure B.25, 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.25a), although these low-EBP firms invest relatively more than high-EBP firms (Panel B.25b). Further, as in the main text, the impulse responses are hump shaped and are of a comparable magnitude.

FIGURE B.25
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



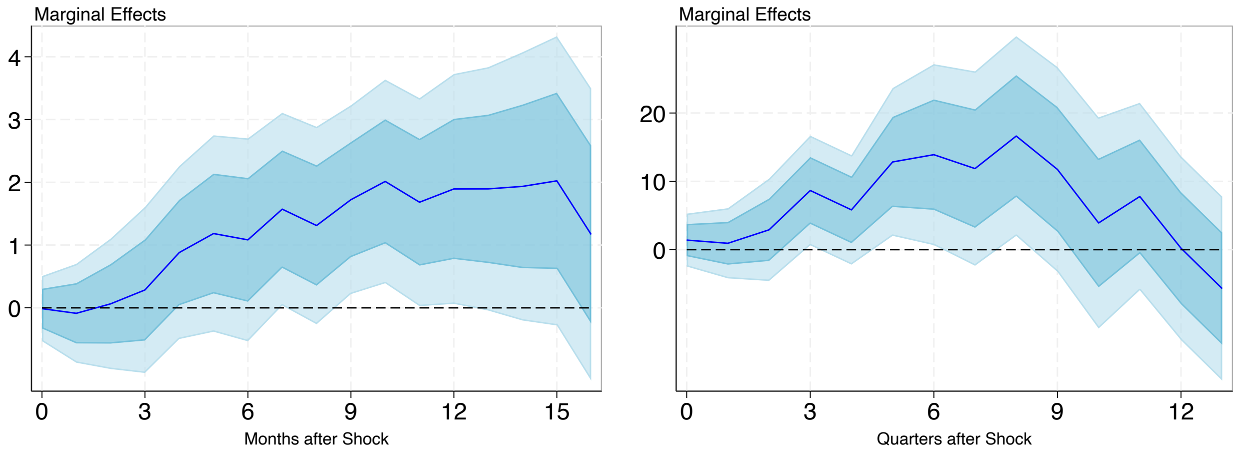

*Note.* Figure B.25 reports the dynamic responses of bond-level credit spreads and firm-level investment to high-frequency FF0 monetary policy shocks, as calculated by Acosta and Saia (2020) and Nakamura and Steinsson (2018). Panel B.25a plots the $\beta_1^h$s from regressions (5) with the FF0 shocks, 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.25b plots the $\beta_1^h$s from regressions (7) 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.10 Monetary Policy's Effects ex. Zero-lower-bound Period

In this section, we re-estimate our baseline regressions from Section excluding the zero-lower-bound periods (2009-2015 and 2020-2021). This aligns with the timing studied in Ottonello and Winberry (2020). The results are presented in Figure B.26 and highlight very similar results to our full-sample baseline: low-EBP firms' spreads decline less following a monetary easing, whereas they increase their investment by relatively more.

FIGURE B.26
Response of Firms' Spreads & Investment to Monetary Policy Shocks excluding ZLB period

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




*Note.* Figure B.26 reports the dynamic responses of bond-level credit spreads (Panel a) and firm-level investment (Panel b) to our baseline monetary policy shock series (Bu et al. (2021)) excluding the zero-lower-bound periods (2009-2015 and 2020-2021). The remaining notes from Figures 3 and 4, respectively, apply.

## B.11 Robustness: Aggregate Implications of EBP Heterogeneity

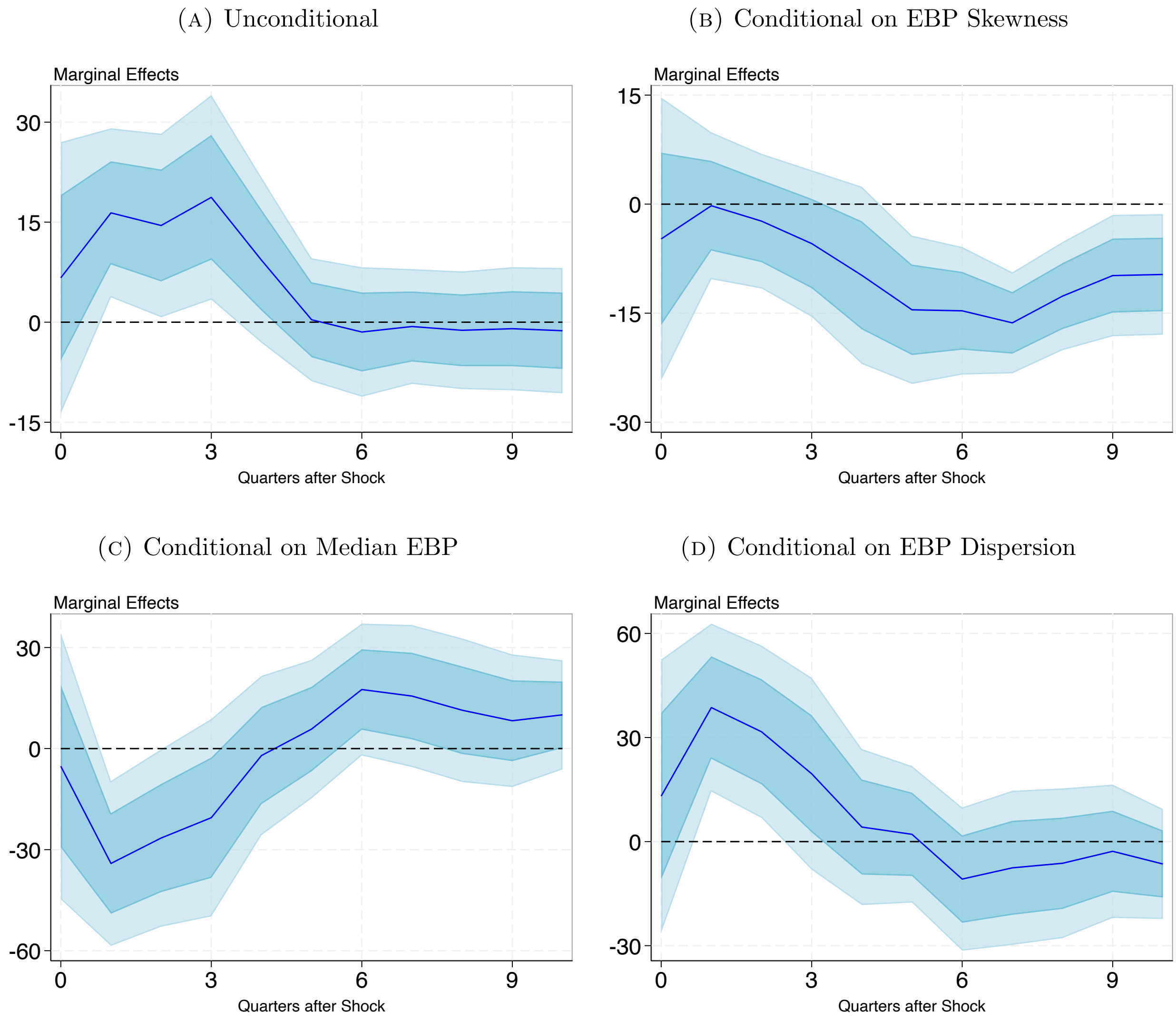
In this section, we show that our results from Section 7, where we documented that the cross-sectional EBP distribution is an important empirical driver of the aggregate effectiveness of monetary policy, are robust to a horserace with monetary policy's interaction with various recession indicators, as well as to using the mean rather than median of the EBP distribution.

First, 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 (14) from the main text.

The results are displayed in Figures B.27 and B.28, respectively. We find that the conditioning power of EBP skewness is unaffected by including the recession indicator interactions, with a right-skewing of the EBP distribution associated with a dampening of the effects of monetary policy shocks on aggregate investment growth. Interestingly, the results for the conditioning power of the median and dispersion of the EBP distribution are weakened when accounting for the well-documented weaker effects of monetary policy in recessions (Tenreyro and Thwaites (2016)), although they are still significant at some horizons. Overall, our findings highlight that the importance of the skewness of the EBP distribution for monetary policy's aggregate potency holds both in and out of recessions.

Second, we re-estimate our baseline specification but replace the interaction between the monetary policy shock and the median EBP with one using the mean EBP (and same for the predicted spread). The results are presented in Figure B.29, and reveal very similar results to our baseline specification.

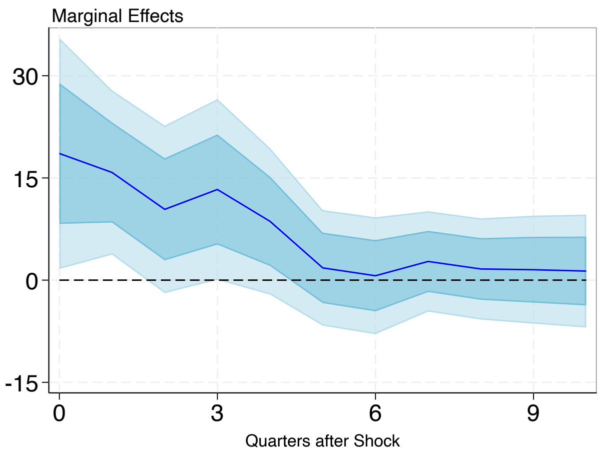
Figure B.27
Monetary Policy's Effect on Aggregate Investment Growth:
Horserace between EBP moments and Recession Probability Variable



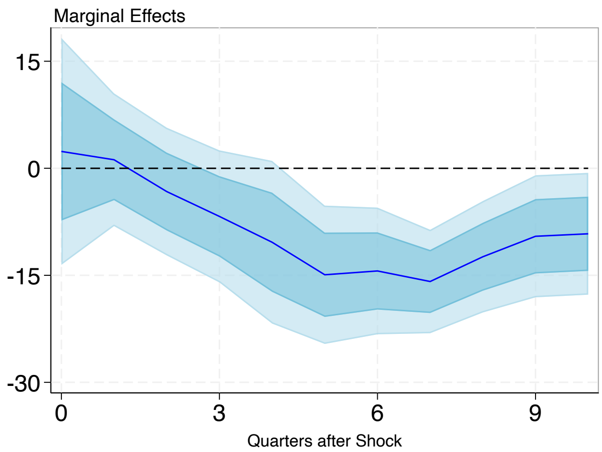

*Note.* Figure B.27 reports the regression results from estimating a modified regression (14) that includes the interaction between the monetary policy shock and the Chauvet (1998) recession probability variable. Panel B.27a shows unconditional effects, $\beta_1^h$. Panels B.27b, B.29c and B.29d show the effects conditional on the skewness, median and dispersion of the EBP distribution, measured in standard deviations, which are three of the elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

FIGURE B.28
Monetary Policy's Effect on Aggregate Investment Growth
Horserace between EBP moments and NBER Recession Indicator

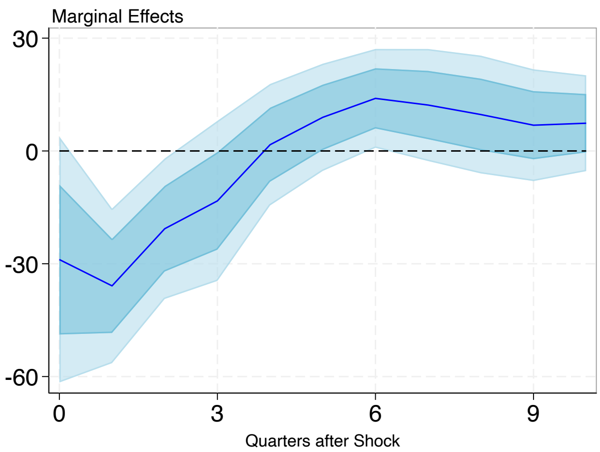
(A) Unconditional



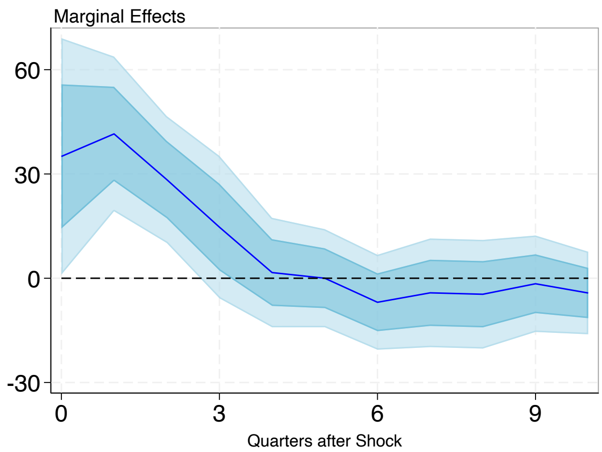

(B) Conditional on EBP Skewness




(C) Conditional on Median EBP

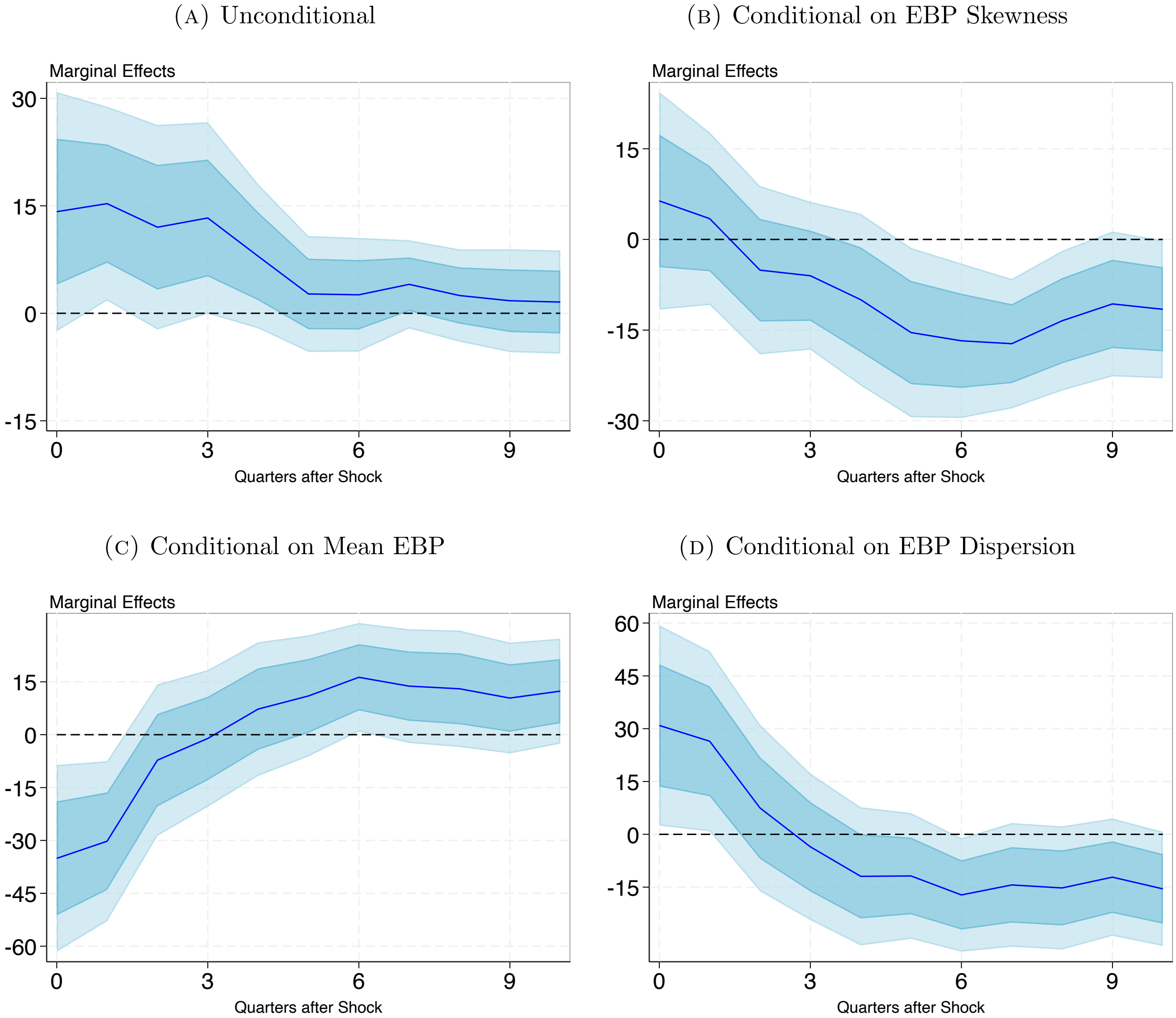



(D) Conditional on EBP Dispersion




*Note.* Figure B.28 reports the regression results from estimating a modified regression (14) that includes the interaction between the monetary policy shock and the NBER-recession indicator variable. Panel B.28a shows unconditional effects, $\beta_1^h$. Panels B.28b, B.28c and B.28d show the effects conditional on the skewness, median and dispersion of the EBP distribution, measured in standard deviations, which are three of the elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

Figure B.29
Monetary Policy's Effect on Aggregate Investment Growth:
Mean in lieu of Median EBP




(a) Unconditional

(b) Conditional on EBP Skewness

(c) Conditional on Mean EBP

(d) Conditional on EBP Dispersion

*Note.* Figure B.29 reports the regression results from estimating a modified regression (14) that includes the interaction between the monetary policy shock and the mean EBP in lieu of the median EBP. Panel B.27a shows unconditional effects, $\beta_1^h$. Panels B.27b, B.29c and B.29d show the effects conditional on the skewness, mean and dispersion of the EBP distribution, measured in standard deviations, which are the three elements in $\boldsymbol{\beta}_2^h$. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

# C Model Appendix

## C.1 Model Parameterization

In this section, we discuss the parameterization we use for the model in Section 6. We stress that the model is not designed to quantitatively match our empirical results. Instead, our aim is to use a stylized supply-demand model of capital markets that can transparently illustrate different transmission mechanisms—shifts and tilts in the supply and demand curves—and discipline the relative sizes of these shifts and tilts so as to qualitatively match the heterogeneous effects we document in the data. The below parameterization offers one example.

TABLE C.1
Model Parameterization

| **Parameter** | **Value** | **Description** |
|---|---|---|
| $\overline{p} \cdot \overline{\mu}$ | 0.012 | Expected Default Loss (excluding covariance) |
| $\rho_L$ | 0 | Covariance between $p$ and $\mu$ for Low-EBP firm |
| $\rho_H$ | 0.047 | Covariance between $p$ and $\mu$ for High-EBP firm |
| $\alpha$ | 0.97 | Firm Capital Elasticity |
| $\overline{z}$ | 1.012 | Expected Productivity |
| $\theta$ | 0.08 | Intermediary Agency Friction Parameter |
| $N_1$ | 0.0003 | Intermediary Net-Worth Pre-Shock |
| $N_2$ | 0.0008 | Intermediary Net-Worth Post-Shock |
| $R_1$ | 1.06 | Interest Rate Pre-Shock |
| $R_2$ | 1.05 | Interest Rate Post-Shock |

Table C.1 presents our model's parameterization. The first parameter is the 'risk-neutral' expected default loss on firms' debt, $\overline{p} \cdot \overline{\mu}$, which we set to 1.20%.[31] This is between the range of values used in Ottonello and Winberry (2020) (1.38%, the product of a 3% default rate and a 46% loss share) and the average corporate credit-loss rate in Emery et al. (2009) (0.91%). Next, we turn to the covariance between firms' probability of default and the default loss share $\rho$. We normalize this covariance to be 0 ($\rho_L = 0$) for the less cyclical

[31]The model does not require us to individually specify firms' expected default probability $\overline{p}$ and firms' expected loss share given default $\overline{\mu}$. There are many potential decompositions of $\overline{p} \cdot \overline{\mu}$ consistent with a well-defined joint distribution of $p$ and $\mu$.

firm and set the covariance to be 0.047 ($\rho_H = 0.047$) for the more cyclical firm. Thus, while the expected loss share for low-EBP firms remains 1.2%, the loss share inclusive of this covariance rises to 5.9% for high-EBP firms. Given the other parameters of the model, this covariance differential allows us to match that low-EBP (i.e., firms in the bottom quintile of the cross-sectional EBP distribution) firms have on-average about a 1.8pp lower EBP than high-EBP firms do. Of course, differences in EBPs across firms are not solely driven by $\rho$, but using default-risk cyclicality can serve as a stand-in for various premia and convenience yields as shown in Appendix C.2. However, it requires a large quantity of default risk cyclicality to achieve it.

Turning to the production function parameters, we set $\alpha = 0.97$, in line with the parameterization in Anderson and Cesa-Bianchi (2024), which ensures, given the other model parameters, that low-EBP firms sit on materially flatter segments of their MB curves in equilibrium compared to high-EBP firms. We set expected productivity to be 1.2% ($\overline{z} = 1.012$), similar to the average value of TFP growth according to Fernald (2014). In addition, we set the fraction of intermediaries' revenue that they can abscond with to 8% ($\theta = 0.08$), also similar to the value used in Anderson and Cesa-Bianchi (2024).

Finally, we turn to the parameters that we use for the comparative statics. On the demand side, we study a 1pp reduction in the risk-free benchmark rate from $R_1 = 1.06$ to $R_2 = 1.05$—with these values bracketing the average 10Y U.S. Treasury yield over our sample. On the supply side, motivated by the financial accelerator mechanism of monetary policy transmission, we study an increase in intermediary net worth from $N_1 = 0.0003$ to $N_2 = 0.0008$ for intermediaries on both islands.[32] Crucially, the increase in net worth is large enough relative to the reduction in the risk-free rate so that firms' credit spreads decline when changes in $N$ and $R$ are studied in the model together, in line with the empirical evidence. This, in turn, allows us to match the heterogeneous effects of monetary policy and credit supply shocks as well.

[32]These *levels* of intermediary net worth ensure that equilibria occur along the upward sloping region of firms' MC curves. They are consistent with a leverage (debt/asset) ratio for the financial intermediaries of between $92\% - 97\%$ in equilibrium.

## C.2 Model Extensions

In Section 6.1, we outlined a stylized model featuring risk-neutral intermediaries, idiosyncratic firm default risk, and aggregate risk in the form of a state-dependent loss share given default. In this appendix, we extend the model along three dimensions. First (i), we show that the model with a state-dependent loss share given default and risk-neutral intermediaries is isomorphic to one with a constant loss share and risk-averse intermediaries that price firms' debt. Second (ii), we generalize idiosyncratic risk in the model to go beyond firm default risk. Third (iii), we show how non-pecuniary convenience yields, i.e., compensation/discounts uncorrelated with aggregate risk/intermediaries' stochastic discount factor (SDF) can be mapped into the model. Altogether, these generalizations show how firms' EBPs can reflect multidimensional borrowing premia in the model, and that these premia and convenience yields affect firms' MC curves similarly to how default-risk cyclicality does in the main text.

Beginning with (i), assume that the loss share is no-longer state contingent, and is given by $\overline{\mu}$, and define the intermediaries' stochastic discount factor as:

$$M \equiv \frac{\mu}{\overline{\mu}}, \qquad M \geq 0, \qquad \mathbb{E}[M] = 1, \tag{C.1}$$

where $\mu$ is a relabeled version of the earlier aggregate state that takes on higher values when intermediaries value returns more, e.g., when their equity capital is low, as in the intermediary asset pricing literature (e.g., He and Krishnamurthy, 2013).[33] As before, $\mu$ and $p_j$ are drawn from a joint probability distribution $F_j(p_j, \mu)$ that carries the covariance $\rho_j$.

The expected discount on the return $R^k$ per unit of capital $K$ that intermediaries require given $M$ is then:

$$\mathbb{E}[M(1 - p_j\overline{\mu})] = \mathbb{E}[M] - \overline{\mu}\mathbb{E}[Mp_j] = 1 - \overline{\mu}[\overline{p} + Cov(M, p_j)] = 1 - \overline{p\mu} - \rho_j. \tag{C.2}$$

Since the deposit side of the intermediaries' problem $R(K_j - N)$ is non-stochastic, these

[33] The normalization $\mathbb{E}[M] = 1$ implies that riskless payoffs are priced at face value.

risk-averse intermediaries' problem with a constant loss share in default is identical to the one given by equations (11) and (12) in Section 6.1, and yields therefore the same marginal cost curve as given in equation (13). Specifically, define $V_j \equiv 1 - \overline{p\mu} - \rho_j$, then the intermediaries' problem becomes:

$$\max_{K_j} V_j R_j^K K_j - R(K_j - N) \quad \text{s.t.} \quad (1-\theta) V_j R_j^K K_j \geq R(K_j - N), \tag{C.3}$$

which gives the marginal cost curve:

$$\frac{R_j^K}{R} = \begin{cases} \frac{1}{V_j} & K_j < \frac{N}{\theta} \\ \frac{1}{V_j} \frac{K_j - N}{K_j(1-\theta)} & K_j \geq \frac{N}{\theta}, \end{cases} \tag{C.4}$$

Thus, firms whose default risks are higher in states where intermediaries value returns more highly $\rho_j \uparrow \implies V_j \downarrow$ have upward shifted and steeper MC curves, reproducing the result from the main text with the same exact functional form.

Next, we move to (ii) and consider generalized premia beyond simply firm default risk. To begin, notice that the expected discount in equation (C.2) can be rewritten in the generalized form:

$$\mathbb{E}[M(1 - l_j)] = 1 - \mathbb{E}[l_j] - Cov(M, l_j) \tag{C.5}$$

where $l_j$ is any idiosyncratic cost borne by intermediaries when investing in firms' debt that covaries with intermediaries' SDF and hence the aggregate state. In the baseline (C.2), this loss is the probability of default times the loss given default: $l_j = p_j \overline{\mu}$. In practice, intermediaries may price an array of state-dependent costs when investing, beyond vanilla default risk—e.g., fire-sale/liquidation costs in the event that intermediaries need to sell firms' debt to meet some obligations in adverse states. Thus, let $l_j \equiv \sum\limits_k l_{jk}$ where each $l_{jk}$ is a distinct source of risk for intermediaries when investing in island-$j$ debt. In this case,

$$V_j^l \equiv \mathbb{E}[M(1 - l_j)] = 1 - \sum_k \mathbb{E}[l_{jk}] - \sum_k Cov(M, l_{jk}) \tag{C.6}$$

and a generalized marginal cost curve for an arbitrary set of priced risk factors:

$$\frac{R_j^K}{R} = \begin{cases} \frac{1}{V_j^l} & K_j < \frac{N}{\theta} \\ \frac{1}{V_j^l} \frac{K_j - N}{K_j(1-\theta)} & K_j \geq \frac{N}{\theta}. \end{cases} \tag{C.7}$$

Importantly, this marginal cost curve has the same structure as the one in the main text, highlighting how different risk factors beyond firm default risk can be summarized into the same MC curve faced by firms. Thus, while EBPs will likely embed many sources of premia, focusing on firms' default risk cyclicality in the main text allows us to cleanly study monetary policy transmission in our capital supply and demand framework without loss of generality.

Finally, we turn to (iii), where we allow intermediaries to have a 'taste' or 'preference' for a firms' debt that does not co-vary with its SDF $M$. If these tastes can be expressed per unit of return $R^k$, then the covariance term simply drops out of (C.5), but there is not change to the structure of the MC curve. Often, however, such tastes—i.e., non-pecuniary convenience yields due to, e.g., relationships or mandates—are expressed per unit of capital. In this case, the generalized version of the intermediaries' problem in (C.3) becomes:

$$\max_{K_j} \; V_j R_j^K K_j + \delta_j K_j - R(K_j - N) \quad \text{s.t.} \quad (1-\theta) V_j R_j^K K_j + \delta_j K_j \geq R(K_j - N), \tag{C.8}$$

where $\delta_j K_j$ is the non-pecuniary benefit intermediaries earn from investing $K_j$ in island-$j$ debt, which we have assumed is non-divertable.[34] In this case, the marginal cost curve becomes:

$$\frac{R_j^K}{R} = \begin{cases} \frac{1}{V_j^l} \frac{1-\delta_j}{R} & K_j < \frac{N}{\theta} \frac{1}{1-\delta_j/R} \\ \frac{1}{V_j^l(1-\theta)} \left[ \frac{K_j - N}{K_j} - \frac{\delta_j}{R} \right] & K_j \geq \frac{N}{\theta} \frac{1}{1-\delta_j/R}, \end{cases} \tag{C.9}$$

Relative to the baseline, the form of the MC curve differs in 3 ways: (i) a parallel downward

[34]The intuition for $\delta_j K_j$ being divertable is that, e.g., absconding intermediaries can also make off with a fraction of the 'relationship' as well. This results in a pure downward translation of the MC curve when $\delta_j > 0$, as we discuss in Appendix C.3 .

shift in the flat region of the MC curve by $\frac{\delta_j}{V_j R}$; (ii) a parallel downward shift in the upward sloping region of the curve by $\frac{\delta_j}{V_j(1-\theta)R}$, but with no change in the curve's slope in this region; and (iii) a rightward shift (extending the flat region) due to a relaxation of the intermediaries' incentive to divert.[35] Thus, like a priced risk premium, a convenience yield affects the intercept(s) of the curve, but, unlike a risk premium, it does not influence the slope of the curve.

The key takeaway, however, is that, while a non-pecuniary convenience yield is not isomorphic to a priced risk premia in its effect on firms' MC curves, lower risk-premia and higher-convenience yield firms both imply MC curves that place these firms on flatter segments of their MB curves in equilibrium, although the convenience yield mechanism operates only by adjusting the intercept. Thus, the channel advocated in the main text holds even if a portion of firms' EBPs arise due to convenience yields rather than risk premia. Of note, a key difference is that shifts in MB curves may induce more homogeneous effects conditional on firms' EBPs when differences in EBPs reflect mostly differences in tastes rather than premia, since the resulting MC curves will have similar slopes.

## C.3 Alternative Haircut Form

The recovery value conditional on firm default in Section 6 is specified as a fraction $1-\mu$ of firms' promised return on capital $R^k K$, whereas in, e.g., Bernanke et al. (1999) it is specified as a fraction of the principle $K$. In this section, we show that our results are little changed if we move to this form. In particular, the difference is analogous to the distinction between priced risk premia and convenience yields: the former and the haircut on returns both shift and tilt firms' MC curves, while the latter and haircuts on principle only shift them.[36] As a result, while these two haircut forms are not exactly equivalent, they both have similar implications for the slope of firms' MB curves around equilibrium, i.e., flatter for firms with greater default-risk cyclicality.

[35] Adjustment (iii) is not present when intermediaries can divert the non-pecuniary convenience yield, and adjustment (ii) becomes a shift of $\frac{\delta_j}{V_j R}$ rather than $\frac{\delta_j}{V_j(1-\theta)R}$.

[36] Specifically, the analogue is the case where the convenience yield is divertable.

In particular, the intermediaries expected return per unit of capital when intermediaries recover $(1-\mu)K_j$ is:

$$W_j \equiv (1-\mathbb{E}[p_j])R^k + \mathbb{E}[p_j(1-\mu)] = (1-\overline{p})R^k + 1 - \overline{p\mu} - \rho_j \tag{C.10}$$

such that intermediaries problem becomes:

$$\max_{K_j} \; W_jK_j - R(K_j - N) \quad \text{s.t.} \quad (1-\theta)W_jK_j \geq R(K_j - N), \tag{C.11}$$

which gives the marginal cost curve:

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

Relative to the baseline MC curve, $\rho_j$ no longer affects the slope of the upward sloping region, but lower $\rho_j$ firms continue to have more downward-shifted MC curves. This shift implies that low-$\rho_j$ firms have lower EBPs and their MC curves intersect their MB curves at flatter regions, preserving the intuition form the main text.