Firm Financial Conditions and the Transmission of Monetary Policy*

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Abstract

We study how the transmission of monetary policy to firms' investment and credit spreads depends on their financial conditions, finding a major role for their excess bond premia (EBPs), the component of credit spreads in excess of default risk. While monetary policy easing shocks compress credit spreads more for firms with higher ex-ante EBPs, it is lower-EBP firms that invest more. We rationalize these findings using a model with financial frictions in which lower-EBP firms have flatter marginal product of capital curves. We also show empirically that the cross-sectional distribution of firm EBPs determines the aggregate effectiveness of monetary policy.

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

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1 Introduction

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

In this paper, we examine the responsiveness of firms' investment and credit spreads to monetary policy shocks and show that differences in firms' marginal *benefit* curves for capital are a major driver of their heterogeneous responses. Motivated by the evidence that firms' future marginal productivity can be inferred from credit spreads (Philippon, 2009), we proxy for differences in firms' marginal benefit curves using their excess bond premia (EBPs), the component of their credit spreads in excess of default risk (Gilchrist and Zakrajšek, 2012). Empirically, we show that while monetary policy easing shocks compress credit spreads more for firms with higher ex-ante EBPs, it is firms with lower EBPs that invest more. We rationalize these findings using a model with leverage constraints on financial intermediaries in which lower-EBPs firms, in equilibrium, have marginal products of capital that diminish relatively slowly as they invest, that is, flatter marginal benefit curves. In this setup, monetary policy easings shift firms' marginal cost curves outward along their differentially-sloped marginal benefit curves, leading to movements in credit spreads and investment that match our empirical findings. We also show, consistent with our model, that the transmission of monetary policy to *aggregate* investment depends on the moments, especially the skewness, of the cross-sectional EBP distribution. This result empirically ties the aggregate potency of monetary policy to granular, firm financial conditions.

We begin by estimating the heterogeneous responses of firms' credit spreads and investment to monetary policy shocks. We do so by building a unique data set that combines bond-level corporate yields and firm-level balance sheets for U.S. non-financial firms from 1973 to 2021 with a monetary policy shock series that bridges periods of conventional and unconventional policy. We find, on the one hand, that monetary policy easing shocks compress credit spreads more for firms with higher ex-ante EBPs—that is, for firms with tighter ex-ante financial conditions. On the other hand, we find that monetary policy easing shocks induce larger investment responses from firms with lower ex-ante EBPs. In both cases, the heterogeneity is economically significant: the peak response of investment and credit spreads for a firm with an EBP one standard deviation from the firm-level mean is about twice the size of the mean firm's response. We also show that, as a state variable for monetary policy, a firm's EBP plays a larger role than its default risk, measured both by "distance to default" (Merton, 1974) and leverage, and is statistically distinct from other firm characteristics tied to financial frictions such as size, share of liquid assets, and age.

We then build a model that rationalizes our empirical results for credit spreads and investment. Different from the existing literature, firms in our model differ in the capital intensities of their production technologies, implying heterogeneity in the slopes of their marginal benefit (MB) curves for capital. The model also features upward-sloping marginal cost (MC) curves for capital, which arise from leverage constraints on financial intermediaries (Gertler and Kiyotaki, 2010, Gertler and Karadi, 2011 and Anderson and Cesa-Bianchi, 2021). As intermediaries' shadow cost of leverage can differ for different firms, the slopes of firms' MC curves are heterogeneous as well. We calibrate the parameters governing firms' MB and MC curves, respectively, by estimating distinct production functions and default-risk 'betas' for low- and high-EBP firms. We find that low-EBP firms have greater capital intensities—i.e., flatter MB curves—and their default risk co-moves less with the market—i.e., flatter and more outward-shifted MC curves—than high-EBP firms. Using this calibration, we show that our model predicts, under segmented markets, that lower-EBP firms have flatter MB curves in equilibrium. This is due to low-EBP firms' greater capital intensities as well as their flatter and more outward-shifted MC curves, which push low-EBP firms' equilibrium to an even flatter portion of their MB curves.

Using a comparative statics exercise, we then show that firms' EBPs govern the responsiveness of their investment and credit spreads to monetary policy due to the slopes their marginal benefit curves. By increasing financial intermediaries' net worth, a monetary policy easing leads to an outward shift in firms' marginal cost curve that traces along their respective marginal benefit curves. Thus, a monetary easing engenders a relatively large increase in investment by lower-EBP firms—due to their flatter marginal benefit curves—despite a relatively mild fall in their credit spreads. Conversely, higher-EBP firms increase investment relatively little despite a larger fall in their credit spreads. These results match our empirical findings and establish that the slopes of firms' marginal benefit curves, as captured by their EBPs, are central to determining firms' sensitivity to monetary policy.[1]

We provide support for the model's economic mechanism by showing that two additional implications of the model hold empirically. First, the slope of firms' marginal benefit curves should be relevant not just for the transmission of monetary policy, but also for any shift in the marginal cost curve. To test this hypothesis, we build on the inverse relationship between firm-level credit spreads and investment documented by several studies (e.g., Gilchrist and Zakrajšek, 2007), which is consistent with credit supply shocks being dominant in capital markets. In this case, lower-EBP firms should invest more following a reduction in their credit spreads, due to their flatter marginal benefit curves. We find robust evidence supporting this hypothesis in the data.

From micro to macro, the second implication of our model is that the cross-sectional distribution of firm EBPs should influence the aggregate effectiveness of monetary policy. Specifically, when a larger mass of firms has lower EBPs—i.e., is on a flatter segment of their marginal benefit curves—the transmission of monetary policy to aggregate investment should be more potent. We test this prediction using moments of the cross-sectional EBP distribution as aggregate state variables and interact them with our monetary policy shocks. Consistent with the model, in times when the EBP distribution is more left-skewed, expansionary monetary policy shocks induce larger increases in aggregate investment growth. This implies that variations in the aggregate potency of monetary policy emerge from fluctuations in granular, firm-level EBPs.

[1]While monetary policy can elicit heterogeneous responses across firms due to asymmetric shifts in firms' MB and MC curves as well as changes in the slope of firms' MC curves, we show that these other channels, while complementary, cannot rationalize our empirical results for both spreads and investment.

Literature Review: Our paper relates to three strands in the literature. The first investigates firms' heterogeneous responses to monetary policy. Much of this literature is motivated by theories in which firms' access to external funds is subject to financial frictions, such as agency costs (Bernanke and Gertler, 1989, and Bernanke et al., 1999), collateral constraints tied to firms' physical capital (Kiyotaki and Moore, 1997) and earnings (Lian and Ma, 2021), as well as frictions in financial intermediation (e.g., Gertler and Kiyotaki, 2010, and Gertler and Karadi, 2011). Importantly—as highlighted by Ottonello and Winberry (2020), for example—financial frictions influence the shape of the marginal cost curve faced by firms. On the empirical front, the literature has used many firm-level characteristics to proxy for the severity of these financial frictions, such as liability structure (Ippolito et al., 2018; Gürkaynak et al., 2022), age (Bahaj et al., 2022; Durante et al., 2022), age & dividends (Cloyne et al., 2023), size (Gertler and Gilchrist, 1994; Crouzet and Mehrotra, 2020), leverage (Anderson and Cesa-Bianchi, 2021; Caglio et al., 2021; Wu, 2018; Lakdawala and Moreland, 2021), credit default swap spreads (Palazzo and Yamarthy, 2022), liquid assets (Jeenas, 2019; Jeenas and Lagos, 2022), liquidity-constraints (Kashyap et al., 1994), marginal productivity (González et al., 2021), and information frictions (Ozdagli, 2018; Chava and Hsu, 2020).[2] We contribute to this literature by showing that a firm's EBP is an important determinant of its responsiveness to monetary policy. Moreover, we provide evidence that firm EBPs convey the slope of their marginal benefit curves for capital by considering the responses of both firms' investment and credit spreads to monetary shocks.

Second, our paper adds to the longstanding literature on the determinants of investment, especially the user cost of capital theory (Jorgenson, 1963) and the Q theory (Tobin, 1969).[3] To address the empirical weakness of Q theory when assessed using equity prices, Philippon (2009) builds a model in which the "bond market's Q" is captured predominantly by firm credit spreads, which he finds to be a strong predictor of U.S. aggregate investment.[4]

[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. Jeenas and Lagos, 2022 also focus on a non-financial-frictions channel by studying the effects of an instrumented Tobin's q on firm equity issuance and investment conditional on firms' asset liquidity.

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

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

Relatedly, Gilchrist and Zakrajšek (2007) and Gilchrist et al. (2014) find similar results for firm-level credit spreads, which are the main source of variation in firms' user-cost of capital. Gilchrist and Zakrajšek (2012) clarify that it is the non-default-risk component of credit spreads, the EBP, that best predicts aggregate economic activity. Our contribution to this literature is twofold: (i) we show that the sensitivity of firms' investment to changes in credit spreads depends on their ex-ante EBP; and (ii) we provide evidence that firms' EBPs are linked to the slope of their marginal product of capital curves.[5]

Third, our paper contributes to the literature investigating the time-varying aggregate effects of monetary policy, especially its weaker effects during recessions. Vavra (2014) and McKay and Wieland (2021) build models in which monetary policy is less effective in recessions due to cyclicality in the cross-sectional distribution of price adjustments and durable expenditures, respectively. Tenreyro and Thwaites (2016) document that the decreased power of U.S. monetary policy in recessions is particularly evident for durables expenditure and business investment, while Jordà et al. (2020) show this pattern holds internationally. Our paper contributes to this literature by providing a new firm-level rationale for monetary policy's time-varying aggregate effects and its weaker transmission in recessions: variation in the slope of firms' marginal benefit curves for capital, as reflected in the moments of the cross-sectional distribution of firm EBPs.

2 Data and Descriptive Statistics

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

[5]We also show that differences in EBPs across firms are partially attributable to differences in firms' marginal cost curves, due to differences in the correlation between firms' default risk and the market.

2.1 Monetary Policy Shocks

As a baseline, we use the monetary policy shocks in Bu et al. (2021). These shocks combine three appealing features, which together distinguish them from other monetary policy shocks in the literature. First, by extracting high-frequency interest-rate movements from the entire U.S. Treasury yield curve, these shocks stably bridge periods of conventional and unconventional monetary policy. Second, these shocks are devoid of the central bank information effect, the notion that monetary policy announcements, in addition to providing a pure monetary policy surprise, may also reveal information about the central bank's views on the macroeconomy. Third, the shocks are not predicted ex-ante by available information, such as Blue Chip forecasts, "big data" measures of economic activity, news releases, and consumer sentiment.[6] We calculate these shocks for the period January 1985 to December 2021, and, for regressions at a monthly (quarterly) frequency, aggregate the shocks by summing them within the month (quarter). In our regressions, we normalize the shocks so that positive values refer to monetary policy easings. Appendix A.1 provides details. Appendix B.5 shows that our results are robust to using alternative monetary policy shocks.

2.2 Data Sources and EBP Calculation

To provide a comprehensive picture of the firm, we use four databases: (i) the Center for Research in Security Prices (CRSP) Database and (ii) the CRSP/Compustat Merged Database, Wharton Research Data Services, for firms' equity prices and balance sheets, respectively; (iii) the 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 unique investigation into monetary policy's effects on U.S. non-financial firms' quantities (investment) and prices (credit spreads). The combined sample period of these databases is 1973 to 2021, which is a significantly longer time period than is used in the existing literature on monetary policy and firm heterogeneity.

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

To calculate the excess bond premium, we follow an approach similar to Gilchrist and Zakrajšek (2012). We first compute the credit spread S_{ikt} on the bond k issued by firm i at time t as the difference between the bond's yield and the yield on a U.S. Treasury that shares the same maturity, with the latter calculated by Gürkaynak et al. (2007). Then, we decompose each bond's credit spread S_{ikt} into two components. The first is driven by the firm's default risk, as well as a vector of bond characteristics, and is termed the predicted spread $\hat{S}_{ikt}$. The second, and residual, component is the excess bond premium, EBP_{ikt}.

More precisely, we assume the following decomposition for bond-level credit spreads:

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

where DD_{it} is firm i's distance to default, which captures firm i's expected default probability (Merton, 1974); $\mathbf{Z}_{ikt}$ includes a vector of the bond's characteristics, such as its duration, par value and age, as well as industry and credit rating fixed effects; and υ_{ikt} is the error term. We estimate regression (1) by ordinary least squares (OLS) and compute the predicted credit spread $\hat{S}_{ikt}$ as

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

where $\hat{\beta}$ and $\hat{\gamma}$ denote the OLS estimates from regression (1) and $\hat{\sigma}^2$ denotes the estimated variance of the error term, which we assume to be normally distributed. While the model is simple, it explains a significant share of the variation in credit spreads—the R^2 is 0.68—driven largely by the firm's default risk.

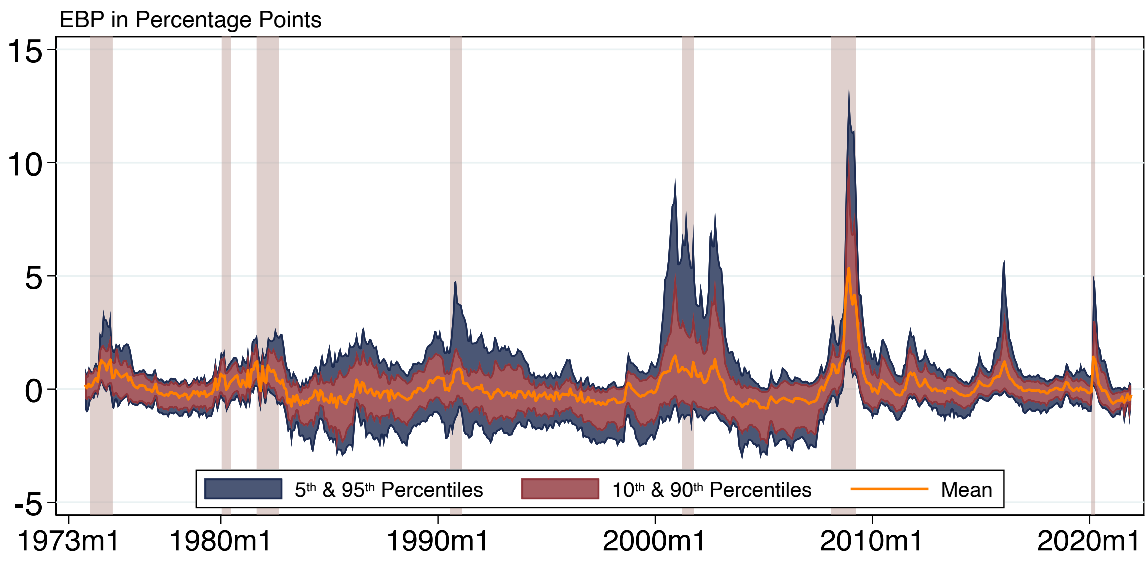
We define the excess bond premium (EBP) of firm i's bond k at time t as

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

Thus, the EBP_{ikt} is the component of the bond's credit spread that is unexplained by the firm's default risk and the bond's salient characteristics.[7] A higher EBP_{ikt} implies that,

[7]In Appendix A.3, we document that the correlation between our mean credit spreads and that of Gilchrist and Zakrajšek (2012) is 96%. The correlation between our EBP and that of those authors is 86%.

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



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

controlling for its default risk, the firm faces a higher marginal borrowing rate on its debt, and, thus, faces tighter financial conditions.[8] Appendix B.6 shows that our results in the subsequent sections are robust to using a modified EBP_{ikt} that accounts for a potential nonlinear relationship between spreads and distance to default.

After implementing this procedure for the bonds in the Lehman-Warga (1973–1998) and ICE (1997–2021) databases whose firm's balance sheet information and equity prices are available in Compustat and CRSP, respectively, our dataset contains 11,913 bonds from 1,872 firms at a monthly frequency from 1973 to 2021.[9] While our focus on bond-financed firms tilts our sample towards large firms, inspecting firms' marginal borrowing rates is crucial to understand the transmission of monetary policy to firms' investment. Further, large firms have been shown to play an outsized role in driving U.S. business cycles (Carvalho and Grassi, 2019). For more details about our dataset, including variable definitions, sample selection and summary statistics, see Appendix A.

[8]See Appendix A.3 for more details on the EBP and distance to default calculations.
[9]We clean the data as in Gilchrist and Zakrajšek (2012); see Appendix A.2 for details.

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.

2.3 The Cross-Sectional EBP Distribution

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

Although the percentiles of the EBP distribution vary considerably over time, a bond's place within the EBP distribution is reasonably persistent. Table 1 displays the Markov transition matrix for bond-level EBPs. It shows that the probability of a bond's EBP staying in its quintile in the next month (diagonal entries) is much higher than transitioning to any other quintile, with this result being particularly strong in the lowest and highest quintiles of the distribution. We see this result as necessary, but not sufficient, for firm-level EBPs to encode important information about the economic state of firms.

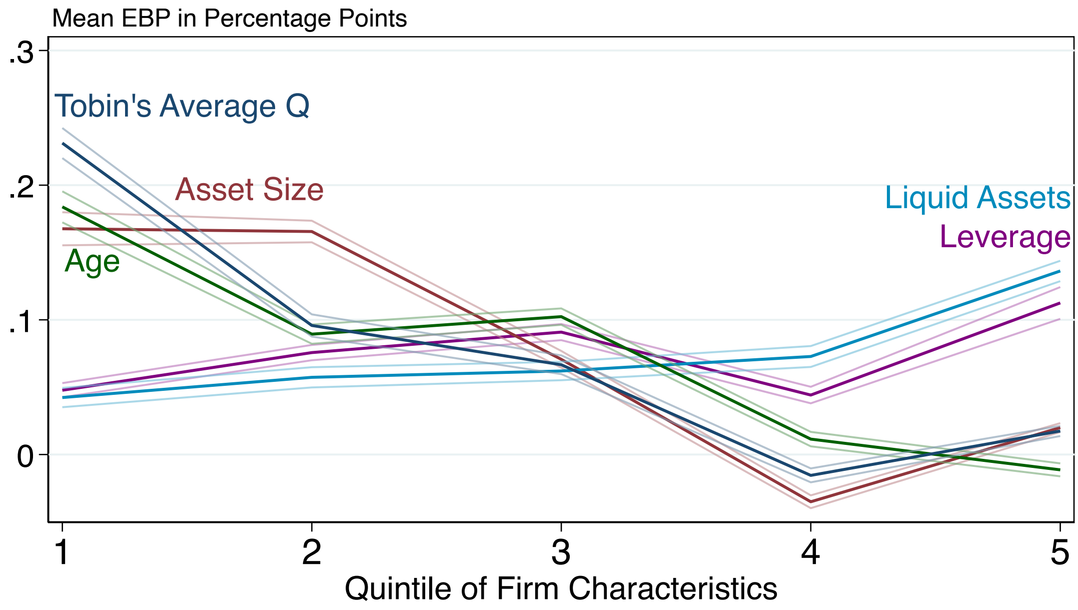
We also document the cross-sectional relationship between firm EBPs and other firm characteristics (Figure 2). Specifically, we focus on the average relationship between the EBP and the following variables: leverage (debt over assets), liquid assets (cash over assets), age (time since IPO), size (asset value), and average Tobin's Q (market over book value of assets). First, there is limited cross-sectional association between firms' EBPs and their leverage or liquid asset share, two prominent measures of firms' financial constraints. In contrast, older and larger firms tend to have lower EBPs, suggesting that firms' age and size encode information beyond the extent of their financial frictions (Crouzet and Mehrotra, 2020). Finally, we see that firms with higher average Tobin's Q—as calculated from equity prices—generally have lower EBPs, which is consistent with our interpretation of firms' EBPs as capturing their future investment prospects. Despite these cross-sectional correlations, the results that follow highlight that the information contained in firms' EBPs are statistically and economically distinct from these other variables.

2.4 Common Features of Regression Specifications

To estimate the effects of monetary policy conditional on a firm's characteristic, we follow Jeenas (2019) by averaging the characteristic's value over the previous year. For example, EBP^{ma}_{ikt} denotes the average EBP of firm i's bond k at time t over the previous year.[10] This helps purge uninformative high-frequency variation in our conditioning variables, as well as possible seasonality. Our conclusions, however, are not tied to this particular functional form. In Appendix B.2, we show that our results are robust to conditioning on a dummy variable for whether the value of a firm's characteristic is above or below the associated median across all firms in a given period (Cloyne et al., 2023, Anderson and Cesa-Bianchi, 2021). For interpretability, we also standardize the conditioning variables to have zero mean and unit variance over the entire sample. We then run local projections (Jordà, 2005) featuring the interaction between firm characteristics, notably the EBP^{ma}_{ikt}, and monetary policy shocks to gauge the heterogenous effects of monetary policy on firm outcomes.

[10] This corresponds to the previous 12 months for monthly data and 4 quarters for quarterly data.

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.

Throughout the paper, our specifications include both firm-level and aggregate controls, which we denote by $\mathbf{Z}_{it}$. Firm-level controls are leverage, size, sales growth, age, share of liquid assets, short-term asset share (current over total assets), and Tobin's average Q. Aggregate controls focus on economic and financial conditions using three lags of the following variables: Chicago Fed's national activity index for monthly regressions and GDP growth for quarterly regressions, the economic policy uncertainty index of Baker et al. (2016), and the first three principal components of the U.S. Treasury yield curve. Our baseline regressions use macro-financial controls because they allow us to compare the unconditional effect of monetary policy shocks with the effects conditional on firms' characteristics. That said, our results for the effects of monetary policy conditional on a firm's EBP are robust to including sector-time fixed effects, as shown in Appendix B.1. Finally, for all panel regressions, the sample is from 1985 to 2021 and inference is conducted using standard errors that are two-way clustered by firm and time period.

3 Monetary Policy and Bond-Level Credit Spreads

In this section, we document that expansionary monetary policy shocks decrease credit spreads more for high-EBP bonds than for low-EBP bonds. We also show that the sensitivity of credit spreads to monetary policy shocks is primarily determined by a bond's EBP, rather its firm's default risk.

Our baseline specification estimates the transmission of monetary policy to bond-level credit spreads both unconditionally and conditional on a bond's *ex-ante* EBP. Specifically, we estimate the following regressions at a monthly frequency for a series of horizons h:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{4}$$

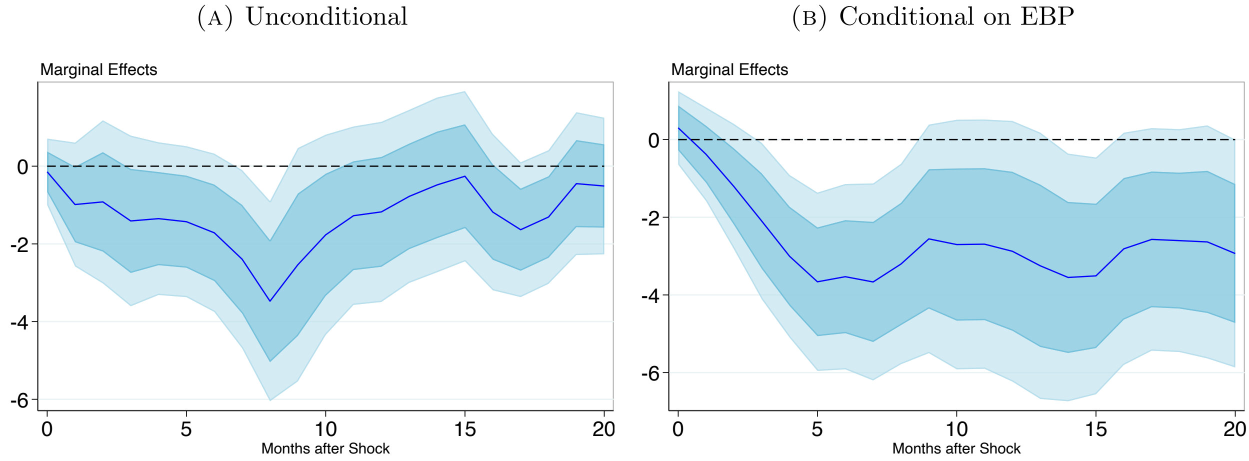
where S_{ikt} denotes firm i's bond k credit spread; ε_t^m refers to the monetary policy shock (where positive values reflect easings); EBP_{ikt-1}^{ma} represents firm i's standardized EBP as conveyed by its bond k; β_k^h is a bond fixed effect; and $\mathbf{Z}_{it-1}$ is the vector of control variables described in Section 2.4, plus EBP_{ikt-1}^{ma}. Importantly, EBP_{ikt-1}^{ma} is lagged, as are the controls, to ensure they are not influenced by the contemporaneous monetary policy shock.

Figure 3 shows that monetary policy has quantitatively important effects on credit spreads. Panel 3a traces the average response of credit spreads to a surprise monetary easing (β_1^h). We find that a 1 percentage point easing shock induces a decline in the average bond's credit spreads of nearly 4 percentage points, which occurs eight months after the shock. This result points to a delayed peak effect of monetary policy on firms' marginal borrowing rates, an issue overlooked by short-horizon studies.[11]

Panel 3b shows that the effect of a monetary policy easing on credit spreads is larger for high-EBP bonds, that is, for firms facing tighter ex-ante financial conditions. In particular, firms whose bonds carry an EBP one standard deviation above the sample mean face an additional decline in their credit spreads of nearly 4 percentage points. Similar to the unconditional effects, this EBP-dependent decline in credit spreads builds up over time,

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

Figure 3
Monetary Policy's Effect on Bond-Level Credit Spreads



Note. Figure 3 reports the dynamic effects of a monetary policy easing shock ε_t^m on the h-month change in bond credit spreads, $S_{ikt+h} - S_{ikt-1}$, which we estimate using regression (4). Panel 3a shows the unconditional effects, β_1^h. Panel 3b shows the effects conditional on $EBP_{ik,t-1}^{ma}$, β_2^h, which measures the additional response of the outcome variable for a firm with a conditioning variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

reaching its maximum effect between five and seven months after the shock.

We also show that it is mainly the EBP, rather than default risk, that regulates the response of credit spreads to monetary policy. To demonstrate this, we run a "horserace" between our EBP interaction, $EBP_{ikt-1}^{ma} \times \varepsilon_t^m$, and a default-risk interaction, $x_{it-1}^{ma} \times \varepsilon_t^m$:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^m + \beta_3^h x_{it-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \quad (5)$$

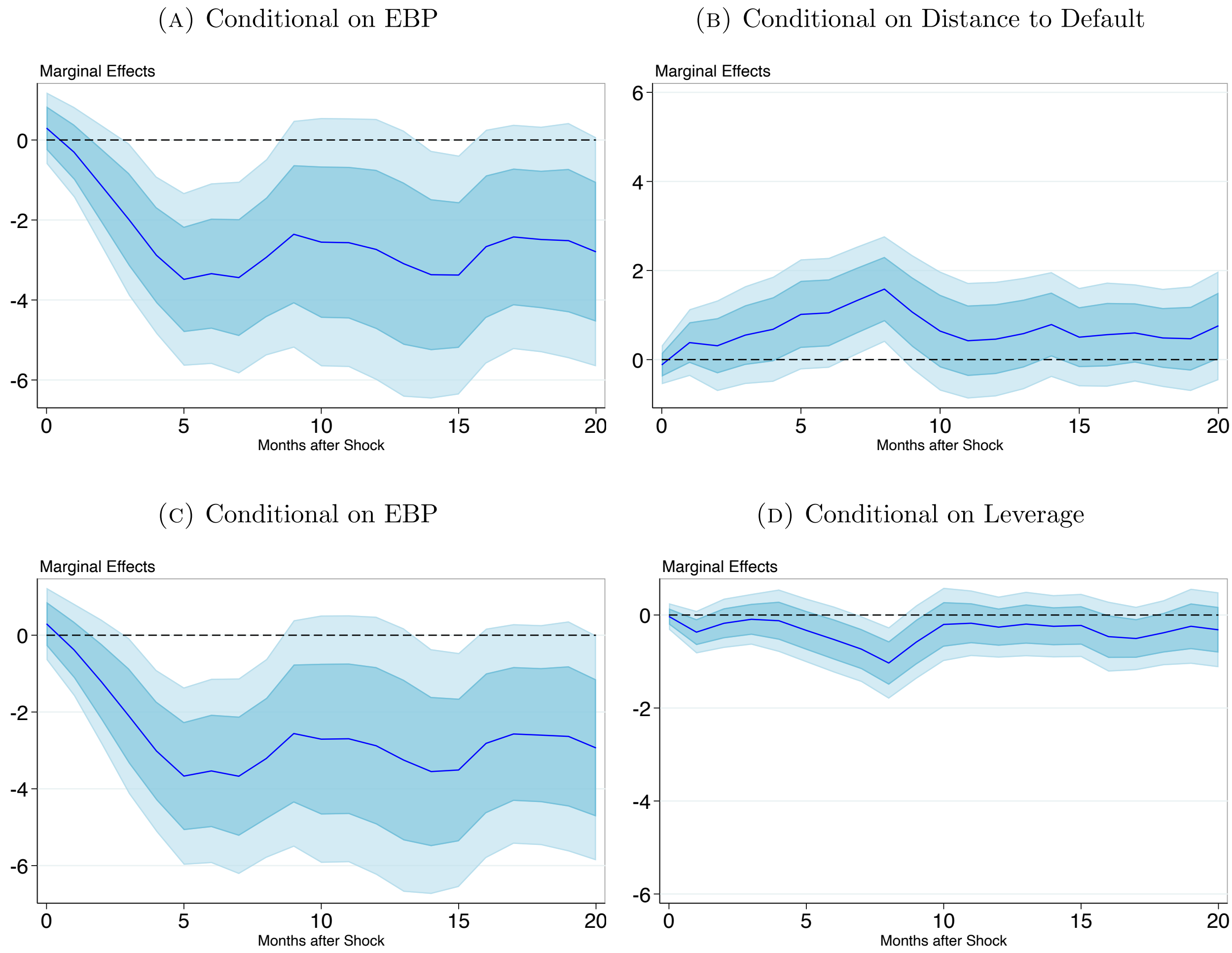
where x_{it-1}^{ma} is the yearly moving-average of firm i's default risk, which we measure in two ways: (i) firm i's distance to default; and (ii) firm i's leverage.[12] Panels 4a and 4b report the EBP and default-risk interaction coefficients, respectively, when x_{it-1}^{ma} is measured by distance to default, while Panels 4c and 4d do the same for leverage. In both cases, we find that the sensitivity of firms' credit spreads to monetary policy is primarily a function of their EBPs, rather than their default risk.[13] Moreover, the conditional effects by EBP are

[12]Note that, in this case, both EBP_{ikt-1}^{ma} and x_{it-1}^{ma} are also included in $\mathbf{Z}_{it-1}$.

[13]To provide comparability with other studies, we also establish that default-risk is a statistically significant state variable for the transmission of monetary policy to credit spread when the EBP is not included as a competing state variable (Appendix B.3).

Figure 4

Monetary Policy's Effect on Bond Credit Spreads: EBP vs. Default Risk



Note. Figure 4 reports the dynamic effects of a monetary policy easing shock ε_t^m on the h-month change in bond credit spreads, $S_{ikt+h} - S_{ikt-1}$, which we estimate using two versions of regression (5). First, panels 4a and 4b report, respectively, the interaction coefficients on EBP_{ikt-1}^{ma} (β_2^h) and our first proxy for default risk x_{it}^{ma}, the distance to default, (β_3^h). Second, panels 4c and 4d report, respectively, the interaction coefficients on EBP_{ikt-1}^{ma} (β_2^h) and our second proxy for default risk x_{it}^{ma}, leverage, (β_3^h). In all cases, the interaction terms measure the additional response of the outcome variable for a firm with a conditioning variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and month.

largely unchanged relative to our baseline results in Figure 3b.

Robustness: We also show that our results are robust to many variants of our empirical approach, including: (i) controlling for time-sector fixed effects (Appendix B.1); (ii) conditioning on the EBP using dummy variables (Appendix B.2); (iii) conditioning on other state variables emphasized in the literature, namely age, liquid asset share, credit rating, Tobin's average Q, size, and sales growth (Appendix B.4); (iv) using alternative monetary policy shocks (Appendix B.5); and (v) conditioning on an EBP purged of its potential higher-order dependence on distance to default (Appendix B.6).

4 Monetary Policy and Firm-Level Investment

In this section, we document that expansionary monetary policy shocks increase investment more for low-EBP firms than for high-EBP ones. Thus, conditional on EBP, firms whose investment is more responsive to monetary policy issue bonds whose credit spreads are less responsive. Moreover, we again highlight that the sensitivity of firms' investment to monetary policy is mainly a function of their EBP, rather than their default risk.

To evaluate the dynamic response of firm-level investment to monetary policy, our baseline specification measures both the unconditional effect of a monetary policy shock, as well as the effect conditional on firms' ex-ante EBP. Specifically, we estimate the following local projections at a quarterly frequency for a series of horizons h:

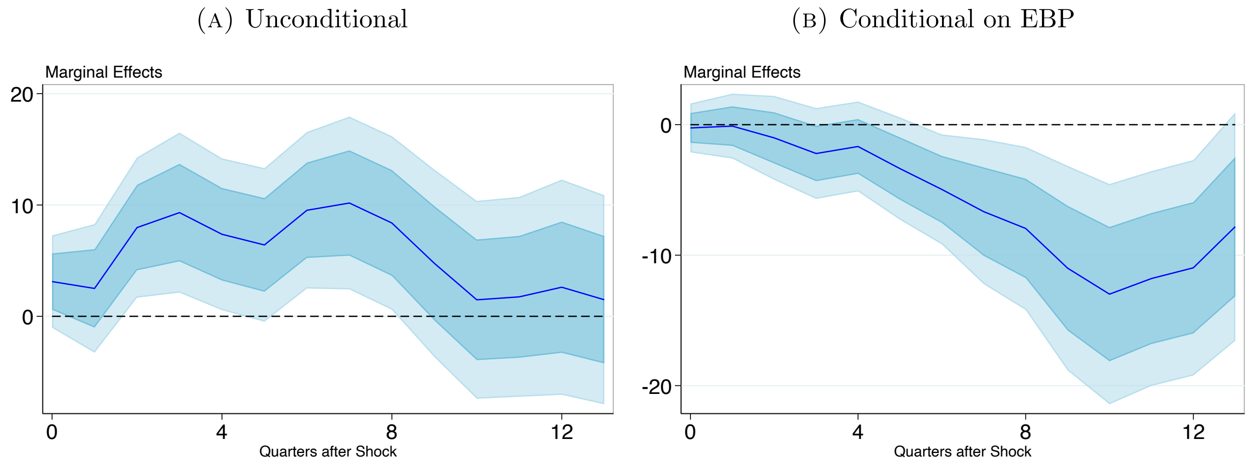
$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{6}$$

where K_{it} is the real book value of firm i's tangible capital stock (as in Ottonello and Winberry, 2020), EBP_{it-1}^{ma} is the average EBP_{ikt-1}^{ma} on firm i's bonds within a given quarter; β_i^h are firm fixed effects; and $\mathbf{Z}_{it-1}$ is the vector of control variables described in Section 2.4 plus EBP_{it-1}^{ma}.

Figure 5 displays firms' investment responses to monetary policy shocks. The unconditional response, displayed in Panel 5a, is hump-shaped. Quantitatively, a 1 percentage point monetary easing induces a 10 percentage point increase in investment for the average firm, with a peak-effect seven quarters after the shock.[14] The negative marginal effects in Panel 5b imply that the increase in investment is diminished for firms with higher ex-ante EBPs. This dampened response for higher-EBP firms is economically significant and reaches its

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

FIGURE 5
Monetary Policy's Effect on Firm-Level Investment



Note. Figure 5 reports the dynamic effects of a monetary policy easing shock ε_t^m on the h-quarter cumulative investment of firm i, $\log(K_{it+h}/K_{it-1})$, which we estimate using regression (6). Panel 5a shows the unconditional effects, β_1^h. Panel 5b shows the effects conditional on EBP_{it-1}^{ma}, β_2^h, which measures the additional response of the outcome variable for a firm with a conditioning variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

largest magnitude ten quarters after the shock.[15]

We find once more that a firm's EBP supersedes its default risk as a state-variable for the transmission of monetary policy, this time for investment. As in the previous section, we do so by running a horserace between the interactions of these two firm characteristics with a monetary policy shock:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^m + \beta_3^h x_{it-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \quad (7)$$

where default risk x_{it-1}^{ma} is again measured in two ways: distance to default and leverage.[16] As shown in Figure 6, the sensitivity of firms' investment response to monetary policy is primarily a function of their EBPs (Panels 6a and 6c) rather than their default risk (Panels 6b and 6d).[17] And, once again, the conditional effects by firm EBP are largely unchanged

[15] Appendix B.2 presents separate impulse responses for low- and high-EBP firms, and shows they are always either statistically greater than or equal to zero.

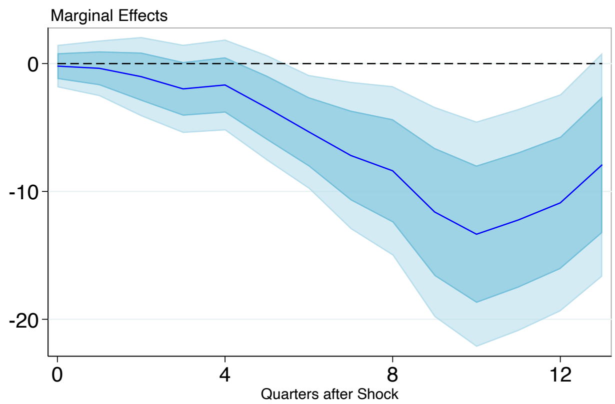
[16] Again, both EBP_{it-1}^{ma} and x_{it-1}^{ma} are included in $\mathbf{Z}_{it-1}$.

[17] To provide comparability with other studies, we again establish that default-risk is a statistically significant state variable for the transmission of monetary policy to investment when the EBP is not included as a competing state variable (Appendix B.3).

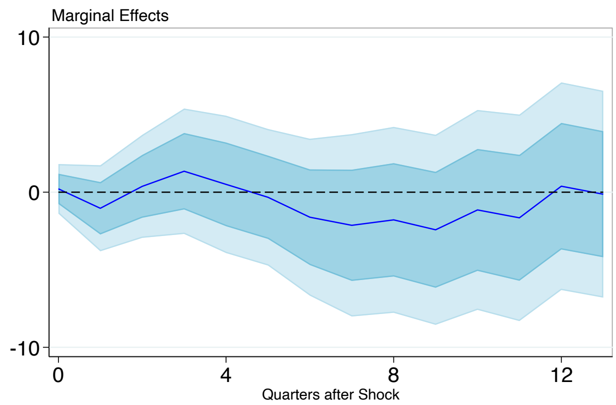
Figure 6

Monetary Policy's Effect on Firm Investment: EBP vs. Default Risk

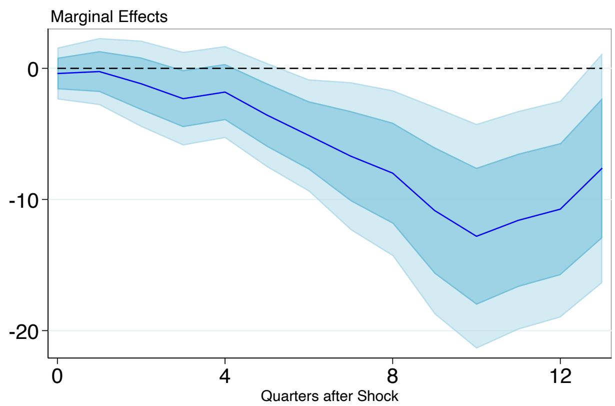
(A) Conditional on EBP



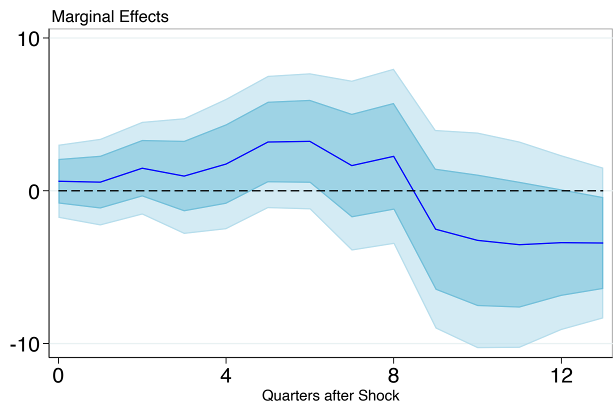
(B) Conditional on Distance to Default



(C) Conditional on EBP



(D) Conditional on Leverage



Note. Figure 6 reports the dynamic effects of a monetary policy easing shock ε_t^m on the h-quarter cumulative investment of firm i, $\log(K_{it+h}/\log K_{it-1})$, which we estimate using 2 versions of regression (7). First, Panels 6a and 6b report, respectively, the interaction coefficients on EBP_{it-1}^{ma} (β_2^h) and our first proxy for default risk x_{it-1}^{ma}, the distance to default, (β_3^h). Second, panels 6c and 6d report, respectively, the interaction coefficients on EBP_{it-1}^{ma} (β_2^h) and our second proxy for default risk x_{it-1}^{ma}, leverage, (β_3^h). In all cases, the interaction terms measure the additional response of the outcome variable for a firm with a conditioning variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

relative to our baseline results.

When viewed through the lens of the financial accelerator mechanism presented in other models (e.g., Bernanke et al., 1999 and Ottonello and Winberry, 2020), our results from this section seem at odds with our findings from Section 3. Specifically, we have shown that while firms facing tight financial conditions—high EBPs—experience large decreases in their credit spreads in response to monetary easings, these high-EBP firms increase investment only modestly. Conversely, low-EBP firms experience mild declines in their marginal borrowing costs, and, nevertheless, increase investment considerably. The discrepancy between these results and the predictions of financial accelerator models owes to the latter's emphasis on differences in firms' default risk and hence the slope of their marginal cost of capital curves. Instead, in the next section, we rationalize our findings with a model in which firms' heterogeneous responses to monetary policy, conditional on their EBPs, are due to differences in their investment prospects as reflected in their marginal benefit curves.

Robustness: We show that our results are robust to: (i) controlling for time-sector fixed effects (Appendix B.1); (ii) conditioning on EBP using dummy variables (Appendix B.2); (iii) conditioning on other state variables emphasized in the literature: age, liquid asset share, credit rating, Tobin's average Q, size, and sales growth (Appendix B.4); (iv) using alternative monetary policy shocks (Appendix B.5); and (v) conditioning on an EBP purged of potential higher-order dependence on distance to default (Appendix B.6). We also show that low-EBP firms issue more debt than high-EBP firms in response to a monetary easing, despite the smaller fall in marginal borrowing costs of the former (Appendix B.7).

5 Interpretation of Empirical Results

In this section, we develop a stylized model that rationalizes our empirical results. In the model—which we outline in Section 5.1 and calibrate in Section 5.2—low-EBP firms have flatter-sloped marginal benefit curves for capital, which we demonstrate in Section 5.3. As a result, we show in Section 5.4 that the responsiveness of firms' investment and credit spreads to monetary policy depends on their EBPs, in a manner consistent with our empirical results.

5.1 Theoretical Setup

Our framework focuses on two types of agents: firms who demand capital for production and financial intermediaries who, subject to financial frictions similar to those proposed by Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), supply capital to firms. Different from previous papers, we highlight the importance of the slope of firms' capital demand curves for the transmission of monetary policy.

Financial intermediaries are endowed with net worth N and issue deposits D to households (not explicitly modeled here) at an exogenous interest rate R.[18] These intermediaries have access to a capital producing technology that transforms N and D on a one-to-one basis into capital K_S, which they supply to firms for a return R_K. As long as this return on capital exceeds the deposit rate ($R_K > R$), intermediaries have an incentive to leverage-up to increase the return on their equity. Motivated by real-world regulatory capital requirements and risk-management practices, we assume that intermediaries face a constraint that requires them to have sufficient skin in the game when lending to firms. This is modelled as an agency friction in which intermediaries can abscond with a fraction θ of their revenue $R_K K_S$. Similar to Gabaix and Maggiori (2015), we assume that this fraction is increasing in the size of intermediaries' balance sheet: $\theta = \theta(K_S)$ and $\theta'(K_S) > 0$. In turn, households only fund intermediaries that satisfy an incentive compatibility constraint: $R_K K_S - RD \geq \theta R_K K_S$. The optimization problem of the intermediaries is then

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

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

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

we obtain the following capital supply curve:

$$\frac{R_K}{R} = \begin{cases} \frac{K_S - N}{K_S(1-\theta)} & K_S \geq \frac{N}{\theta} \\ 1 & K_S < \frac{N}{\theta}, \end{cases} \tag{8}$$

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

The key fundamental shaping the marginal cost curve faced by firms is θ, which parameterizes the tightness of financial intermediaries' constraints and reflects intermediaries' shadow cost of leveraging-up to lend to firms. This shadow cost, or "lending appetite", will be a key determinant of firms' EBPs, consistent with Gilchrist and Zakrajšek (2012). A higher θ implies an increase in the shadow cost of leverage, which reduces intermediaries' appetite for lending. This manifests, as can be gleaned from equation (8), as both an inward shift and a steepening of firms' MC curves that will increase firms' marginal borrowing rate in equilibrium. While we abstract from firms' default risk for simplicity, the shadow cost parameter θ may reflect the compensation that intermediaries require for the co-movement between firms' default risk and the market, i.e., a price of default risk.

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

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

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

$$\frac{R_K}{R} = \frac{1}{R}\alpha K_D^{\alpha-1}. \tag{9}$$

Due to decreasing returns to scale, $\alpha \in (0, 1)$, firms' marginal benefit curves are downward sloping in credit spreads R_K/R.

On the capital demand side, the key fundamental is firms' capital intensity α, which shapes the level and slope of their marginal benefit curves for capital. While the level of the curve traced in equation (9) reflects firms' marginal product of capital, the slope is the rate at which this marginal product depletes as firms invest. A flatter-sloped marginal benefit curve implies that, as firms invest, their marginal products of capital or "investment prospects" remain resilient, i.e., diminish relatively little. Importantly, a higher capital intensity α implies a flattening of firms' marginal benefit curves.[19] We show below that firms' capital intensities are also a key determinant of their EBPs.

5.2 Determinants of Capital Market Equilibrium

In this section, we empirically estimate the relationship between firms' EBPs and the two key fundamentals of our model: firms' capital intensities α and intermediaries' lending appetite θ. We will use these estimates to calibrate the model's marginal benefit and cost curves for low- and high-EBP firms.

First, we examine the link between firms' capital intensities and their EBPs by estimating production functions for low- and high-EBP firms. For completeness, we estimate two panel specifications: (i) with capital as the single input (as in our model); and (ii) which additionally controls for inputs that can be frictionlessly adjusted (Hall, 1986, 1988) as well as firms' unobservable idiosyncratic productivity (Olley and Pakes, 1996):

$$\log Y_{i,t} = \beta_i + \alpha \log K_{i,t} + \varepsilon_{i,t}, \tag{10}$$

$$\log Y_{i,t} = \beta_i + \alpha \log K_{i,t} + \omega_{i,t} + \gamma \log M_{i,t} + \delta \log O_{i,t} + \varepsilon_{i,t}, \tag{11}$$

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

[19] As $\alpha \to 1$, firms' production functions approach the constant returns to scale benchmark (Bernanke et al. (1999)) and their marginal benefit curves become horizontal.

TABLE 2
Firm-specific Characteristics and EBP

(A) Production Function Estimates for Low- and High-EBP Firms

$\log Y_{i,t}$	(1) Low-EBP	(2) High-EBP	(3) Low-EBP	(4) High-EBP
$\log K_{i,t}$	0.89***	0.71***	0.18***	0.14
	(.059)	(.050)	(.058)	(.154)
$\log M_{i,t}$			0.58***	0.60***
			(.038)	(.046)
$\log O_{i,t}$			0.26***	0.27***
			(.020)	(.012)

(B) Default Risk Cyclicality for Low- and High-EBP Firms

$\Delta DD_{i,t}$	(1) Low-EBP	(2) High-EBP
R_t^{Mkt}	0.86***	1.09***
	(.21)	(.34)

Note: Table 2a presents estimates of the capital intensity (α) of firms with EBP_{it}^{ma}s in the bottom (low-EBP) and top (high-EBP) quartiles of the EBP distribution. The first two columns report estimates from the specification (10), where capital is the single factor input, while the last two columns report estimates from the specification (11), which accounts for frictionless inputs and unobserved productivity. Standard errors are two-way clustered by firm and quarter in columns (1) and (2) and bootstrapped in columns (3) and (4). Table 2b presents estimates of the coefficient β^{Mkt} of firms with EBP_{it}^{ma}s in the bottom (low-EBP) and top (high-EBP) quartiles of the EBP distribution from regression (12), where $\mathbf{Z}_{it}$ is the vector of firm-level control variables described in Section 2.4. Standard errors are two-way clustered by firm and quarter. *** denotes statistical significance at the 1% level. Further details and robustness exercises are described in Appendix C.3 and C.4.

We estimate each of these specifications separately for firms whose EBP_{it}^{ma}s are in the bottom (low-EBP) and top (high-EBP) quartiles of the EBP distribution. While we estimate the single-input specification (10) using OLS, we achieve consistent estimates of the factor elasticities in specification (11) by (i) instrumenting the variable inputs with their lags; and (ii) using a variable input as a proxy variable for unobserved productivity (see Levinsohn and Petrin, 2003 and Ackerberg et al., 2015).[20]

Across both production function specifications, Table 2a showcases that low-EBP firms have larger capital elasticities than do high-EBP firms.[21] This implies that low-EBP firms'

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

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

marginal benefit curves are flatter than high-EBP firms'. In Appendix C.3, we show that our estimates for low- and high-EBP firms' αs are statistically distinct from each other, robust to including time and sector-time fixed effects, and similar when using other percentiles of the EBP distribution to classify low- and high-EBP firms.

Second, we assess the relationship between firms' EBPs and the lending appetite of the intermediaries that finance them. We do so by assuming that intermediaries' shadow cost of leverage θ for a particular firm derives from the co-movement between the firm's default risk and the market factor. Therefore, we estimate the loading of changes in low- and high-EBP firms' distance to default on the market return using the following specification:

$$\Delta DD_{i,t} = \beta_i + \beta^{Mkt} R_t^{Mkt} + \gamma \mathbf{W}_{it-1} + \varepsilon_{i,t}, \tag{12}$$

where β_i is a firm fixed effect, R_t^{Mkt} is the log-return of the U.S. Wilshire 5000 index, and $\mathbf{W}_{it}$ is the vector of firm-level control variables described in Section 2.4.

Table 2b highlights that low-EBP firms' default risk loads less on the market factor than does high-EBP firms'. As compensation for this, risk-averse intermediaries would offer low-EBP firms a greater price of default risk, that is, a lower θ. As a result, low-EBP firms would face an outward shifted and flatter marginal cost curve. Again, Appendix C.4 shows that our estimates for low- and high-EBP firms' market loadings β^{Mkt} are statistically distinct from each other, robust to including time and sector-time fixed effects, and similar when using other percentiles of the EBP distribution to classify low- and high-EBP firms.

In sum, our results indicate that low-EBP firms have greater capital intensities of production and their default risk co-moves less with the market than high-EBP firms'.[22] In the context of our model, this maps to low-EBP firms having relatively high αs on the capital demand side and facing relatively low θs on the capital supply side.

[22] We leave for future research the possibility that firms' capital intensities and their default-risk cyclicality are connected.

5.3 Firm EBPs and the Slope of Firms' Marginal Benefit Curves

We now characterize capital market equilibrium in the model. Our main result is that heterogeneity in firms' capital intensities and intermediaries' appetites for lending generate a link between firms' EBPs and the slopes of their marginal benefit curves for capital in equilibrium. In particular, low-EBP firms have flatter marginal benefit curves. This result will allow us to rationalize our empirical findings from Sections 3 and 4.

For simplicity, we consider two islands that are each populated by a continuum of financial intermediaries and firms that trade in perfectly competitive capital markets. Guided by our empirical estimates from the previous section, island A features high-α firms and low-θ intermediaries, while island B features low-α firms and high-θ intermediaries.[23] We further assume that capital markets are segmented according to intermediaries' lending appetite θ. As a result, intermediaries supply capital to firms only on their own island. This hypothesis is consistent with the evidence that financial intermediaries may face different internal constraints or have different preferences for risk-taking (see e.g., Chernenko and Sunderam (2012), Greenwood and Vissing-Jorgensen, 2018 and Anderson and Cesa-Bianchi, 2021).

Figure 7 displays the capital market equilibria on the two islands, which occur at the intersection of the MB curves (in blue) and the MC curves (in purple) in each panel. Since firms carry no default risk in our framework, firms' equilibrium credit spreads may be interpreted as their EBPs.[24] Thus, consistent with the empirical results from Section 5.2, the high-α firm and low-θ intermediary equilibrium displayed in Panel 7a features a lower EBP than the low-α firm and high-θ intermediary equilibrium in Panel 7b. Matching this untargeted moment helps validate our theoretical setup.[25,26]

Clearly, firms' equilibrium EBPs depend on slopes of both their marginal benefit and marginal cost curves. While other papers in the literature have focused exclusively on the

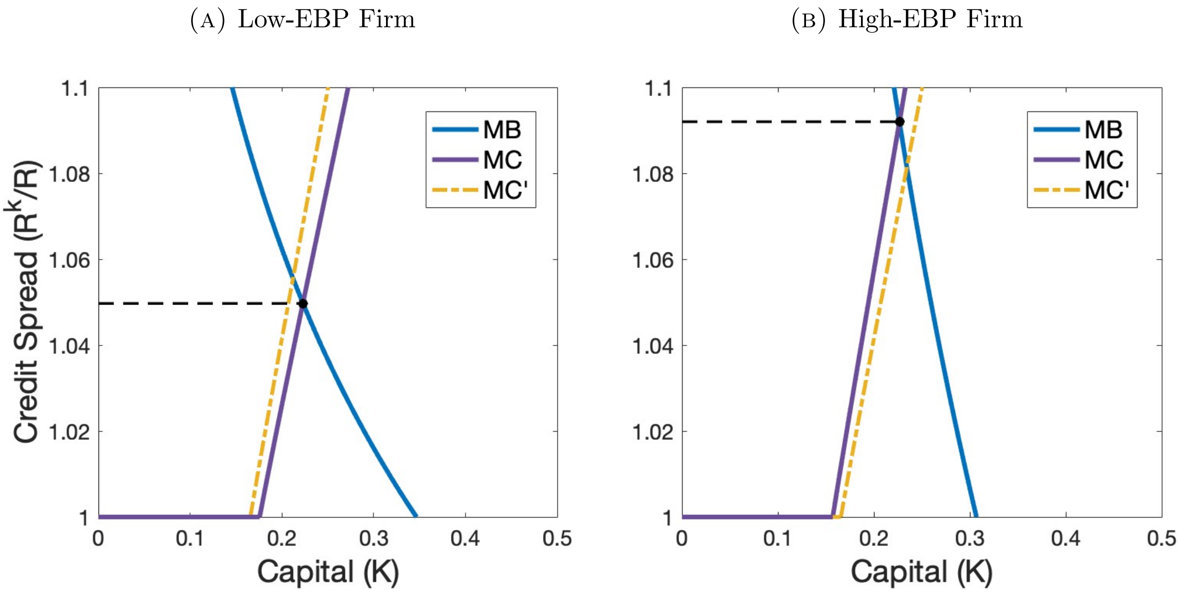
[23] We calibrate α and θ on each island using the results from Section 5.2. For details, see Appendix C.1.

[24] The parameter θ reflects firms' shadow cost of leverage, which we calibrate to the price of default risk that intermediaries require to lend to firms, not firms' default risk itself.

[25] In Appendix C.2, we show that this result holds for most levels of intermediary net worth. The only exception is if intermediary net worth is so high that firms' credit spreads are nearly 1, which is exceedingly rare in the data.

[26] A higher α and a lower θ have offsetting effects on the equilibrium capital stock. As a result, K and EBP are unrelated in Figure 7. In Appendix C.5, we show this is also the case in the data.

Figure 7
Capital Market Equilibrium



Note. Figure 7 displays the capital market equilibrium on two islands in which firms differ in their capital intensities (α) and financial intermediaries differ in their lending appetite (θ). The equilibrium occurs at the intersection of the MB curve in blue and the MC curve in purple in each panel; the yellow curves represent a counterfactual MC curve in which intermediaries on both islands have the same θ. Island 1 in Panel 7a shows the low-EBP equilibrium featuring high-α firms and low-θ intermediaries, while Island 2 in Panel 7b shows the high-EBP equilibrium featuring low-α firms and high-θ intermediaries. Details on the calibration can be found in Appendix C.1.

slopes of firms' marginal cost curves for the transmission of monetary policy, we emphasize that the slopes of firms' marginal benefit curves play a central role. To this end, Figure 7 showcases our key result from this section: low-EBP firms (Panel 7a) have flatter marginal benefit curves—i.e., more-resilient investment prospects—compared to high-EBP firms (Panel 7b). This result, which arises due to heterogeneity in both α and θ, will be crucial to match the impulse responses of *both* credit spreads and investment to monetary shocks, as we detail below.

We can decompose our result that low-EBP firms have flatter MB curves into the contributions of α and θ using the yellow curves in Figure 7, which trace-out counterfactual MC curves under the assumption that all intermediaries have the same θ. Comparing the counterfactual equilibria in each panel, which occur at the intersection of the blue MB curves and yellow MC curves, reveals that variation in capital intensities (α) across firms are sufficient to induce lower-EBP firms to have flatter MB curves. Differences in lending appetite across intermediaries then amplifies this result. Decreasing θ in Panel 7a—i.e., moving from the yellow to the purple MC curve—further lowers the high-α firms' EBP and pushes the equilibrium to an even flatter portion of the firms' MB curve. Similarly, increasing θ in Panel 7b further raises the low-α firms' EBP and pushes the equilibrium to a steeper portion of the firms' MB curve.

5.4 Monetary Policy Comparative Statics by Firm EBPs

In this section, we use our theoretical framework to study how the transmission of monetary policy to firms' credit spreads and investment depends on their EBPs. Motivated by the large literature documenting monetary policy's effects on credit supply via the balance-sheet channel (e.g., Bernanke and Gertler, 1995, Kashyap and Stein, 2000 and Adrian and Liang, 2018), we model a monetary policy easing as a uniform increase in the net worth of financial intermediaries across the two islands. This increase in intermediary net worth leads to a rightward shift in intermediaries' supply of capital curves—i.e., firms' marginal cost curves—as seen in Figure 8.

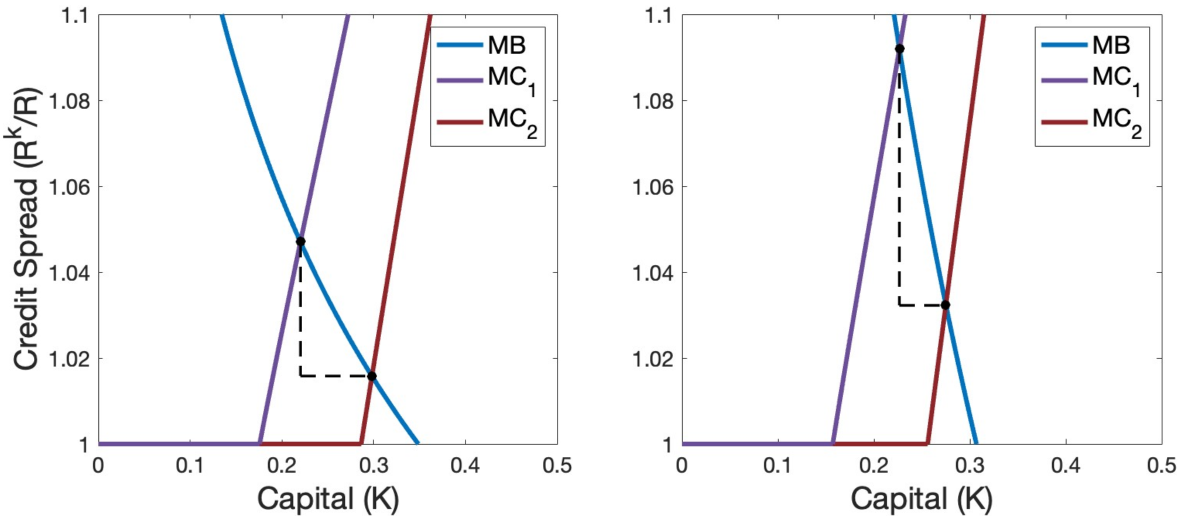
The heterogeneous responses of firms' investment and credit spreads to this shift in the marginal cost curve depend principally on the slope of their marginal benefit curves. Specifically, low-EBP firms with flatter marginal benefit curves invest considerably following a monetary easing, despite a relatively mild fall in their credit spreads (Panel 8a). This is due to the relative resilience of these firms' marginal product of capital, which decreases at a relatively slow rate as they invest. Conversely, high-EBP firms with steeper marginal benefit curves are afforded a larger fall in their credit spreads, but invest relatively little due to the rapid depletion of their sufficiently productive investment opportunities (Panel 8b). In all, this comparative statics exercise rationalizes our empirical results for the sensitivity of firms' investment and credit spreads to monetary policy, conditional on their EBPs, by appealing to the slope of firms' marginal benefit curves for capital.

Although our model focuses on the role of the slope of firms' MB curves, monetary policy influences firms' credit spreads and investment heterogeneously also via asymmetric

FIGURE 8

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

(A) Low-EBP Firm (B) High-EBP Firm



Note. Figure 8 presents the comparative statics to a monetary policy easing, modelled as a uniform increase in intermediaries' net worth N across the two islands displayed Panels 8a and 8b in which firms differ in their capital intensities (α) and financial intermdiaries differ in their lending appetite (θ). The remaining notes from Figure 7 apply here as well.

shifts in firms' MB and MC curves and by differentially altering the slope of firms' MC curves (see Ottonello and Winberry, 2020). We discuss each of these other transmission channels below. We emphasize that these other channels, while complementary, cannot rationalize our empirical results.

First, monetary policy may elicit asymmetric shifts in firms' marginal cost curves. Although we model a monetary easing as a uniform increase in intermediaries' net worth, this channel is present in our setup as well. In particular, Figure 8 highlights that low-EBP firms' marginal cost curves shift more than high-EBP firms' in response to the same increase in intermediary net worth, due to low-EBP firms' relatively low θs (see equation (8)). However, this greater rightward shift in low-EBP firms' MC curves induces their investment *and* credit spreads to react more to monetary policy. Thus, asymmetric shifts in firms' MC curves alone cannot explain our empirical results.

Second, monetary policy may differentially influence the slope of firms' marginal cost curves. This channel, which Ottonello and Winberry (2020) emphasize in the context of firms' default risk, is again present in our setup due to differences in θ across intermediaries (see equation (8)).[27] Similar to a larger shift, firms whose MC curves flatten more in response to a monetary easing invest more *and* experience a larger fall in their credit spreads. These dynamics are again inconsistent with our empirical findings, implying that differences in the slope of firms' MC curves are not driving the heterogeneous responses conditional on firms' EBPs.

Third, monetary policy may induce firms' MB curves to shift rightward, due to discounting and increases in aggregate demand. Such a shift in MB, all else constant, implies firms' credit spreads should increase following a monetary easing. Since we find empirically that monetary easings decrease credit spreads, this implies that shifts in MB are quantitatively less important than shifts in MC. Furthermore, since low-EBP firms have relatively flat MC curves (due to lower θs), an added shift in their MB curves would significantly increase the investment response but only mildly dampen the fall in credit spreads induced by shifts in their MC curves. Thus, shifts in MB curves alone cannot rationalize the relatively mild reduction of low-EBP firms' credit spreads.[28]

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

6 Micro- and Macro-economic Implications

In this section, we test two implications of our model—one at the firm-level and one in the aggregate—to provide further support our model's mechanism. Specifically, we show that

[27]This channel is quantitatively small in our calibration, which allows us to isolate the role of the slope of firms' MB curves.

[28]Differences in the cyclicality of firms' default risk may be driven by differences in the cyclicality of their final demand, implying differential shifts in low- and high-EBP firms' MB curves. For similar reasons, heterogeneous shifts in MB cannot explain our empirical findings.

a firm's EBP regulates the sensitivity of its investment to movements in its credit spreads (Section 6.1) and that the cross-sectional EBP distribution determines the aggregate effectiveness of monetary policy (Section 6.2). This second result suggests a granular origin for monetary policy's time-varying aggregate effects.

6.1 Firm-level Credit Spreads and Investment

The theoretical framework outlined in Section 5.1 illustrates that the slope of firms' marginal benefit curves matters not just for their sensitivity to monetary policy, but more generally for their responsiveness to any shift in their marginal cost curves. In this section, we build on the well-documented negative correlation between firms' credit spreads and their future investment (e.g. Gilchrist and Zakrajšek, 2007), which is consistent with credit supply shocks being dominant in capital markets. Specifically, we investigate how this spreads-investment relationship depends on the slope of firms' marginal benefit curves as proxied their EBPs. We find that increases in credit spreads are associated with smaller declines in investment for high-EBP firms.

To show this, we estimate quarterly firm-level regressions of investment on changes in credit spreads, using a firm's ex-ante EBP as a state variable:

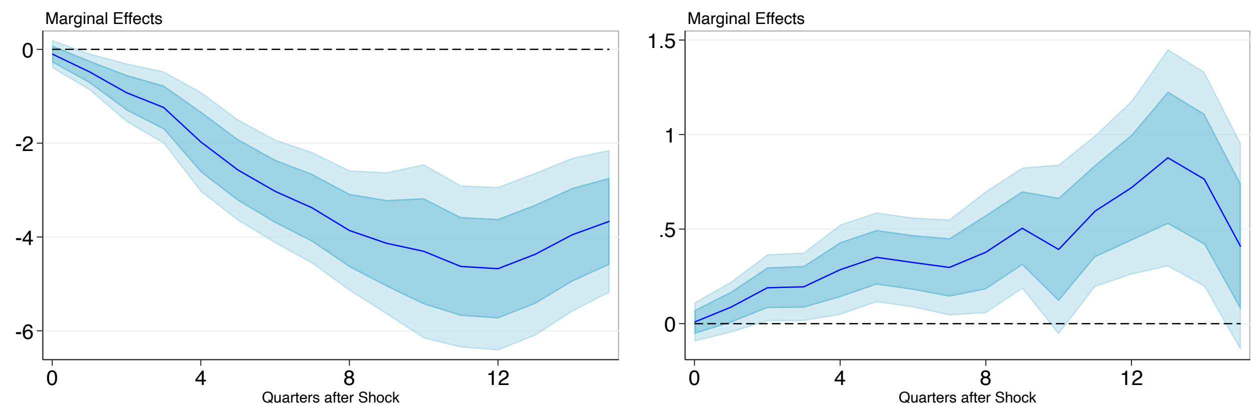
$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \Delta S_{it} + \beta_2^h \Delta S_{it} \times EBP_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{13}$$

where $\mathbf{Z}_{it-1}$ includes the controls discussed in Section 2.4, plus EBP_{it-1}^{ma}. As before, Our results are robust to including time-sector fixed effects (Appendix B.1), to conditioning on EBP using dummy variables (Appendix B.2), and to conditioning on an EBP purged of its potential higher-order dependence on distance to default (Appendix B.6).

Consistent with credit supply being the primary source of variation in bond markets, Panel 9a highlights that increases in firms' credit spreads are associated with significant and persistent declines in their investment. Furthermore, Panel 9b highlights that increases in credit spreads predict less-pronounced declines in investment for firms with higher EBPs, that is, for those with steeper marginal benefit curves. While many papers have explored

Figure 9
Firm-Level Credit Spreads and Investment

(a) Unconditional (b) Conditional on EBP



Note. Figure 9 reports the dynamic response of the h-quarter cumulative investment of firm i, $\log(K_{it+h}/\log K_{it-1})$, to a change in firm i's credit spread $\Delta S_{i,t}$, which we estimate using regression (13). Figure 9a shows unconditional effects, β_1^h. Figure 9b shows effects conditional on EBP_{it-1}^{ma}, β_2^h, which measures the additional response of the outcome variable for a firm with a conditioning variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

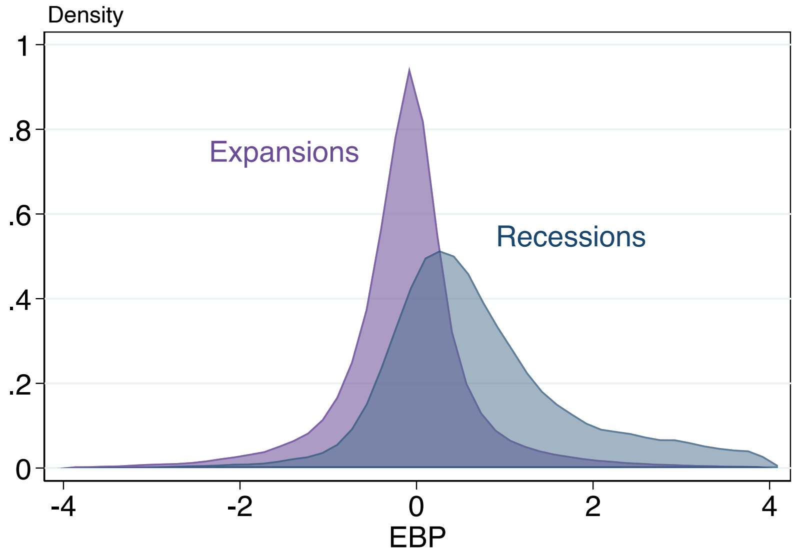
the firm-level relationship between credit spreads and investment (e.g., Gilchrist et al., 2014 and Lin et al., 2018), we document *which* firms' investment is most responsive to movements in their marginal borrowing costs by conditioning on firms' EBPs.

These results highlight that the slope of a firm's marginal benefit curve is a key determinant of its responsiveness to changes in credit supply. To further support this claim, Appendix B.8 uses the intermediary capital risk factor from He et al. (2017) as a source of exogenous variation in credit supply. Consistent with our model, we find that the responses of credit spreads and investment, conditional on firms' EBPs, from this shock to intermediary net worth are qualitatively similar to those from a monetary policy shock.

6.2 EBP Distribution and Monetary Policy's Aggregate Effects

In this section, we provide evidence that the cross-sectional distribution of firm EBPs, which are tied to the slopes of firms' marginal benefit curves in our model, determines the effectiveness of the transmission of monetary policy to the macroeconomy. Figure 10

FIGURE 10
Bond-level EBP Distribution in Recessions and Expansions



Note. Figure 10 presents kernel-density estimated bond-level EBP distributions during NBER-classified recessions and expansions over the period 1973:M1 to 2021:M12.

displays one motivation for our investigation, showing a considerable shift in mass from the left tail to the right tail of the EBP distribution during recessions. Further, the distribution of firms' EBPs should be particularly relevant for monetary policy in the aggregate since our firm-level results are based on a sample tilted towards large (bond-financed) firms, who play an outsized role in driving the U.S. business cycle (Carvalho and Grassi, 2019).

Our argument extends the framework from Section 5.1 with two types of firms to one with a continuum of firms that differ in their EBPs. In such a heterogeneous firm setup, the response of aggregate investment to monetary policy would depend on the cross-sectional distribution of firm EBPs. Specifically, monetary policy should be less effective at stimulating aggregate investment when a larger mass of firms are on a steeper segment of their marginal benefit curves (higher EBPs) and more effective when a larger mass of firms are on a flatter segment (lower EBPs).

To evaluate these predictions, we use local projections similar to those from previous sections, but with two important modifications: (i) we use annualized U.S. aggregate investment growth as our dependent variable, and (ii) we use the first three cross-sectional moments of the EBP distribution as state variables. Greater skewness, all else equal, implies a shift in mass from the left tail to the right tail of the EBP distribution, which should render the transmission of monetary policy to aggregate investment less potent. Similarly, all else equal, a higher median EBP implies a rightward shift of the EBP distribution, which should also make monetary policy less effective. Conversely, while the effect of a more dispersed EBP distribution is ex-ante ambiguous, it provides an indication of whether firm EBPs in the left or right tail exert a greater influence over the aggregate effectiveness of monetary policy.

Specifically, we estimate the following local projection at a quarterly frequency:

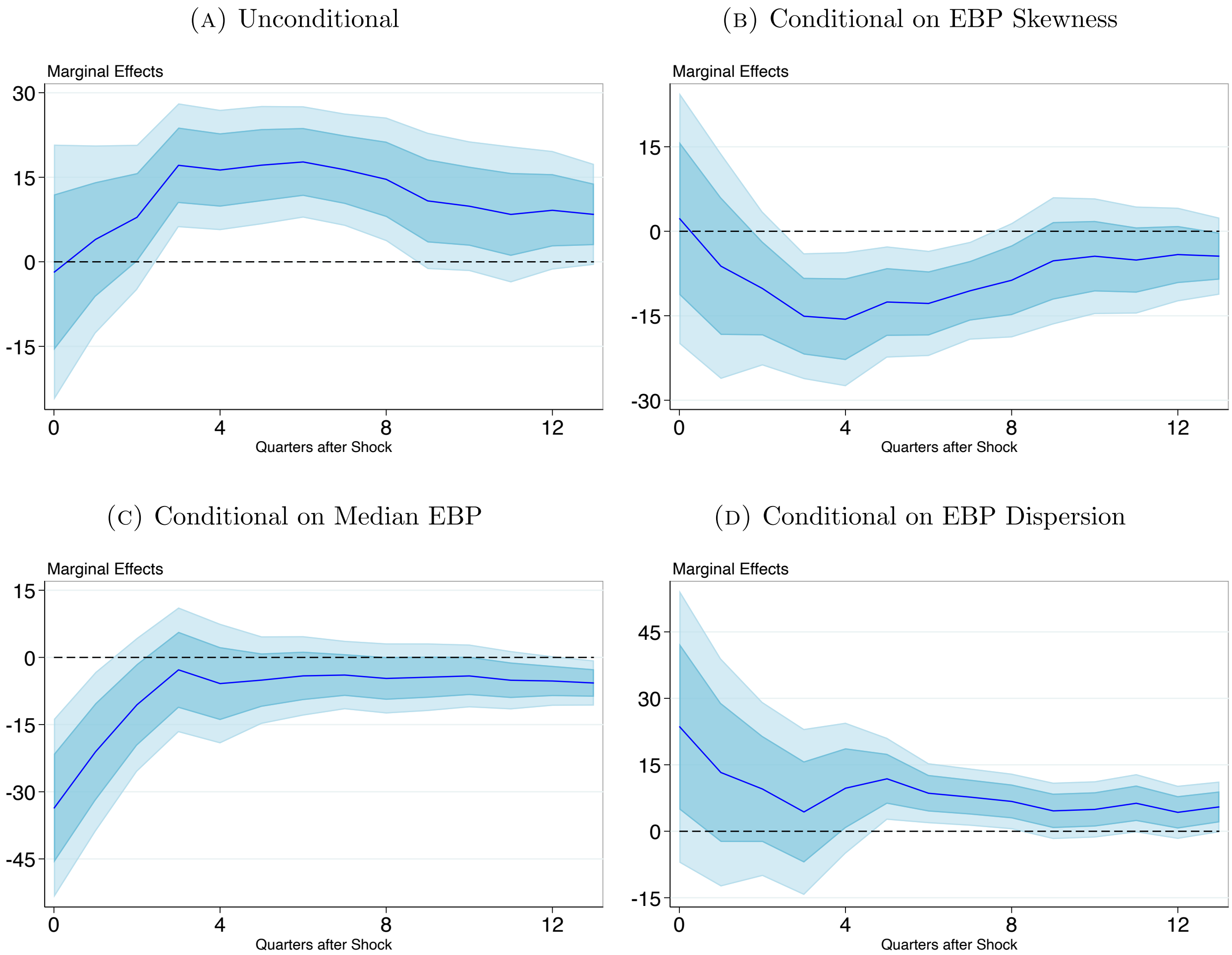
$$\frac{400}{h+1}\log\left(\frac{I_{t+h}}{I_{t-1}}\right) = \beta_0^h + \beta_1^h \varepsilon_t^m + \boldsymbol{\beta}_2^h \boldsymbol{M}_{t-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\delta}_l^h \mathbf{Y}_{t-1} + e_{th}, \tag{14}$$

where I_t is U.S. aggregate investment, $\boldsymbol{M}_{t-1}^{ma}$ is a vector that contains the median, dispersion and Kelly-skewness of the bond-level cross-sectional EBP distribution, and $\mathbf{Y}_{t-1}$ includes the aggregate controls of Section 2.4 plus the vector $\boldsymbol{M}_{t-1}^{ma}$. [29] In our baseline, we measure dispersion and skewness using 10th and 90th percentiles of the EBP distribution. We use Newey-West standard errors with 12 lags.

The results are displayed in Figure 11 and are consistent with the predictions of our model. First, Panel 11a traces the unconditional response of aggregate investment growth to a monetary easing shock. As expected, investment growth increases in a hump-shaped fashion, with a peak response 6 quarters after the shock. Panels 11b, 11c and 11d chart the effects of a monetary policy easing shock conditional on the skewness, median, and dispersion of the EBP distribution, respectively. Focusing first on skewness, the negative marginal effects highlight that a more right-skewed EBP distribution dampens the effects of monetary policy on aggregate investment growth. Similarly, a higher median EBP also lessens the potency of monetary policy. Finally, a more dispersed EBP distribution amplifies the transmission of monetary policy, suggesting that the added stimulus from a lower left tail

[29] For this regression, we substitute GDP growth for investment growth in the aggregate controls $\mathbf{Y}_{t-1}$ to again align ourselves with the existing literature (e.g., Gilchrist and Zakrajšek, 2012). For the same reason, we use annualized aggregate investment growth as our dependent variable, with similar results emerging if we use the level of aggregate investment.

FIGURE 11
Monetary Policy's Effect on Aggregate Investment Growth



Note. Figure 11 reports the dynamic effects of a monetary policy easing shock ε_t^m on h-quarter annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, which we estimate using regression (14). Panel 11a shows unconditional effects, β_1^h. Panels 11b, 11c and 11d show the effects conditional on the skewness, median and dispersion of the EBP distribution, the three elements in $\boldsymbol{\beta}_2^h$, respectively. The conditional effects measure the additional response of the outcome variable when the conditioning variable is one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

of the EBP distribution overcomes the drag from a higher right tail. Thus, the investment prospects of left-tail EBP firms, those with the flattest marginal benefit curves, are more responsible for the transmission of monetary policy to the macroeconomy.[30] Overall, these findings highlight the macroeconomic significance of our firm-level results.[31]

[30] We provide further support for this by interacting our monetary policy shock with the percentiles of the EBP distribution in Appendix B.9.

[31] Our results are robust to using alternative monetary policy shocks and to measuring the cross-sectional

Finally, Appendix B.9 shows that the results from this section are general and are not tied solely to business cycle variation. Specifically, we find that the aggregate effects of monetary policy conditional on the skewness of the EBP distributions are unchanged when controlling for the interaction between monetary policy shocks and recession indicators similar to those used by Tenreyro and Thwaites (2016). This result is consistent with the amplification mechanism for monetary policy we argue for in this paper—the slope of firms' marginal benefit curves for capital—being distinct from the decreased power of monetary policy in recessions.

7 Conclusion

We examine how and why the responsiveness of firms' credit spreads and investment to monetary policy depends on their financial conditions, as measured by their EBPs. Our paper has three main parts. First, using a comprehensive bond- and firm-level database, we find that while expansionary monetary policy shocks compress credit spreads more for firms with ex-ante higher EBPs, it is firms with lower EBPs that invest more. Second, we rationalize these results using a model in which firms with flatter curves of marginal benefit for capital—i.e., with marginal products of capital that diminish relatively slowly as they invest—have lower EBPs. Third, we provide additional empirical support for the importance of firms' marginal benefit curves for the transmission of economic shocks. Most importantly, we show that the effect of monetary policy on aggregate investment depends on the moments, in particular the skewness, of the cross-sectional EBP distribution.

Policymakers and researchers often discuss three key aspects of the transmission of monetary policy: its distributional effects, its aggregate potency, and the channels through which it operates. Our paper contributes to this debate. On the distributional front, we show that monetary policy is less effective at stimulating the investment of firms with higher EBPs, due to their steeper marginal benefit curves. On the aggregate front, our paper not only provides a theoretical argument for monetary policy's time-varying effects, but also

moments using different percentiles (see Appendix B.9).

offers a specific observable—the cross-sectional EBP distribution—to monitor them. On the modelling front, our paper provides new evidence on the salience of firms' marginal benefit curves to feed the construction of richer models of the macroeconomy.

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Internet Appendix

(Intended for online publication only)

Firm Financial Conditions and the

Transmission of Monetary Policy

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

February 1, 2024

A Data Summary

B Additional Empirical Results and Robustness

C Model Appendix

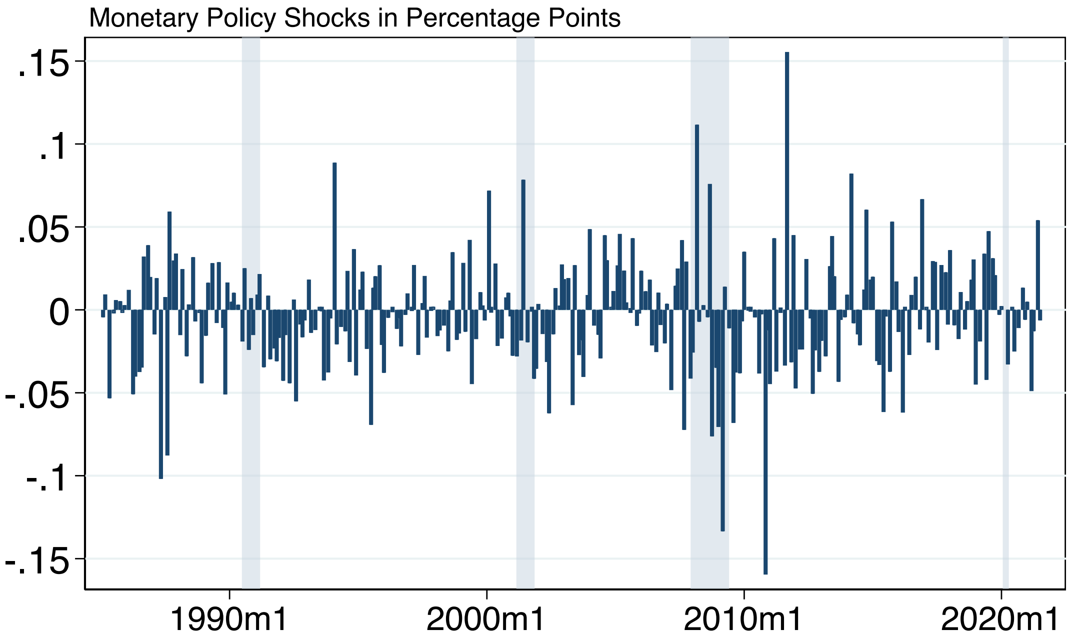
A Data Summary

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 December 2021. Figure A.1 shows the times series of shocks at a monthly frequency. This "extended" series is longer than the original series of the paper, which runs from January 1994 to September 2019.

FIGURE A.1
Monetary Policy Shocks



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

As discussed in the original paper, the Bu et al. (2021) monetary policy shocks are constructed using a two-step Fama-Macbeth procedure with identification achieved via a heteroskedasticity-based instrumental variable approach. The resulting shocks display a moderately-high correlation with other shock series in the literature, but have a number of notable properties: (i) they stably bridges periods of conventional and unconventional policy, providing us with a significantly larger sample than other empirical work in this area; (ii) they are devoid of the central bank information effects; and (iii) they are unpredictable from the information set available at the time of the shock. That said, as shown in Appendix B.5, our results are robust to using the Swanson (2021) shocks. For more details on the calculation of the Bu et al. (2021) shock series, see the original paper. Summary statistics for the Bu et al. (2021) monetary policy shock series are presented in Appendix A.4.

A.2 Variable Definitions and Sample Selection

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

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

investment spells of 20 quarters or more.

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).

3. *Distance to default*: firm's expected default risk defined by 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 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 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 use 4-digit SIC codes.

13. *GDP and Aggregate Investment*: measured as real chained gross domestic product (GDPC1 in FRED) and real chained investment (RINV in FRED). Growth rates calculated as log-differences.

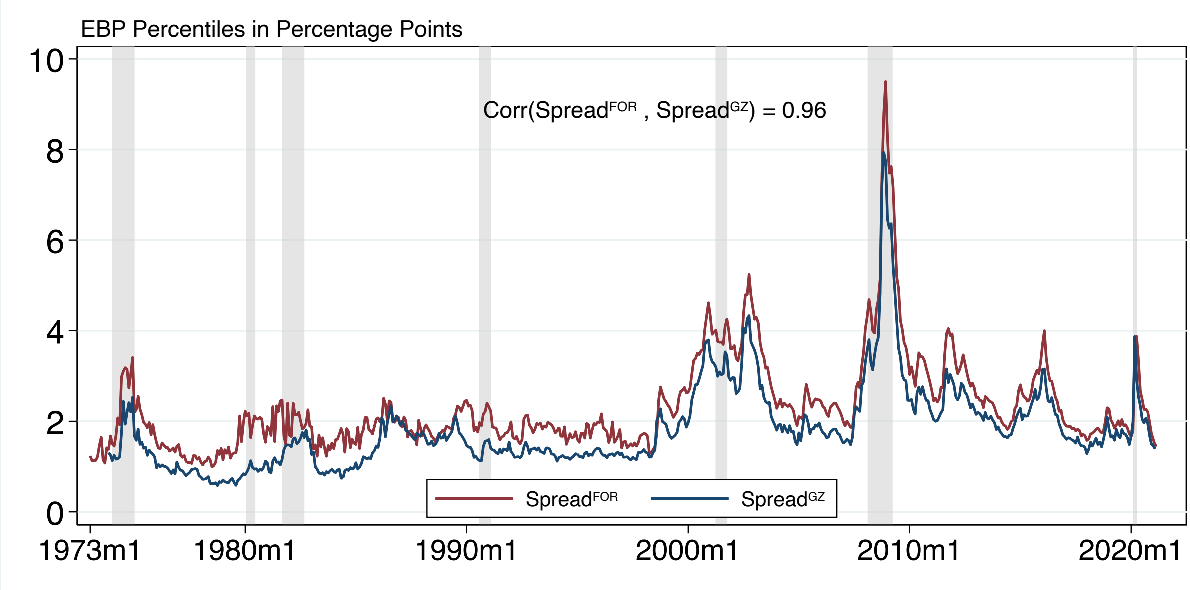
Sample selection: we focus on the non-financial firms whose equity prices are available in the Center for Research in Security Prices (CRSP) database, whose balance sheets are available from the CRSP/Compustat Merged Database, Wharton Research Data Services and whose bond yields data are available in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

A.3 Calculating Distance to Default and the EBP

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

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.

To derive each bond's EBP_{ikt}, as discussed in the main text, following Gilchrist and Zakrajšek (2012), we estimate:

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

where DD_{it} is firm i's distance to default (Merton, 1974), and $\mathbf{Z}_{ikt}$ includes: (i) the bond's duration, age, par value, coupon rate (all in logs); (ii) a dummy for if the bond is callable; (iii) interactions between the characteristics listed in (i) and the call dummy in (ii); (iv) interactions between the call dummy in (ii) and DD_{it}, the first three principal components of the U.S. Treasury yield curve, and the volatility of the 10-year Treasury yield; and (v) industry and credit rating fixed effects. Table A.1 provides the results from estimating regression (A.1). We discuss how we calculate DD_{it} later in this section.

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

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

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	

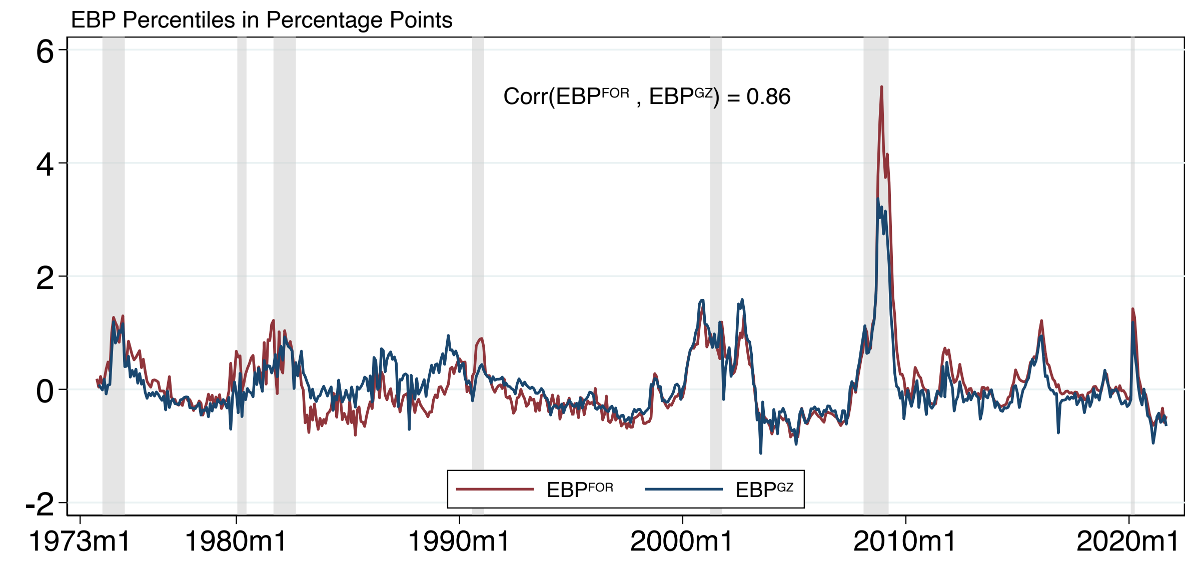
Note. Table A.1 present the estimated coefficients, standard errors and T-statistics from estimating regression (A.1) by OLS. The sample period is October 1973 to December 2021 and includes 682,316 observations. LEV_t, SLP_t, CRV_t refer to the level, slope and curvature (first three principal components)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

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,

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.

after data cleaning as described in Appendix A.2, a sample of monthly EBPs for 11,913 bonds from 1,872 firms. Figure A.3 plots the time series of our mean EBP and that of Gilchrist and Zakrajšek (2012) and highlights that the correlation is 86%.

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

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

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

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

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

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

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

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

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

Assuming a time to maturity of one year ($T = 1$) and daily data on one-year Treasury yields r, the face value of firm debt D, the market value of firm equity E, and its one-year historical volatility σ_E, equations (A.5) and (A.6) provide a two equation system that can be used to solve for the two unknowns V and σ_V.[32] 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 σ_V into equation (A.5) to solve for the market value V for each of these days. Second, from our new estimated V series, we calculate a year-long series of daily log-returns to the firm's value, $\Delta \log V$, which we then use to compute a new estimate for σ_V as well as for μ_V.[33] We then iterate on σ_V until convergence.

Given solutions (V, σ_V, μ_V) to the Merton DD model, we are able to calculate the

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

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

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 distance a firm is above default, given an expected asset growth rate μ_V and volatility σ_V until T, in units of standard deviations.

A.4 Summary Statistics

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

The first columns in Panels A.2a and A.2b report summary statistics for bond-level EBPs at a monthly frequency and firm-level EBPs at a quarterly frequency, respectively. The quarterly firm-level EBP series is constructed by averaging the bond-level EBP series across a firm's outstanding bonds in a given month and then across the months in a given quarter.[34] The summary statistics for the monthly bond-level and quarterly firm-level EBPs are broadly in line with one another. Further, unsurprisingly given the results documented in Appendix A.3, our mean monthly bond-level EBP is very similar to the corresponding mean value from Gilchrist and Zakrajšek (2012).

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

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

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

(a) Monthly Variables

	EBP_{ikt}	S_{ikt}	ε_t^m
Mean	.084	1.98	-.003
Median	-.071	1.28	0
S.D.	1.58	2.37	0.028
5^{th} Perc.	-1.32	.380	-.045
95^{th} Perc.	1.81	5.66	.042
# Obs.	682,297	750,722	439

(b) Quarterly Variables

	EBP_{it}	$\Delta log(K_{it})$	ε_t^m
Mean	.166	.490	-.008
Median	-.065	-.006	-.007
S.D.	2.01	6.75	.048
5^{th} Perc.	-1.76	-3.84	-.091
95^{th} Perc.	2.57	6.27	.072
# Obs.	67,500	49,281	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 11913 (13439) bonds issued by 1872 (2216) firms. The quarterly firm-level EBP (investment) series includes 1866 (998) firms.

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 firms' credit spreads are crucial to inspect the transmission of monetary policy to firms' investment. Further, large firms have been shown to be the primary driver of U.S. business cycles (e.g., Carvalho and Grassi, 2019). Still, relative to both the literatures on monetary policy's effects on firm-level investment (e.g., Ottonello and Winberry, 2020) and on bond-level credit spreads (e.g., Anderson and Cesa-Bianchi, 2021), our use of the Lehman-Warga database and a monetary policy shock series that spans periods of conventional and unconventional policy affords us a significantly longer sample.[35]

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.

[35]In addition, relative to Anderson and Cesa-Bianchi (2021) who also focus on publicly-listed U.S. firms who issue debt in corporate bond markets, our bond-level EBPs are calculated for 2500 more bonds and about 900 more firms.

B Additional Empirical Results and Robustness

In this section, we offer additional empirical results and robustness to complement our findings from the main text. In Section B.1, we show that our results are robust to including time-sector fixed effects. In Section B.2, we show our results are robust to conditioning on bond/firm EBPs using dummy variables. In Section B.3, we show that, when not conditioning on the EBP, default risk indeed regulates firms' responses to monetary policy. In Section B.4, we highlight that heterogeneous responses by EBP are robust to controlling for monetary policy's effects conditional on other firm characteristics. In Section B.5, we re-estimate our main specifications with alternative monetary policy shocks. In Section B.6, we re-estimate our results using an EBP purged of its higher-order dependence on default risk. In Section B.7, we document monetary policy's effects on firm debt issuance by EBP. In Section B.8, we study the conditioning effects of EBP for intermediary net worth shocks. Finally, in Section B.9, we showcase the robustness of our results linking the EBP distribution to the aggregate effectiveness of monetary policy.

B.1 EBP Heterogeneity with Sector-Time Fixed Effects

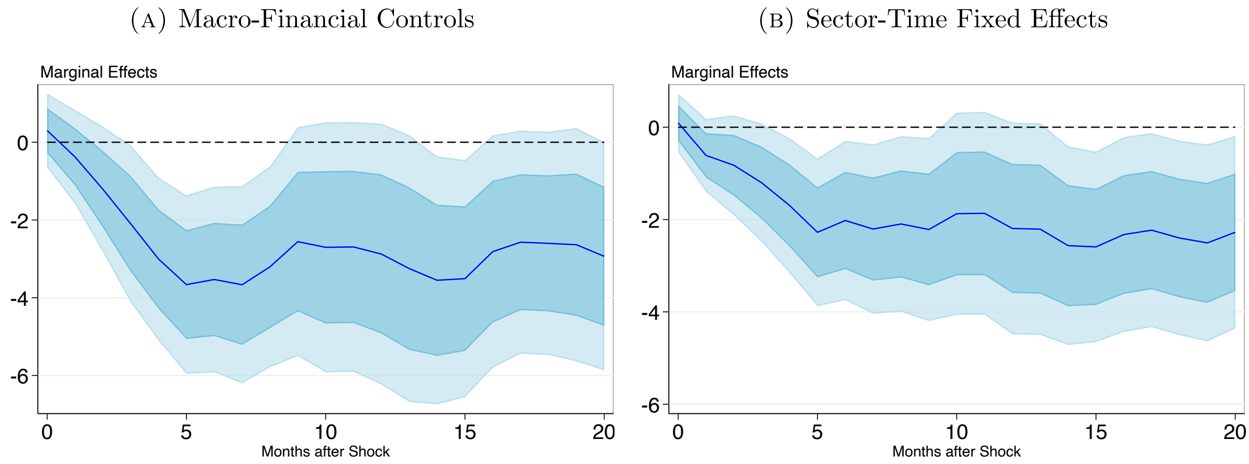
We begin by showing that our results for the heterogeneous responses conditional on EBP are robust to controlling for time-sector fixed effects. Indeed, we show that the spreads of high-EBP bonds and investment of low-EBP firms remain more sensitive to monetary policy shocks. In addition, we show the investment of low-EBP firms is more responsive to movements in their credit spreads. To show this, we define $\mathbf{W}_{it-1}$ as the vector of firm-level controls contained in $\mathbf{Z}_{it-1}$ (see Section 2.4), but excluding the macro-level controls.

Monetary Policy on Credit Spreads:

Beginning with monetary policy's effect on credit spreads, we include sector-time fixed

FIGURE B.1

Monetary Policy's Effect on Bond-Level Credit Spreads Depending on EBP



Note. Figure B.1 compares the effects of the dynamic interaction (β_2^h) between EBP_{ikt-1} and the Bu et al. (2021) monetary policy shock (ε_t^m) on the h-period change in credit spreads, $S_{ikt+h} - S_{ikt-1}$, for two different specifications: one that controls for macro-financial controls as in the main text (4) in Panel B.1a and one that includes time-sector fixed effects (B.1) in Panel B.1b. The frequency of the data is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

effects $\alpha_{s,t}^h$ in the following specification (B.1):[36]

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \alpha_{s,t}^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{W}_{it-1} + e_{ikth}, \tag{B.1}$$

The interaction effects (β_2^hs) are displayed in Panel B.1b of Figure B.1, alongside the results from the original specification in Panel B.1a, which have been recopied from Panel 3b of Figure 3 for comparison. Figure B.1 highlights that our results from section 3 are robust to controlling for sector-time fixed effects: credit spreads of high-EBP bonds are more responsive to monetary policy.

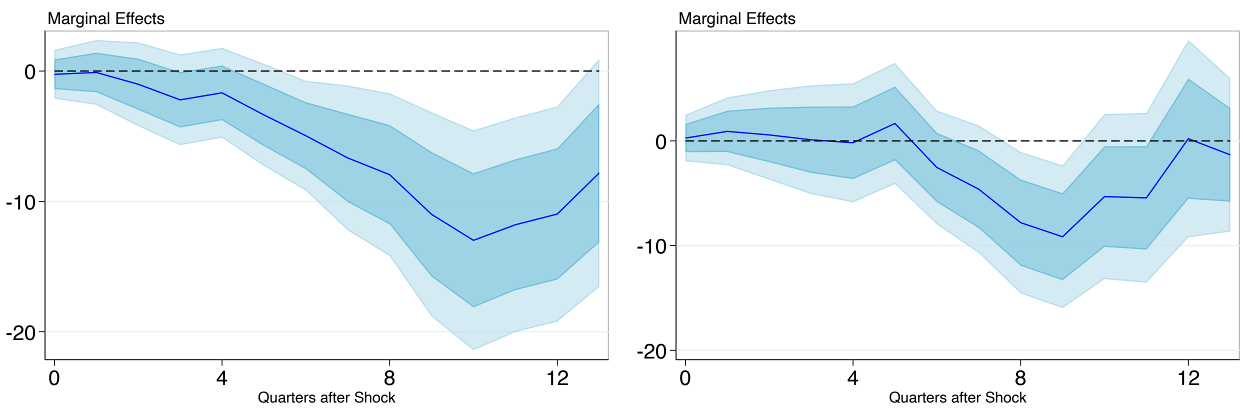
Monetary Policy on Firm Investment:

Next, turning to monetary policy's effects on investment, we include sector-time fixed

[36]Note that macro-financial controls, in addition to the unconditional monetary policy shock ε_t^m, would be absorbed by $\alpha_{s,t}^h$.

Figure B.2
Monetary Policy's Effect on Firm-Level Investment Depending on EBP

(A) Macro-Financial Controls (B) Sector-Time Fixed Effects



Note. Figure B.2 compares the effects of the dynamic interaction (β_2^h) between EBP_{it-1} and the Bu et al. (2021) monetary policy shock (ε_t^m) on h-period investment of firm i, $\log K_{it+h} - \log K_{it-1}$, for two different specifications: one that controls for macro-financial controls as in the main text (6) in Panel B.2a and one that includes time-sector fixed effects (B.2) in Panel B.2b. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

effects $\alpha_{s,t}^h$ in the following specification (B.2):

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \alpha_{s,t}^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^m + \boldsymbol{\gamma}^h \mathbf{W}_{it-1} + e_{ith}. \tag{B.2}$$

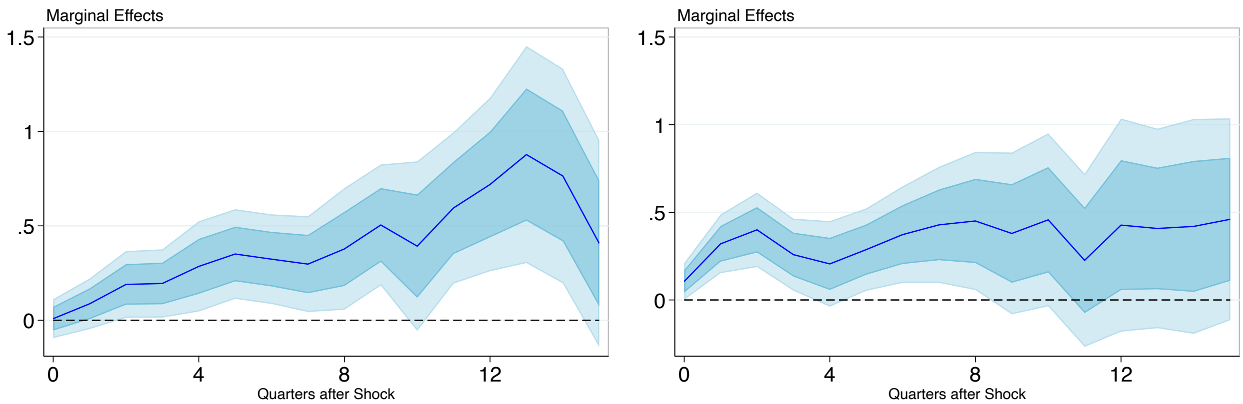
The interaction effect (β_2^hs) are displayed in Panel B.2b of Figure B.2, alongside the results from the original specification in Panel B.2a, which have been recopied from Panel 5b of Figure 5 for comparison. Figure B.2 highlights that our results from Section 4 are robust to controlling for sector-time fixed effects: investment by low-EBP firms is more sensitive to monetary policy shocks.

Firm Credit Spreads on Firm Investment:

We assess the robustness of our results relating firms' investment responses to changes in their credit to the inclusion of sector-time fixed effects $\alpha_{s,t}^h$ using the following specifica-

Figure B.3
Credit Spreads' Effects on Firm Investment Depending on EBP

(a) Macro-Financial Controls (b) Sector-Time Fixed Effects



Note. Figure B.3 compares the effects of the dynamic effect (β_1^h) of a movement in credit spreads ΔS_{it} on h-period investment of firm i, $\log K_{it+h} - \log K_{it-1}$, for two different specifications: one that controls for macro-financial controls as in the main text (13) in Panel B.3a and one that includes time-sector fixed effects (B.3) in Panel B.3b. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

tion (B.3):

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \alpha_{s,t}^h + \beta_1^h \Delta S_{i,t} + \beta_2^h \Delta S_{i,t} \times EBP_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{W}_{it-1} + e_{ith}, \qquad \text{(B.3)}$$

The interaction effect (β_2^hs) are displayed in Panel B.3b of Figure B.3, alongside the results from the original specification in Panel B.3a, which have been recopied from Panel 9b of Figure 9 for comparison. As before, Figure B.3 highlights that our results from section 6 are robust to controlling for sector-time fixed effects: investment by low-EBP firms is more sensitive to movements in their credit spreads.

B.2 EBP Heterogeneity with Dummy Variables

In this subsection, we demonstrate that our findings from the main text are not tied to the functional form of our EBP state variable, the moving yearly mean used by Jeenas (2019). In particular, we perform the same analysis as in the main text using the dummy variable approach used by Cloyne et al. (2023) and Anderson and Cesa-Bianchi (2021), and show that our conclusions are unchanged.

Denote by EBP_{ikt} the EBP on firm i's bond k in period t. Then, define $\mathbf{1}\text{EBP}_{ikt}^{low}$ as a dummy variable taking the value of 1 if EBP_{ikt} lies below the median of the EBP distribution in period t and 0 otherwise. Similarly, define $\mathbf{1}\text{EBP}_{ikt}^{high}$ as a dummy variable taking the value of 1 if EBP_{ikt} lies above the median of the EBP distribution in period t and 0 otherwise. Now, we reconsider the results from sections 3, 4, and 6. When re-assessing each section, we evaluate two specifications. The first allows us to trace the distinct dynamic responses of spreads or investment to either monetary policy shocks or changes in spreads for $\mathbf{1}\text{EBP}_{ikt}^{low}$ and $\mathbf{1}\text{EBP}_{ikt}^{high}$ firms. The second specification allows us to assess the relative response of these two types of firms.

Monetary Policy on Credit Spreads:

To assess the distinct responses of credit spreads from monetary policy shocks for low- and high-EBP bonds, we estimate:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{low} + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \quad \text{(B.4)}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{ikt-1}^{low}$ and $\mathbf{1}\text{EBP}_{ikt-1}^{high}$.

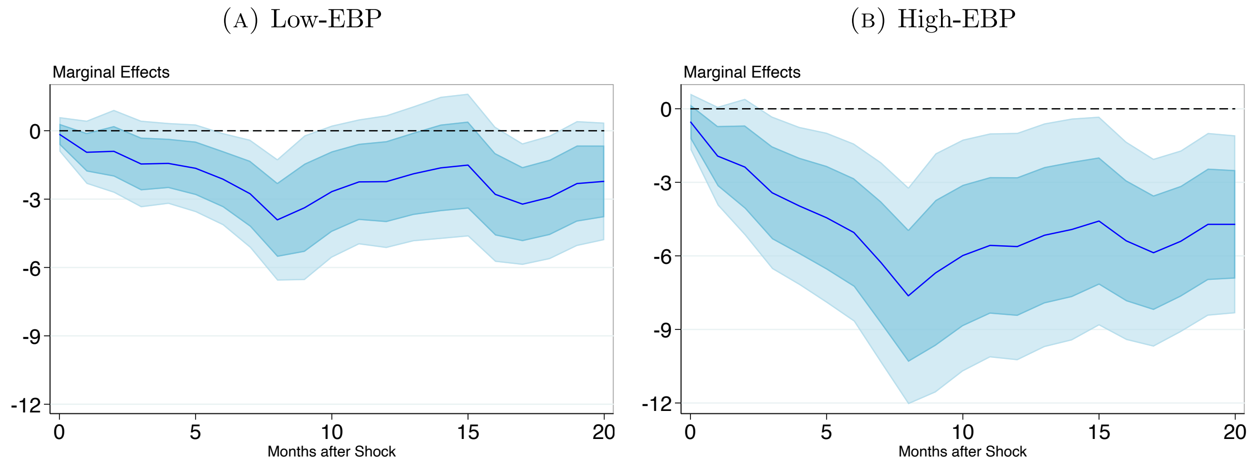
The impulse responses are displayed in Figure B.4, where we see that the credit spreads of high-EBP bonds are significantly more responsive to monetary policy than are the spreads of low-EBP bonds. This is consistent with our findings from the main text.

To see whether these two responses are distinct from one another, we estimate the adapted specification:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \quad \text{(B.5)}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{ikt-1}^{high}$. Since we have included the monetary policy shock ε_t^m on its own, the interaction coefficient β_2^h's interpretation is now the response of the high-EBP bond's spread relative to low-EBP bond's spread

FIGURE B.4
Monetary Policy's Effect on Credit Spreads for Low- vs High-EBP Bonds



Note. Figure B.4 traces the response of spreads for low-EBP ($\mathbf{1}$EBP^{low}) bonds in Panel B.4a and high-EBP ($\mathbf{1}$EBP^{high}) bonds in Panel B.4b to a Bu et al. (2021) monetary policy shock (ε_t^m), from regression (B.4), where the frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

following a shock monetary policy easing. The interaction effect is displayed in Figure B.5 and highlights, as in the main text, that high-EBP bonds' spreads fall by more following a monetary easing than low-EBP bonds' spreads. This showcases that, under an alternative functional form for our state variable, the conclusions from Section 3 are unchanged.

Monetary Policy on Investment:

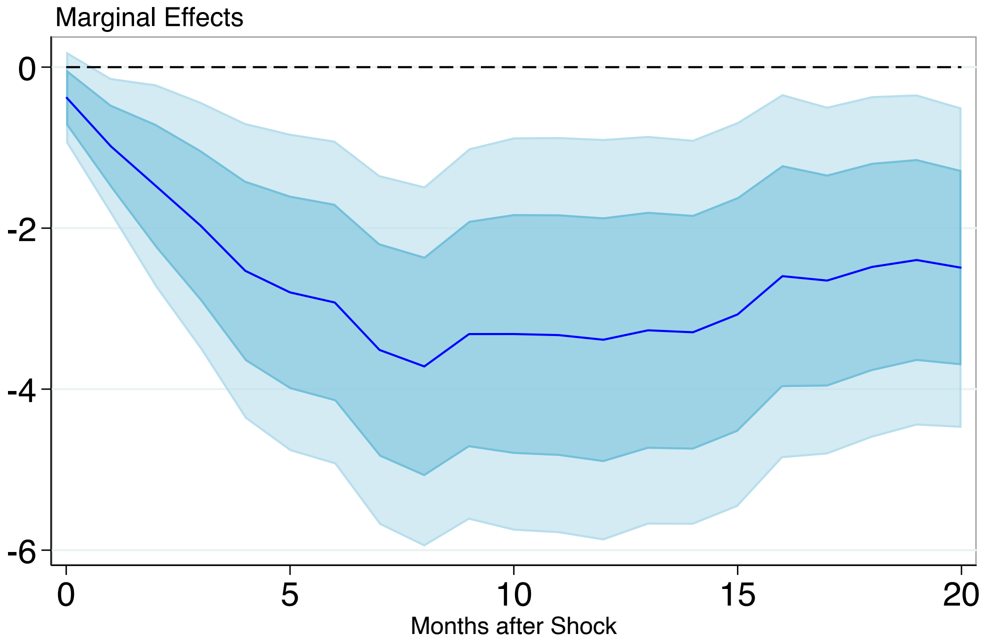
Proceeding as before, to assess the distinct investment responses to monetary policy shocks for low- and high-EBP firms, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \quad \text{(B.6)}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{EBP}_{it-1}^{high}$.

The impulse responses are displayed in Figure B.6, where we see that the investment of low-EBP firms is significantly more responsive to monetary policy than are the investment of high-EBP bonds. This is consistent with our findings from the main text.

FIGURE B.5
Monetary Policy's Effect on Bond-Level Credit Spreads Depends on EBP



Note. Figure B.5 traces the relative response (β_2^h) of high-EBP $\mathbf{1}\text{EBP}_{ikt-1}^{high}$ bond's spreads relative to low-EBP $\mathbf{1}\text{EBP}_{ikt-1}^{low}$ bond's spreads from a Bu et al. (2021) monetary policy shock (ε_t^m), from regression (B.5), where the frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

Again, to see whether these two responses are distinct from one another, we estimate:

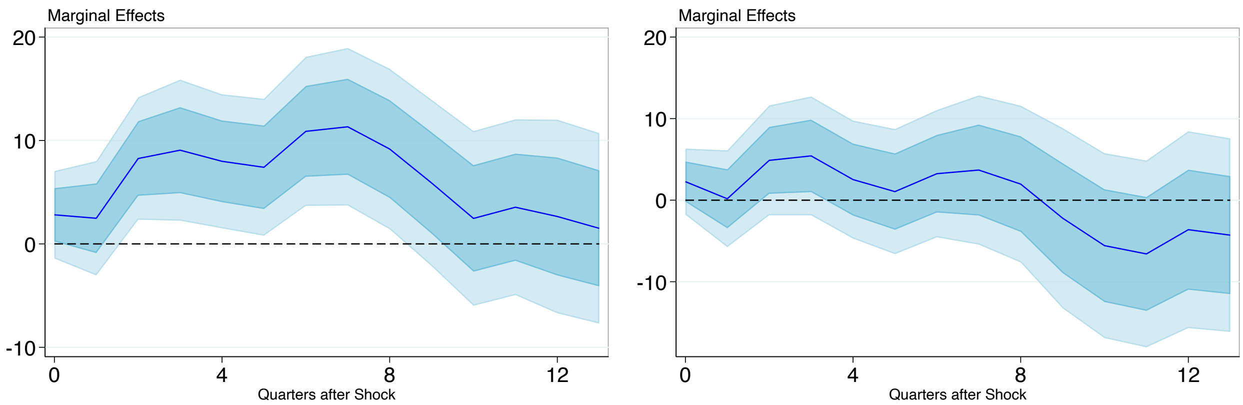
$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.7}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$. Since we have included the monetary policy shock ε_t^m on its own, the interaction coefficient's (β_2^h) interpretation is now the response of low-EBP firms' investment relative to high-EBP firms' investment to a shock monetary policy easing.

The interaction effect is displayed in Figure B.7 and highlights that a shock monetary policy easing increases investment more for low-EBP firms than for high-EBP firms. This signifies, as before, that our conclusions from Section 4 are unchanged when using an alternative functional form for our state variable.

Figure B.6
Monetary Policy's Effect on Firm Investment for Low- vs High-EBP Firms

(a) Low-EBP Firms (b) High-EBP Firms



Note. Figure B.6 traces the response of investment for low-EBP ($\mathbf{1}\text{EBP}^{low}$) bonds in Panel B.6a and high-EBP ($\mathbf{1}\text{EBP}^{high}$) bonds in Panel B.6b to a Bu et al. (2021) monetary policy shock (ε_t^m), from regression (B.6), where the frequency is quarterly. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

Credit Spreads on Investment:

Finally, we assess the distinct investment responses to movements in credit spreads for low- and high-EBP firms by estimating:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \Delta S_{it} \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_2^h \Delta S_{it} \times \mathbf{1}\text{EBP}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \quad \text{(B.8)}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{EBP}_{it-1}^{high}$.

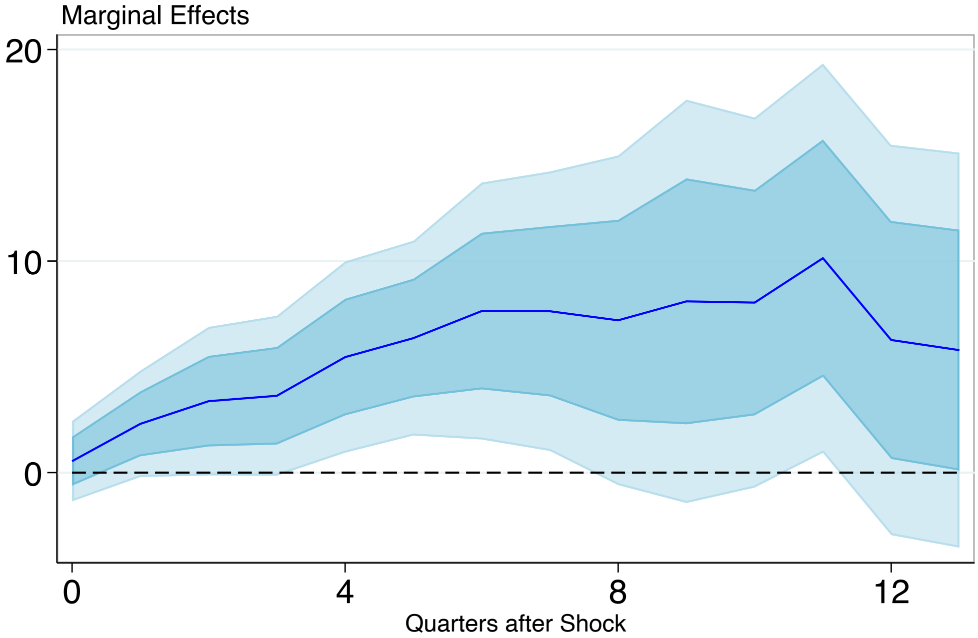
The impulse responses are displayed in Figure B.8, where we see that the investment of low-EBP firms is significantly more responsive to movements in their credit spreads compared to the investment of high-EBP firms. This is consistent with our findings from the main text.

To see whether these two responses are distinct from one another, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \Delta S_{it} + \beta_2^h \Delta S_{it} \times \mathbf{1}\text{EBP}_{it-1}^{low} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \quad \text{(B.9)}$$

Figure B.7

Monetary Policy's Effect on Firm-Level Investment Depends on EBP



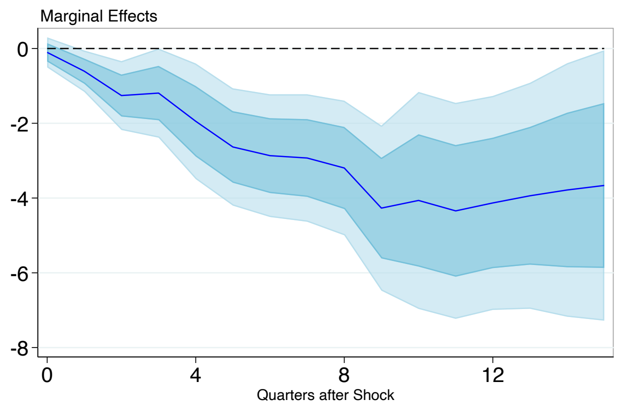
Note. Figure B.7 traces the relative response (β_2^h) of low-EBP $\mathbf{1}\text{EBP}_{it-1}^{low}$ firms' investment relative to high-EBP $\mathbf{1}\text{EBP}_{it-1}^{high}$ firms' investment from a Bu et al. (2021) monetary policy shock (ε_t^m), from regression (B.7), where the frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$. Again, because we have included the credit spread shock ΔS_{it} on its own, the interaction coefficient's (β_2^h) interpretation is now the response of low-EBP firms' investment relative to high-EBP firms' investment to movements in credit spreads ΔS_{it}.

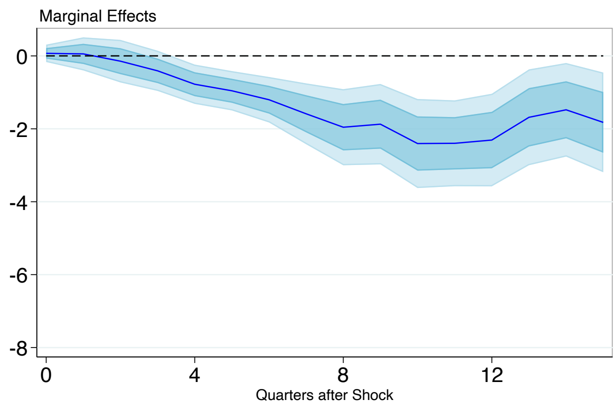
The interaction effect is displayed in Figure B.9 and highlights, as in the main text, that low-EBP firms' investment falls by more following an increase in their credit spreads relatve to high-EBP firms' investment, just as in Section 6.

FIGURE B.8
Credit Spread Shocks and Firm Investment for Low- vs High-EBP Firms

(A) Low-EBP Firms



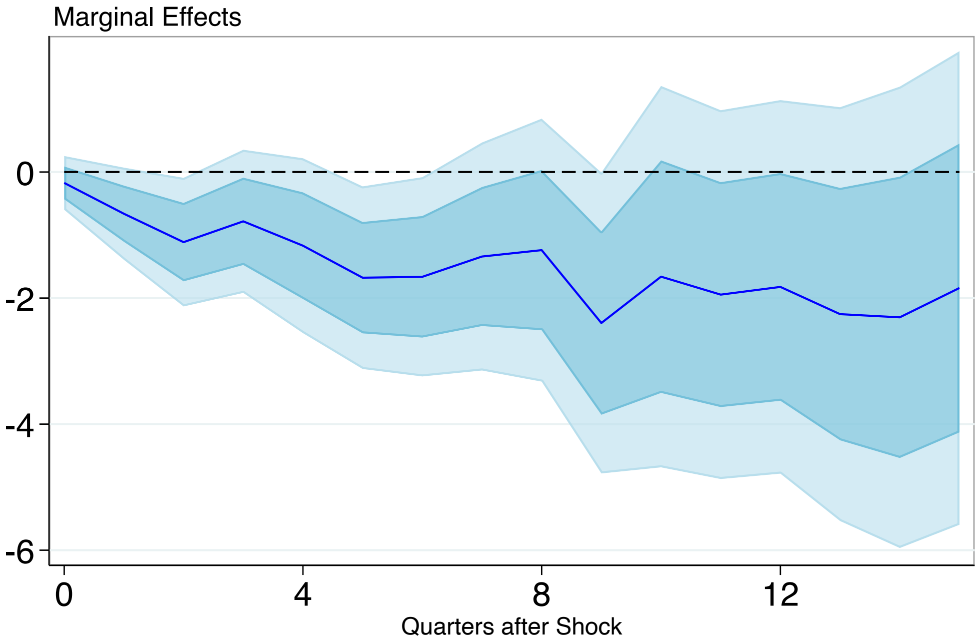
(B) High-EBP Firms



Note. Figure B.8 traces the response of investment for low-EBP ($\mathbf{1}\mathrm{EBP}^{low}$) firms in Panel B.8a and high-EBP ($\mathbf{1}\mathrm{EBP}^{high}$) firms in Panel B.8b to a change in credit spreads ΔS_{it}, from regression (B.8), where the frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

Figure B.9

Credit Spread's Effect on Firm-Level Investment Depends on EBP



Note. Figure B.9 traces the relative response (β_2^h) of low-EBP $\mathbf{1}\text{EBP}_{it-1}^{low}$ firms' investment relative to high-EBP $\mathbf{1}\text{EBP}_{it-1}^{high}$ firms' investment from a change in credit spreads ΔS_{it}, from regression (B.9), where the frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

B.3 Default Risk as a State Variable

In this section, we document that, when not controlling for heterogeneity by EBP, default-risk does indeed regulate the response of firms' credit spreads and investment to monetary policy shocks in a manner consistent with the findings of Anderson and Cesa-Bianchi (2021) and Ottonello and Winberry (2020), respectively.

To demonstrate this, we use the dummy variable approach outlined in the previous section, since this is the functional form used by Anderson and Cesa-Bianchi (2021). Ottonello and Winberry (2020) use a linear functional form that purges firms' default risk of their in-sample firm-specific mean, which is motivated by firms being ex-ante identical in their model. To make our results comparable across as many studies as possible, we use the dummy variable approach.

Monetary Policy on Credit Spreads:

We begin by assessing the responses of bond-level credit spreads to monetary policy shocks for low- vs. high-default-risk firms. Recall that low distance to default and high leverage firms are viewed as having high default-risk. We begin by estimating the following specification at a monthly frequency:

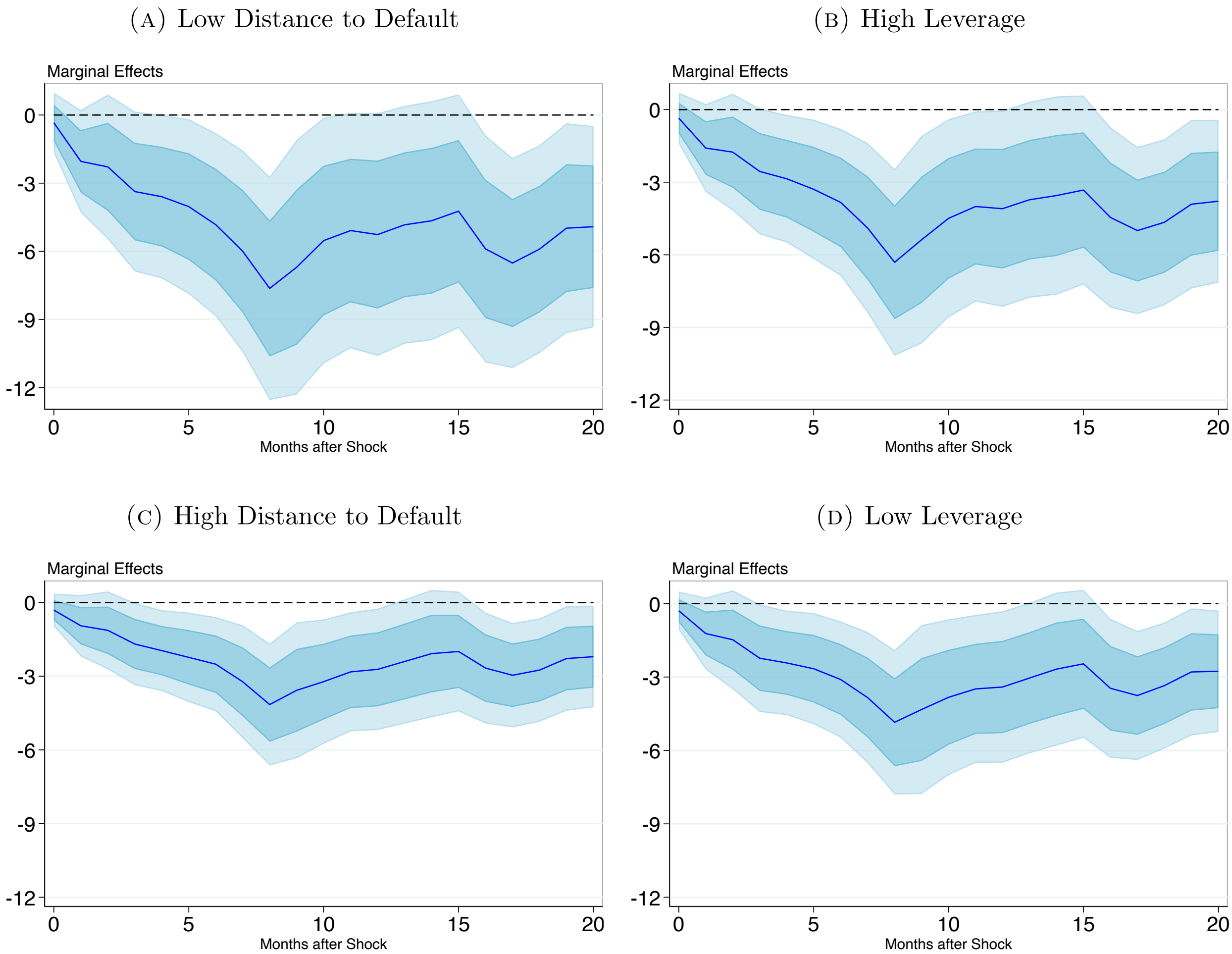
$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{low} + \beta_2^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.10}$$

where x denotes either distance to default or leverage. In the notation of the previous section, $\mathbf{1}\mathrm{x}_{it}^{low}$ is a dummy variable taking the value of 1 if x_{it} lies below the median of the firm-level distance to default or leverage distribution in period t and 0 otherwise. Similarly, define $\mathbf{1}\mathrm{x}_{it}^{high}$ as a dummy variable taking the value of 1 if x_{it} lies above the median of the firm-level distance to default or leverage distribution in period t and 0 otherwise. Note also that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\mathrm{x}_{it-1}^{low}$ and $\mathbf{1}\mathrm{x}_{it-1}^{high}$.

The impulse responses are displayed in Figure B.10, where the Panels B.10a and B.10c trace β_1^h and β_2^h, respectively, when x is distance to default while Panels B.10b and B.10d trace β_2^h and β_1^h, respectively, when x is leverage. Clearly, we see that the marginal effects

Figure B.10

Monetary Policy's Effect on Spreads for Low vs. High Default-Risk Firms



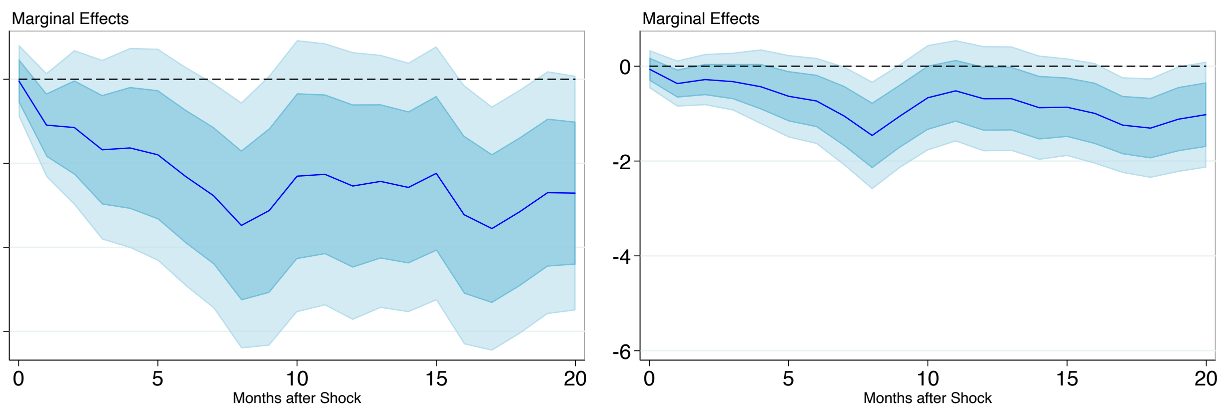
Note. Figure B.10 traces the distinct responses of low- and high- distance to default firms' spreads to a monetary policy shock in Panels B.10a and B.10c from estimating regression (B.10) with x as distance to default, while Panels B.10b and B.10d trace the distinct responses of high- and low-leverage firms' spreads to a monetary policy shock from estimating regression (B.10) with x as leverage. The frequency of the data is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

in the top row (Panels B.10a and B.10b), for low distance to default and high leverage firms, are larger than those in the bottom row. That is, consistent with the findings of Anderson and Cesa-Bianchi (2021), the credit spreads of firms with high default risk are more responsive to monetary policy shocks than are the firms with low default risk.

Following a similar path to the one from the previous section, we next assess whether the response of spreads for high- vs. low-default risk firms are statistically different from

FIGURE B.11
Monetary Policy's Relative Effect on Bond-Level Credit Spreads by Default Risk

(A) Low Distance to Default (B) High Leverage



Note. Figure B.11 traces the response of credit spreads for high-default risk, low distance to default in Panel B.11a and high-leverage in Panel B.11b, to a monetary policy shock from estimating regression (B.11), where the frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

one another using:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{high(low)} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.11}$$

where, we include $\mathbf{1}\mathrm{x}_{it-1}^{low}$ when x is distance to default and $\mathbf{1}\mathrm{x}_{it-1}^{high}$ when x is leverage, to keep the responses comparable. As before, because we have included the monetary policy shock ε_t^m on its own, the interaction coefficient's (β_2^h) interpretation is the response of high-default risk firms' (low distance to default or high leverage) spreads relative to low-default risk firms' spreads to a monetary policy shock. Note also that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\mathrm{x}_{it-1}^{high(low)}$.

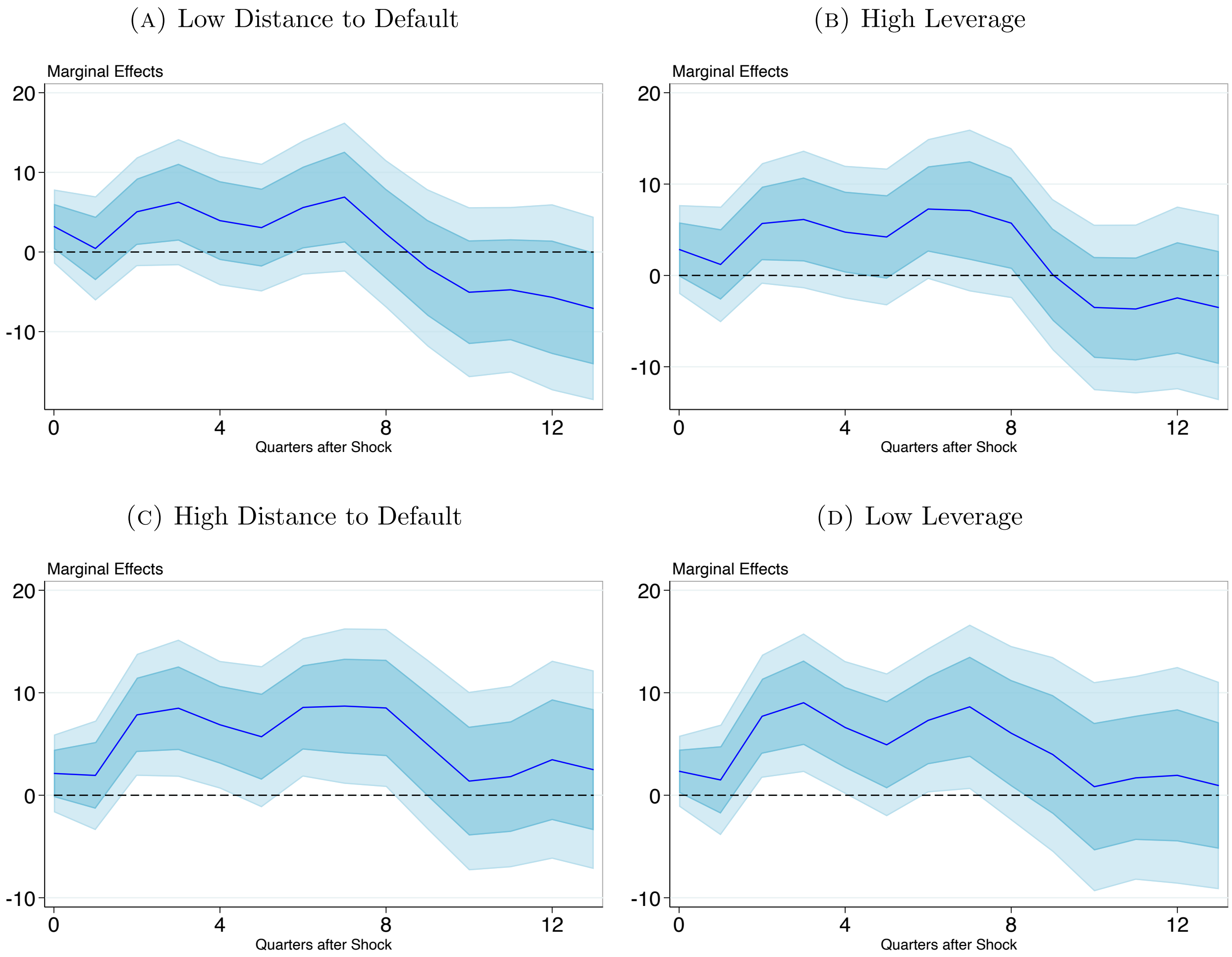
The interaction effect is displayed in Figure B.11 and highlights that high default-risk firms' spreads fall by more following a shock monetary policy easing compared to low default-risk firms', as is found by Anderson and Cesa-Bianchi (2021).

Monetary Policy on Investment:

To assess the distinct investment responses to monetary policy shocks for firms with

Figure B.12

Monetary Policy's Effect on Investment for Low vs. High Default-Risk Firms



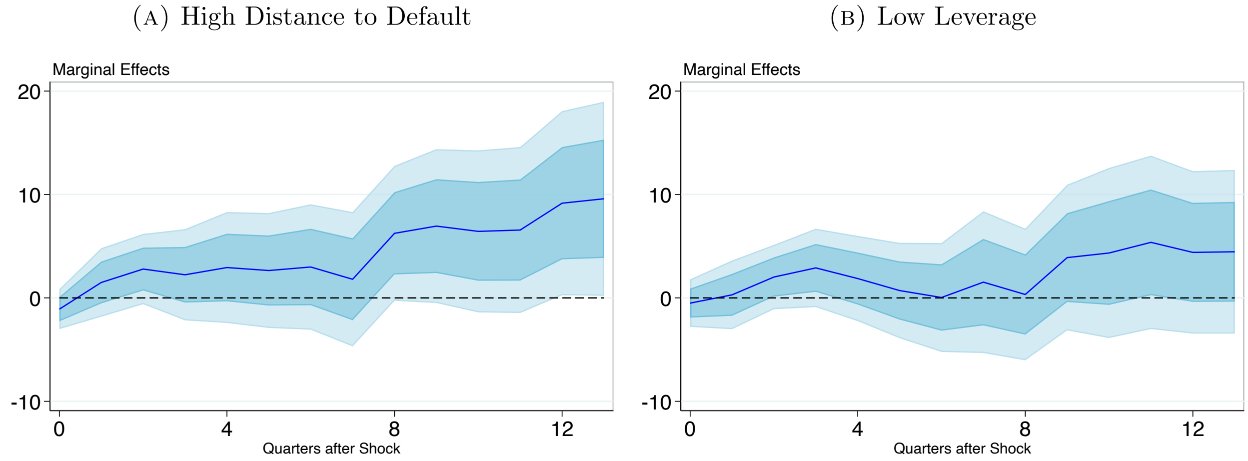
Note. Figure B.12 traces the distinct responses of low- and high- distance to default firms' investment to a monetary policy shock in Panels B.12a and B.12c from estimating regression (B.12) with x as distance to default, while Panels B.12b and B.12d trace the distinct responses of high- and low-leverage firms' investment to a monetary policy shock from estimating regression (B.12) with x as leverage. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

low- vs. high-default risk, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{low} + \beta_2^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.12}$$

where again x refers either to firms' distance to default or leverage and $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\mathrm{x}_{it-1}^{low}$ and $\mathbf{1}\mathrm{x}_{it-1}^{high}$.

FIGURE B.13
Monetary Policy's Relative Effect on Firm-Level Investment by Default Risk



Note. Figure B.13 traces the response of investment for low-default risk, high distance to default in Panel B.13a and low-leverage in Panel B.13b, to a monetary policy shock from estimating regression (B.13), where the frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

The impulse responses are displayed in Figure B.12, where we see that only the investment responses of low default-risk—high distance to default (Panel B.12c) and low leverage (Panel B.12d)—firms are statistically different from zero. This is consistent with the findings of Ottonello and Winberry (2020).

Finally, to see whether the responses of low vs. high default-risk firms are distinct from one another, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{low(high)} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.13}$$

where, we include $\mathbf{1}\mathrm{x}_{it-1}^{low}$ when x is leverage and $\mathbf{1}\mathrm{x}_{it-1}^{high}$ when x is distance to default, to keep the responses comparable. As before, because we have included the monetary policy shock ε_t^m on its own, the interaction coefficient's (β_2^h) interpretation is the response of low-default risk firms' (high distance to default or low leverage) investment relative to low-default risk firms' investment to a monetary policy shock. Note also that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\mathrm{x}_{it-1}^{low(high)}$.

The impulse responses are traced in Figure B.13 and highlight that point estimates for both leverage and distance to default imply that low-default risk firms' investment increases by more than high-default risk firms'. However, only when using distance to default (Panel B.13a) is the effect statistically different from zero, albeit at longer horizons. This is consistent with Ottonello and Winberry (2020) who show that distance to default outperforms leverage in regulating firms' investment response to monetary policy. It is worth pointing out that Jeenas (2019) and Anderson and Cesa-Bianchi (2021) find that it is high-default-risk firms whose investment is more sensitive to monetary policy, while Lakdawala and Moreland (2021) highlight that the sign of heterogeneity by default risk may have changed following the global financial crisis. The differences in results across studies are part of an ongoing debate in the literature, which our results in this section for heterogeneity by default risk contribute to.

B.4 Monetary Policy's Effect by EBP vs. other Characteristics

In this section, we show that the importance of firms' EBPs for determining their responsiveness to monetary policy is robust to conditioning on other competing firm characteristics. We first document that, as for the baseline linear interactions used in the main text, EBP heterogeneity tends to supersede heterogeneity by distance to default and leverage when using the dummy variable approach. Next, we consider heterogeneity by credit rating, age, size (assets) , sales growth, share of liquid assets, and Tobin's average Q and show that the EBP remains a significant state variable for the transmission of monetary policy when conditioning on these firm characteristics as well. To provide comparability with the existing studies, we use the dummy variable approach when assessing the conditioning effects of firms' EBPs relative to their credit rating (Ottonello and Winberry, 2020), age (Cloyne et al., 2023), and size and sales growth (Gertler and Gilchrist, 1994), but use our baseline linear interaction for share of liquid assets (Jeenas, 2019) and Tobin's average q.

B.4.1 Distance to Default and Leverage with dummy variables:

In the main text, we ran horseraces between *linear* EBP interactions and *linear* default risk interactions to highlight that firms' responsiveness to monetary policy was largely a function of their EBPs.[37] In this section, we show that running similar horseraces using the dummy variable approach does not alter our conclusion that a firm's EBP supersedes its default risk as state variable for the transmission of monetary policy to both credit spreads and investment.

Monetary Policy on Credit Spreads:

We begin by running a horserace between the EBP and a measure of default risk x (distance to default or leverage) as a conditioning variable for the impact of monetary policy on credit spreads:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\mathrm{EBP}_{ikt-1}^{high} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\mathrm{x}_{it-1}^{low(high)} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.14}$$

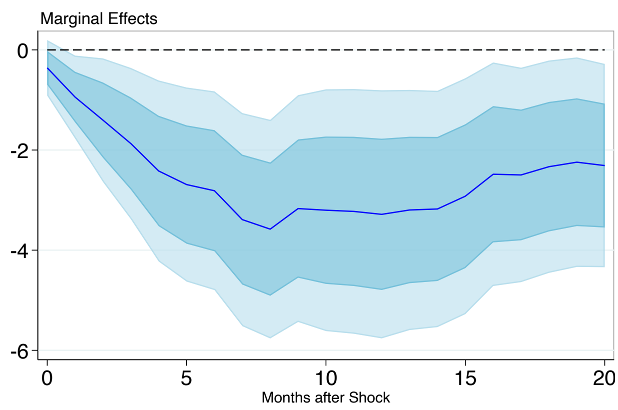
where, as before, because we have included the monetary policy shock ε_t^m on its own, the interaction coefficient associated with $\mathbf{1}\mathrm{EBP}_{ikt-1}^{high}$ (β_2^h) is interpreted as the credit spread response of high-EBP bonds relative to low-EBP bonds due to a monetary policy shock, controlling for heterogeneity by default risk. An analogous interpretation is associated with β_3^h. As before, we use $\mathbf{1}\mathrm{x}_{it-1}^{low}$ when x is distance to default and $\mathbf{1}\mathrm{x}_{it-1}^{high}$ when x is leverage, so as to capture the relative effect of high default risk firms relative to low default risk firms. Note also that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\mathrm{EBP}_{ikt-1}^{high}$ and $\mathbf{1}\mathrm{x}_{it-1}^{low(high)}$.

The results are displayed in Figure B.14 and highlight, as in the main text, that firms' EBPs tend to supersede their default risk in regulating the sensitivity of firms' spreads to monetary policy shocks, and that it is the spreads of firms whose bonds carry high-EBPs that are most responsive.

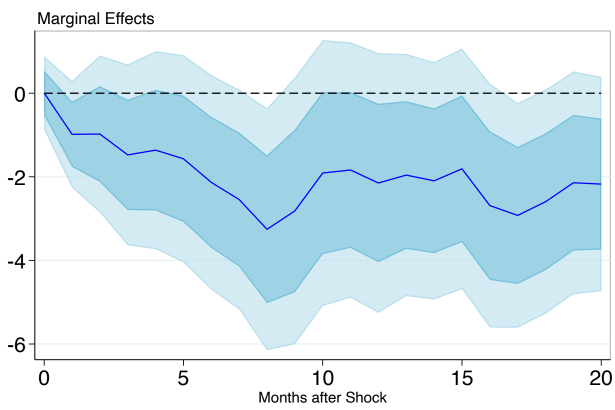
[37]Specifically, we used linear interactions between the one-year moving average of a firm's characteristic (EBP or default risk) and the monetary policy shock, as in Jeenas (2019).

FIGURE B.14
Monetary Policy's Relative Effect on Spreads by EBP vs. Default Risk

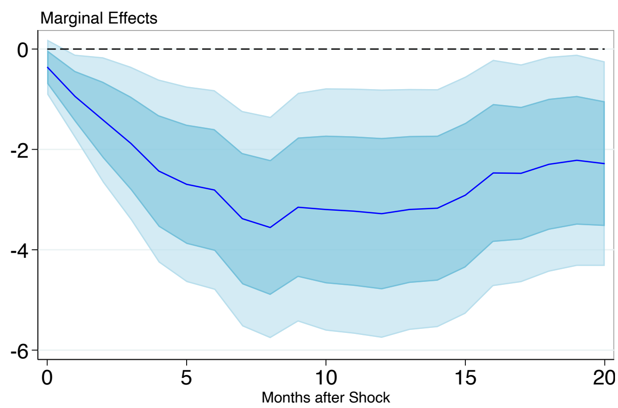
(A) High EBP



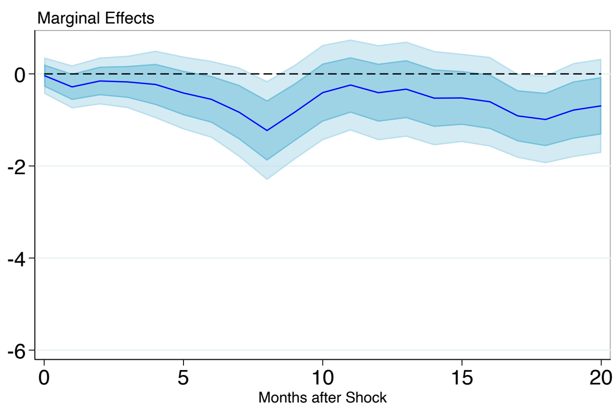
(B) Low Distance to Default



(C) High EBP



(D) High Leverage



Note. Figure B.14 displays dynamic interaction coefficients from a horserace between (A) the relative response of high-EBP bonds' spreads compared to low-EBP bonds' (Panels B.14a and B.14c) and (B) the relative response of high-default-risk firms' spreads compared to low-default-risk firms' (low distance to default in Panel B.14b and high leverage in Panel B.14d) from a monetary policy shock ε_t^m from estimating regression (B.14). Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

Monetary Policy on Investment:

Next, we show the same for monetary policy's effect on investment, using the following local projection:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{x}_{it-1}^{high(low)} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.15}$$

where, we include $\mathbf{1}\text{x}_{it-1}^{high}$ when x is distance to default and $\mathbf{1}\text{x}_{it-1}^{low}$ when x is leverage, so as to capture the relative effect of low default risk firms' investment response vs. to high default risk firms, and compare them to the relative response of low-EBP firms' investment, as compared to high-EBP firms'. Again, $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{x}_{it-1}^{high(low)}$.

The results are displayed in Figure B.15. As in the main text, we see that firms' EBPs tend to supersede their default risk in regulating the sensitivity of firms' investment to monetary policy shocks, and that it is firms with low-EBPs whose investment is most responsive.

B.4.2 Credit Rating:

In their appendix, Ottonello and Winberry (2020) assess the conditioning power of firms' default risk as measured by their credit ratings, using the dummy variable approach. Here, we use the dummy variable approach to highlight that heterogeneity by EBP is robust to controlling for heterogeneity by credit rating.

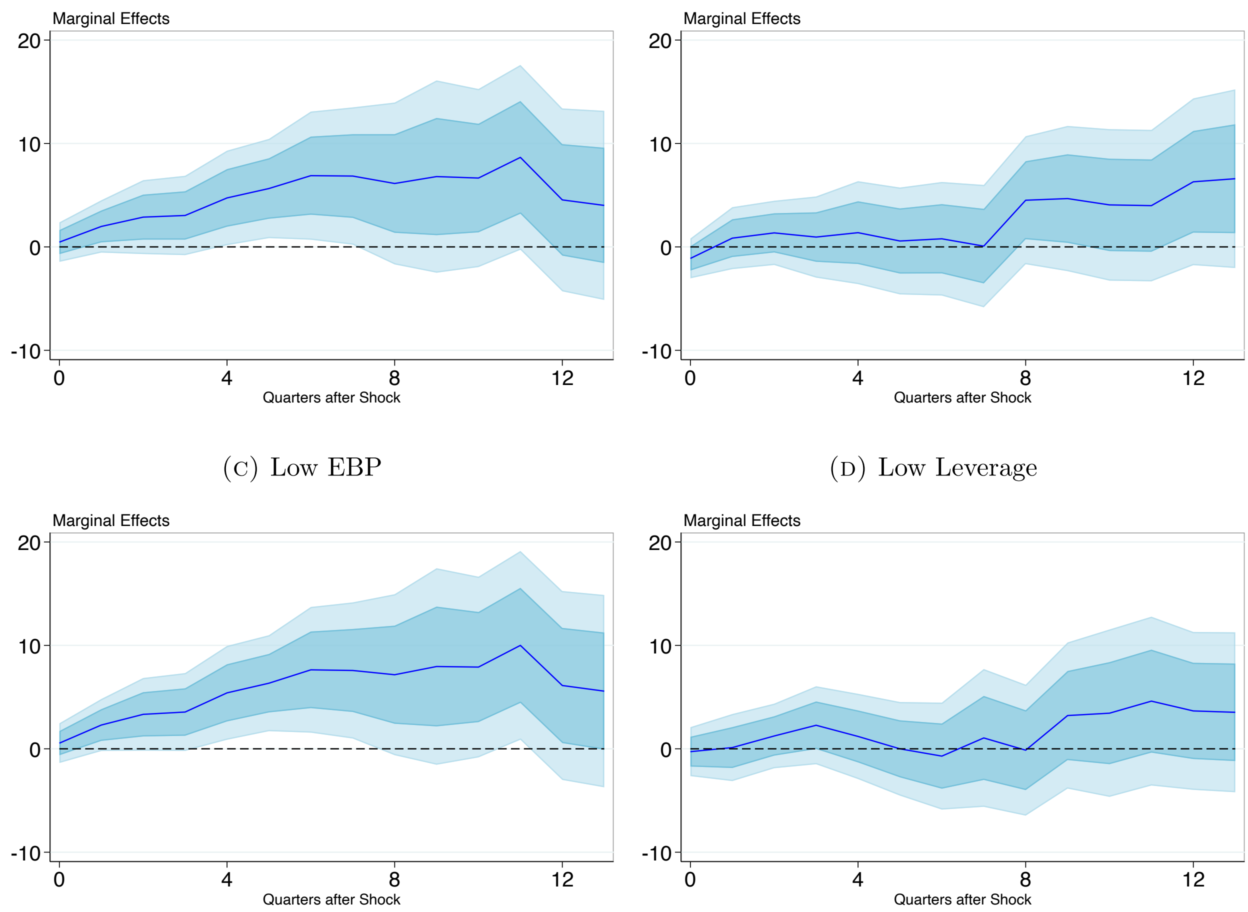
Monetary Policy on Credit Spreads:

We begin by running the following local projection:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{high} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Rate}_{it-1}^{low} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.16}$$

where $\mathbf{1}\text{Rate}^{low}$ denotes a dummy variable taking the value of one if the firms' credit rating lies below the median of the cross-sectional credit rating distribution in the period prior to the monetary surprise, that is, the firm is viewed as relatively risky. Note again that $\mathbf{Z}_{it-1}$

Figure B.15
Monetary Policy's Relative Effect on Investment by EBP vs. Default Risk



(A) Low EBP

(B) High Distance to Default

(C) Low EBP

(D) Low Leverage

Note. Figure B.15 displays dynamic interaction coefficients from a horserace between (A) the relative response of low-EBP firms' investment compared to high-EBP firms' (Panels B.15a and B.15c) and (B) the relative response of low-default-risk firms' investment compared to high-default-risk firms' (high distance to default in Panel B.15b and low leverage in Panel B.15d) from a monetary policy shock ε_t^m from estimating regression (B.15). Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{ikt-1}^{high}$ and $\mathbf{1}\text{Rate}_{it-1}^{low}$.

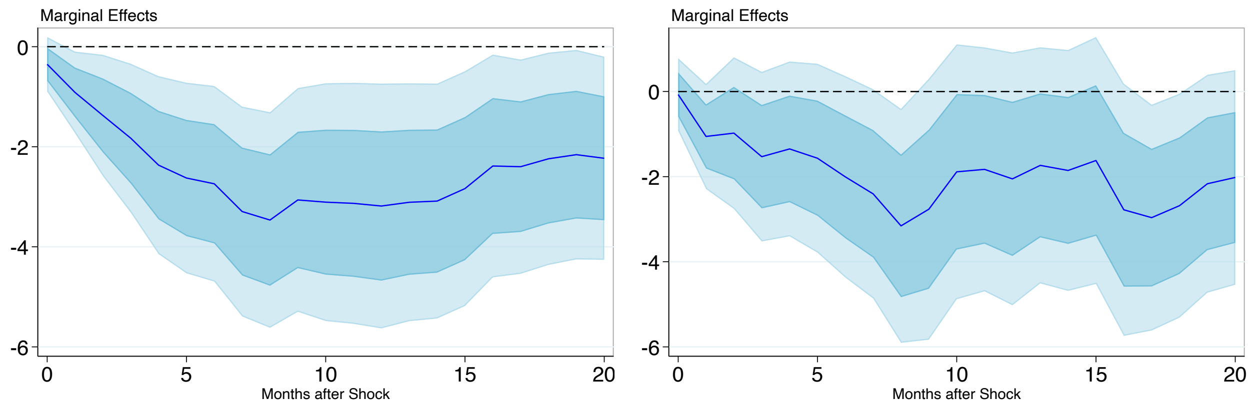
In Figure B.16, we see that while high-risk firms' spreads are more responsive to monetary shocks (Panel B.16b), the EBP continues to be an important determinant of the sensitivity of firms' spreads to monetary policy.[38]

[38] Interestingly, since rating agencies rely on the Merton (1974) model as a primary determinant of the credit rating, the impulse responses for credit rating look similar to those for distance to default in this

Figure B.16

Monetary Policy's Relative Effect on Spreads by EBP vs. Credit Rating

(A) High EBP (B) Low Credit Rating



Note. Figure B.16 displays dynamic interaction coefficients from a horserace between (A) the relative response of high-EBP bonds' spreads compared to low-EBP bonds' (Panel B.16a) and (B) the relative response of low-credit-rating (risky) firms' spreads compared to high-rating (safe) firms' (Panel B.16b) from a monetary policy shock ε_t^m from estimating regression (B.16). Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

Monetary Policy on Investment:

Next, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Rate}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.17}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{Rate}_{it-1}^{high}$.

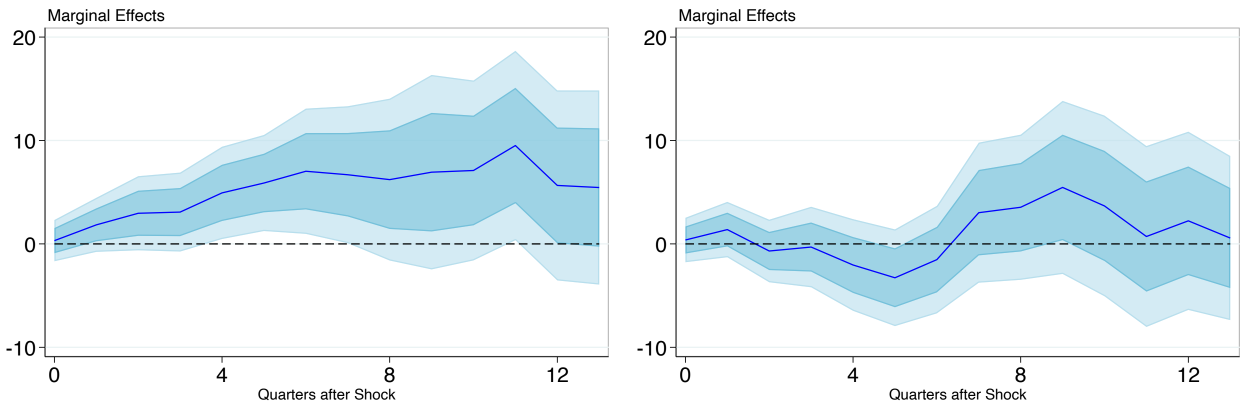
The impulse responses are presented in Figure B.17. We see again that the EBP regulates firms' investment response to monetary policy (Panel B.17a), as in the main text, superseding heterogeneity by credit rating (Panel B.17b).

case.

Figure B.17

Monetary Policy's Relative Effect on Investment by EBP vs. Credit Rating

(A) Low EBP (B) High Credit Rating



Note. Figure B.17 displays dynamic interaction coefficients from a horserace between (A) the relative response of low-EBP firms' investment compared to high-EBP firms' (Panel B.17a) and (B) the relative response of high-credit-rating firms' investment compared to low-rating firms' (Panel B.17b) from a monetary policy shock ε_t^m from estimating regression (B.17). Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

B.4.3 Age:

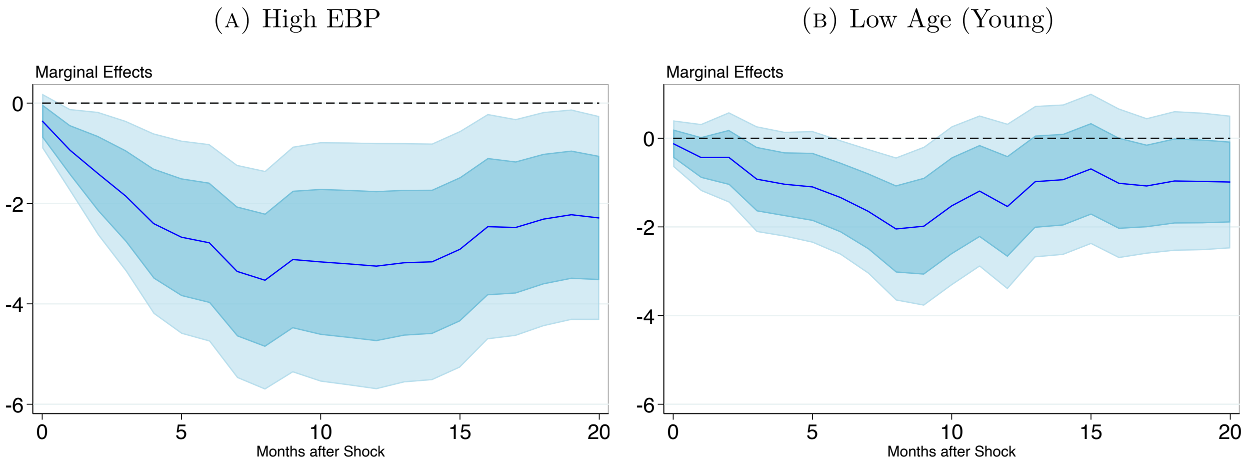
Next, we turn to demonstrate the robustness of our EBP state to firms' age, which Cloyne et al. (2023) show regulates the sensitivity of firms' investment to monetary policy shocks. Like Anderson and Cesa-Bianchi (2021), we use age since IPO, since this variable is available in the Compustat database. Admittedly, this is different from the age since incorporation variable used by Cloyne et al. (2023).

Monetary Policy on Credit Spreads:

Cloyne et al. (2023) use the dummy variable approach in establishing their empirical findings, and we follow them in our robustness check and run the following horserace regression:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{high} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Age}_{it-1}^{low} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.18}$$

FIGURE B.18
Monetary Policy's Relative Effect on Spreads by EBP vs. Age



Note. Figure B.18 displays dynamic interaction coefficients from a horserace between (A) the relative response of high-EBP bonds' spreads compared to low-EBP bonds' (Panel B.18a) and (B) the relative response of low-age (young) firms' spreads compared to high-age (old) firms' (Panel B.18b) from a monetary policy shock ε_t^m from estimating (B.18). Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

where $\mathbf{1}\text{Age}_{it-1}^{low}$ is a dummy variable taking the value of 1 if a firms' age is below the median of firms' age distribution in the period before the monetary surprise, and zero otherwise. Note again that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{ikt-1}^{high}$ and $\mathbf{1}\text{Age}_{it-1}^{low}$.

Consistent with the direction of the heterogeneity in Cloyne et al. (2023), Panel B.18b of Figure B.18 highlights that the spreads of young firms are relatively more responsive to monetary policy shocks. Still, we see that our findings for heterogeneity by EBP from the main text are robust to conditioning on age (Panel B.18a).

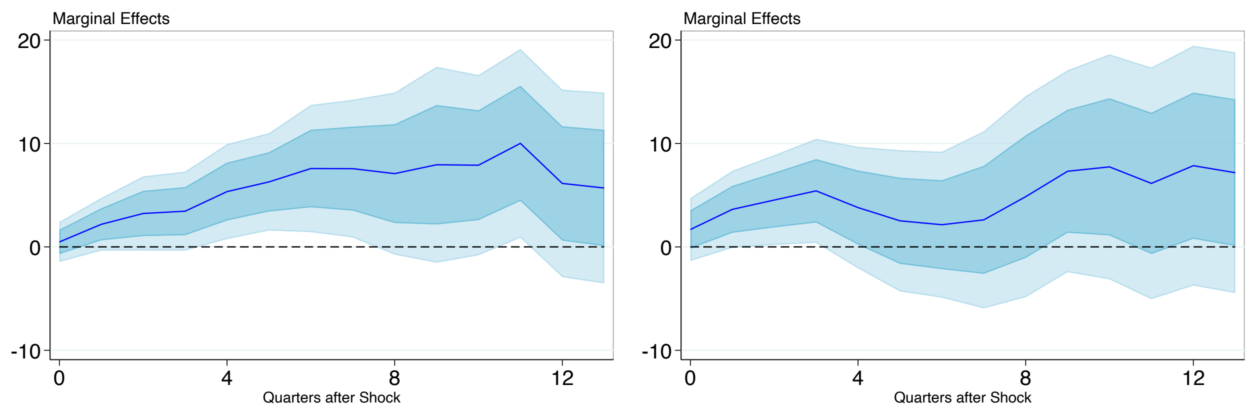
Monetary Policy on Investment:

Next, we turn to confirm that the heterogeneous effects of monetary policy on invest-

FIGURE B.19

Monetary Policy's Relative Effect on Investment by EBP vs. Age

(A) Low EBP (B) High Age (Old)



Note. Figure B.19 displays dynamic interaction coefficients from a horserace between (A) the relative response of low-EBP firms' investment compared to high-EBP firms' (Panel B.19a) and (B) the relative response of high-age (old) firms' investment compared to low-age (young) firms' (Panel B.19b) from a monetary policy shock ε_t^m from estimating (B.19). Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

ment by firms' EBPs are robust to controlling for heterogeneity by age. We do so using:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Age}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.19}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{Age}_{it-1}^{high}$. The results displayed in Figure B.19 highlight that the EBP indeed continues to regulate the responsiveness of firms' investment to monetary policy. Surprisingly, we see in Panel B.19b that it is old firms whose investment response is larger compared to young firms following a monetary shock, in contrast to Cloyne et al. (2023), albeit only marginally. There are a few potential explanations. First, Cloyne et al. (2023) use a different measure of investment to what is used by Ottonello and Winberry (2020) and in our paper and, in addition, study investment growth rather than the level of investment. Since our model speaks to investment, we prefer our measure. Second, we focus on firms who use bond finance, which tend to be larger and older firms, such that our samples are not identical. Third, Cloyne et al. (2023)'s monetary policy shocks are constructed from a proxy-VAR. Nonetheless, we show that heterogeneity by EBP is robust to controlling for heterogeneity by age.

B.4.4 Size:

As in Cloyne et al. (2023), Gertler and Gilchrist (1994) employ a dummy variable approach to assess how a firm's size determines its sensitivity to monetary policy shocks. In this section, we measure size in assets and, as a measure of growth in size, we use sales growth, and compare each of their abilities to regulate firms' responses to monetary policy to firms' EBPs.

Monetary Policy on Credit Spreads:

We begin with monetary policy's effect on credit spreads:

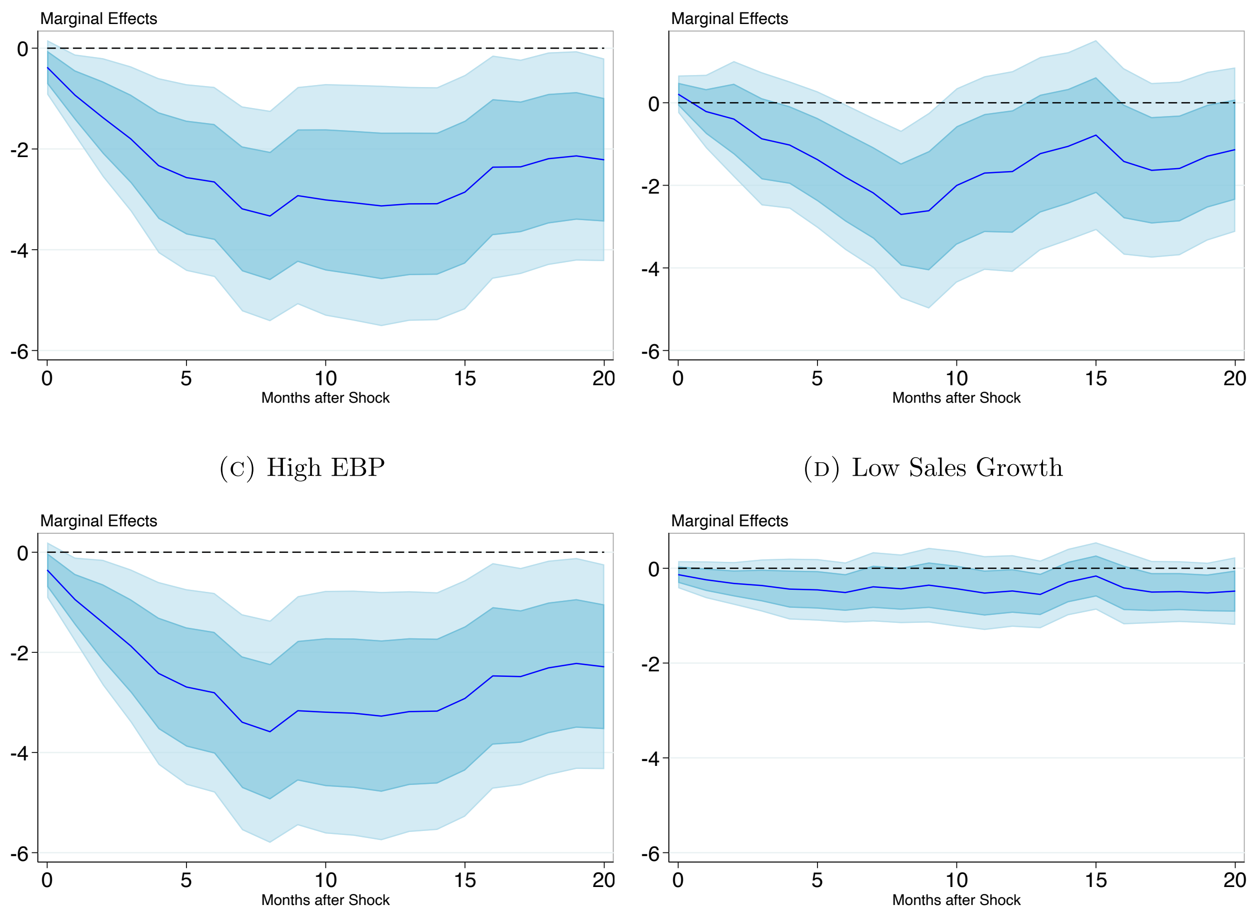
$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{ikt-1}^{high} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Size}_{it-1}^{low} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.20}$$

where $\mathbf{1}\text{Size}^{low}$ is a dummy taking the value of 1 if a firms' assets (sales growth) are below the median in the period before the monetary shock, and 0 otherwise. Note again that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{ikt-1}^{high}$ and $\mathbf{1}\text{Size}_{it-1}^{low}$.

The results are displayed in Figure B.20. We see that while firms' with low assets, that is small firms, have spreads who are more responsive to monetary policy, consistent with the findings in Gertler and Gilchrist (1994), sales growth does not seem to be a key determinant of the sensitivity of spreads. In both cases, heterogeneity by EBP is robust to controlling for the conditioning effects of these measures of (growth in) size.

Monetary Policy on Investment:

FIGURE B.20
Monetary Policy's Relative Effect on Spreads by EBP vs. Size



(A) High EBP

(B) Low Assets (Small)

(C) High EBP

(D) Low Sales Growth

Note. Figure B.20 displays dynamic interaction coefficients from a horserace between (A) the relative response of high-EBP bonds' spreads compared to low-EBP bonds' (Panel B.20a) and (B) the relative response of low-asset-size (small) firms' spreads compared to large firms' (Panel B.20b) from a monetary policy shock ε_t^m from estimating (B.20). Panels B.20c and B.20d do the same but replace small (in assets) firms with low sales growth firms. Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

Next, turning to investment, we estimate:

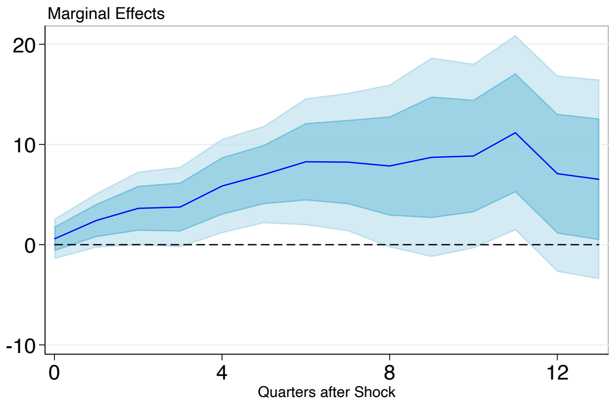
$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_3^h \varepsilon_t^m \times \mathbf{1}\text{Size}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.21}$$

where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus $\mathbf{1}\text{EBP}_{it-1}^{low}$ and $\mathbf{1}\text{Size}_{it-1}^{high}$.

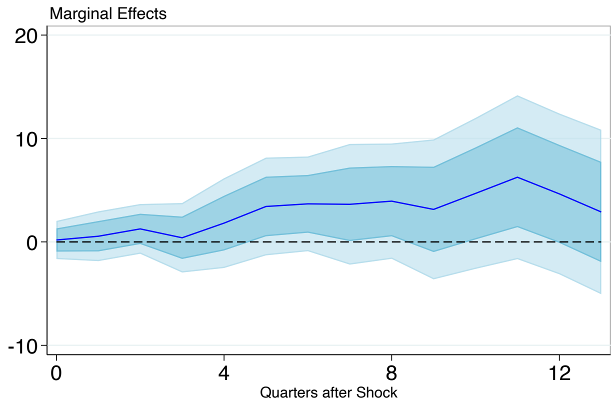
Figure B.21

Monetary Policy's Relative Effect on Investment by EBP vs. Size

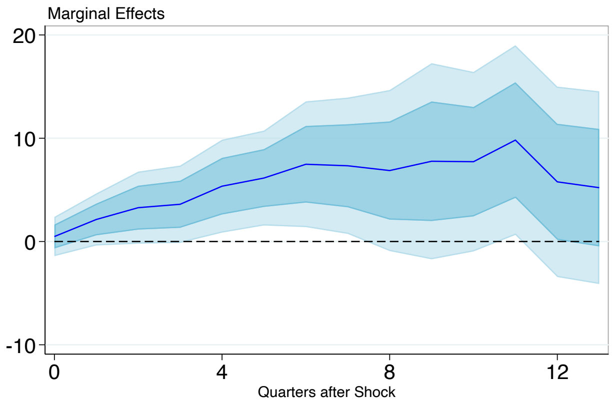
(a) Low EBP



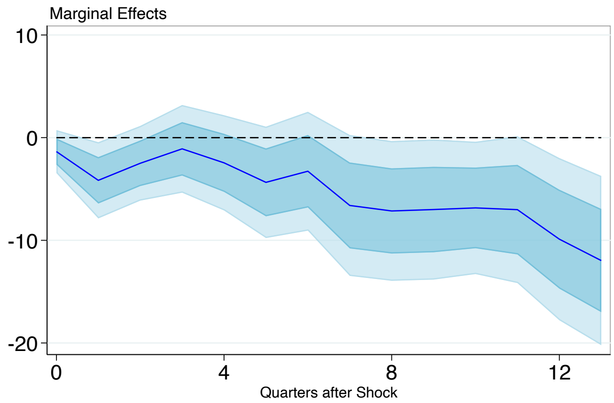
(b) Low Assets (Small)



(c) Low EBP



(d) Low Sales Growth

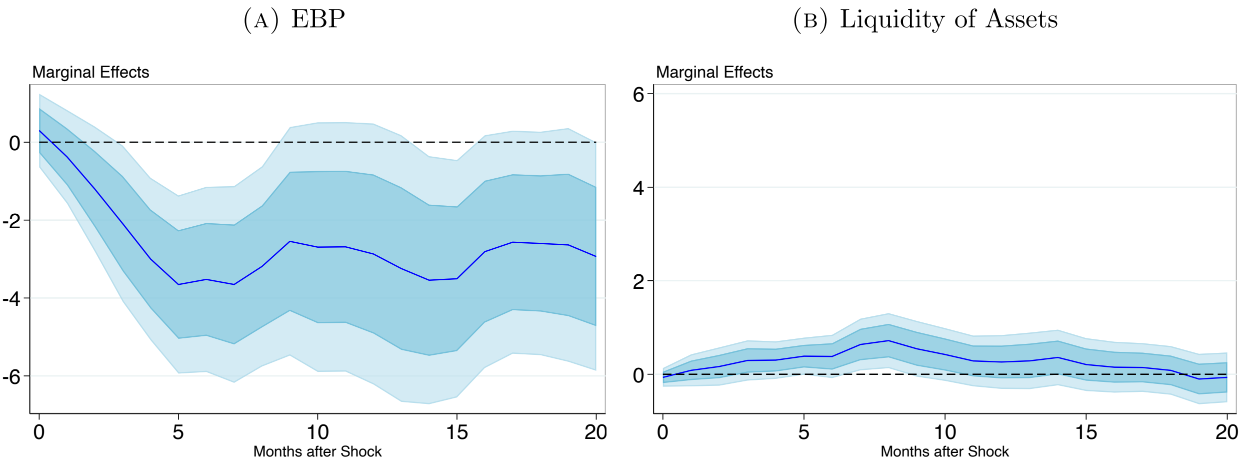


Note. Figure B.21 displays dynamic interaction coefficients from a horserace between (A) the relative response of low-EBP firms' investment compared to high-EBP firms' (Panel B.21a) and (B) the relative response of low-assets (small) firms' investment compared to large firms' (Panel B.21b) from a monetary policy shock ε_t^m from estimating (B.21). Panels B.21c and B.21d do the same but replace small (in assets) firms with low sales growth firms. Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

We display the results in Figure B.21. The point-estimates in Panel B.21b indicate that, consistent with Gertler and Gilchrist (1994), small firms adjust investment more than large firms in response to monetary policy shocks. In addition, firms with high sales growth also adjust investment more following monetary shocks, as seen in Panel B.21d. In both cases, however, the EBP remains significant as a determinant of firms' investment response to monetary policy.

Figure B.22

Monetary Policy's Effect on Spreads by EBP vs. Liquidity of Assets



Note. Figure B.22 displays dynamic interaction coefficients from a horserace between the interaction between a monetary policy shock and (A) the EBP (Panel B.22a) and (B) firms' liquidity of assets (Panel B.22b) on the h-period change in credit spreads, $S_{ikt+h} - S_{ikt-1}$ from estimating (B.22). Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

B.4.5 Liquidity of Assets:

Jeenas (2019) documents that the investment response to monetary policy of firms with lower share of liquid assets is relatively large, where liquidity is measured as the ratio of cash and short-term investments to total assets. He does so using our functional form from the main text, so we revert back to the conditioning on the average value of a firms' characteristic over the previous year.

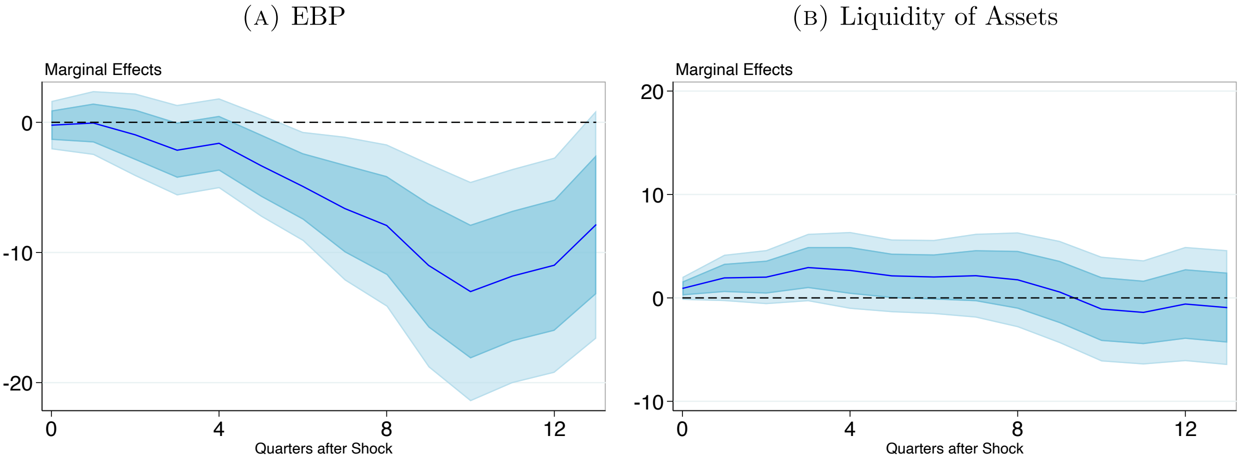
Monetary Policy on Credit Spreads:

We start by estimating:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^m + \beta_3^h \varepsilon_t^m \times Liq_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.22}$$

where Liq_{it-1}^{ma} refers to the average share of liquid assets of firm i over the previous year. Note again that $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus EBP_{ikt-1}^{ma} and Liq_{it-1}^{ma}.

FIGURE B.23
Monetary Policy's Effect on Investment by EBP vs. Liquidity of Assets



Note. Figure B.23 displays dynamic interaction coefficients from a horserace between the interaction between a monetary policy shock and (A) the EBP (Panel B.23a) and (B) firms' liquidity of assets (Panel B.23b) on h-period cumulative investment $logK_{it+h} - logK_{it-1}$ from estimating (B.23). Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

The results are displayed in Figure B.22. We see that, consistent with the results in Jeenas (2019), firms with lower share of liquid assets experience a larger reduction in their credit spreads following a monetary easing (Panel B.23b), although the effects are relatively small. By contrast, the heterogeneous effects conditional on firms' EBPs are larger and more significant.

Monetary Policy on Investment:

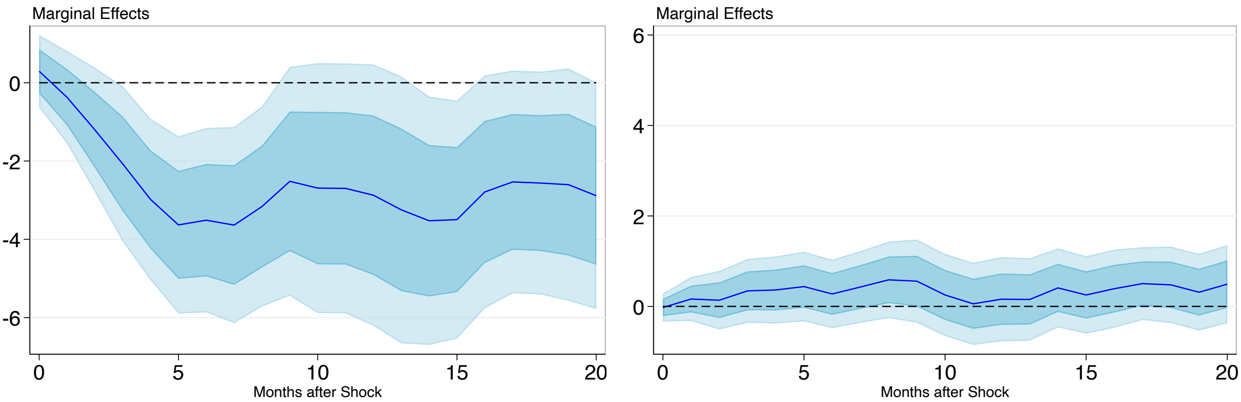
Turning now to investment, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^m + \beta_3^h \varepsilon_t^m \times Liq_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}. \quad \text{(B.23)}$$

The results are displayed in Figure B.23. We see that controlling for liquidity of assets has little impact on on the EBP's ability to regulate firms' investment response to monetary policy. Heterogeneiety by firms' liquid asset share is not statistically significant.

FIGURE B.24
Monetary Policy's Effect on Spreads by EBP vs. Tobin's Average Q

(A) EBP (B) Tobin's Average Q



Note. Figure B.24 displays dynamic interaction coefficients from a horserace between the interaction between a monetary policy shock and (A) the EBP (Panel B.24a) and (B) firms' average Tobin's Q (Panel B.24b) on the h-period change in credit spreads, $S_{ikt+h} - S_{ikt-1}$ from estimating (B.24). Frequency is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t.

B.4.6 Tobin's average Q:

Tobin's average Q has received comparatively less attention in the recent literature relative to other state variables we have examined in this section. Still, we show that heterogeneity by EBP is robust to controlling for the conditioning effects by Tobin's average Q.

Monetary Policy on Credit Spreads:

We begin by augmenting our main specification from the main text with the interaction between the monetary policy shock and Tobin's average Q:

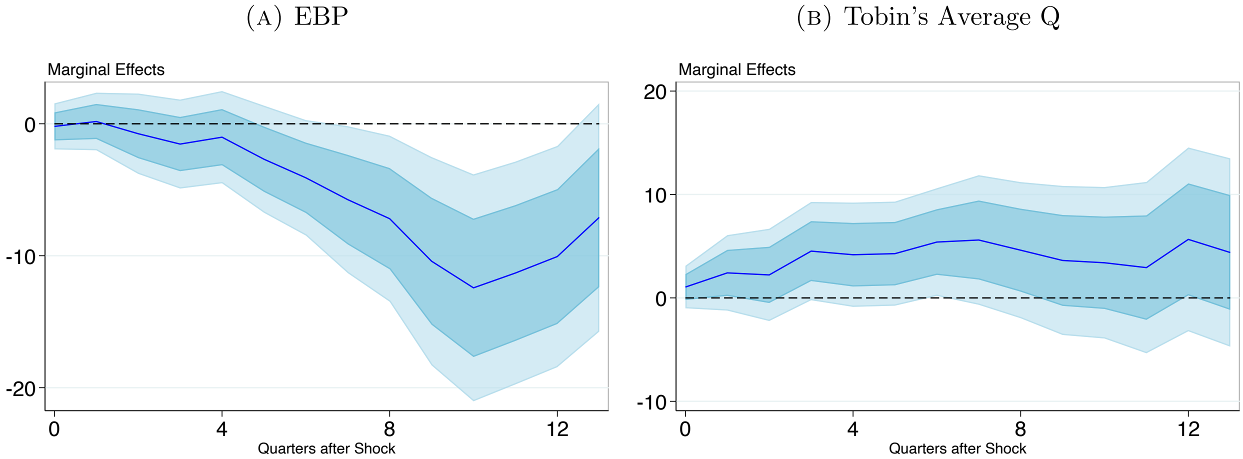
$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^m + \beta_3^h \varepsilon_t^m \times Q_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.24}$$

where Q_{it-1}^{ma} refers to the average Q of the firm over the preceding year, as in Jeenas (2019).

The results are displayed in Figure B.24, and highlight that Tobin's Q's impact on the sensitivity of firms' spreads to monetary policy shocks is not statistically significant.

FIGURE B.25

Monetary Policy's Effect on Investment by EBP vs. Tobin's Average Q



Note. Figure B.25 displays dynamic interaction coefficients from a horserace between the interaction between a monetary policy shock and (A) the EBP (Panel B.25a) and (B) firms' average Tobin's Q (Panel B.25b) on h-period cumulative investment $logK_{it+h} - logK_{it-1}$ from estimating (B.25). Frequency is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t.

Moreover, this variable does not affect the role of the EBP as a state variable for the transmission of monetary policy to firm credit spreads.

Monetary Policy on Investment:

Turning now to investment, we estimate:

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^m + \beta_3^h \varepsilon_t^m \times Q_{it-1}^{ma} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \quad \text{(B.25)}$$

The results are displayed in Figure B.25. In Panel B.25b, the positive point-estimates, which are more statistically significant than for the credit spread regression, indicate that the investment of firms with higher Tobin's Qs are more sensitive to monetary policy shocks. Still, heterogeneity by EBP is larger and more significant (Panel B.25a).

B.5 Alternative Monetary Policy Shocks

In this subsection, we demonstrate the robustness of our results to the use of alternative monetary policy shocks, namely those of Swanson (2021). Swanson (2021) constructs a series of three distinct types of monetary policy shocks: (i) conventional interest rate shocks; (ii) forward guidance shocks; and (iii) asset purchase shocks. To provide comparability with our baseline Bu et al. (2021) monetary policy shock, which provides a unified measure of both conventional and unconventional U.S. monetary shocks, we sum across the three types of Swanson (2021) shocks. In what follows, we show that, as in the main text, the spreads of high-EBP bonds and investment of low-EBP firms are more responsive to this aggregated Swanson (2021) monetary policy shock series. Furthermore, the shapes of the impulse responses are very similar to those in our baseline specification.

Monetary Policy on Credit Spreads:

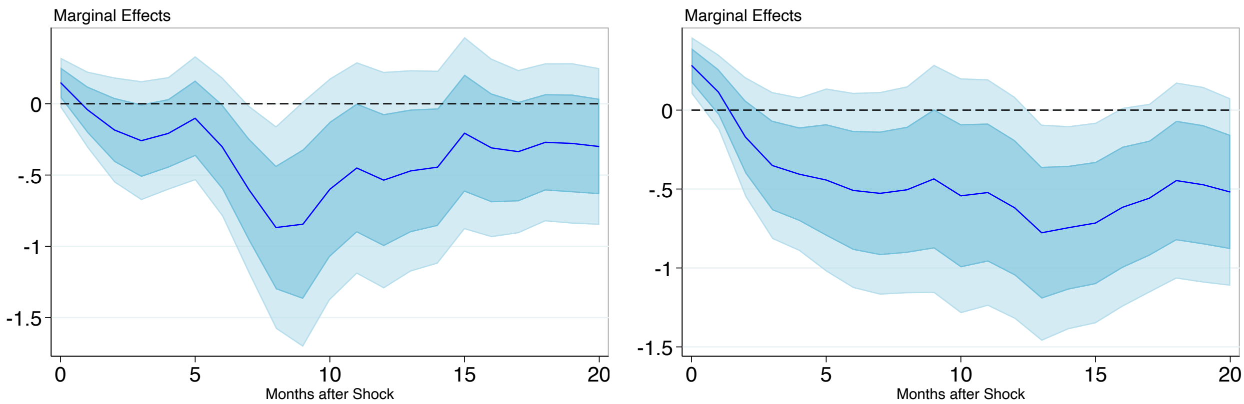
We begin by assessing the effects of a monetary policy easing on bond-level credit spreads, both unconditionally and conditional on a bond's EBP, by estimating the local projections in equation (4) from the main text using the aggregated Swanson (2021) monetary policy shock series. The results are displayed in Figure B.26. They highlight that, as in the main text, a monetary policy easing induces a significant decline in credit spreads for the average firm (Panel B.26a). Moreover, consistent with our baseline results, the decline in credit spreads is larger for firms whose bonds carry a higher ex-ante EBP (Panel B.26b).

Monetary Policy on Firm Investment:

Next, we turn to evaluate the effects of a monetary policy easing on firm-level investment, both unconditionally and conditional on a bond's EBP, by estimating the local projections in equation (6) from the main text using the aggregated Swanson (2021) monetary policy shock series. The results are displayed in Figure B.27. As in the main text, we see that a monetary easing induces an increase in investment for the average firm (Panel B.27a). Furthermore, Panel B.27b highlights that this increase is larger for firms with ex-ante lower EBPs, which is consistent with our findings from the main text. In sum, the results showcase that our findings are not specific to the Bu et al. (2021) shock series.

Figure B.26
Monetary Policy's Effect on Bond-Level Credit Spreads Depends on EBP

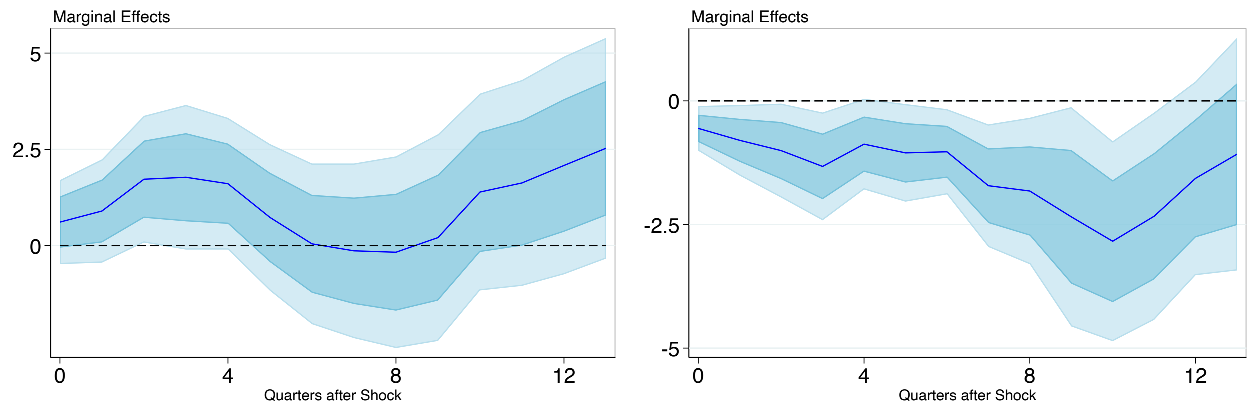
(A) Unconditional (B) Conditional on EBP



Note. Figure B.26 presents the dynamic interaction effects (β_2^h) between EBP_{ikt-1} and a Swanson (2021) monetary policy shock on the h-period change in credit spreads, $S_{ikt+h} - S_{ikt-1}$ from estimating regression (4) from the main text. The frequency of the data is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

Figure B.27
Monetary Policy's Effect on Firm-Level Investment Depends on EBP

(A) Unconditional (B) Conditional on EBP



Note. Figure B.27 presents the dynamic interaction effects (β_2^h) between EBP_{it-1} and a Swanson (2021) monetary policy shock (ε_t^m) series on h-period cumulative investment , $logK_{it+h} - logK_{it-1}$ from estimating regression (6) from the main text. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

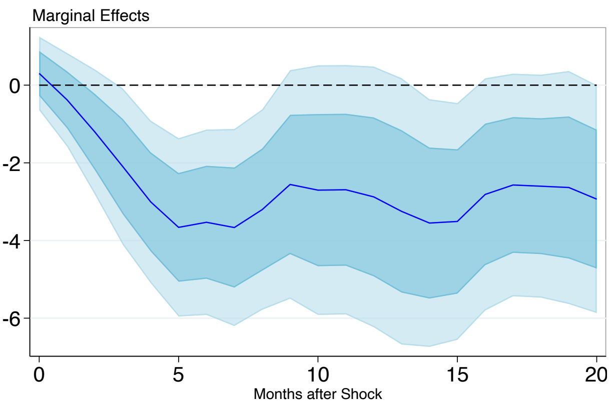
B.6 EBP purged of Higher-Order Default-Risk

In this section, we demonstrate that our results from the main text are robust to conditioning on firm EBPs that have been purged of potential higher-order dependence on default risk. Specifically, we re-estimate our credit spread regression (1) with the square of firms' distance to default (DD_{it}^2) as an additional regressor. Then, following the same steps as in the baseline, we output a new EBP that is purged of its dependence on the square of its distance to default. We then re-assess our conclusion from sections 3, 4, and 6 that the EBPs regulate firms' responsiveness to monetary policy using this new EBP measure.

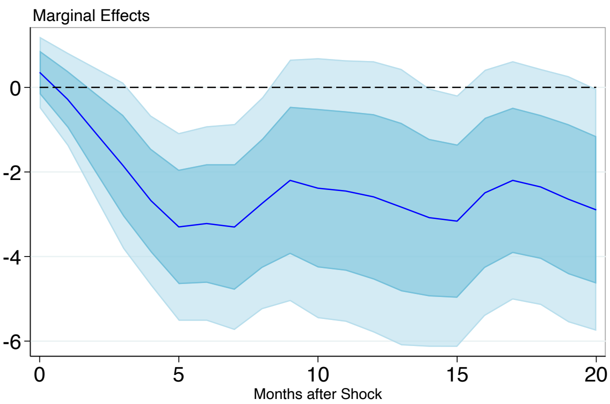
The results are displayed in Figures B.28, B.29 and B.30 for, respectively, the effects of monetary policy on credit spreads, monetary policy on investment, and credit spreads on investment. In all cases, our results are robust to using this new measure of firms' EBP that is purged of the square of firms' distance to default.

FIGURE B.28
Monetary Policy's Effect on Bond-Level Credit Spreads by EBP ex. DD^2

(A) Baseline Conditional on EBP



(B) Conditional on EBP ex. DD^2



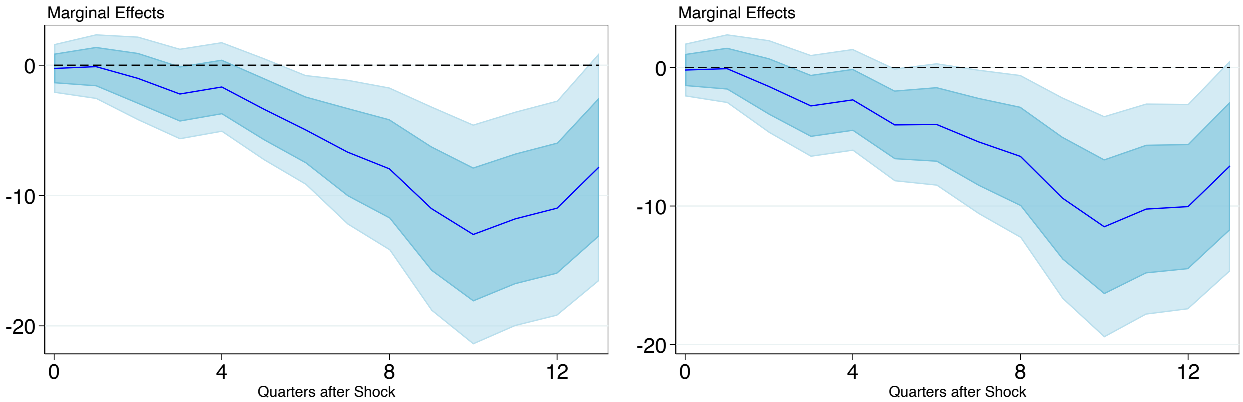
Note. Figure B.28 compares the effects of the dynamic interaction (β_2^h) between EBP_{ikt-1} and the Bu et al. (2021) monetary policy shock (ε_t^m) on the h-period change in credit spreads, $S_{ikt+h} - S_{ikt-1}$, from estimating regression (4) for 2 different EBPs. The first is our baseline EBP (Panel B.28a) and the second is the EBP purged of DD^2 (Panel B.28b). The frequency of the data is monthly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and month t, respectively.

Figure B.29

Monetary Policy's Effect on Firm-Level Investment by EBP ex. DD^2

(A) Baseline Conditional on EBP

(B) Conditional on EBP ex. DD^2



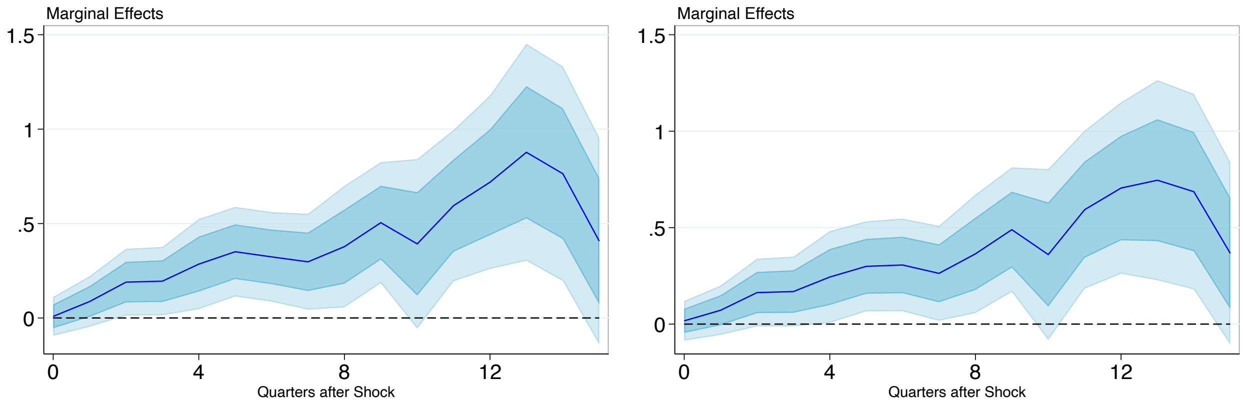
Note. Figure B.29 compares the effects of the dynamic interaction (β_2^h) between EBP_{ikt-1} and the Bu et al. (2021) monetary policy shock (ε_t^m) on the h-quarter cumulative investment of firm i, $\log K_{it+h} - \log K_{it-1}$, from estimating regression (6) for 2 different EBPs. The first is our baseline EBP (Panel B.29a) and the second is the EBP purged of DD^2 (Panel B.29b). The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond, respectively, to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

Figure B.30

Credit Spread's Effects on Firm Investment by EBP ex. DD^2

(A) Baseline Conditional on EBP

(B) Conditional on EBP ex. DD^2



Note. Figure B.30 compares the effects of the dynamic effect (β_2^h) between EBP_{ikt-1} and a change in credit spreads ΔS_{it} on h-period Investment of firm i, $\log K_{it+h} - \log K_{it-1}$, from estimating regression (13) for 2 different EBPs. The first is our baseline EBP (Panel B.30a) and the second is the EBP purged of DD^2 (Panel B.30b). The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

B.7 Monetary Policy's Effect on Firm-Level Debt Issuance

In this section, we show that—just as how investment increases by more for low-EBP firms following a shock monetary policy easing than for high-EBP firms—low-EBP firms increase debt-issuance compared to high-EBP ones following a monetary easing. We demonstrate this using the dummy-variable conditioning method outlined in Section B.2. Results are similar with our baseline linear functional form for the EBP interaction, but are more noisy.

As in our investment specification, to assess the distinct responses of low- and high-EBP firms' growth in debt issuance following a monetary shock, we estimate:

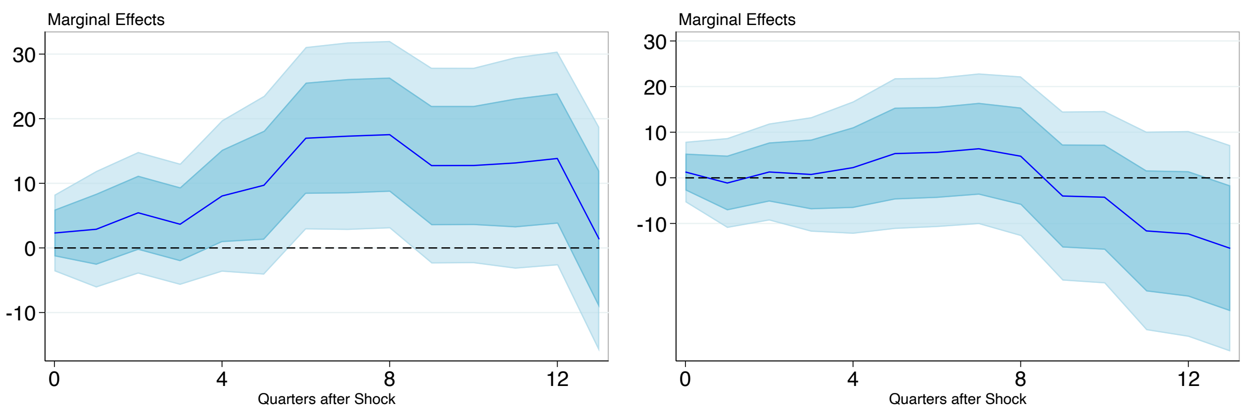
$$\log\left(\frac{D_{it+h}}{D_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{low} + \beta_2^h \varepsilon_t^m \times \mathbf{1}\text{EBP}_{it-1}^{high} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.26}$$

where $D_{i,t}$ is firm i's real outstanding debt (short- plus long-term) in period t and where $\mathbf{Z}_{it-1}$ includes the controls from the main text, plus EBP_{it-1}^{low} and EBP_{it-1}^{high}. The results are displayed in Figure B.31 and highlight that only low-EBP firms increase debt following a monetary easing, which is consistent with our investment results.

Figure B.31

Monetary Policy's Effect on Firm Debt Issuance for Low- vs High-EBP Firms

(A) Low-EBP Firms (B) High-EBP Firms



Note. Figure B.31 traces the response of debt issuance growth for low-EBP ($\mathbf{1}\text{EBP}^{low}$) firms in Panel B.31a and high-EBP ($\mathbf{1}\text{EBP}^{high}$) firms in Panel B.31b to a Bu et al. (2021) monetary policy shock (ε_t^m), from estimating regression (B.26), where the frequency is quarterly. The frequency of the data is quarterly. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t, respectively.

B.8 Intermediary Net Worth Shocks and EBP Heterogeneity

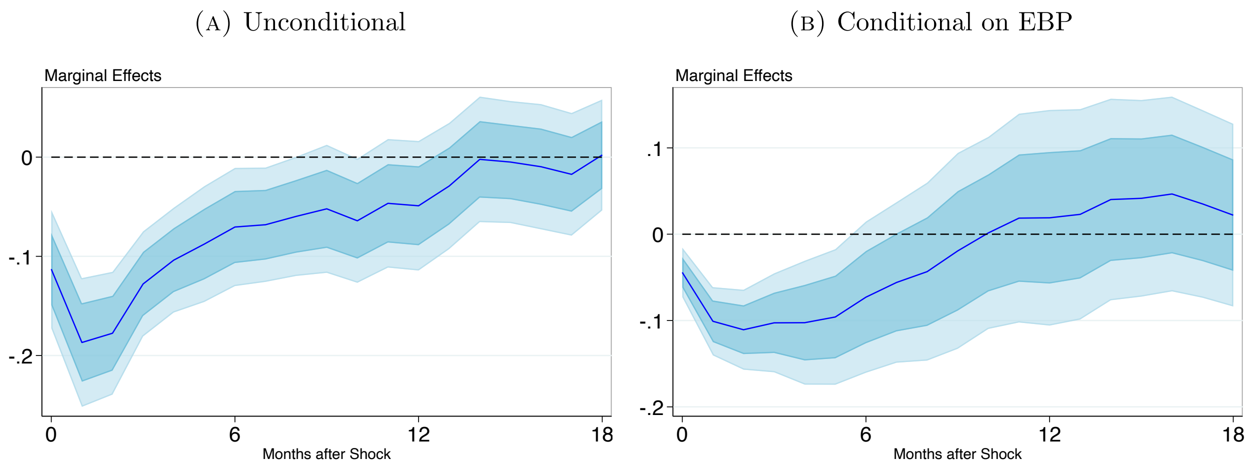
In this section, we study how shocks to the net worth of financial intermediaries influence firms' credit spreads and investment conditional on their EBPs. We measure these shocks using the orthogonalized intermediary capital risk factor of He et al. (2017).

We first assess the effect on credit spreads by replacing the monetary policy shock ε_t^m in our baseline monetary policy specification (4) with the net-worth shock ε_t^{NW}:

$$S_{ikt+h} - S_{ikt-1} = \beta_k^h + \beta_1^h \varepsilon_t^{NW} + \beta_2^h EBP_{ikt-1}^{ma} \times \varepsilon_t^{NW} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ikth}, \tag{B.27}$$

The unconditional (Panel B.32a) and conditional (Panel B.33b) results are displayed in Figure B.32. They show that a shock increase in intermediary net worth lowers firms' credit spreads, and that this decrease is larger for firms with higher EBPs. Thus, the effects of intermediary net-worth shocks are qualitatively similar to those of monetary policy shocks.

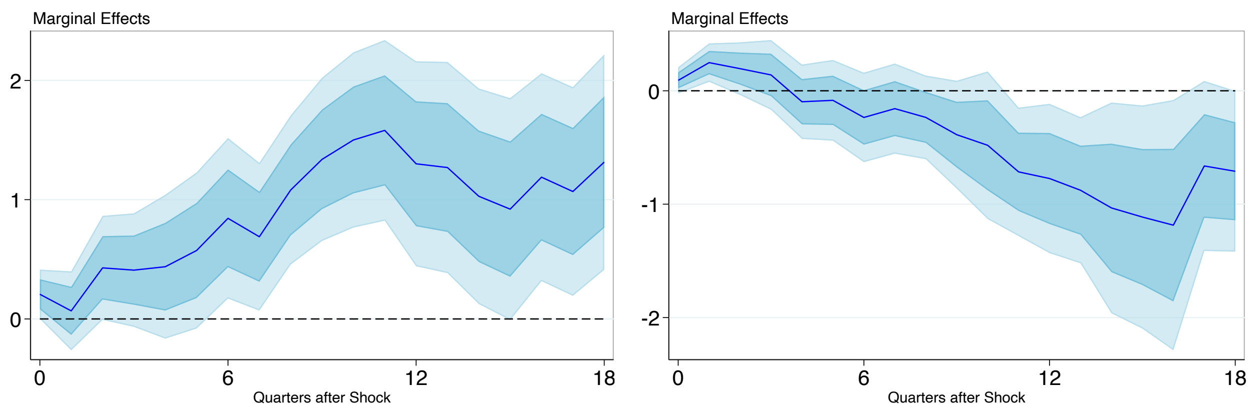
FIGURE B.32
Intermediary Net Worth Shocks on Credit Spreads by EBP



Note. Figure B.32 reports the dynamic effects of an intermediary net worth shock ε_t^{NW} on the h-month change in bond credit spreads, $S_{ikt+h} - S_{ikt-1}$, which we estimate using regression (B.27). Panel B.32a shows the unconditional effects, β_1^h. Panel B.33b shows the effects conditional on $EBP_{ik,t-1}^{ma}$, β_2^h. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. 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.33
Intermediary Net Worth Shocks on Investment by EBP

(A) Unconditional (B) Conditional on EBP



Note. Figure B.33 reports the dynamic effects of an intermediary net worth shock ε_t^{NW} on the h-quarter cumulative investment of firm i, $\log(K_{it+h}/K_{it-1})$, which we estimate using regression (B.28). Panel B.33a shows the unconditional effects, β_1^h. Panel B.33b shows the effects conditional on $EBP_{ik,t-1}^{ma}$, β_2^h. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm and quarter.

Next, we perform a similar exercise by using the intermediary net worth shock in our baseline investment specification (6):

$$\log\left(\frac{K_{it+h}}{K_{it-1}}\right) = \beta_i^h + \beta_1^h \varepsilon_t^{NW} + \beta_2^h EBP_{it-1}^{ma} \times \varepsilon_t^{NW} + \boldsymbol{\gamma}^h \mathbf{Z}_{it-1} + e_{ith}, \tag{B.28}$$

The results are displayed in Figure B.33 and highlight that a shock increase in intermediary net worth leads to an increase in firms' investment (Panel B.33a) which is larger for firms with lower EBPs (Panel B.33b). Again, this consistent with our baseline monetary policy results. Overall, this exercise reinforces the notion that firm EBPs reflect the slope of firms' marginal benefit curves for capital and are an important state variable for understanding firms' responsiveness to shifts in their marginal cost curves.

B.9 Aggregate Implications of EBP Heterogeneity

In this section, we highlight the robustness of our conclusions from Section 6.2, where we showed that variation in the cross-sectional distribution of firm EBPs has important implications for the aggregate effectiveness of monetary policy. Specifically, we document that our results are robust to: (i) measuring moments of the EBP distribution using different percentiles; (ii) conditioning directly on the percentiles of the EBP distribution; (iii) using the aggregated Swanson (2021) monetary policy shocks; (iv) a horserace between monetary policy's interaction with the moments of the EBP distribution and its interaction with various recession indicators.

First, we show that our results from Section 6.2 are not tied to the particular percentiles we use to construct the moments of the EBP distribution, the 10^{th} and 90^{th} percentiles. To demonstrate this, we re-estimate regression (14) by constructing our moments using the 5^{th} and 95^{th} percentiles, the 15^{th} and 85^{th} percentiles, the 20^{th} and 80^{th} percentiles, and the 25^{th} and 75^{th} percentiles of the EBP distribution. Figure B.34 presents the results, focusing on the skewness of the EBP distribution. In all cases, we see that an increase in skewness dampens the impact of a monetary easing on aggregate investment, consistent with our conclusions from the main text.

Second, rather than conditioning on the moments of the EBP distribution, we condition on the percentiles used to construct these moments, in particular, the 10^{th}, 50^{th} (median), and 90^{th} percentiles. The results are displayed in Figure B.35 and highlight that on-impact a rise in median EBP and a fall in the 90^{th} percentile of the EBP distribution dampens the effect of monetary policy on aggregate investment. Further, only the left-tail of the EBP distribution matters at medium horizons, where an increase meaningfully dampens the effects of expansionary monetary policy shocks on aggregate investment. This suggests that the 10^{th} percentile of the EBP distribution is responsible for the conditioning effects of the EBP distribution's skewness and dispersion from our baseline specification.

Third, we re-estimate our baseline specification using the aggregated Swanson (2021) monetary policy shocks discussed in Appendix B.5. The impulse responses displayed in

Figure B.36 are qualitatively similar to those from the main text.

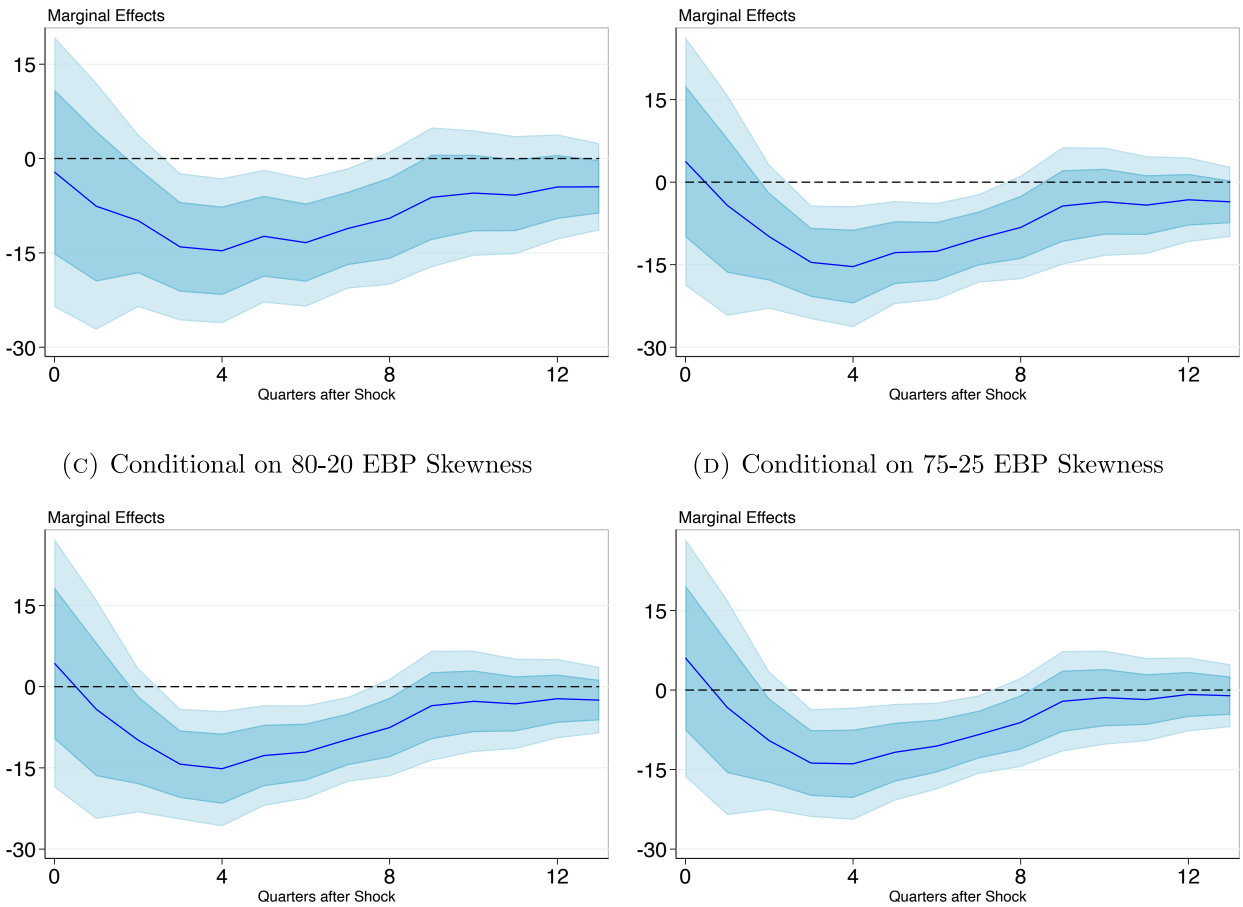
Finally, we examine the extent to which the EBP distributions's impact on the aggregate effectiveness of monetary policy is related to the well-documented weaker effects of monetary policy in recessions. We do so by running horseraces between our moment interactions and interactions between the monetary 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). The results are displayed in Figures B.37 and B.38.

There are three key takeaways. First, an increase in the probability of a U.S. recession or the incidence of a recession severely dampens the expansionary power of an easing U.S. monetary policy shock, consistent with the existing evidence. Second, the inclusion of these interactions does not distort the conditioning power of the skewness of the EBP distribution, nor the dispersion, highlighting the generality of the relationship between the slope of firms' marginal benefit curves and the aggregate effectiveness of monetary policy. Third, the conditioning effects of the median of the EBP distribution are crowded out by the recession indicators. This is consistent with Gilchrist and Zakrajšek (2012)'s result that aggregate EBP rises in recessions and suggests a potential new transmission channel for monetary policy's weaker effects in recessions: the steeper slopes of firms' marginal benefit curves around equilibrium.

Figure B.34
EBP Skewness and Monetary Policy's Effect on Aggregate Investment

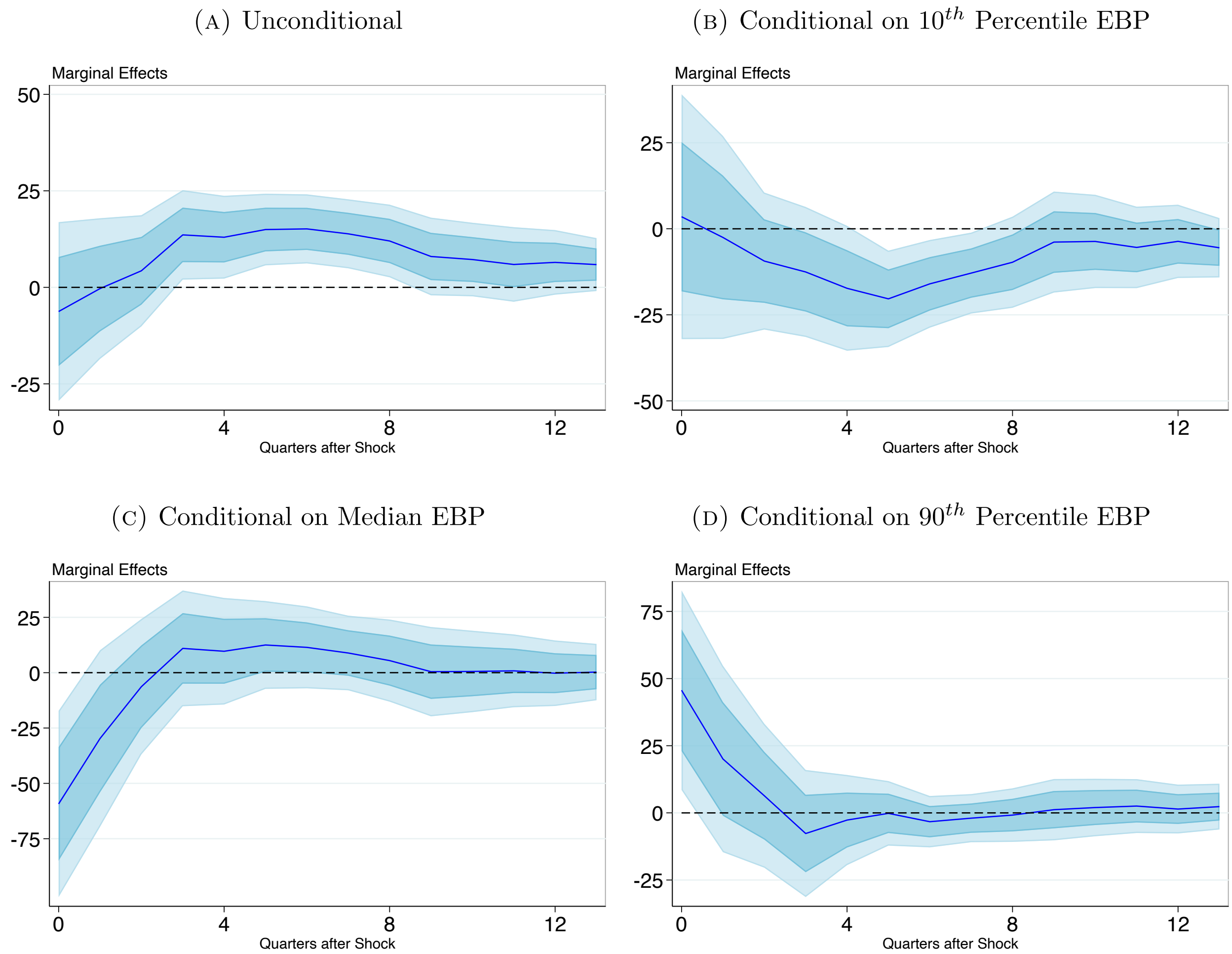
(A) Conditional on 95-05 EBP Skewness (B) Conditional on 85-15 EBP Skewness

(C) Conditional on 80-20 EBP Skewness (D) Conditional on 75-25 EBP Skewness



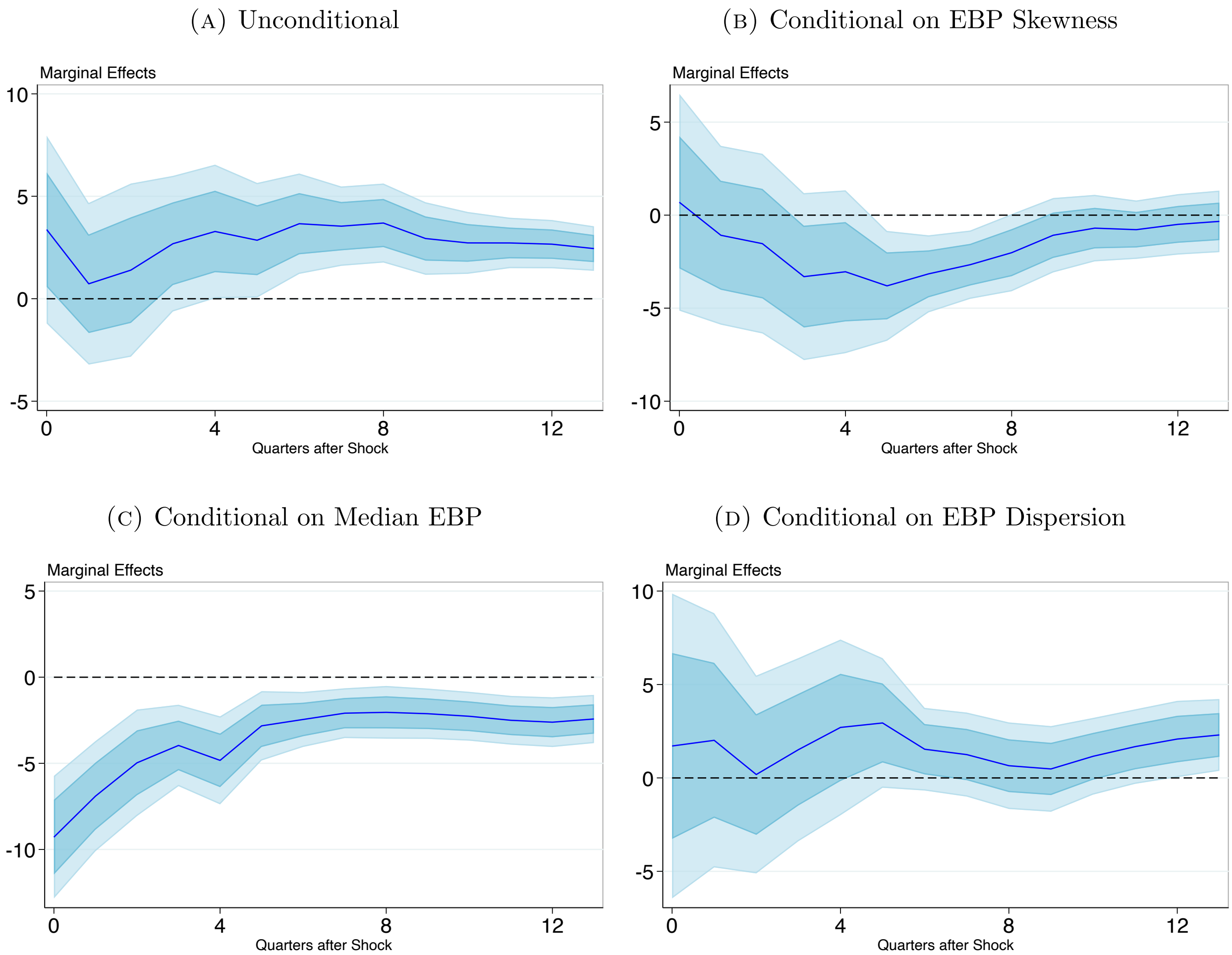
Note. Figure B.34 reports the dynamic effects from monetary policy shocks, conditional on the skewness of the EBP distribution (β_2^h),on the h-quarter cumulative aggregate investment, $400/(h+1)\log(I_{t+h}/I_{t-1})$, estimated using regressions (14). Panel B.34a, B.34b, B.34c, and B.34d measure skewness using the 95-05, 85-15, 80-20 and 75-25 percentiles of the EBP distribution, respectively. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond, respectively, to the 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

Figure B.35
EBP Percentiles and Monetary Policy's Effect on Aggregate Investment



Note. Figure B.35 reports the dynamic effects from monetary policy easing shocks on h-quarter cumulative aggregate investment, $400/(h+1)\log(I_{t+h}/I_{t-1})$, estimated using a variant of regression (14). Panel B.35a shows unconditional effects (β_1^h). Panels B.35b, B.35c and B.35d shows effects conditional on the 10, 50 and 90th percentiles of the EBP distribution, respectively. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas correspond, respectively, to the 68% and 90% confidence intervals constructed using Newey-West standard errors.

Figure B.36
Monetary Policy's Effect on Aggregate Investment Growth

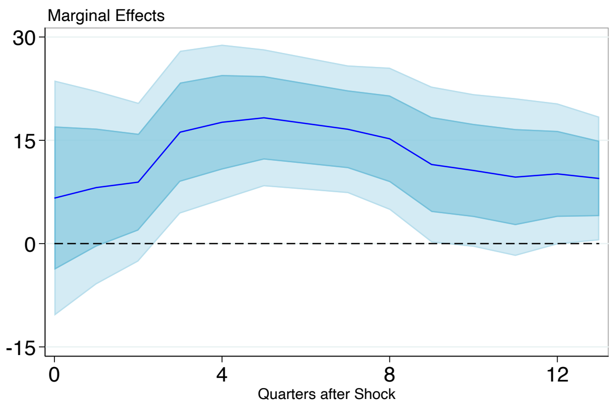


Note. Figure B.36 reports the dynamic effects of a Swanson (2021) monetary policy easing shock ε_t^m on h-quarter annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, which we estimate using regression (14). Panel B.36a shows unconditional effects, β_1^h. Panels B.36b, B.36c and B.36d show the effects conditional on the skewness, median and dispersion of the EBP distribution, the three elements in $\boldsymbol{\beta}_2^h$, respectively. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

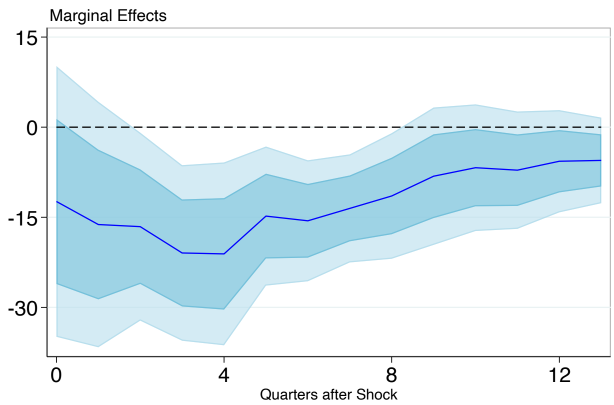
Figure B.37

Monetary Policy's Effect on Aggregate Investment Growth

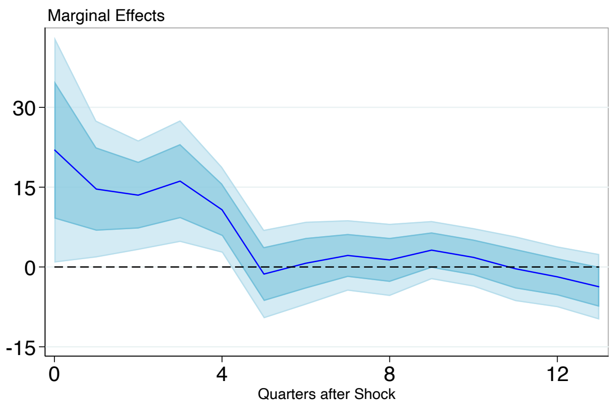
(a) Unconditional



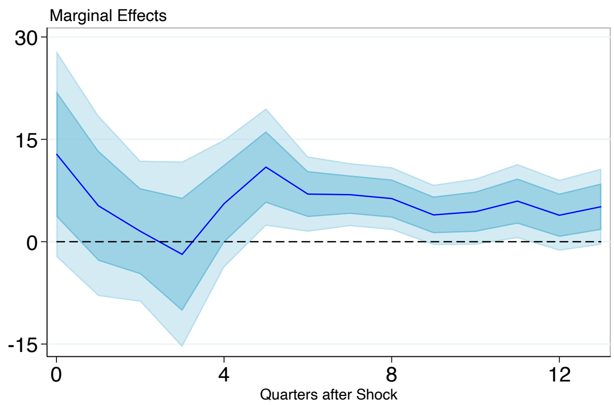
(b) Conditional on EBP Skewness



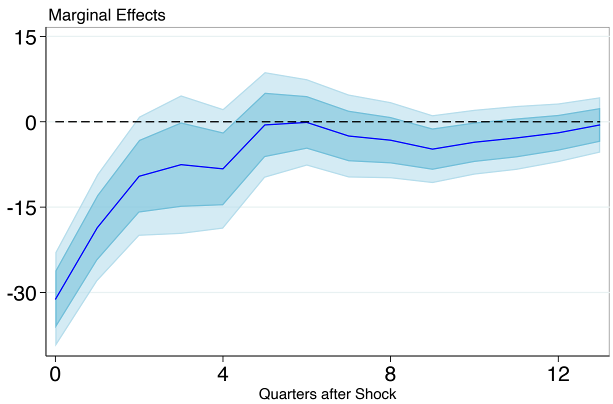
(c) Conditional on Median EBP



(d) Conditional on EBP Dispersion

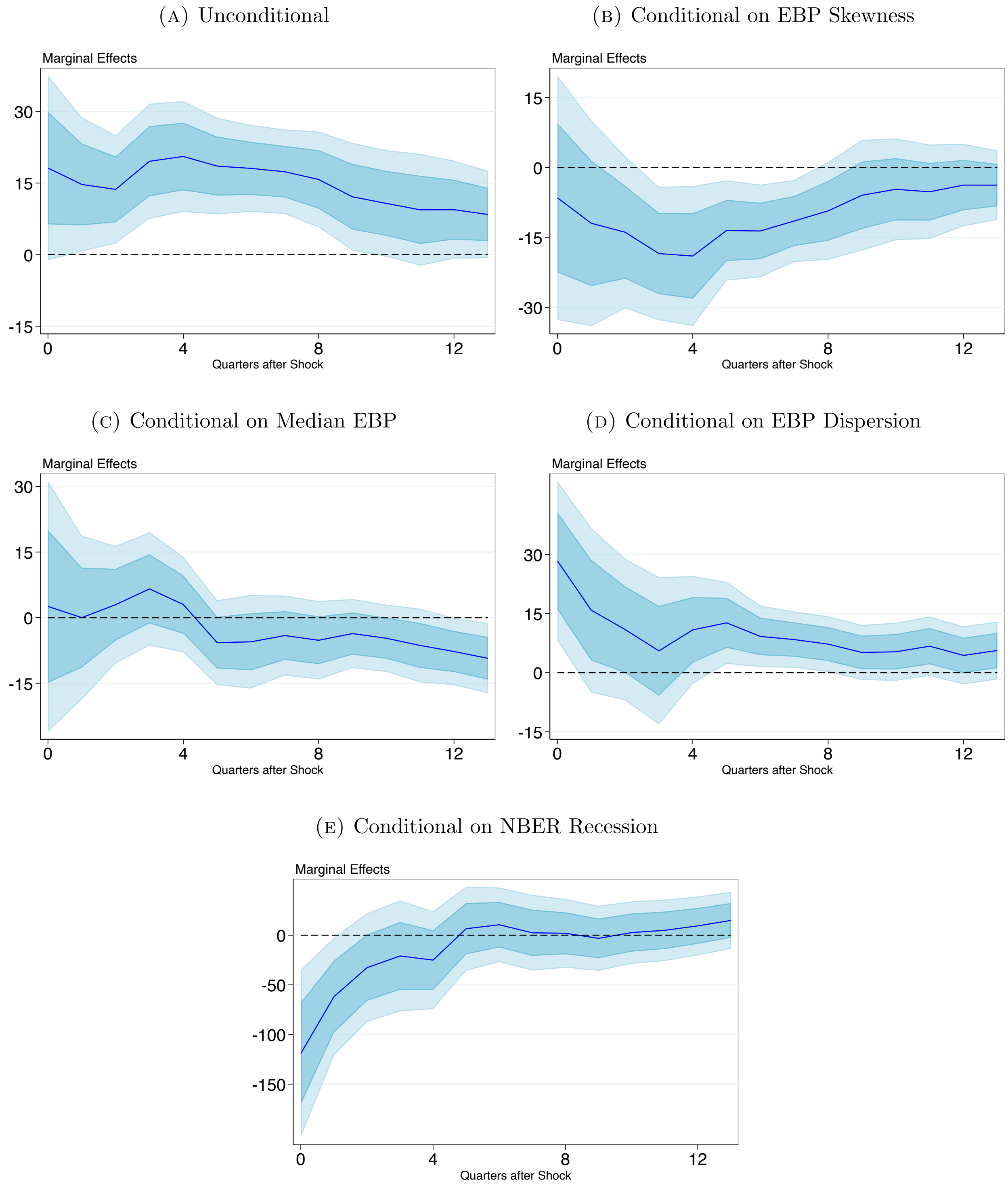


(e) Conditional on Recession Probability



Note. Figure B.37 reports the dynamic effects of a monetary policy easing shock ε_t^m on h-quarter annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, which we estimate using regression (14). Panel B.37a shows unconditional effects, β_1^h. Panels B.37b, B.37c and B.37d show the effects conditional on the skewness, median and dispersion of the EBP distribution, the three elements in $\boldsymbol{\beta}_2^h$, respectively. Panel B.37e shows the effects conditional on the probability of a recession. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

Figure B.38
Monetary Policy's Effect on Aggregate Investment Growth



(a) Unconditional

(b) Conditional on EBP Skewness

(c) Conditional on Median EBP

(d) Conditional on EBP Dispersion

(e) Conditional on NBER Recession

Note. Figure B.38 reports the dynamic effects of a monetary policy easing shock ε_t^m on h-quarter annualized aggregate investment growth, $400/(h+1)\log(I_{t+h}/I_{t-1})$, which we estimate using regression (14). Panel B.38a shows unconditional effects, β_1^h. Panels B.38b, B.38c and B.38d show the effects conditional on the skewness, median and dispersion of the EBP distribution, the three elements in $\boldsymbol{\beta}_2^h$, respectively. Panel B.38e shows the effects conditional on an NBER-classified recession. Conditional results describe the additional effect of having the variable one standard deviation above the sample mean. Inner and outer shaded areas are, respectively, 68% and 90% confidence intervals constructed using Newey-West standard errors with 12 lags.

C Model Appendix

In this section, we provide further information about our model. In particular, we present the model's calibration (Section C.1); detail the relationship between a firm's EBP and the slope of its marginal benefit curve in the model (Section C.2) and provide robustness for this relationship in the data (Section C.3); provide robustness for the relation between a firm's EBP and the slope of its marginal cost curve in the data (C.4); and discuss the empirical and model-implied link between firm EBPs and their capital stock (Section C.5).

C.1 Model Calibration

TABLE C.1
Benchmark Model Calibration

Parameter	**Value**	**Description**
N_1	0.014	Intermediary Net-Worth Pre-Shock
N_2	0.042	Intermediary Net-Worth Post-Shock
R	1	Safe Interest Rate
α_H	0.71	Capital Elasticity of High-EBP Firm
α_L	0.89	Capital Elasticity of Low-EBP Firm
$\theta_H(K_t)$	$0.9\mathrm{K}_t^{1.25}$	Agency Friction of High-EBP Firm
$\theta_L(K_t)$	$0.7\mathrm{K}_t^{1.25}$	Agency Friction of Low-EBP Firm

Table C.1 presents our model's calibration. Among the parameters are the net-worth of intermediaries before and after the shock, which we select such that intermediaries' constraints bind for both firms. The safe interest rate, R, is set to 1 in the model for simplicity. As mentioned in the main text, we vary the slope of firms' marginal benefit curves for capital by adjusting α, the intensity of capital in firms' Cobb-Douglas production functions. We calibrate $\alpha_H = 0.71$ and $\alpha_L = 0.89$ by estimating production functions for firms in the bottom (L) and top (H) quartiles of the EBP_{it}^{ma} distribution using regression (10).

In addition, we follow Gabaix and Maggiori (2015) by assuming that the fraction of their revenues intermediaries can divert is increasing in the size of their balance-sheet: $\theta(K_t)$. The functional form $K_t^{1.25}$ is selected to generate an (approximately) linear marginal cost of capital curve, which allows us to highlight heterogeneity in the slope of firms' marginal benefit curves, but does not influence our results. We calibrate $\theta_L = 0.7$ and $\theta_H = 0.9$ to approximately match the gap in the default-risk cyclicality (β^{Mkt}) between firms in the bottom (L) and top (H) quartiles of the EBP_{it}^{ma} distribution using regression (12).

C.2 Firm EBPs and Marginal Benefit Curves in the Model

Figure 7 in the main text documents the relationship between a firm's EBP and the slope of its marginal benefit curve for capital in our model. Specifically, using our parameterization in Table C.1, firms with flatter marginal benefit curves near the equilibrium have lower equilibrium EBPs. In what follows, we show that this result holds for most levels of intermediary net worth (N). To keep things simple, we keep constant θ across the two intermediaries. As discussed in the main text, differences in θ reinforce our result.

In the equilibria shown in Figure 7, the high-α (α_H) firm has both a lower EBP and a flatter marginal benefit curve (Panel 7a). From inspection, there are two potential ways this result could be violated: (i) intermediaries have sufficiently high net worth; and (ii) intermediaries have sufficiently low net worth. We discuss these two cases in turn.

Case (i): intermediaries have sufficiently high net worth. As the marginal benefit curve of the firm with low α (α_L) (Panel 7b) intersects the horizontal axis ($R^K = R$) before the firm with α_H (Panel 7a), we know that for sufficiently high intermediary net-worth, the α_L-firm will have a lower equilibrium EBP. Thus, there exists an equilibrium in which (a) intermediaries' net worth is $\varepsilon > 0$ below this level, and (b) the α_L-firm has both the lower-EBP and the steeper marginal benefit curve. We now bound this level of intermediary net worth and show that it is almost identical to the intermediary net worth for which the α_L-firm has a credit spread of 1 under our parameterization.

When intermediary net worth N, and hence equilibrium capital, is sufficiently high, the α_H-firm always has a flatter marginal benefit curve but only has a lower EBP if $\alpha_H K_H^{\alpha_H - 1} < \alpha_L K_L^{\alpha_L - 1}$, where K_H and K_L denote the α_H- and α_L-firms' equilibrium capital stock, respectively. The cutoff level of capital stock K^* for which this ceases to hold occurs at the intersection of the two firms' marginal benefit curves:

$$K^* = \left[\frac{\alpha_L}{\alpha_H}\right]^{\frac{1}{\alpha_H - \alpha_L}}. \tag{C.1}$$

The N for which the α_H-firm has $K_H < K^*$ can be found from $\alpha_H K_H^{\alpha_H - 1} = \frac{K_H - N}{K_H(1-\theta)}$, or:

$$\begin{aligned} N =& K_H - \alpha_H K_H^{\alpha_H}(1-\theta) \\ N <& \left[\frac{\alpha_L}{\alpha_H}\right]^{\frac{1}{\alpha_H - \alpha_L}} - \alpha_H \left[\frac{\alpha_L}{\alpha_H}\right]^{\frac{\alpha_H}{\alpha_H - \alpha_L}} (1 - \theta(\left[\frac{\alpha_L}{\alpha_H}\right]^{\frac{1}{\alpha_H - \alpha_L}})) \end{aligned} \tag{C.2}$$

If N is below the value in (C.2), then the α_H-firm has both a flatter marginal benefit curve and a lower EBP in equilibrium. In our baseline parameterization, this is $N \lessapprox 0.07$, which is nearly identical to the N that makes the α_H-firm have a credit spread of 1, which is very rare in practice.[39]

Case (ii): intermediaries have sufficiently low net worth. This condition, as it turns out, does not have any "bite" under our parameterization. When $N \lessapprox 0.07$, and especially for small N, the α_H-firm has the lower EBP but may not have the flatter marginal benefit curve. We show, in fact, that the α_H-firm always has the flatter marginal benefit curve for $N \geq 0$ by setting $N = 0$ and showing:

$$|\alpha_H(\alpha_H - 1)K_H^{\alpha_H - 2}| < |\alpha_L(\alpha_L - 1)K_L^{\alpha_L - 2}|, \tag{C.3}$$

under our paramaterization. Solving for the equilibrium capital stock when $N = 0$ one finds that inequality (C.3) holds.

[39]For this calculation, we set $\theta = 0.9$ rather than $\theta = 0.9K_t^{1.25}$. The latter would restrict this bound further.

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

In the main text, we show empirically that low-EBP firms have higher capital intensities α and hence flatter marginal benefit curves for capital. In this section, we highlight the robustness of these empirical results.

First, while we calibrate our model using the αs of firms in the top and bottom quartiles of the EBP distribution (see Table 2a), the results are similar for other percentiles as well. This is true for both the model-analogue specification with capital as the single input (Table C.2) and the full specification as well (Table C.3).

TABLE C.2
α Estimates for Low- and High-EBP Firms by Percentiles (Model Spec.)

$\log Y_{i,t}$	$\log K_{i,t}$	
Low & High Percentile Cutoffs	Less than EBP^{Low}	Greater than EBP^{High}
50 & 50	0.88***	0.77***
	(.037)	(.037)
33 & 67	0.89***	0.75***
	(.050)	(.043)
25 & 75	0.89***	0.71***
	(.059)	(.050)
20 & 80	0.90***	0.71***
	(.060)	(.055)

Note: Table C.2 presents estimates of the capital intensity (α) of firms with EBP_{it}^{ma} below and above certain percentiles of the firm-level EBP_{it}^{ma} distribution in a given period from estimating regression (10). The percentiles considered are (1) below and above the median, (2) below 33^{rd} and above 67^{th}, (3) below 25^{th} and above 75^{th}, (4) below 20^{th} and above 80^{th}. The results from (3), below and above the below 25^{th} and above 75^{th} percentiles, are those presented in Table 2a in the main text and are used to calibrate the α parameters in the model. Standard errors are two-way clustered by firm and quarter and *** denotes statistical significance at the 1% level.

Next, we show that these α estimates for low- and high-EBP firms are statistically distinct from each other. We show this for the model-analogue specification with capital as a single input in Tables C.4 as well as for the full specification C.5.

We also show, for the model analogue case, that our empirical result that low-EBP firms have higher capital intensities are robust to estimating regression (10) including both time as well as sector-time fixed effects. The results are displayed in Table C.6 and C.7.

Table C.3

α Estimates for Low- and High-EBP Firms by Percentiles (Full Spec.)

$\log Y_{i,t}$	$\log K_{i,t}$	
Low & High Percentile Cutoffs	Less than EBP^{Low}	Greater than EBP^{High}
50 & 50	0.19***	0.14
	(.043)	(.099)
33 & 67	0.17**	0.15
	(.074)	(.117)
25 & 75	0.18***	0.14
	(.058)	(.154)
20 & 80	0.14***	0.15
	(.047)	(.140)

Note: Table C.3 presents estimates of the capital intensity (α) of firms with EBP_{it}^{ma} below and above certain percentiles of the firm-level EBP_{it}^{ma} distribution in a given period from estimating regression (11). The percentiles considered are (1) below and above the median, (2) below 33^{rd} and above 67^{th}, (3) below 25^{th} and above 75^{th}, (4) below 20^{th} and above 80^{th}. The results in (3), below and above the below 25^{th} and above 75^{th} percentiles, are those presented in Table 2a in the main text. Standard errors are bootstrapped and *** denote statistical significance at the 1% level.

We cannot, however, include these fixed effects in the full specification.

Finally, the production function estimation results in this appendix as well as in the main text in Section 5.2, are constructed using a sample firms that have at least 30 consecutive observations. We do so because observing firms at many different levels of capital helps improve the estimates of α. That being said, we show in Table C.8 that, in this case for firms above and below-median EBPs, our results are robust to varying the threshold minimum observations for firms to be included in the sample.

TABLE C.4

α Estimate Differences for Low-, High-EBP Firms (Model Spec.)

	Dep. Var.: $\log Y_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$\log K_{i,t}$	0.82***	0.81***	0.81***	0.81***
	(.03)	(.03)	(.03)	(.03)
$\log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t-1}$	0.01*	0.02**	0.03**	0.04**
	(.01)	(.01)	(.01)	(.01)
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Time-Sector FE	No	No	No	No

Note: Table C.4 presents estimates of *differences* in the capital intensity (α) between firms with EBP^{ma}_{it} below and above certain percentiles of the distribution using a modified version of regression (10) in the main text, $\log Y_{i,t} = \beta_i + \alpha \log K_{i,t} + \gamma_1 \log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_2 \log K_{i,t} \times \mathbf{1}EBP^{ma,Med}_{i,t} + \gamma_3 \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_4 \mathbf{1}EBP^{ma,Med}_{i,t} + \varepsilon_{i,t}$, where $\mathbf{1}EBP^{ma,Med}_{i,t}$ is a dummy variable taking the value of 1 if firms' $EBP^{ma}_{i,t}$ lies between $EBP^{ma,Low}_{i,t}$ and $EBP^{ma,High}_{i,t}$. Results for α and γ_1 are presented above. Standard errors are two-way clustered by firm and quarter and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

C.4 Firm EBPs and Marginal Cost Curves in the Data

In the main text, we show empirically that low-EBP firms' default risk co-moves relatively less with the market factor, which maps to a lower θ in the model. In this section, we highlight the robustness of these empirical results.

First, while we calibrate our model based on differences in the the cyclicality of default risk for firms in the top and bottom quartiles of the EBP distribution (see Table 2b), the results are similar for other percentiles as well, as seen in Table C.9.

Next, in Table C.10, we show that differences in cyclicality are statistically significant, at the lower percentiles.

Finally, we show that these differences are statistically significant also when controlling for time and sector-time fixed effects, as shown in Tables C.11 and C.12, respectively.

Table C.5

α Estimate Differences for Low-, High-EBP Firms (Full Spec.)

	Dep. Var.: $\log Y_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$\log K_{i,t}$	0.12^{**}	0.12^{***}	0.12^{***}	0.12^{***}
	(.06)	(.01)	(.02)	(.03)
$\log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t-1}$	0.01^{**}	0.02^{***}	0.03^{***}	0.04^{***}
	(.003)	(.004)	(.006)	(.007)
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Time-Sector FE	No	No	No	No

Note: Table C.5 presents estimates of *differences* in the capital intensity (α) between firms with EBP^{ma}_{it} below and above certain percentiles of the distribution using a modified version of regression (11) in the main text, $\log Y_{i,t} = \beta_i + \alpha \log K_{i,t} + \gamma_1 \log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_2 \log K_{i,t} \times \mathbf{1}EBP^{ma,Med}_{i,t} + \gamma_3 \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_4 \mathbf{1}EBP^{ma,Med}_{i,t} + \omega_{i,t} + \delta_1 \log M_{i,t} + \delta_2 \log O_{i,t} + \varepsilon_{i,t}$, where $\mathbf{1}EBP^{ma,Med}_{i,t}$ is a dummy variable taking the value of 1 if firms' $EBP^{ma}_{i,t}$ lies between $EBP^{ma,Low}_{i,t}$ and $EBP^{ma,High}_{i,t}$. Results for α and γ_1 are presented above. Standard errors are two-way clustered by firm and quarter and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

C.5 Firm EBPs and Capital Stock: Model and Data

Finally, under our calibration in which low-EBP firms have high αs and low θs, Figure 7 in the main text highlights that firms' EBPs and their capital stock are uncorrelated with one another. That is, despite the two firms in Figure 7 having vastly different EBPs, they have similar capital stocks. This is because higher αs tend to restrict firms' capital stock while lower θs tend to increase firms' capital stock. Table C.13 shows that this prediction of our model and calibration is indeed present in the data.

Table C.6

α Estimate Differences for Low-, High-EBP Firms (Model Spec.) with Time Fixed Effects

	Dep. Var.: $\log Y_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$\log K_{i,t}$	0.78***	0.78***	0.77***	0.77***
	(.03)	(.03)	(.03)	(.03)
$\log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t-1}$	0.02**	0.03***	0.03**	0.04***
	(.01)	(.01)	(.01)	(.01)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Time-Sector FE	No	No	No	No

Note: Table C.6 presents estimates of *differences* in the capital intensity (α) between firms with EBP^{ma}_{it} below and above certain percentiles of the distribution using a modified version of regression (10) in the main text, $\log Y_{i,t} = \beta_i + \beta_t + \alpha \log K_{i,t} + \gamma_1 \log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_2 \log K_{i,t} \times \mathbf{1}EBP^{ma,Med}_{i,t} + \gamma_3 \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_4 \mathbf{1}EBP^{ma,Med}_{i,t} + \varepsilon_{i,t}$, where $\mathbf{1}EBP^{ma,Med}_{i,t}$ is a dummy variable taking the value of 1 if firms' $EBP^{ma}_{i,t}$ lies between $EBP^{ma,Low}_{i,t}$ and $EBP^{ma,High}_{i,t}$ and β_t is a time fixed effect. Results for α and γ_1 are presented above. Standard errors are two-way clustered by firm and quarter and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.7

α Estimate Differences for Low-, High-EBP Firms (Model Spec.) with Sector-Time Fixed Effects

	Dep. Var.: $\log Y_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$\log K_{i,t}$	0.92***	0.92***	0.91***	0.91***
	(.06)	(.06)	(.06)	(.06)
$\log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t-1}$	0.01*	0.02	0.01	0.01**
	(.01)	(.01)	(.01)	(.01)
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Time-Sector FE	Yes	Yes	Yes	Yes

Note: Table C.7 presents estimates of *differences* in the capital intensity (α) between firms with EBP^{ma}_{it} below and above certain percentiles of the distribution using a modified version of regression (10) in the main text, $\log Y_{i,t} = \beta_i + \beta_{s,t} + \alpha \log K_{i,t} + \gamma_1 \log K_{i,t} \times \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_2 \log K_{i,t} \times \mathbf{1}EBP^{ma,Med}_{i,t} + \gamma_3 \mathbf{1}EBP^{ma,Low}_{i,t} + \gamma_4 \mathbf{1}EBP^{ma,Med}_{i,t} + \varepsilon_{i,t}$, where $\mathbf{1}EBP^{ma,Med}_{i,t}$ is a dummy variable taking the value of 1 if firms' $EBP^{ma}_{i,t}$ lies between $EBP^{ma,Low}_{i,t}$ and $EBP^{ma,High}_{i,t}$ and $\beta_{s,t}$ is a sector-time fixed effect. Results for α and γ_1 are presented above. Standard errors are two-way clustered by firm and quarter and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

TABLE C.8

α Estimates for Low- and High-EBP Firms by Minimum Firm Observations

(A) Model Analogue

$\log Y_{i,t}$	$\log K_{i,t}$	
Min. Obs.	Low-EBP	High-EBP
20 quarters	0.83***	0.73***
	(.034)	(.034)
25 quarters	0.87***	0.77***
	(.034)	(.035)
30 quarters	0.88***	0.77***
	(.037)	(.037)
35 quarters	0.87***	0.76***
	(.042)	(.039)

(B) Full Specification

$\log Y_{i,t}$	$\log K_{i,t}$	
Min. Obs.	Low-EBP	High-EBP
20 quarters	0.20***	0.13
	(.033)	(.094)
25 quarters	0.18***	0.13
	(.062)	(.118)
30 quarters	0.19***	0.14
	(.043)	(.099)
35 quarters	0.18***	0.13
	(.040)	(.085)

Note. Table C.8 presents estimates of the capital intensity (α) of firms with EBP^{ma}_{it} below and above the firm-level median each period (labeled as "Low-EBP" and "High-EBP", respectively) depending on the threshold minimum number of firms' consecutive observations. Table C.8a presents the results from estimating regression (10). Table C.8b presents the results from estimating regression (11). The thresholds considered are 20, 25, 30 and 35 quarters. The results for 30 quarters are those presented in Table 2a in the main text. Standard errors are two-way clustered by firm and quarter in Table C.8a and bootstrapped in Table C.8b. *** denotes statistical significance at the 1% level.

TABLE C.9

Default Risk Cyclicality β^{Mkt} for Low- and High-EBP Firms by Percentiles

$\Delta DD_{i,t}$	R^{Mkt}_t	
Low & High Percentile Cutoffs	Less than EBP^{Low}	Greater than EBP^{High}
50 & 50	1.04***	1.18***
	(.29)	(.38)
33 & 67	0.94***	1.14***
	(.23)	(.36)
25 & 75	0.86***	1.09***
	(.21)	(.34)
20 & 80	0.82***	1.05***
	(.19)	(.32)

Note: Table C.9 presents estimates of the market beta (β^{mkt}) of firms with EBP^{ma}_{it-1} below and above certain percentiles of the firm-level EBP^{ma}_{it} distribution in a given period from estimating regression (12). The percentiles considered are (1) below and above the median, (2) below 33^{rd} and above 67^{th}, (3) below 25^{th} and above 75^{th}, (4) below 20^{th} and above 80^{th}. The results in (3), below and above the below 25^{th} and above 75^{th} percentiles, are those presented in Table 2b in the main text. Standard errors are bootstrapped and *** denote statistical significance at the 1% level.

Table C.10

Differences in Default Risk Cyclicality β^{Mkt} for Low- and High-EBP Firms

	Dep. Var.: $\Delta DD_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
R_t^{Mkt}	1.19***	1.20***	1.20***	1.19***
	(0.39)	(0.39)	(0.38)	(0.38)
$R_t^{Mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low}$	-0.14	-0.24	-0.31*	-0.34*
	(0.11)	(0.16)	(0.18)	(0.19)
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Time-Sector FE	No	No	No	No

Note: Table C.10 presents estimates of *differences* of the market beta (β^{mkt}) between firms with EBP_{it}^{ma} below and above given percentiles of the distribution using a modified version of regression (12) in the main text, $\Delta DD_{i,t} = \beta_i + \beta^{mkt} R_t^{mkt} + \gamma_1 R_t^{mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low} + \gamma_2 \mathbf{1}EBP_{i,t-1}^{ma,Low} + \boldsymbol{\delta}\mathbf{W}_{it} + \varepsilon_{i,t}$ where $\mathbf{W}_{it}$ is the vector of firm-level control variables described in Section 2.4. Results for β^{mkt} and γ_1 are presented above. Standard errors are two-way clustered by firm and month and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.11

Differences in Default Risk Cyclicality β^{Mkt} with Time Fixed Effects

	Dep. Var.: $\Delta DD_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$R_t^{Mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low}$	-0.09	-0.17*	-0.23**	-0.26**
	(0.06)	(0.10)	(0.11)	(0.11)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Time-Sector FE	No	No	No	No

Note: Table C.11 presents estimates of *differences* of the market beta (β^{mkt}) between firms with EBP_{it}^{ma} below and above given percentiles of the distribution using a modified version of regression (12) in the main text, $\Delta DD_{i,t} = \beta_i + \beta_t + \beta^{mkt} R_t^{mkt} + \gamma_1 R_t^{mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low} + \gamma_2 \mathbf{1}EBP_{i,t-1}^{ma,Low} + \boldsymbol{\delta}\mathbf{W}_{it} + \varepsilon_{i,t}$, which includes time fixed effects and where $\mathbf{W}_{it}$ is the vector of firm-level control variables described in Section 2.4. Results for γ_1 are presented above. Standard errors are two-way clustered by firm and month and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.12

Differences in Default Risk Cyclicality β^{Mkt} with Sector-Time Fixed Effects

	Dep. Var.: $\Delta DD_{i,t}$			
Low Percentile	50^{th}	33^{th}	25^{th}	20^{th}
$R_t^{Mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low}$	-0.06*	-0.11**	-0.13**	-0.16***
	(0.03)	(0.05)	(0.05)	(0.05)
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Time-Sector FE	Yes	Yes	Yes	Yes

Note: Table C.12 presents estimates of *differences* of the market beta (β^{mkt}) between firms with EBP_{it}^{ma} below and above given percentiles of the distribution using a modified version of regression (12) in the main text, $\Delta DD_{i,t} = \beta_i + \beta_{s,t} + \beta^{mkt} R_t^{mkt} + \gamma_1 R_t^{mkt} \times \mathbf{1}EBP_{i,t-1}^{ma,Low} + \gamma_2 \mathbf{1}EBP_{i,t-1}^{ma,Low} + \boldsymbol{\delta}\mathbf{W}_{it} + \varepsilon_{i,t}$, which includes sector-time fixed effects and where $\mathbf{W}_{it}$ is the vector of firm-level control variables described in Section 2.4. Standard errors are two-way clustered by firm and month and ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table C.13

Firm EBPs and Capital Stock

Vars	$\log K_{i,t}$	$\log K_{i,t}$	$\log K_{i,t}$
$EBP_{i,t}^{ma}$	0.01	-.010	-.007
	(.006)	(.010)	(.009)
Firm FE	Yes	Yes	Yes
Time-Sector FE	No	Yes	Yes
Firm Controls	Yes	No	Yes

Note: Table C.13 presents the marginal effects β_1 from the following regression: $logK_{it} = \beta_i + \alpha_{s,t} + \beta_1 EBP_{it}^{ma} + \boldsymbol{\gamma}\mathbf{W}_{it} + \varepsilon_{it}$ where $\mathbf{W}_{it}$ is the vector of firm-level control variables described in Section 2.4. Standard errors at two-way clustered by firm i and quarter t. *** denotes statistical significance at the 1% level.