# Firm Financial Conditions and the Transmission of U.S. Monetary Policy *

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**Abstract**

We study the transmission of U.S. monetary policy using the full cross-sectional distribution of the excess bond premium (EBP), the component of credit spreads linked to the financial sector's firm-specific pricing of risk. We document a puzzle: monetary policy shocks have stronger effects on the EBPs of riskier firms—those in the right-tail of the EBP distribution—but lead to larger investment responses on the part of safer firms. These findings cannot simultaneously hold in models where investment responds uniformly across firms to changes in borrowing costs. We resolve this puzzle by showing that firm-level investment responds heterogeneously to changes in EBP, with safe firms responding relatively more than risky firms. Our results help elucidate the investment channel of monetary policy.

**Key Words**: Cross-Sectional, Excess Bond Premium, Monetary Policy, Firm Dynamics, Financial Conditions, Business Cycles.
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# 1 Introduction

In the aftermath of the global financial crisis, there has been a resurgence of interest in the relationship between financial conditions, monetary policy, and economic growth. Gilchrist and Zakrajšek, 2012 construct a credit spread index with considerable predictive power for future economic activity. Orthogonalized shocks to the (mean) excess bond premium component (EBP) of that spread lead to significant declines in economic activity and asset prices. Adrian et al., 2019 analyze the *full distribution* of future GDP growth as a function of current aggregate financial conditions, as measured by the Chicago Fed's National Financial Conditions Index. They find that the conditional mean of GDP growth is negatively correlated with conditional volatility in financial conditions and with measures of downside risk. They also find that lower quantiles of the GDP growth distribution are closely related to current aggregate financial conditions, while the upper quantiles of this distribution are not. This has the important implication that conditions such as the buildup of leverage in the financial sector—perhaps resulting from unconventional monetary policy measures designed to boost aggregate demand—have the perverse effect of creating downside risk to the economy, giving rise to financial vulnerability (Adrian and Liang, 2018, Coimbra et al., 2021). This creates potential dilemmas for policymakers over whether and how monetary policy should incorporate risks to financial stability.[1]

In this paper, we provide granular evidence on the investment channel of monetary policy, with particular emphasis on the role of financial conditions. We document how monetary policy affects the full *cross-sectional distribution* of the excess bond premium (EBP), the component of credit spreads linked to the financial sector's time-varying risk-aversion towards a firm (Gilchrist and Zakrajšek (2012)). We document a puzzle from two baseline results: monetary policy shocks have (1) stronger effects on the EBPs of riskier

[1]More generally, Curdia and Woodford, 2010 assess a modification of the Taylor rule in which the intercept, which represents the Fed's view of the equilibrium real Fed Funds rate, is adjusted in response to variations in credit spreads, a proposal made by Taylor, 2008. Such a rule would require that monetary policy be loosened when credit spreads are larger than normal: the Fed Funds rate should be reduced relative to what the standard Taylor rule would prescribe when spreads are high. Analyzing whether this modification would improve the way the economy responds to various disturbances, Curdia and Woodford, 2010 find some favorable evidence, but argue that it is not ideal. An approach that is superior to putting a single measure of financial conditions in the policy rule, they note, is to adjust the policy instrument so as to imply projections for inflation and real activity that are consistent with a target criterion.

firms—those in the right-tail of the EBP distribution—but (2) lead to larger investment responses on the part of safer firms. These findings cannot simultaneously hold in models where investment responds uniformly across firms to changes in borrowing costs. We resolve this puzzle by investigating heterogeneity in how firms change investment when faced with higher EBPs. We show that an increase in the EBPs of the safe, left-tail EBP firms has a larger effect on investment than an increase in the EBPs of right-tail EBP firms.[2]

These findings help elucidate the investment channel of monetary policy and complement the literature on heterogeneity in the transmission of monetary policy across firms. Gertler and Gilchrist (1994) show that small firms' sales decline more rapidly than large firm sales following a monetary policy tightening. Bernanke et al. (1996) also demonstrate that smaller firms are more responsive to monetary policy. Ottonello and Winberry (2020) find that investment by firms with low default risk responds significantly more to monetary policy shocks than investment by firms with high default risk. Cloyne et al. (2019) show the importance of firms' age and dividend payout practices on the response of investment to U.K. monetary policy shocks. Jeenas (2019) reports that firms with fewer liquid assets reduce investment relative to others in response to tightening monetary policy shocks, and Anderson and Cesa-Bianchi (2021) show that the credit spreads of firms with high leverage rise more in response to monetary policy tightening than firms with low leverage. Our results also complement recent papers such as Carvalho and Grassi (2019), who show that large firms play an outsized role in driving the business cycle.[3] Since we document that less-leveraged and larger-sized firms typically have the lowest levels of EBP, our firm-level results on transmission are consistent with these aggregate findings.

[2]Viewed from a slightly different angle, our results point to a tension for monetary policymakers, even aside from the important question "should credit spreads be in the policy rule?". On one hand, our evidence implies that the financial conditions of safer and larger firms are of particular importance to the cyclical fluctuations of the macroeconomy. On the other hand, the results imply that monetary policy is most effective at stimulating the financial conditions of riskier and smaller firms. Missteps in navigating this tension could create the above-mentioned financial vulnerabilities and downside risks to the economy.

[3]See also Giglio et al. (2016), who use a quantile regression approach to evaluate the ability of various measures of systemic risk proposed in the literature to predict real activity. They find that some measures of systemic risk are statistically significant predictors of the left tail of real activity but not the right tail.

## 2 Cross-Sectional EBPs and Firm Characteristics

In this section, we discuss our data sources and the EBP calculation, document firm-level characteristics associated with the EBP, and summarize how the cross-sectional EBP distribution evolves over time. Throughout, we exploit four databases: the CRSP database for stock market returns, Compustat for firm balance sheet information, and Lehman/Warga and Merrill Lynch for corporate bond yields quoted in secondary markets. The sample period is October 1973 to December 2019.

To calculate the excess bond premium, we follow an approach similar to Gilchrist and Zakrajšek (2012). We calculate the credit spread $S_{it}[k]$ for 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 with the exact same maturity using estimates from Gürkaynak et al. (2007).[4] Then, we decompose each bond's credit spread $S_{it}[k]$ into two components. The first is driven by the firm's default risk, as well as its bond characteristics, and is termed the predicted spread $\hat{S}_{it}[k]$. The second, and residual, component is the excess bond premium, $EBP_{it}[k]$.

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

$$\log S_{it}[k] = \beta DD_{it} + \gamma^{'}\mathbf{Z}_{it}[k] + \varepsilon_{it}[k], \tag{1}$$

in which the log of the credit spread $S_{it}[k]$ is a linear function of (i) firm $i$'s distance-to-default $DD_{it}$ (Merton, 1974), capturing firm $i$'s expected default probability, (ii) a vector of bond characteristics $\mathbf{Z}_{it}[k]$, which includes the bond's duration, coupon rate and age, and (iii) an error term $\varepsilon_{it}[k]$. We provide details on calculating a firm's distance-to-default as well as the full list of bond characteristics $\mathbf{Z}_{it}[k]$ in Appendix A.

Assuming the error term $\varepsilon_{it}[k]$ is normally distributed, we can estimate regression (1) by OLS and compute the predicted credit spread $\hat{S}_{it}[k]$ as

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

[4]For simplicity, we abstract from calculating the yield on a synthetic U.S. Treasury with the same cash flow structure.

where $\hat{\beta}$ and $\hat{\gamma}$ denote the OLS estimates and $\hat{\sigma}^2$ denotes the estimated variance of the error term. While the model is simple, it explains in excess of 70% of the variation in credit spreads.[5] Finally, we define the excess bond premium of firm $i$'s bond $k$ at time $t$ as

$$EBP_{it}[k] = S_{it}[k] - \hat{S}_{it}[k]. \tag{3}$$

We implement the procedure above for all bonds issued by non-financial firms whose balance sheet data and equity prices are available from Compustat and CRSP, respectively. This procedure yields a monthly sample of 10,598 bonds from 1,894 firms, which we term the bond-level EBP distribution.

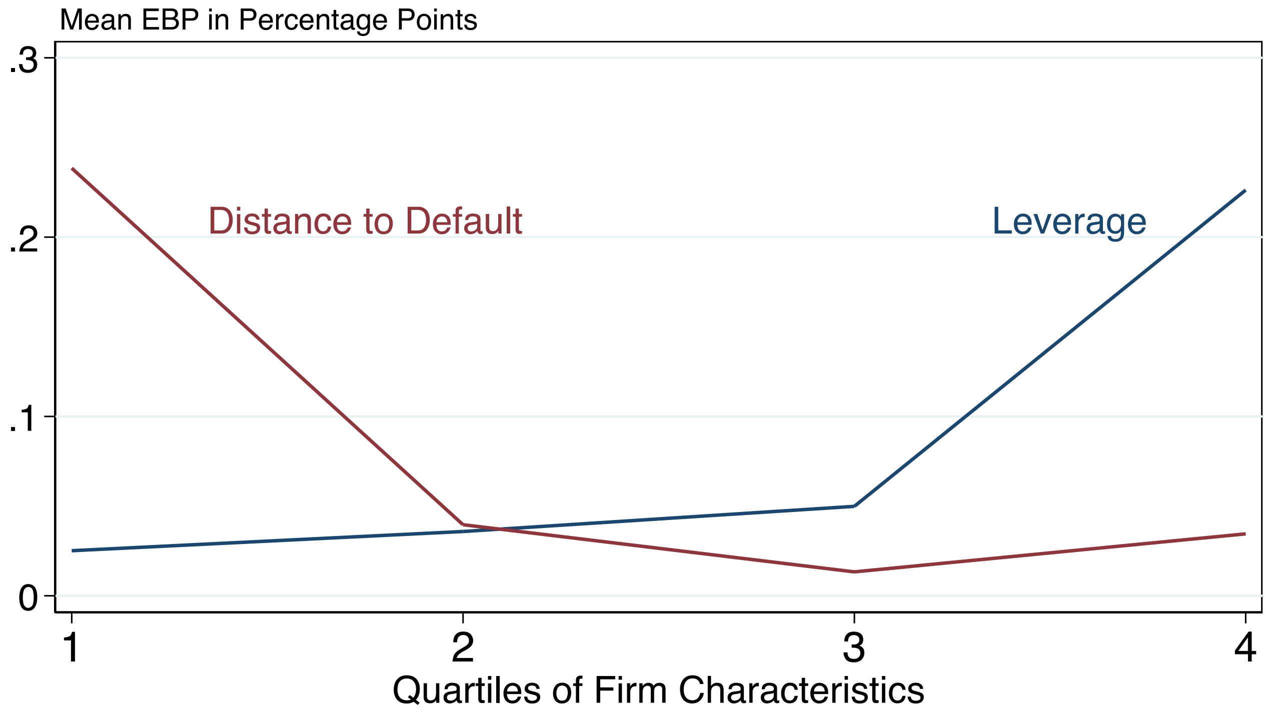
As in Gilchrist and Zakrajšek (2012), our credit spread model (1) assumes a constant price of default risk for all firms at all times. Specifically, the coefficient on the distance-to-default, $\beta$, is both time- and firm-invariant. Thus, variation in the predicted spread $\hat{S}_{it}[k]$ is due mainly to variation in the *quantity* of risk, as captured by $DD_{it}$. As a result, the residual component of the credit spread, the $EBP_{it}[k]$, may capture the financial sector's time-varying and firm/bond-specific pricing of default risk. We interpret this time-varying price of risk as a bond-specific financial condition, or similarly, following Gilchrist and Zakrajšek (2012), as the financial sector's time-varying risk-aversion towards firm $i$'s bond $k$.[6]

Figure 1 documents the cross-sectional heterogeneity in EBP as a function of firms' financial characteristics, namely distance to default and leverage. It shows that firms with low distance to default and high leverage—those we term high *quantity-of-risk* firms—have the highest average EBP and thus tend to be the firms in the right tail of the EBP distribution. Conversely, firms with high distance to default and low leverage—low *quantity-of-risk* firms—have the lowest average EBP and thus tend to be the firms in the left tail of the EBP distribution. Thus, these results show that, on average, high quantity-of-risk firms face a higher price of risk (EBP) relative to low quantity-of-risk ones.

[5] The distance-to-default alone explains 65% of the variation in credit spreads.

[6] Gilchrist and Zakrajšek (2012) show that an adverse shock to the equity value of primary dealers (financial intermediaries) leads to a rise in their CDS spreads that is matched, nearly one-to-one, with a rise in the mean EBP across firms.

FIGURE 1
Average EBP per Quartile of Distance to Default and Leverage



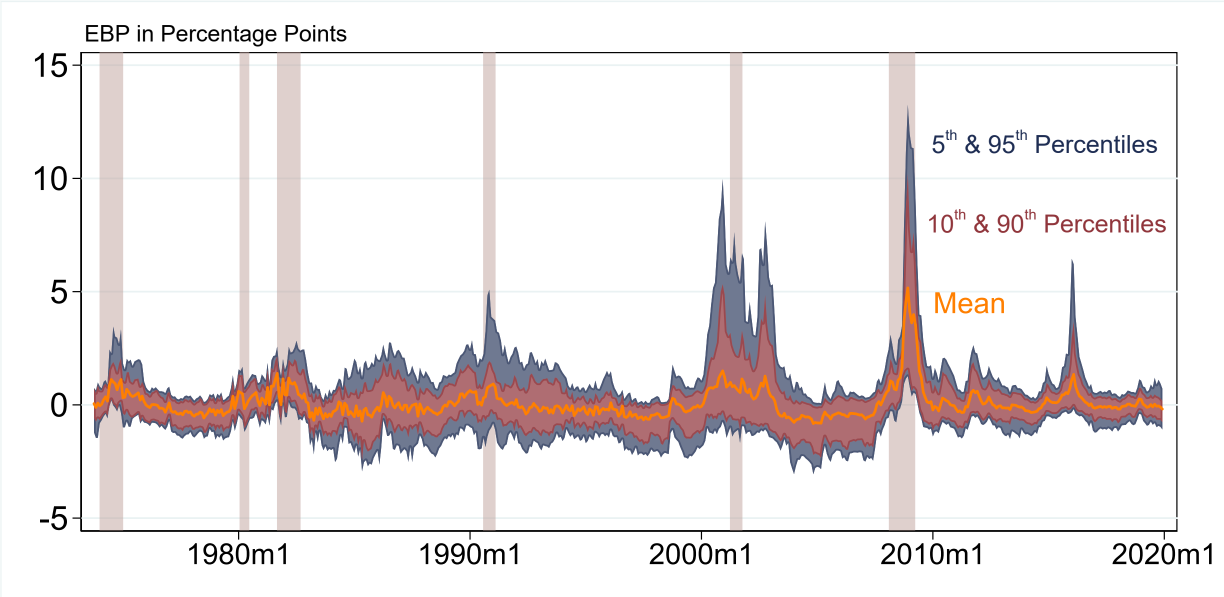

*Note.* Figure 1 reports the average EBP for each quartile of firm distance-to-default (DD) and leverage, measured as debt over assets. Bond EBPs and firm characteristics are calculated as the within-firm average over the sample. EBPs are then averaged for each quartile of DD and leverage.

Figure 2 highlights that the tails of the EBP distribution move non-uniformly over the business cycle. The right-tail of the EBP distribution tend to co-move with the mean, rising during periods of stress and falling during calmer times.[7] However, the right tail is volatile, with significant increases outside recessions, such as in the mid-1980s and post-2000 recession. The left-tail has more contained fluctuations, with a significant rise above zero only during the 2008 Global Financial Crisis.

The results from this section highlight that focusing on the mean EBP overlooks substantial heterogeneity in the EBP distribution both across firms and across time. Moreover, this heterogeneity is associated with firm-level characteristics tied to important business cycle theories (Bernanke et al., 1999).

[7] Of note, the correlation between our mean credit spread and EBP and those of Gilchrist and Zakrajšek (2012) are 96% and 85%, respectively.

FIGURE 2
Cross-Sectional EBP Distribution over the Business Cycle




*Note.* Figure 2 shows the percentiles and mean of the cross-sectional distribution of EBP. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.

# 3 Monetary Policy Drives EBP Heterogeneity

In this section, we assess monetary policy's effects on the cross-sectional distribution of credit spreads, focusing primarily on the Excess Bond Premium component. We find that the financial conditions of high price-of-risk firms, as well as high leverage and low distance-to-default firms, are particular sensitive to monetary shocks.

We begin by estimating the dynamic response of bond-level EBPs and predicted spreads $\hat{S}$ to monetary policy shocks at a monthly frequency using the following Jordà (2005) local projection:

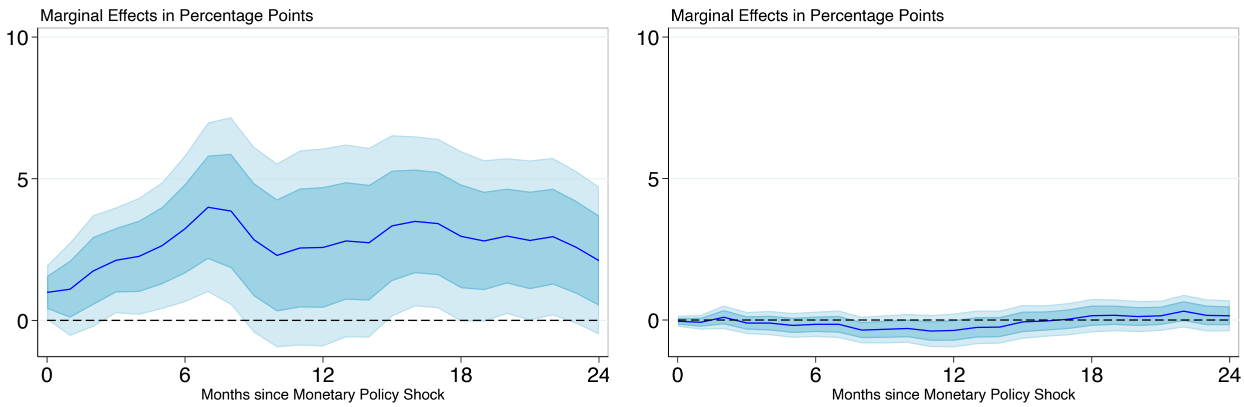
$$S_{it+h}[k] - S_{it}[k] = \beta_0 + \beta_1 \varepsilon_t^m + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \gamma_l' \Delta \mathbf{Y}_{t-l} + \alpha_k + e_{ithk} \tag{4}$$

where $S_{it}[k] \in \{EBP_{it}[k], \hat{S}_{it}[k]\}$ denotes either the bond-k EBP or predicted spread , and $\varepsilon_t^m$ denotes a Bu et al. (2021) monetary policy shock.[8] Additionally, $\mathbf{Z}_t$ controls for firm

[8]In Appendix C, we show that our results from this section are similar when using the Jarociński and Karadi (2020) monetary policy shock (see Figures C.6, C.7, and C.8).

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

(A) Excess Bond Premium (B) Predicted Spread




*Note.* Figure 3 reports the dynamic effects ($\beta_1$) of a Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) on the h-period change in credit spreads $S_{it+h}[k] - S_{i,t}[k]$ where $S_{it}[k]$ is $EBP_{it}[k]$ in Panel 3a and $S_{it}[k]$ is $\hat{S}_{it}[k]$ in Panel 3b from regression (4), where the frequency of the data is monthly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

characteristics, namely leverage, size and distance-to-default; $\Delta \mathbf{Y}_t$ controls for changes in macroeconomic conditions using the Chicago FED's national activity index as well as the Baker et al., 2016 economic policy uncertainty index; and $\alpha_k$ denotes bond fixed effects. Throughout, confidence intervals are constructed using two-way clustered standard errors by firm $i$ and month $t$ (Cameron et al., 2011).

Panel 3a highlights that a monetary policy tightening leads to a significant and persistent rise in bond-level EBPs on average. At its peak about eight months after the shock, a 100 basis point monetary policy tightening is associated with a nearly 5 percentage point rise in a bond's EBP, on average. Conversely, Panel 3b shows that the predicted spread component is very unresponsive to monetary policy. Thus, monetary policy's effect on the marginal borrowing costs of firms—their credit spreads—is due almost entirely to changing the price of risk faced by firms, as opposed to changing the risk profile of the firms themselves. These dynamic effects complement the findings of Anderson and Cesa-Bianchi (2021), who show that only the EBP component of credit spreads adjusts to monetary policy shocks *on-impact*, using a high-frequency approach. In light of the results in Figure

3, throughout the rest of the paper we focus on the EBP component of spreads.

Next, to investigate the heterogeneous effects of monetary policy on bond-level financial conditions, we estimate an augmented version of our earlier local projection:

$$\begin{aligned}EBP_{it+h}[k] - EBP_{it}[k] =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3 x_{it-1} \\ &+ \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^{'} \Delta \mathbf{Y}_{t-l} + \alpha_k + e_{ikth}, \end{aligned} \tag{5}$$

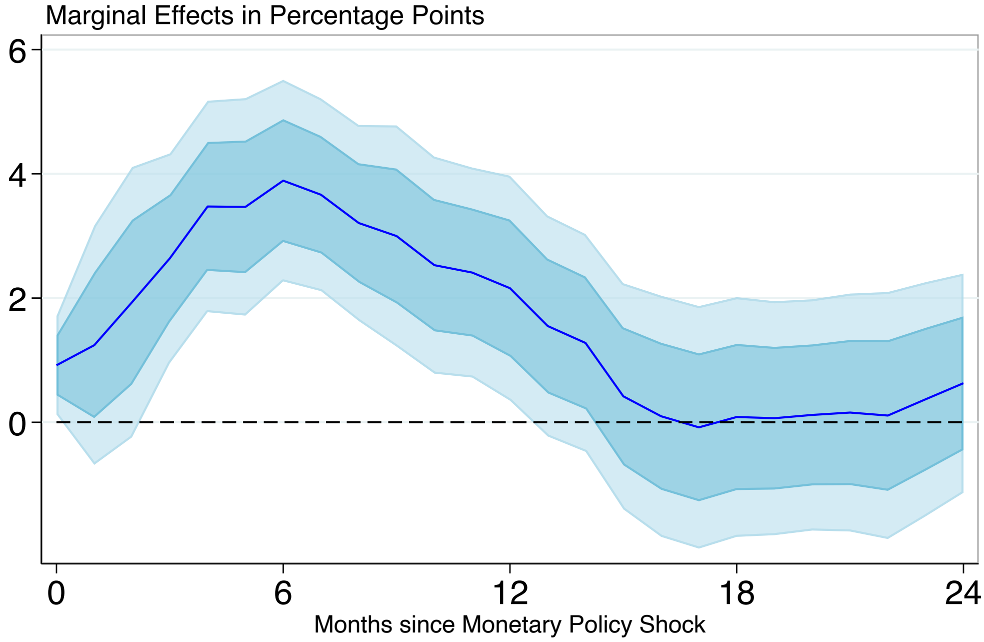
which now includes the interaction between a firm's financial characteristic $x_{it}$ and the monetary policy shock $\varepsilon_t^m$. As in Ottonello and Winberry (2020), we use the interaction between the *within-firm* variation in a firm's financial position and the monetary shock $[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$ to focus on how a given firm responds to a monetary policy shock when it is more or less risky than usual. In our baseline, we set $x_{it}$ to be either firm leverage $lev_{it}$, as in Anderson and Cesa-Bianchi (2021), firm distance-to-default $dd_{it}$, as emphasized for investment in Ottonello and Winberry (2020), and, new to the literature, the price of risk of bond $k$ captured by the $EBP_{it}[k]$.

Figure 4 reports the marginal effects for the interaction between within-firm EBP and the monetary shock from estimating (5). In conjunction with the positive unconditional effect displayed in Panel 3a, the positive coefficients in Figure 4 imply that the EBPs of high price-of-risk firms—right-tail EBP firms—are substantially more responsive to monetary policy than low price-of-risk firms. Specifically, at its peak, a firm one standard deviation above its average price of risk is nearly twice as responsive to a monetary shock compared to a firm at its historical average.

When we estimate (5) using $dd_{it}$ and $lev_{it}$, we find the magnitudes of the point estimates for the interaction terms are similar to those for $EBP_{it}[k]$, but the marginal effects are less precisely estimated, as seen in Figure 5. The sign of the coefficients implies that the financial conditions of low distance-to-default firms and high leverage firms—high quantity-of-risk firms—are significantly more responsive to monetary policy than are the financial conditions of safe firms.

The summary statistics in Figure 1, however, document a cross-sectional relationship

Figure 4
Monetary Policy's Effect on Bond-Level EBP by Firm Price-of-Risk



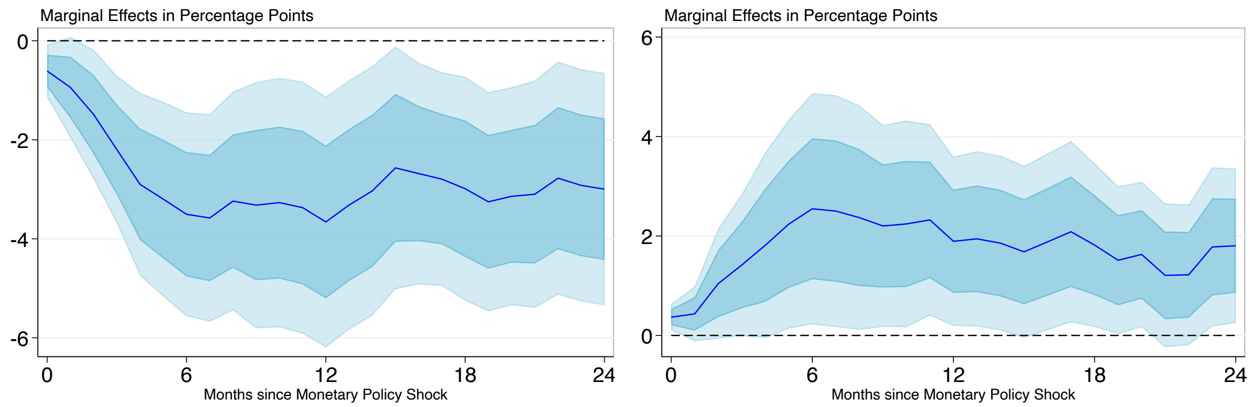

*Note.* Figure 4 reports the dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's price-of-risk $EBP_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$) on the h-period change in EBP, $EBP_{it+h}[k] - EBP_{i,t}[k]$, from regression (5), where the frequency of the data is monthly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

between EBP and risk: high quantity-of-risk firms face a higher price of risk on-average. To see whether quantity or price of risk is most-responsible for the heterogeneous effects of monetary policy on firm financial conditions, in Appendix C, we estimate (5) with both an EBP interaction and a quantity-of-risk interaction, using either leverage or distance to default. The results are displayed in Figure C.1 and highlight that the results are largely driven by the price of risk, the EBP.

Together, the results from this section highlight than monetary policy affects the credit spreads of firms by regulating the price-of-risk charged by the financial sector. In addition, it is high price-of-risk firms, as well as high quantity-of-risk firms, whose financial conditions are most responsive to monetary shocks.

Figure 5
Monetary Policy's Effect on Bond-Level EBP by Firm Quantity-of-Risk

(a) Conditional on Distance to Default (b) Conditional on Leverage




*Note.* Figure 5 reports the dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's quantity-of-risk $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$), where $x_{i,t}$ is $dd_{i,t}$ in Panel 5a and is $lev_{i,t}$ in Panel 5b, on the h-period change in EBP, $EBP_{it+h}[k] - EBP_{i,t}[k]$, from regression (5). The frequency of the data is monthly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

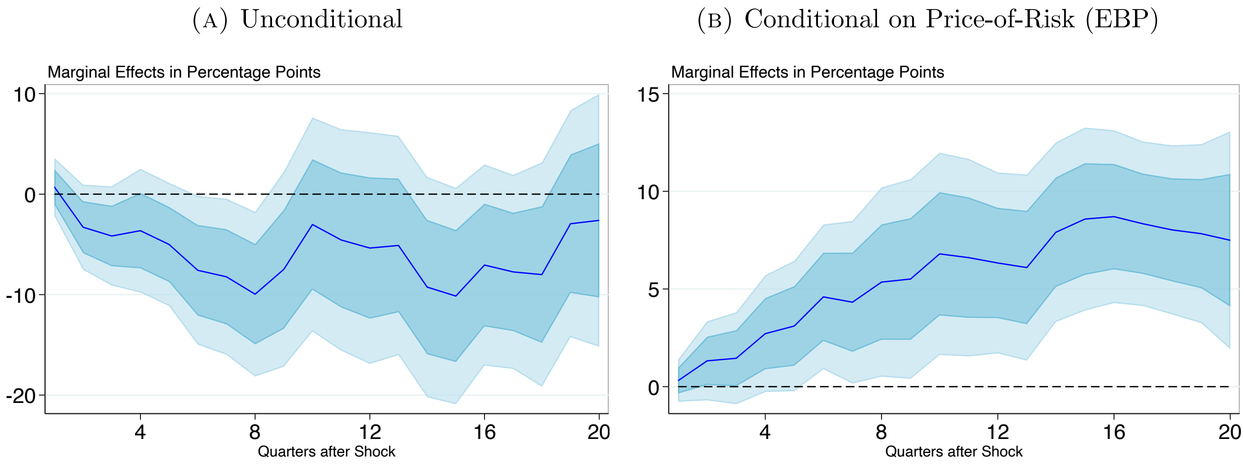
# 4 Monetary Policy and Firm-Level Investment

In this section, we estimate the heterogeneous effects of monetary policy on firm-level investment. We find that investment done by low price- (EBP) and quantity- (leverage and dd) of-risk firms are most responsive to monetary policy shocks. This stands in contrast to our findings from Section 3, where the borrowing costs of high price- and quantity-of-risk firms were most responsive to monetary shocks. We resolve this tension in the next section.

We begin by using quarterly firm-level balance sheet data from the Compustat database to construct a measure of firm $i$'s real investment $\Delta log K_{it}$, where $K_{it}$ is equal to the (real) book value of firm $i$'s tangible capital stock at time $t$, as in Ottonello and Winberry (2020). We then estimate the following firm-level investment local projection at a quarterly frequency:

Figure 6

Monetary Policy's Effect on Firm-Level Investment




*Note.* Figure 6 reports the dynamic effects of a Bu et al. (2021) monetary policy shock ($\beta_1$) in Panel 6a and of the interaction ($\beta_2$) between within-firm variation in a firm's price-of-risk $EBP_{i,t}$ and the monetary shock, $[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (6). The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\begin{aligned}\log K_{it+h} - \log K_{it} =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m \\ &+ \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \gamma_l' \mathbf{Y}_{t-l} + \alpha_i + e_{ith}, \end{aligned} \tag{6}$$

where $\varepsilon_t^m$ is the Bu et al. (2021) monetary policy shock summed to a quarterly frequency and $x_{it}$ is either leverage or distance-to-default, as in Ottonello and Winberry (2020), or our preferred measure of a firm's financial condition, the EBP.[9] With $\mathbf{Z}_{it}$, we control for firm characteristics, namely leverage, distance-to-default, real size, and real sales growth; with $\mathbf{Y}_{it}$ we control for macro-financial conditions using U.S. real GDP growth and the first three principal components of the U.S. treasury yield curve, as estimated by Gürkaynak et al. (2007); and $\alpha_i$ denotes firm fixed effects. As always, confidence intervals are constructed using two-way clustered standard errors by firm $i$ and month $t$ (Cameron et al., 2011).

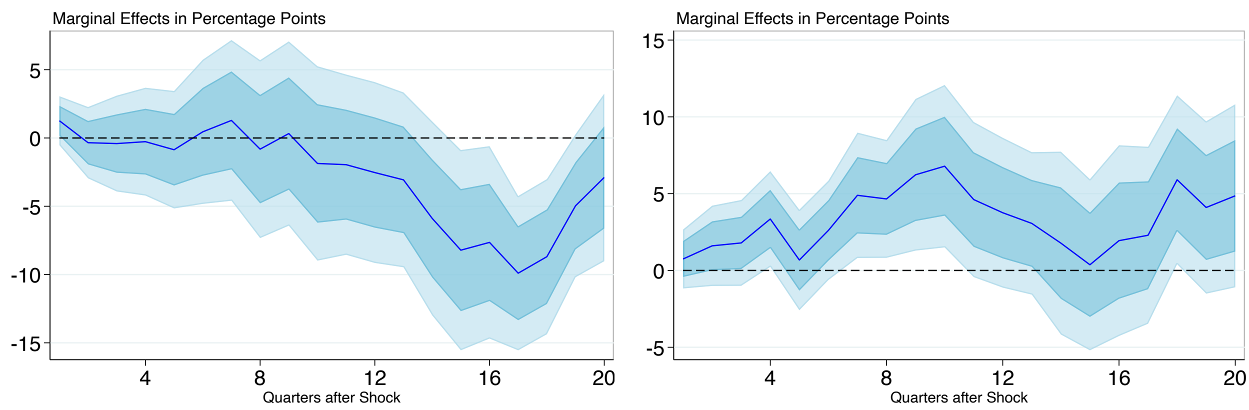
Figure 6 presents the results from estimating equation (6) with $x_{it} = EBP_{it}$. Panel 6a highlights that a shock tightening in monetary policy predicts a significant fall in investment

[9]In Appendix C, we show that our results from this section are similar when using the Jarociński and Karadi (2020) monetary policy shock (see Figures C.9, and C.10).

FIGURE 7

Monetary Policy's Effect on Firm-Level Investment by Firm Quantity-of-Risk

(A) Conditional on Distance to Default (B) Conditional on Leverage




*Note.* Figure 7 reports the dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's quantity-of-risk $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$), where $x_{i,t}$ is $dd_{i,t}$ in Panel 7a and is $lev_{i,t}$ in Panel 7b, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (6). The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

for the average firm. In Panel 6b, we see that this effect is larger for low price-of-risk (low EBP) firms.

We then re-estimate (6) using distance-to-default and leverage as measures of financial position. The dynamic interaction effect coefficients are displayed in Figure 7. Consistent with Ottonello and Winberry (2020), we find that investment done by low leverage and high distance-to-default—low quantity of risk— firms is relatively more responsive to monetary policy shocks.

Again, in Appendix C we estimate a variant of equation (6) with two monetary policy shock interaction terms: one with the EBP; and a second with a measure of the quantity of firm risk. Figure C.2 shows that the significance of the quantity-of-risk interactions falls slightly, while the effects on the price-of-risk interaction are generally unchanged or even stronger.

Our results thus far point to a tension: monetary policy loosenings generate only a small easing in the marginal borrowing rate of low price-of-risk (safe) firms but trigger a large increase in these firm's investment. In the next section, we remedy this tension by documenting, for the first time, heterogeneity in responsiveness of firm investment to changes in a firm's financial conditions.

# 5 Firm-Level EBP and Investment

In this section, we assess the direct role of firm financial conditions, the component of credit spreads affected by monetary policy, on investment. First, we show that much of the observed heterogeneity in monetary policy's effects on investment works *through* firm financial conditions. Next, we document that that investment done by low price-of-risk and quantity-of-risk firms is the most responsive to changes in financial conditions. This helps rationalize the disconnect between monetary policy's effects on spreads and investment.

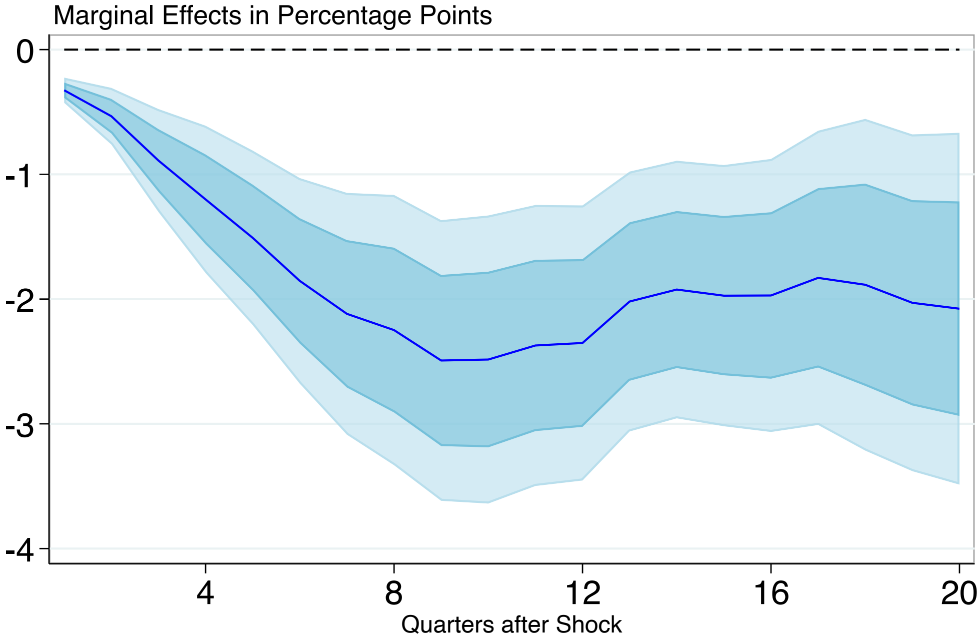
To begin, we augment our investment local projection (6) estimated in Section 4 with the two components of credit spreads: the EBP and the predicted spread $\hat{S}$:

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3 EBP_{it} + \beta_4 \hat{S}_{it} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \gamma_l' \mathbf{Y}_{t-l} + \alpha_i + e_{ith}, \tag{7}$$

Figure 8 plots the marginal effects ($\beta_3$) of $EBP_{it}$ on investment at different horizons from estimating (7). The results highlight that a rise in $EBP_{it}$, a deterioration in firm $i$'s financial conditions, predicts a significant and persistent fall in firm $i$'s investment, on average. At its peak roughly 8 quarters after the shock, a 100 basis point increase in firm $i$'s EBP is associated with a 2.5 percentage point drop in its investment. Importantly, Figure C.3 in Appendix C shows that significance and magnitude of the interaction term $[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$ estimated from (7) fall considerably relative to estimates from Section 4. This suggests that much of the observed heterogeneity in monetary policy's effects on investment was working *through* the excess bond premium component credit spreads.[10]

[10] Figure C.4 plots the dynamic response of $\hat{S}$ on investment and shows that its effects are *larger* than the EBP. This points to a further tension for monetary policy, as monetary policy has no ability to regulate $\hat{S}$.

FIGURE 8
Firm-Level Effects of EBP on Investment




*Note.* Figure 8 reports the dynamic effects ($\beta_3$) of the Excess Bond Premium (EBP) on the h-period Investment of firm i $\log K_{it+h} - \log K_{it}$ from regression (7), where the frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

To better understand the heterogeneous effects of EBP on investment, we estimate an augmented version of specification (7):

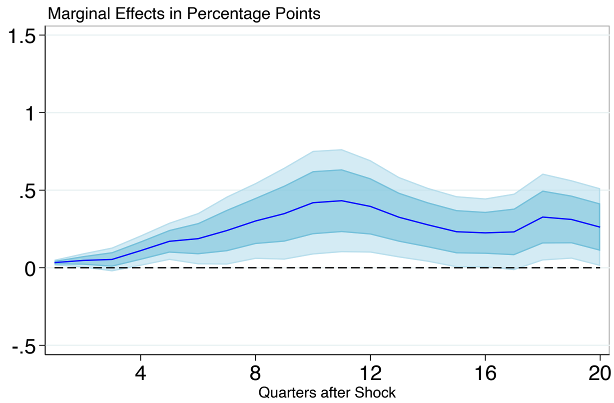
$$\begin{aligned}\log K_{it+h} - \log K_{it} =& \beta_1 \varepsilon_t^m + \beta_2 EBP_{it} + \beta_3 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_4 [x_{it-1} - \mathbb{E}_i(x_{it})] EBP_{it} \\ &+ \beta_5 \hat{S}_{it} + \theta_1' \mathbf{S}_{it-1} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \beta_0 + \alpha_i + e_{ith}, \end{aligned} \quad (8)$$

which crucially adds the interaction term $[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it}$ between the within-firm variation in a firm's financial position and the $EBP$.[11] Figure 9 plots the dynamic interaction effects $\beta_4$ for each of our firm financial position indicators $x_{it}$. For both distance-to-default and EBP in Panels 9a and 9b, respectively, the results suggest that investment done by low quantity-of-risk and price-of-risk firms is substantially more responsive to movements in financial conditions, as compared to firms at the other end of the distribu-

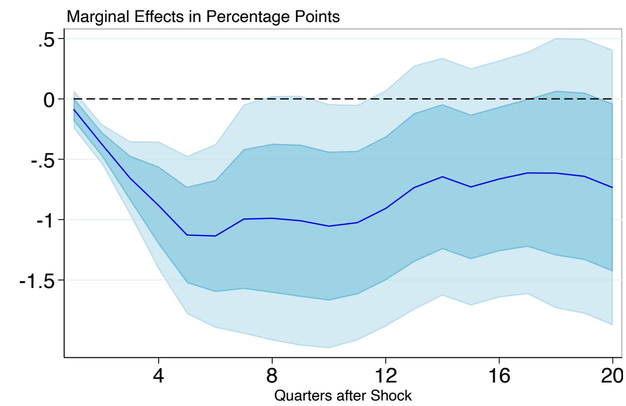
[11] It also controls for both credit spread components in $\mathbf{S}_{it}$.

FIGURE 9
Firm-Level EBP's Effect on Investment by Firm Financial Position

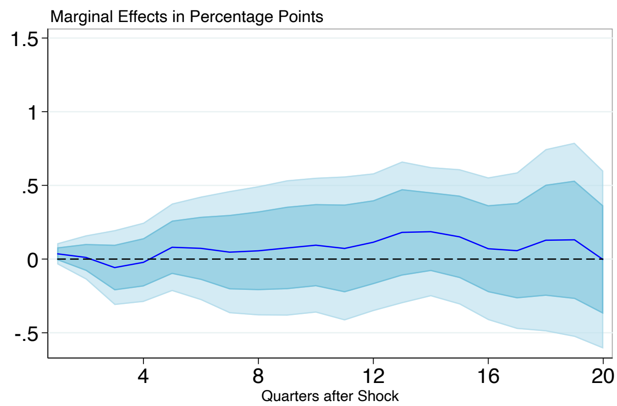
(A) Conditional on Price-of-Risk (EBP)




(B) Conditional on Distance-to-Default




(C) Conditional on Leverage




*Note.* Figure 9 reports the dynamic effects ($\beta_4$) of the interaction between within-firm variation in a firm's financial position $x_{i,t}$ and the EBP, $[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$, where $x_{i,t}$ is the price of risk (EBP) in Panel 9a, the distance to default $dd_{i,t}$ in Panel 9b and leverage $lev_{i,t}$ in Panel 9c, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (8). The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

tion. While the point estimate has the correct sign, we find little evidence of heterogeneity based on leverage.[12]

These findings help settle the disconnect between monetary policy's effects on credit spreads and investment. In Ottonello and Winberry (2020)'s model, low-risk firms are more responsive to monetary policy due to relatively easier access to funding. However, we

[12]In Appendix C, Figure C.5 shows that this heterogeneity by price-of-risk is robust to including an interaction with quantity-of-risk, whereas the quantity-of-risk interaction effects become more muted.

showed this cannot be the case since high price- and quantity-of-risk firms' credit spreads are *more* responsive to monetary shocks. Instead, we show that the heterogeneous effects of monetary policy on firm investment works through their credit spreads: safer firms have a higher elasticity of investment to changes in their financial conditions. This is may be due to low price- and quantity-of-risk firms having access to more productive investment opportunities.

# 6 Conclusion

In this paper, we trace the effects of U.S. monetary policy, through the distribution of firm financial conditions (the EBP), and onto firm investment. We find that in response to changes in funding costs, low price- and quantity-of-risk firms' investment responds more than high-risk firms'. This helps rationalize the puzzle that risky firms' spreads but safe firms' investment is more responsive to monetary policy. In Appendix B, we show that these granular findings also exist in the aggregate.

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# A Appendix: Distance-to-Default and the EBP

As in Gilchrist and Zakrajšek (2012), we obtain, from the Lehman/Warga and Merrill Lynch databases, the month-end secondary-market bond prices for the sample of U.S. firms covered by the S&P's Compustat database and the Center for Research in Security Prices (CRSP). We calculate then credit spread $S_{it}[k]$ for 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 yield with the exact same maturity, using estimates from Gürkaynak et al. (2007).

Next, following Gilchrist and Zakrajšek (2012), we decompose the firm-level credit spreads $S_{it}[k]$ into a component driven by firm-level default risk—the predicted spread—and a residual component—the EBP—which we interpretet as the financial sector's subjective risk sentiment vis-a-vis firm $i$ with respect to bond $k$. To do so, we assume that the log of the bond-$k$ credit spread at time $t$ is a linear function of issuing firm $i$'s Merton (1974) Distance-to-Default ($DD_{it}$), which we discuss in detail shortly, and a vector of bond characteristics $\mathbf{Z}_{it}[k]$ such that

$$logS_{it}[k] = \beta DD_{it} + \gamma' \mathbf{Z}_{it}[k] + \varepsilon_{it}[k] \tag{A.1}$$

where $\mathbf{Z}_{it}[k]$ includes the bond's duration, amount outstanding, coupon rate and age.[13] Further, we include both industry and credit rating fixed effects.

Assuming the error term is normally distributed, the predicted spread of bond $k$ issued by firm $i$ at time $t$ is given by

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

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

[13] Additionally, we include interaction terms between $DD_{it}$, $\mathbf{Z}_{it}[k]$, the first 3 principal components of the U.S. Treasury yield curve and an indicator variable that equals one if the bond is callable and zero if not.

premium on firm $i$'s bond $k$ at time $t$ as

$$EBP_{it}[k] = S_{it}[k] - \hat{S}_{it}[k] \tag{A.3}$$

The key predictor in our credit spread model from above is the firm's Merton (1974) Distance-to-Default (DD), an indicator of the firm's expected default risk. The DD framework assumes that the total value of the firm, denoted by $V$, is governed by following the stochastic differential equation:

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

where $\mu_V$ is the expected growth rate of $V$, $\sigma_V$ is the volatility of $V$, and $Z_t$ denotes the standard Brownian motion. Assuming additionally 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 cumulative standard normal distribution function, 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 A.5, by Ito's lemma, we can relate the volatility of the firm's value to the volatility of the firm's equity

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

Assuming a time to maturity of one year ($T = 1$) and daily data on one-year Treasury yields $r$, the face value of firm debt $D$, the market value of firm equity $E$, and its one-year historical volatility $\sigma_E$, A.5 and A.6 provide a two equation system that can be used to solve for the two unknowns $V$ and $\sigma_V$.[14] However, as emphasized in Vassalou and Xing (2004), large swings in market leverage $V/E$ lead to excessive volatility in the estimated value for $\sigma_V$ from A.6, which are at odds with data on the frequency of default and asset price movements. To address this, we follow Gilchrist and Zakrajšek (2012) by implementing the iterative procedure from Bharath and Shumway (2008), which proceeds in two steps. First, we initialize the procedure by setting $\sigma_V = \sigma_E$ for each day in a one-year rolling window and then substitute $\sigma_V$ into A.5 to solve for the market value $V$ for each of these days. Second, from our new estimated $V$ series, we calculate a year-long series of daily log-returns to the firm's value, $\Delta \log V$, which we then use to compute a new estimate for $\sigma_V$ as well as for $\mu_V$.[15]. We then iterate on $\sigma_V$ until convergence.

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

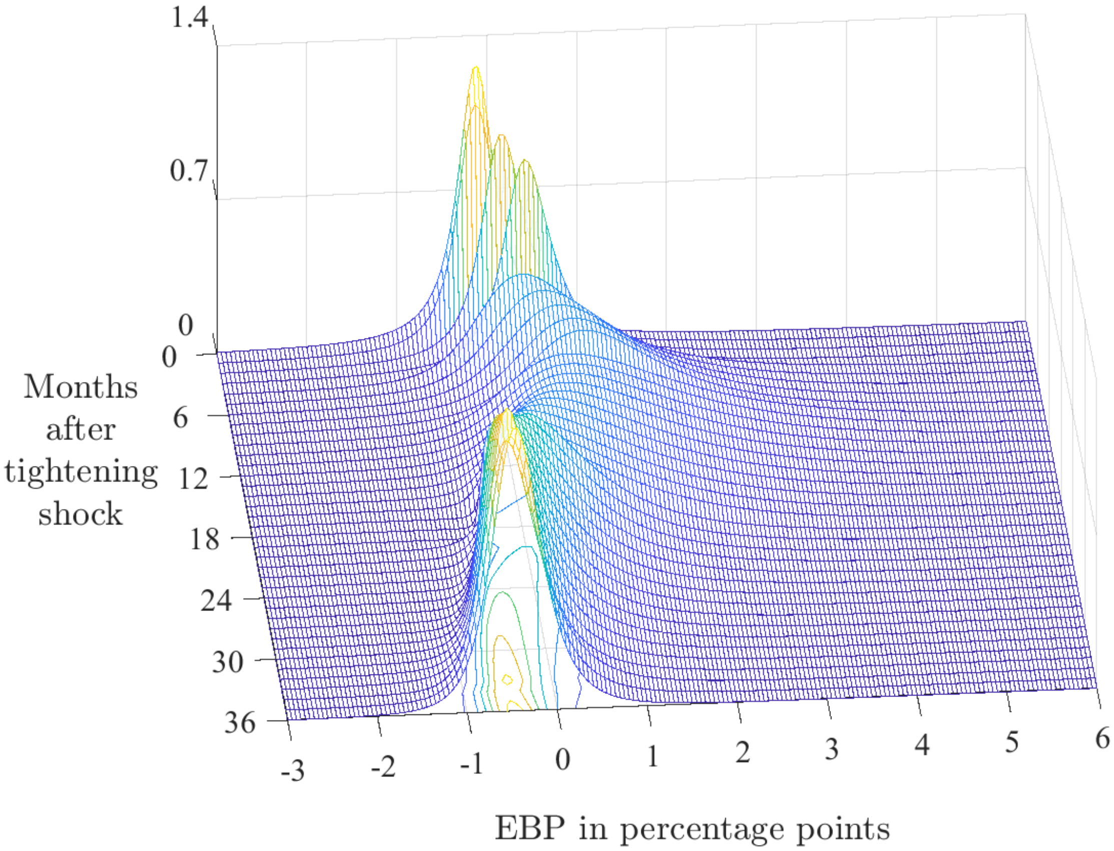
$$DD = \frac{\log(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V} \tag{A.7}$$

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

[14]Daily data for $E$ is from CRSP and is used to calculate a daily 252-day historical rolling-window equity volatility $\sigma_E$. Quarterly data on firm debt $D =$ Current Liabilities $+ \frac{1}{2}$Long-Term Liabilities is from Compustat and is linearly interpolated to form a daily series.

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

Figure B.1
Monetary Policy's Effect on Cross-Sectional Distribution of EBP




*Note.* Figure B.1 reports how the full cross-sectional distribution of EBP evolves over time after a monetary policy shock. These distributions are estimated using a two-step procedure analogous to Adrian et al. (2019). First, we estimate how the quantiles evolve after a monetary policy shock using the VAR described in of Section B. Second, we approximate the probability density function at each time period using a skewed-t distribution. Prior to the monetary policy shock, we suppose the cross-sectional distribution of EBPs is the unconditional one over the sample 1994M1–2019M12.

# B Appendix: Aggregate Effects of EBP Heterogeneity

We begin by quantifying monetary policy's effects on the *full* cross-sectional distribution of EBP, where we find considerable changes to the shape of these distributions. We follow a two-step procedure analogous to Adrian et al. (2019). First, we estimate the IRFs of the 95th, 75th, 50th, 25th and 5th quantiles of the cross-sectional distribution of EBP to a monetary policy shock using Bayesian VARs with the cumulative Bu et al. (2021) monetary policy shock, industrial production, consumer prices, and different quantiles of the EBP distribution. [16] Second, we approximate the probability density function at each

[16] We use the median IRFs of these variables.

time period using a skewed-t distribution. Prior to the monetary policy shock, we suppose the cross-sectional distribution of EBPs is the unconditional one over the sample 1994M1–2019M12. Figure B.1 shows the results, capturing the gradual increase in the first three moments of cross-sectional distribution of EBP until the 12th month after the monetary policy shock, as well as the return of the distribution to its previous shape.

Next, we forecast growth in economic activity using percentiles of the EBP distribution. Specifically, we estimate:

$$\nabla^h Y_{t+h} = \beta_0 + \beta_1 EBP_t^{mean} + \beta_2 EBP_t^{\tau} + \gamma^{'} \mathbf{YC}_t + \nabla Y_t + \varepsilon_{t+h} \tag{B.1}$$

where $\nabla^h Y_{t+h}$ denotes the h-period-ahead growth rate of either GDP, domestic private investment, or industrial production, $EBP_t^{mean}$ is the mean of the EBP distribution, $EBP_t^{\tau}$ denotes a percentile of the EBP distribution, and $\mathbf{YC}_t$ are the first three principal components (level, slope and curvature) of the U.S. Treasury yield curve calculated by Gürkaynak et al. (2007).[17]

Tables B.1a and B.1b report the regression coefficients from estimating (B.1) using the $25^{th}$ and $75^{th}$ percentiles of the EBP distribution, respectively. Table B.1a shows that $EBP_t^{25}$ drowns out the forecasting power of $EBP_t^{mean}$ for one-year-ahead growth in economic activity. This suggests that financial sector risk aversion towards the large, safe firms in the left-tail of the EBP distribution is of particular significance for the health of the macroeconomy, an important nuance to the key result in Gilchrist and Zakrajšek (2012). Conversely, although the significance is mixed, the marginal effects for $EBP_t^{75}$ in Table B.1b shows that increases in EBP for the small, risky firms in the distribution actually stimulates growth, after controlling for the mean firm. Together, these aggregate forecasting results confirm that the wider cross-sectional EBP distribution, and in particular the distributions' left-tail, provides a useful signal of future economic activity above the information contained in the "mean" firms' financial conditions.

[17] H-period-ahead growth of Y is calculated as $\nabla^h Y_{t+h} = \frac{c}{h+1} \ln\left(\frac{Y_{t+h}}{Y_{t-1}}\right)$, where c = 400 for quarterly variables (GDP and INV) and c = 1200 for monthly variables (IP).

Table B.1
The Cross-Sectional EBP Distribution and One-Year-Ahead Economic Activity

(a) $25^{th}$ Percentile

| Variables | GDP | INV | IP |
|---|---|---|---|
| $\text{EBP}_t^{\text{mean}}$ | 0.37 | 0.71 | 0.76* |
| | (0.25) | (1.26) | (0.42) |
| $\text{EBP}_t^{25}$ | -0.91*** | -2.69** | -2.02*** |
| | (0.25) | (1.25) | (0.37) |
| Obs | 180 | 180 | 540 |
| $R^2$ | 0.455 | 0.332 | 0.279 |
| Controls | YES | YES | YES |

(b) $75^{th}$ Percentile

| Variables | GDP | INV | IP |
|---|---|---|---|
| $\text{EBP}_t^{\text{mean}}$ | -1.09*** | -3.72* | -4.39*** |
| | (0.40) | (2.01) | (0.69) |
| $\text{EBP}_t^{75}$ | 0.68 | 2.04 | 3.40*** |
| | (0.51) | (2.40) | (0.67) |
| Obs | 180 | 180 | 540 |
| $R^2$ | 0.417 | 0.317 | 0.264 |
| Controls | YES | YES | YES |

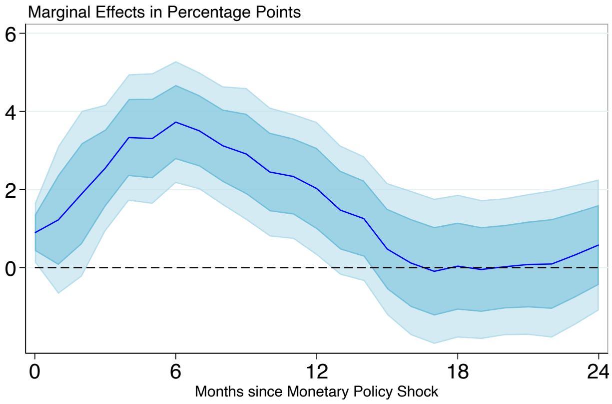
*Note.* Table B.1 reports the marginal effects of $EBP_t^{mean}$ and $EBP_t^{\tau}$ for $\tau \in \{25, 75\}$ in Panels B.1a, and B.1b, respectively, from estimating regression (B.1) for $Y \in \{\text{GDP, INV, IP}\}$. Controls are the first three principal components of the U.S. Treasury yield curve and the contemporaneous growth rate of the dependent variable. Standard errors are based on 1000 bootstrapped samples and are reported in parentheses. Statistical significance tests the null hypothesis that the coefficient associated to a regressor is zero, where *, **, and *** denote significance levels of 0.1, 0.05 and 0.01, respectively.

# C Appendix: Additional Results

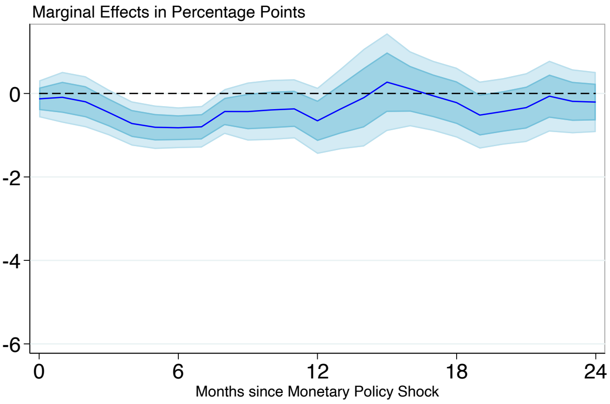
FIGURE C.1

Monetary Policy on EBP: Double Interaction by Price- and Quantity-of-Risk

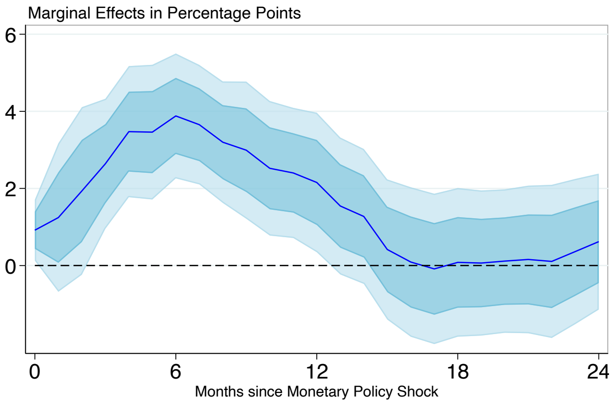
(A) $\hat{\beta}_3$: EBP Interaction



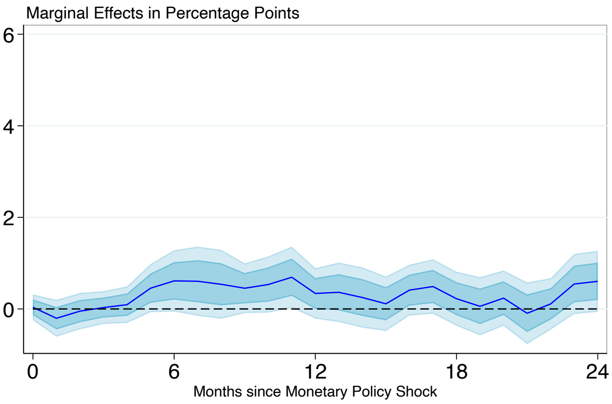

(B) $\hat{\beta}_2$: Distance to Default Interaction




(C) $\hat{\beta}_3$: EBP Interaction




(D) $\hat{\beta}_2$: Leverage Interaction



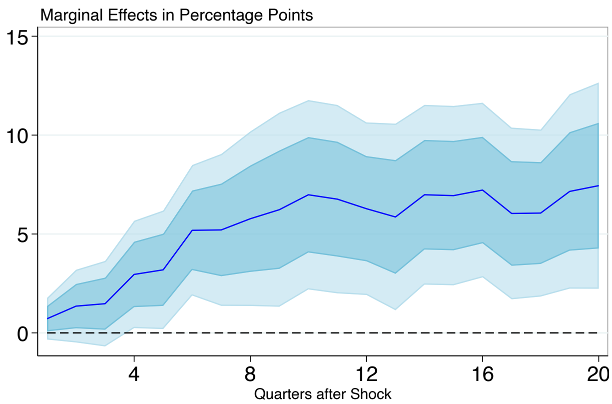

*Note.* Figure C.1 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's price-of-risk $EBP_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$) and (B) the interaction of within-firm variation in a firm's quantity-of-risk $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$), on the h-period change in EBP, $EBP_{i,t+h}[k] - EBP_{i,t}[k]$. Panels C.1a and C.1b report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation C.1 with $x_{i,t} = dd_{i,t}$, while Panels C.1c and C.1d report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation C.1 with $x_{i,t} = lev_{i,t}$. The frequency of the data is monthly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\begin{aligned} EBP_{it+h}[k] - EBP_{it}[k] =& \beta_0 + \beta_1\varepsilon_t^m + \beta_2[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\ &+ \beta_4 EBP_{it-1} + \sum_{l=1}^{3}\gamma_l'\mathbf{Z}_{it-l} + \sum_{l=1}^{3}\delta_l'\Delta\mathbf{Y}_{t-l} + \alpha_k + e_{ikth}, \qquad \text{(C.1)} \end{aligned}$$

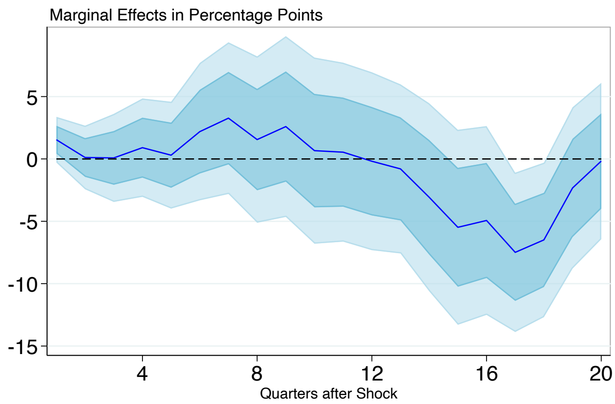
Figure C.2

Monetary Policy on Investment: Double Interaction by Price- and Quantity-of-Risk

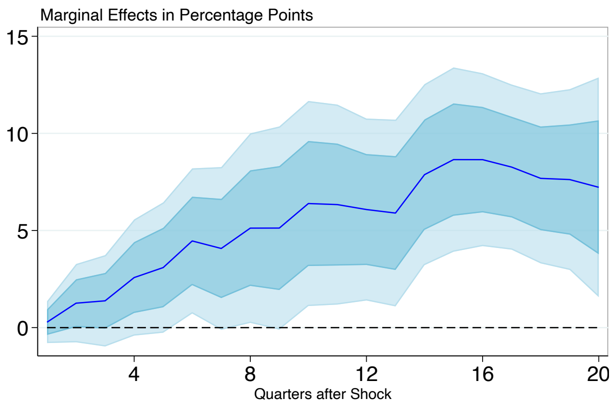
(A) $\hat{\beta}_3$: EBP Interaction



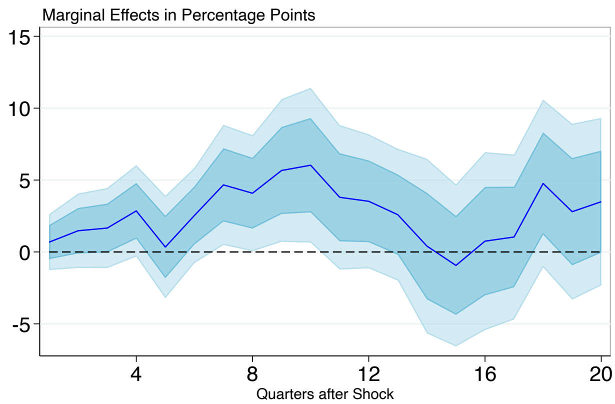

(B) $\hat{\beta}_2$: Distance to Default Interaction




(C) $\hat{\beta}_3$: EBP Interaction




(D) $\hat{\beta}_2$: Leverage Interaction



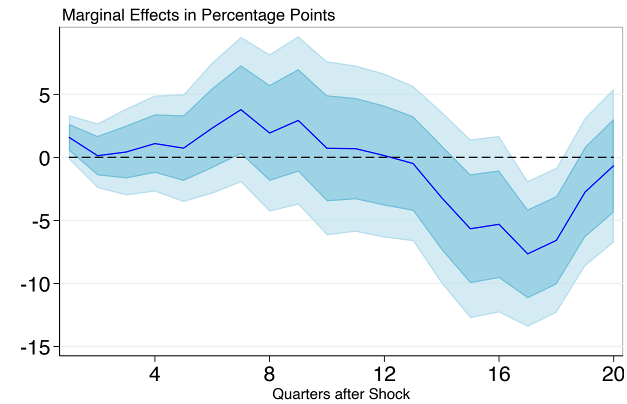

*Note.* Figure C.2 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's price-of-risk $EBP_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$) and (B) the interaction of within-firm variation in a firm's quantity-of-risk $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$), on the h-period change firm i's Investment, $\log K_{it+h} - \log K_{it}$. Panels C.2a and C.2b report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation C.2 with $x_{i,t} = dd_{i,t}$, while Panels C.2c and C.2d report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation C.2 with $x_{i,t} = lev_{i,t}$. The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1\varepsilon_t^m + \beta_2[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$$
$$+ \sum_{l=1}^{3}\gamma_l'\mathbf{Z}_{it-l} + \sum_{l=1}^{3}\gamma_l'\mathbf{Y}_{t-l} + \alpha_i + e_{ith}, \tag{C.2}$$

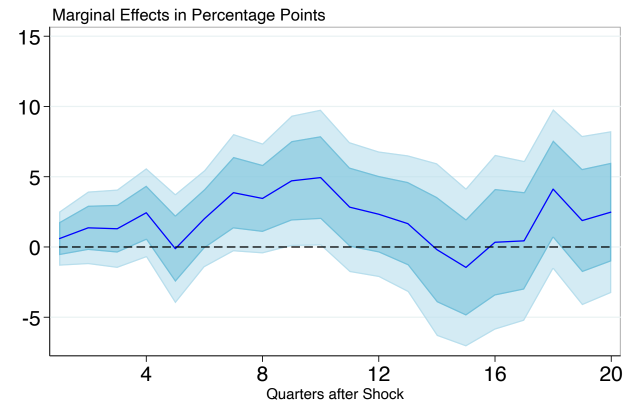
FIGURE C.3

Monetary Policy on Investment by Firm Financial Position, Augmented with EBP

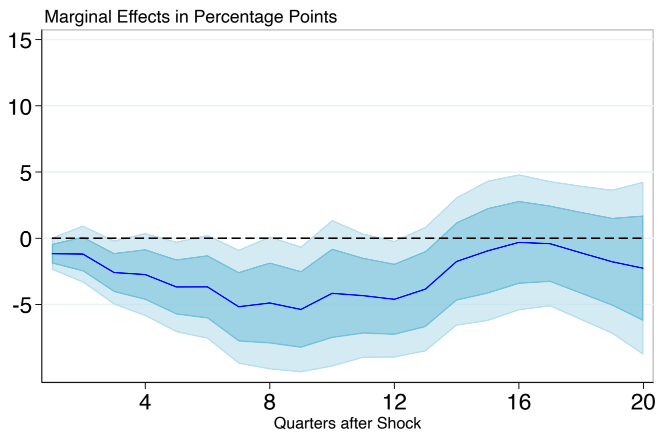
(A) $\hat{\beta}_2$: Distance to Default Interaction




(B) $\hat{\beta}_2$: Leverage Interaction



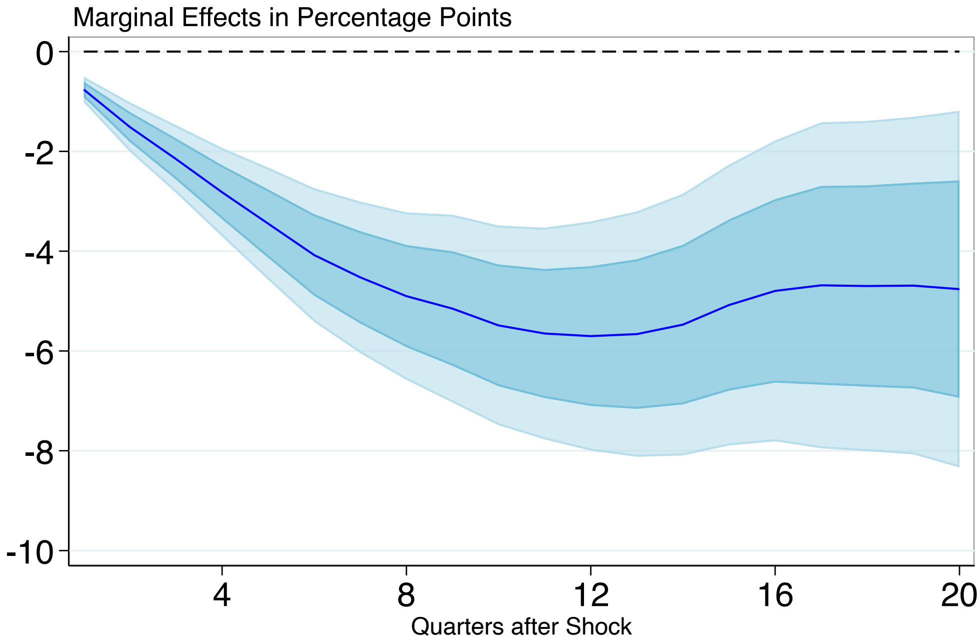

(C) $\hat{\beta}_2$: EBP Interaction




*Note.* Figure C.3 reports the dynamic interaction effects ($\beta_2$) of within-firm variation in a firm's financial position $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$) on the h-period Investment of firm i $\log K_{it+h} - \log K_{it}$ from regression (C.4), which includes the $EBP_{i,t}$. $x_{i,t}$ is distance to default in Panel C.3a, leverage in Panel C.3b, and price-of-risk (EBP) in Panel C.3c. The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3 EBP_{it} + \beta_4 \hat{S}_{it} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \gamma_l' \mathbf{Y}_{t-l} + \alpha_i + e_{ith}, \tag{C.3}$$

FIGURE C.4
Firm-Level Effects of $\hat{S}$ on Investment



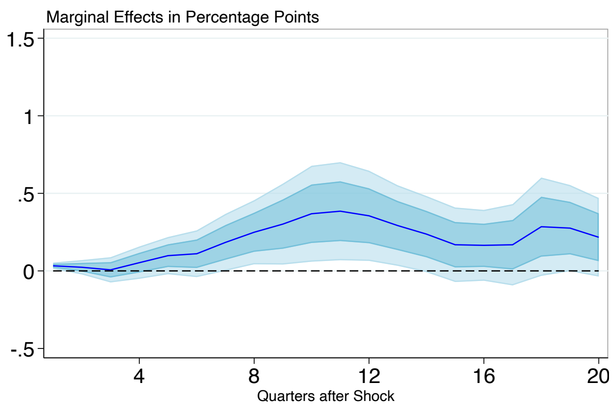

*Note.* Figure C.4 reports the dynamic effects ($\beta_4$) of the Predicted Spread ($\hat{S}$) on the h-period Investment of firm i $\log K_{it+h} - \log K_{it}$ from regression (C.4), where the frequency of the data is quarterly. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3 EBP_{it} + \beta_4 \hat{S}_{it} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Y}_{t-l} + \alpha_i + e_{ith}, \tag{C.4}$$

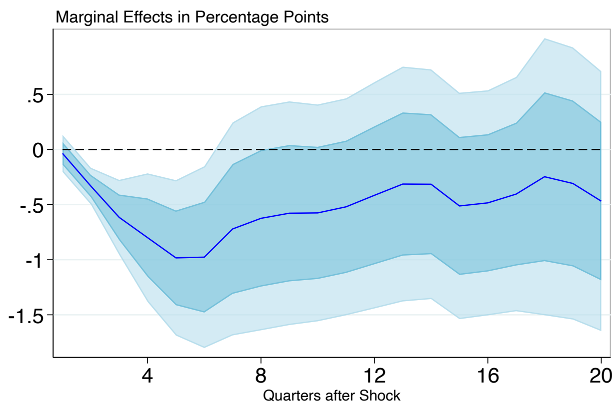
FIGURE C.5

EBP on Investment: Double Interaction with Price- and Quantity-of-Risk

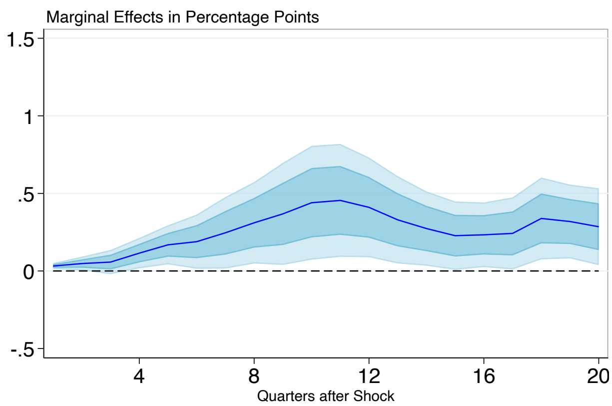
(A) $\hat{\beta}_3$: EBP Interaction



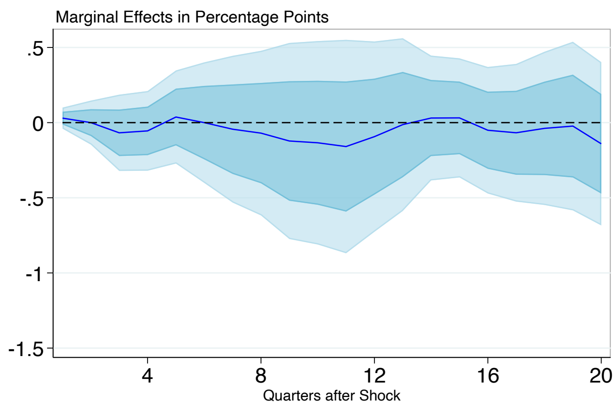

(B) $\hat{\beta}_4$: Distance to Default Interaction




(C) $\hat{\beta}_3$: EBP Interaction




(D) $\hat{\beta}_4$: Leverage Interaction

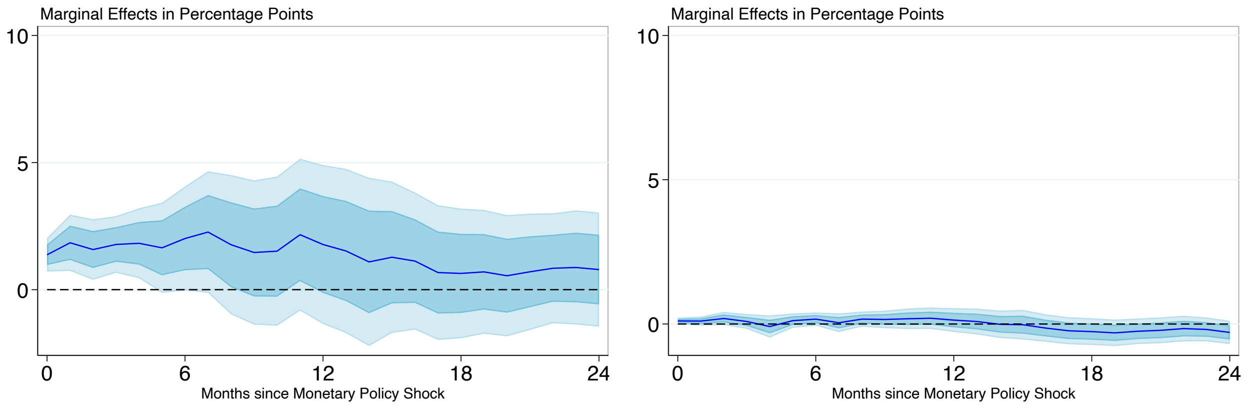



*Note.* Figure C.5 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's price-of-risk and the EBP ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]EBP_{it}$) and (B) the interaction of within-firm variation in a firm's quantity-of-risk $x_{i,t}$ and the EBP ($[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it}$), on the h-period change firm i's Investment, $\log K_{it+h} - \log K_{it}$. Panels C.5a and C.5b report the interaction coefficients $\beta_3$ and $\beta_4$, respectively, from estimating equation C.5 with $x_{i,t} = dd_{i,t}$, while Panels C.5c and C.5d report the interaction coefficients $\beta_3$ and $\beta_4$, respectively, from estimating equation C.5 with $x_{i,t} = lev_{i,t}$. The frequency of the data is quarterly. 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 (Cameron et al., 2011), respectively, implemented with the statistical module of Correia (2016).

$$\begin{aligned}\log K_{it+h} - \log K_{it} =& \beta_1 \varepsilon_t^m + \beta_2 EBP_{it} + \beta_3[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]EBP_{it} + \beta_4[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it} \\ &+ \beta_5[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_6[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\ &+ \beta_7 \hat{S}_{it} + \theta_1' \mathbf{S}_{it-1} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \beta_0 + \alpha_i + e_{ith}, \qquad \text{(C.5)}\end{aligned}$$

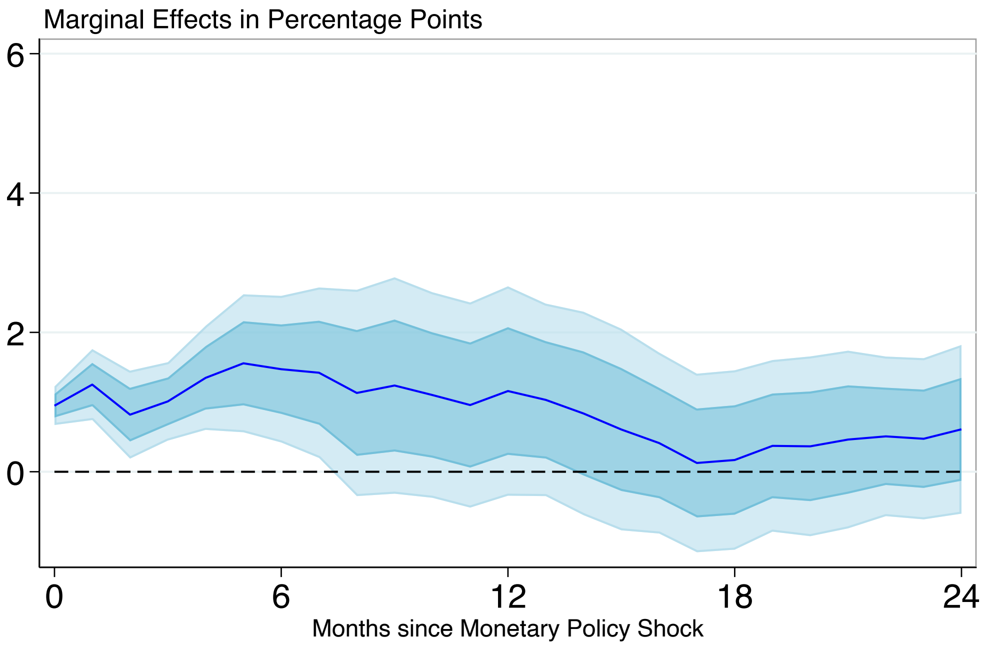
Figure C.6
Monetary Policy's Effect on Bond-Level Credit Spreads

(A) EBP (B) Predicted Spread




*Note.* The analogue of Figure 3 with a Jarociński and Karadi (2020) monetary policy shock.

Figure C.7
Monetary Policy's Effect on Bond-Level EBP by Firm Price-of-Risk

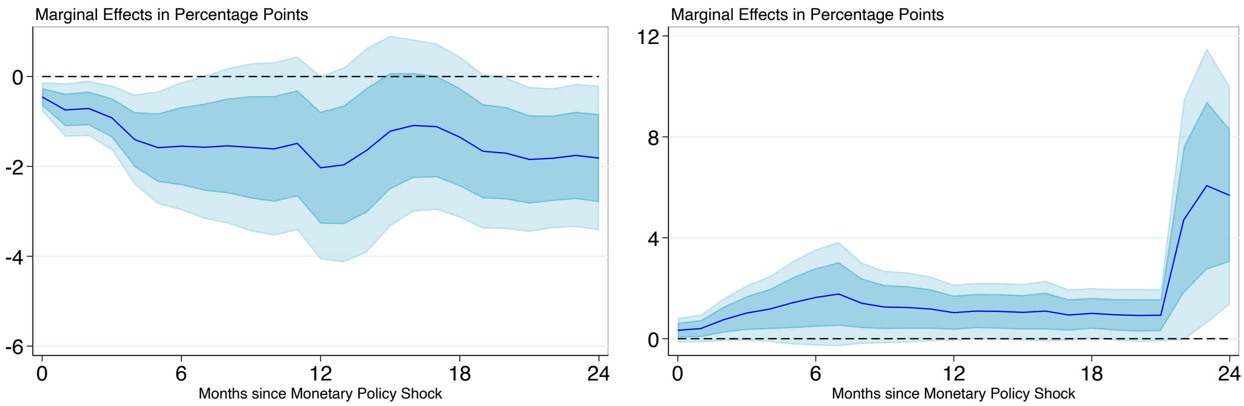



*Note.* The analogue of Figure 4 with a Jarociński and Karadi (2020) monetary policy shock.

FIGURE C.8

Monetary Policy's Effect on Bond-Level EBP by Firm Quantity-of-Risk

(A) Distance to Default (B) Leverage

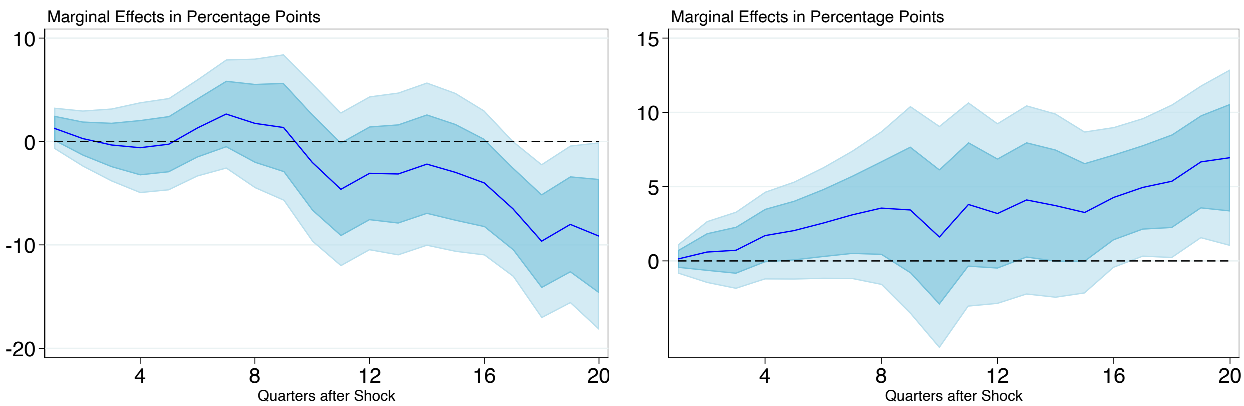



*Note.* The analogue of Figure 5 with a Jarociński and Karadi (2020) monetary policy shock.

FIGURE C.9

Monetary Policy's Effect on Firm-Level Investment

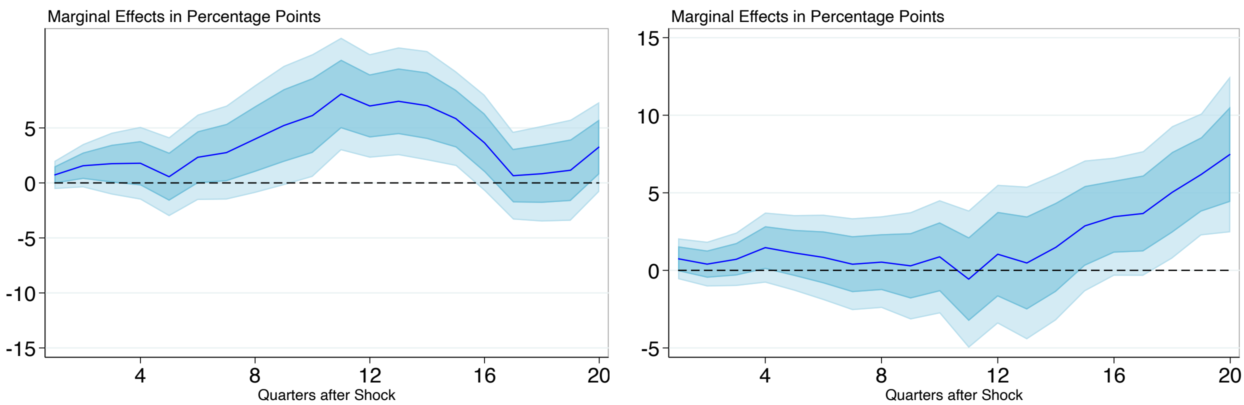
(A) $\hat{\beta}_1$: Unconditional (B) $\hat{\beta}_2$: EBP Interaction




*Note.* The analogue of Figure 6 with a Jarociński and Karadi (2020) monetary policy shock. .

Figure C.10
Monetary Policy's Effect on Firm-Level Investment by Firm Quantity-of-Risk

(A) $\hat{\beta}_2$: Distance to Default Interaction (B) $\hat{\beta}_2$: Leverage Interaction




*Note.* The analogue of Figure 7 with a Jarociński and Karadi (2020) monetary policy shock. .