# Firm Financial Conditions and the Transmission of Monetary Policy*

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**Abstract**

We examine how the sensitivity of firms' investment to monetary policy depends on their financial conditions, measured as the component of credit spreads unrelated to default risk, i.e., firms' excess bond premia (EBP). We undertake a novel two-stage decomposition of this investment channel: (i) monetary policy's effect on firm credit spreads; and (ii) firm credit spreads' effect on firm investment. We find that while monetary policy shocks exert greater influence over the credit spreads of firms with tighter financial conditions—those in the right-tail of the EBP distribution—they lead to larger investment responses for firms with looser financial conditions. We rationalize these findings in a model where a firm's financial condition (EBP) is linked to its expected future productivity—its Tobin's q—via the slope of its capital demand curve. An implication of our model, which we then verify in the data, is that heterogeneity in the transmission of monetary policy to firm investment arises from stage (ii) of our decomposition: firms with looser financial conditions increase investment more when their spreads fall due to their greater productivity.

**Key Words**: Excess Bond Premium, Credit Spreads, Firm Dynamics, Tobin's q.
**JEL Classification**: E32, E37, E44, E52.

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# 1 Introduction

In the aftermath of the global financial crisis, there was a resurgence of interest in the relationship between monetary policy, financial conditions, and economic growth. Empirically, Gilchrist and Zakrajšek (2012) and Adrian et al. (2019), among others, highlight that aggregate financial conditions contain considerable predictive power for future economic activity. Gertler and Karadi (2015) and Caldara and Herbst (2019), in turn, show that a substantial portion of monetary policy's effects on real activity operates *through* aggregate financial conditions. Although monetary policy can be effective at easing financial conditions in the short-run, Adrian and Liang (2018) and Coimbra et al. (2021) show that accommodative policies increase financial vulnerabilities over the medium-term, creating downside risks for the economy.

This literature on monetary policy and aggregate financial conditions has generally run parallel to the literature emphasizing the salience of firm heterogeneity for the transmission of monetary policy. Much of this literature has focused on the link between a firm's default risk and its sensitivity to the investment channel of monetary policy. For example, Ottonello and Winberry (2020) show empirically that investment by firms with low default-risk responds significantly more to monetary policy shocks than investment by firms with high default-risk. They rationalize these findings in a quantitative model in which low default-risk firms' investment is relatively more responsive to monetary shocks because their credit spreads are more reactive, a consequence of the flatter capital supply curve they face. However, the sign of these heterogeneous effects remains unsettled. Jeenas (2019) shows instead that the investment of high default-risk firms are more sensitive to monetary shocks; Anderson and Cesa-Bianchi (2021) show that the credit spreads of high default-risk firms react more to monetary policy; and Lakdawala and Moreland (2021) provide evidence that the direction of heterogeneity by default-risk has flipped following the Global Financial Crisis. There are also other characteristics that have been shown to regulate firms' sensitivities to monetary policy, namely age (Cloyne et al. (2019)), liquidity (Jeenas (2019)), and size (Gertler and Gilchrist (1994) and Bernanke et al. (1996)).

In this paper, we bridge the gap between these two literatures by providing granular evidence on how firms' sensitivities to the investment channel of monetary policy depend on their financial conditions, which we measure as the component of a firm's credit spread unexplained by its default risk—its excess bond premium (EBP).[1] Our empirical analysis rests on a novel two-stage decomposition of the investment channel: (i) monetary policy's effect on firm credit spreads and (ii) the effect of a firm's credit spread on its investment. Using Jordà (2005) local projections, we show that heterogeneity in both stages, as well as in monetary policy's direct effect on firm investment, depends on a firm's EBP. Furthermore, we show that the importance of the EBP tends to supersede that of firms' default-risk.

Our decomposition is crucial to disentangling the source of the heterogeneous effects of monetary policy on firm investment. In models emphasizing differences in default risk across firms, these heterogeneous effects derive from stage (i), monetary policy's effect on spreads. For this reason, our results reveal what at first seems to be a puzzle: monetary policy shocks have (1) stronger effects on the credit spreads of firms with tighter financial conditions, those in the right-tail of the EBP distribution, but (2) lead to larger investment responses on the part of firms with looser financial conditions. Thus, while a monetary easing leads to a relatively small decrease in the marginal borrowing rate for low-EBP firms, these firms respond with a relatively large increase in investment. This suggests that heterogeneity in the investment channel is not coming from heterogeneity in stage (i), but arises *in spite* of it.[2]

We rationalize our results in a financial accelerator model in the spirit of Bernanke and Gertler (1989) and Bernanke et al. (1999). Rather than featuring heterogeneity by firm net worth and hence default risk, which manifests as differences in the slope of the supply of capital curve faced by firms, we emphasize heterogeneity by EBP, which we show maps naturally to differences in the slope of firm's capital demand curve. Specifically, firms with flatter capital demand curves (near equilibrium) have lower credit spreads since these firms

[1] Gilchrist and Zakrajšek, 2012 and López-Salido et al., 2017 demonstrate a link between aggregate EBP and the risk-bearing capacity or risk-sentiment of the financial sector vis-à-vis corporate bond markets.

[2] Interestingly, a similar pattern emerges when considering heterogeneity by default risk, although these effects are dampened when controlling for heterogeneity by EBP. Monetary policy shocks have stronger effects on the credits spreads of high default-risk firms, as in Anderson and Cesa-Bianchi (2021), but lead to larger investment responses for firms with low default risk, as in Ottonello and Winberry (2020). This contradiction appears at odds with a story of default risk.

are expected to be more productive in the future—their marginal product of capital, or their bond market Tobin's q (Philippon (2009)), will decrease only slightly in response to an expansionary shock to capital supply. Since these locally more productive firms' lower credits spreads are unrelated to their intrinsic riskiness, as captured by their net worth, locally more productive firms have a lower EBP-component of credit spreads.

By influencing the net worth of firms, a monetary policy shock is one such shock that shifts the capital supply curve faced by firms. Due to their flatter capital demand curves near equilibrium, a monetary easing leads to a relatively large increase in investment for low-EBP firms, despite a relatively mild fall in their credit spreads. This is consistent with our empirical findings. Conversely, when considering heterogeneity by net worth, we show that monetary easings lead to larger investment responses and larger falls in spreads for low default-risk firms. This "co-movement" is at odds with our empirical findings.

Finally, our model provides a testable prediction for the sign of firms' sensitivities to stage (ii) of our decomposition, a relation which has yet to be explored in the literature: any movement in credit spreads, whatever the cause, should lead to larger investment responses for low-EBP firms. We then verify this prediction holds in the data. A consequence is that heterogeneity in the transmission of monetary policy to firm investment arises from stage (ii) of our decomposition: firms with looser financial conditions increase investment more when their spreads fall. This highlights that a firm's future productivity, as priced into the EBP component of its credit spread, is key to explaining its sensitivity to monetary policy.

**Literature Review:**

Our paper relates to three strands in the literature. First, the literature on firm heterogeneity and the investment channel of monetary policy. As mentioned earlier, a large body of research has emphasized heterogeneity by default risk. Ottonello and Winberry (2020) find that investment by firms with low default-risk responds significantly more to monetary policy shocks. Conversely, Anderson and Cesa-Bianchi (2021) show that the credit spreads of firms with high leverage respond more to monetary policy shocks. In addition, Cloyne et al. (2019) show the importance of firms' age and dividend payout practices on the response of investment to monetary policy shocks while Jeenas (2019) reports that firms with fewer liquid assets reduce investment relative to others in response to tightening monetary policy shocks. This research complements earlier papers on firm size, such as Gertler and Gilchrist (1994) who show that small firms' sales decline more rapidly than large firm sales following a monetary policy tightening, Bernanke et al. (1996) who also demonstrate that smaller firms are more responsive to monetary policy, and, more recently, Carvalho and Grassi (2019), who show that large firms play a relatively large role in the business cycle. Relative to the existing literature, we show that a firm's sensitivity to the investment channel depends also on its EBP, which captures its future productivity as priced by the financial sector.[3] In addition, we contribute to this literature by decomposing the investment channel of monetary policy into two stages to investigate the source of the heterogeneity.

Second, our paper relates to the longstanding literature on the q-theory of investment (Tobin (1969)).[4] Specifically, we interpret our findings based on Philippon (2009), who shows that firm credit spreads are inversely proportional to q—the firm's marginal product of capital—under some mild assumptions. Relative to measures of q estimated from equity prices, this bond market q is significantly better at explaining aggregate investment presumably because bond prices, like equity prices, encode information about firms future productivity, but are less susceptible to "mispricing".[5] This link between credit spreads and q informs our link between the EBP and firm's capital demand, which is simply the marginal product of capital (MPK) in the frameworks of Bernanke and Gertler (1989) and Bernanke et al. (1999), since the default component of spreads can be inferred from capital supply.

In a recent paper, González et al. (2021) show that a monetary expansion increases the investment of high-MPK firms relatively more than that of low-MPK ones. Relative to them, as discussed above, our proxy for the MPK is forward looking, inferred from bond prices, while there's is backward looking and computed from balance sheet quantities. A second recent paper by Jeenas and Lagos (2022) uses stock turnover as an instrument to

[3] We run horseraces between a monetary policy shock interacted with the EBP and its interaction with the other state variables listed above and find that the EBP always remains significant.

[4] See also important contributions by Lucas Jr and Prescott (1971), Abel (1979) and Hayashi (1982).

[5] See Gilchrist and Zakrajšek (2007) and Lin et al. (2018) who show that firm-level q forecasts well firm-level investment.

study how changes in the cost of equity finance following monetary policy shocks affect firm investment, which they term the q-monetary transmission. Relative to them, our EBP measure for q is priced in bond markets, while there's comes from equity markets.

Third, we build on the vast theoretical and empirical literature on financial frictions. On the theoretical side, our model is related to Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Bernanke et al. (1999), Gertler and Kiyotaki (2010), and Gertler and Karadi (2011). However, unlike these models, we focus on heterogeneity in firm's capital demand curve, rather than heterogeneity in net worth which affects the capital supply curve faced by firms. On the empirical front, our work builds on Gilchrist and Zakrajšek (2012) who decompose an aggregate credit spread index into a default-risk component and a residual component, the EBP, which they show relates to the risk-bearing capacity of the financial sector. They find that this EBP-component, in particular, forecasts well future economic activity. We show that a firm-specific EBP is a key state variable for the transmission of monetary policy and demonstrate that differences in EBP across firms reflect differences in their expected future productivity, which may explain their original findings as well.

# 2 Data

In this section, we describe the EBP calculation, document firm-level characteristics associated with the EBP, summarize how the cross-sectional EBP distribution evolves over time, demonstrate the persistence of a firm's EBP within the wider distribution, and discuss the measure of monetary policy shocks used throughout the paper.

## 2.1 EBP Calculation

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 2021.

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).[6] 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:

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

in which the log of the credit spread $S_{it}[k]$ is a 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 $\upsilon_{it}[k]$. 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 $\upsilon_{it}[k]$ is normally distributed, we can estimate regression (1) by ordinary least squares (OLS) and compute the predicted credit spread $\hat{S}_{it}[k]$ as

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

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. While the model is simple, it explains nearly of 70% of the variation in credit spreads, as is also shown in Appendix A, driven mostly by firms' distance to default. Finally, we define the excess bond premium (EBP) of firm $i$'s bond $k$ at time $t$ as

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

Thus, $EBP_{it}[k]$ is the component of a bond j's credit spread unexplained by firm i's default risk and other bond characteristics.

[6]The correlation between our mean credit spread and that of Gilchrist and Zakrajšek (2012) is 92%.

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 yields monthly EBPs for 11,319 bonds from 1,913 firms, which we term the bond-level EBP distribution.[7] Relative to Anderson and Cesa-Bianchi (2021), who do not use the Lehman/Warga bond price data from 1973-1999 and whose sample ends in 2017, our longer time-series provides us with a monthly EBP dataset with additional 2500 bonds and 938 firms. Ottonello and Winberry (2020), on the other hand, include about 3000 firms in their quarterly investment dataset.[8] Relative to them, our sample includes a smaller cross-section of firms, since we restrict ourselves to firms with credit spreads, but covers a longer time-series, ending in December 2021 rather than in December 2007 in their case, which is due to the Bu et al. (2021) monetary policy shock we use being able to stably bridge periods of conventional and unconventional monetary policy.[9]

Building on Gilchrist and Zakrajšek (2012), Favara et al. (2016), and López-Salido et al. (2017), who interpret the aggregate EBP (averaged across bonds and firms in each time period) as a measure of the risk-bearing capacity or risk-sentiment of the financial sector vis-à-vis the corporate bond market, we interpret the firm/bond-specific EBP as firm/bond-specific financial condition.[10] In section 5, we show that firm-specific financial conditions, above default risk, can arise due to differences in firm's expected future productivity, as priced by the financial sector.

## 2.2 EBP across Firm Characteristics and over Time

Figure 1 documents the cross-sectional relationship between a firm's EBP and other firm characteristics that have been previously studied in the literature, namely credit rating,

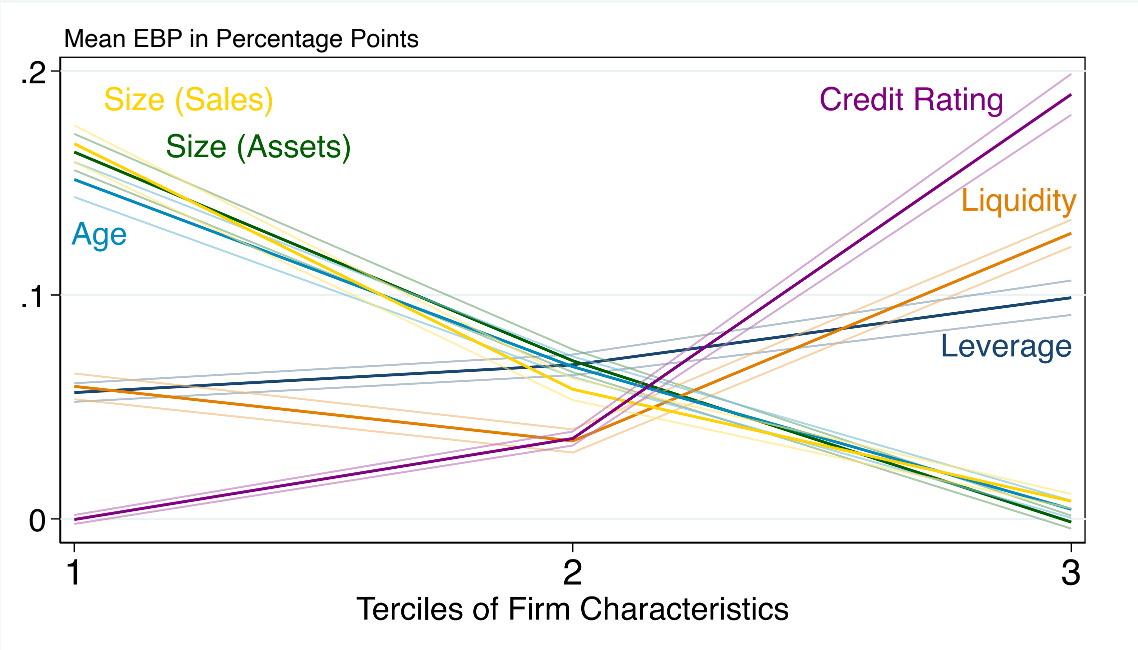
[7]In Appendix A, we highlight that the correlation between our mean EBP and that of Gilchrist and Zakrajšek (2012) is 86%.

[8]Ottonello and Winberry (2020) do not actually specify the number of firms used in their empirical analysis. We view 3000 firms as an upper bound, since their regression with macro controls includes nearly 120,000 observations and they include a firm if it has at least 40 consecutive quarters of investment data.

[9]Of note, like in Ottonello and Winberry (2020), our sample is also restricted by the availability of investment data in Compustat.

[10]This interpretation derives from Gilchrist and Zakrajšek (2012) who show that an adverse shock to the equity value of primary dealers (financial intermediaries) leads to a rise in their CDS spreads that is closely matched by a rise in the mean EBP across non-financial firms.

Figure 1
Average EBP in each Tercile of Firm Characteristics



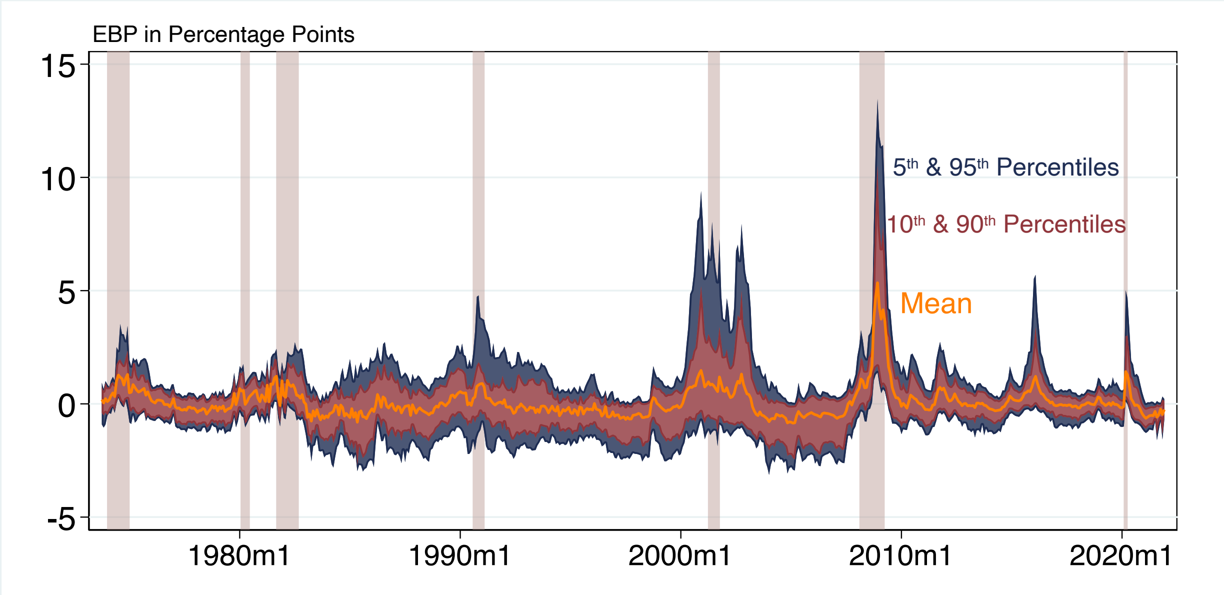

*Note.* Figure 1 reports the average EBP, and 90% confidence intervals, in each tercile of firm leverage (measured as debt over assets), liquidity (measured as cash and short-term investments over assets), credit rating (higher values indicate greater credit risk), age (since incorporation), and size (both in sales and in assets). EBPs and firm characteristics are calculated as the within-firm average over the sample. EBPs are then averaged within each tercile of the firm characteristic.

leverage, liquidity, age, and size (measured both terms of in sales and assets). First, we see that firms in the highest tercile of credit rating and, to a lesser extent, the highest tercile of leverage—high default-risk firms—have a higher average EBP and so tend to face tighter financial conditions.[11] Conversely, firms in the lowest terciles of credit ratings and leverage—low default-risk firms—have a lower average EBP and so tend to face looser financial conditions. This suggests a cross-sectional relationship between default risk and EBP. In addition, younger and smaller firms tend to have higher EBPs (tighter financial conditions) on average, while the relationship between EBP and liquidity is non-monotonic.

Figure 2 shows that the tails of the EBP distribution move non-uniformly over the business cycle. The right-tail co-moves with the mean, rising in periods of stress and falling during calmer times. However, the right tail is significantly more volatile. The left-tail, on the other hand, has more contained cyclical fluctuations, with a significant rise above zero

[11] High values for credit rating indicate more credit risk as judged by rating agencies.

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.

only during the 2008 Crisis. These results highlight that focusing on the mean EBP masks substantial heterogeneity in the EBP distribution across time.

Although the percentiles of the EBP distribution vary considerably over time, a firm's place within the wider EBP distribution is quite persistent. This can be inferred from the relatively large percentages along the diagonal of the EBP's Markov transition matrix displayed in Table 1. The EBP is particularly persistent in the tails, that is, for the lowest and highest quintiles of the distribution. Altogether, these results demonstrate that a firm's EBP provides both time-series and cross-sectional information regarding the state of the firm.

## 2.3 Monetary Policy Shocks

Throughout this paper, we use the Bu, Rogers and Wu (2021) monetary policy shock series, which we plot in Appendix B. This series combines three appealing features, which together distinguish it from other shock series in the literature. First, by using the full maturity spectrum of interest rates, this series is able to stably bridge periods of conventional

Table 1
Markov Transition Matrix for Monthly Bond-Level EBP

| | | $EBP_{t+1}$ Quintiles | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| $EBP_t$ 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 Markov transition probabilities for the monthly EBP 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 period.

and unconventional monetary policy. Second, the shock is largely devoid of the central bank information effect, the notion that monetary policy announcements, in addition to providing a pure monetary surprise, also reveal information regarding the central bank's future macroeconomic outlook (Nakamura and Steinsson (2018) and Jarociński and Karadi (2020)). And third, the Bu et al. (2021) monetary policy shock series is largely unpredictable from available information, including Blue Chip forecasts, "big data" measures of economic activity, news releases and consumer sentiment—it is truly exogenous.[12] That said, we examine robustness using the Jarociński and Karadi (2020) series in Appendix D. Our sample period in this paper is dictated by the coverage of the Bu et al. (2021) series. In Sections 3 and 4 our sample period is January 1985 to December 2019. We consider the COVID-19 period (January 2020—December 2021) in Appendix E.[13]

# 3 Monetary Policy and Bond-Level Spreads

In this section, we discuss our first set of empirical results, which relate to monetary policy's dynamic effects on the cross-sectional distribution of bond-level credit spreads. We uncover

[12] See, for example, Ramey (2016), Miranda-Agrippino (2016), and Bauer and Swanson (2020) for critiques of earlier monetary policy shock series that exhibited predictability.

[13] The start-date (January 1985) of our sample is determined by the start-date of the "extended" Bu et al. (2021) monetary policy shock. We also benefit from this extended series to study the COVID-19 period. The original published series spans January 1994 until September 2019.

three main findings. First, monetary easings decrease credit spreads *much more* than one-to-one. Second, credit spreads fall more for firms and bonds with tighter financial conditions (higher EBPs). And third, we demonstrate that the sensitivity of firms' spreads to monetary shocks is driven primarily by their financial conditions not their default risk. Robustness is discussed at the end of the section.

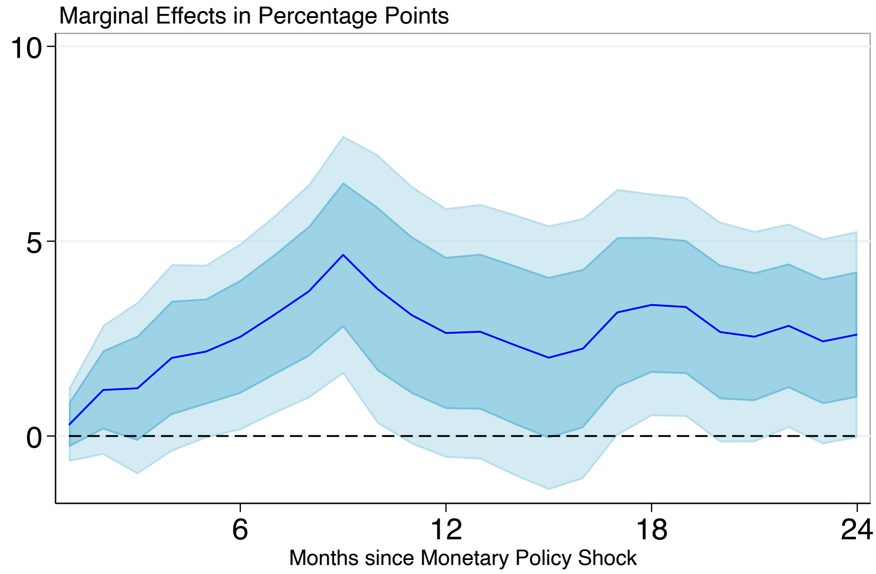
Our first specification is intended to estimate the average dynamic response of bond-level credit spreads $S$ to monetary policy shocks at a monthly frequency. We do so using the following Jordà (2005) local projection:

$$S_{it+h}[k] - S_{it}[k] = \alpha_k^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \gamma^h \mathbf{Z}_{it-1} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}[k], \quad (4)$$

where $S_{it}[k]$ denotes the bond-k credit spread, and $\varepsilon_t^m$ denotes the Bu et al. (2021) monetary policy shock. We follow the literature by controlling for both firm-level characteristics ($\mathbf{Z}_t$) and aggregate economic conditions ($\mathbf{Y}_t$). Firm characteristics include firm's leverage and distance-to-default, as well as firm size (measured in assets), sales growth, age, liquidity, credit rating and short-term asset share. We control for macroeconomic conditions using the Chicago FED's national activity index, uncertainty using the Baker et al., 2016 economic policy uncertainty index, and financial conditions using the first three principal components of the U.S. Treasury yield curve. We include bond fixed effects $\alpha_k$ to control for unobserved, time-invariant differences across bonds. Inference is drawn from two-way clustered standard errors by firm $i$ and month $t$ (Cameron et al., 2011).

Figure 3 traces the average response of credit spreads to monetary policy shocks ($\beta_1^h$) at different horizons $h$. The positive marginal effects highlight that a monetary policy easing predicts a significant relaxing of bond-level credit spreads. At its peak nine months after the shock, a 1 percentage point monetary policy easing results in a nearly 5 percentage point decrease in a bond's credit spread, on average. Focusing on a one-week time frame around policy announcements, Anderson and Cesa-Bianchi (2021) find only about a one-to-one relationship between monetary policy easings and decreases in credit spreads. Our first result demonstrates that dynamic effects must be considered to fully appreciate the extent of monetary policy's influence over firms' marginal borrowing rates.

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



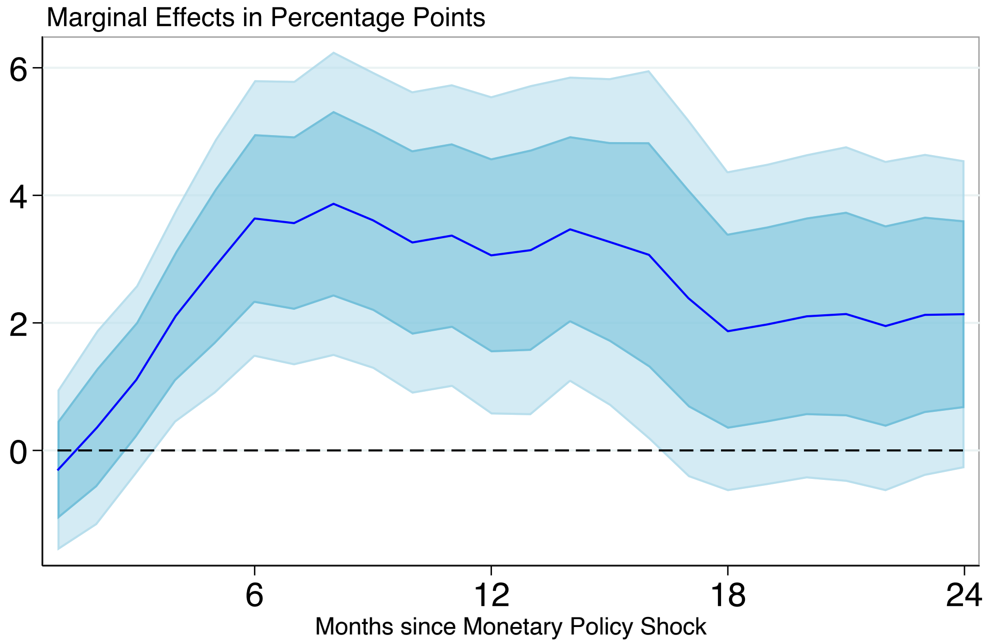

*Note.* Figure 3 reports the dynamic effects ($\beta_1^h$) of a Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) on the h-period change in credit spreads, $S_{it+h}[k] - S_{i,t}[k]$, from regression (4), where the frequency of the data is monthly. The inner and outer shaded areas correspond 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.

Next, we investigate how the sensitivity of a bond's credit spread to monetary policy depends on its EBP using the following local projection:

$$S_{it+h}[k] - S_{it}[k] = \alpha_k^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times EBP_{it-1}[k] \\ + \beta_3^h EBP_{it-1}[k] + \gamma^h \mathbf{Z}_{it-1} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}[k]. \tag{5}$$

Relative to specification (4), (5) additionally includes a bond's financial condition $EBP_{it-1}[k]$ both as a control and, of particular interest to us, in an interaction with the monetary policy shock $\varepsilon_t^m$. Importantly, we lag our $EBP_{it-1}[k]$ state variable, as with our other controls, to ensure it is not influenced by the monetary policy shock. Following Jeenas (2019), to lessen noise in our state variable, we smooth $EBP_{it-1}[k]$ using a moving average process with five lags $\frac{1}{5}\sum_{l=1}^{5} EBP_{it-l}[k]$. This procedure is also desirable since it allows us to capture a middle-ground between conditioning on the purely permanent component of EBP, $\mathbb{E}(EBP_{it-1}[k]) = \lim_{t \to T} \frac{1}{t} \sum_{l=1}^{t} EBP_{it-l}[k]$, and the purely idiosyncratic component,

FIGURE 4
Monetary Policy's Effect on Bond-Level Credit Spreads Depending on EBP




*Note.* Figure 4 traces the effects of the dynamic interaction ($\beta_2^h$) between $EBP_{i,t-1}$ and a Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) on the h-period change in credit spreads, $S_{it+h}[k] - S_{i,t}[k]$, 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.

$EBP_{it-1}[k] - \mathbb{E}(EBP_{it-1}[k])$, as is considered in Ottonello and Winberry (2020), which may have different effects.[14]

Figure 4 traces the dynamic interaction effects between the monetary policy shock and a bond's EBP on their credit spreads. In conjunction with the positive unconditional effects displayed in Figure 3, the positive marginal effects here indicate that monetary easings relax the credit spreads of firms and bonds with higher EBPs (tighter financial conditions) more than they do for firms and bonds with lower EBPs.

As shown in Anderson and Cesa-Bianchi (2021), monetary policy's influence over credit spreads depends also on firms' default risk, which we confirm in Appendix ??.[15] In line with

[14] See Ottonello and Winberry (2020) and Jeenas (2019) for a discussion.

[15] While Anderson and Cesa-Bianchi (2021) find a highly significant interaction effect between monetary policy shocks and firm leverage *on-impact*, we show in Appendix ?? that distance-to-default regulates firms' sensitivities significantly more after one month.

them, our results highlight that the marginal borrowing rate (spreads) of firms with greater default risk are more sensitive to monetary policy.[16] To investigate whether default risk or EBP is most responsible for the sensitivity of firms' spreads to monetary policy, we run a horserace between the monetary policy shock $\varepsilon_t^m$ interacted with (A) the $EBP_{i,t-1}[k]$ ($\beta_2^h$) and (B) a measure of firms' default-risk $x_{i,t-1}$ ($\beta_3^h$), either leverage or distance-to-default, using the following specification:

$$S_{it+h}[k] - S_{it}[k] = \alpha_k^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times EBP_{it-1}[k] + \beta_3^h \varepsilon_t^m \times x_{it-1} + \beta_4^h EBP_{it-1}[k] + \gamma^h \mathbf{Z}_{it-1} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}[k], \tag{6}$$

where $x_{i,t-1}$ here refers to the idiosyncratic component of firm's default risk, as in Ottonello and Winberry (2020). The interaction effects $\beta_2^h$ and $\beta_3^h$ are displayed in Figure 5. The results demonstrate that default risk's regulation, whether using distance-to-default (Panel 5b) or leverage (5d), of monetary policy's effect on credit spreads, is attenuated when jointly conditioning the EBP, while the EBP's effect is largely unchanged.

**Robustness:** Our results are robust to a wide array of variations to our empirical approach, namely: (i) alternative monetary policy shocks, (ii) including time-sector fixed effect or other macro controls, (iii) horseraces between the EBP and other state variables (age, size, liquidity and credit rating), and (iv) alternative functional forms for the EBP and other candidate state variables.

# 4 Monetary Policy and Firm-Level Investment

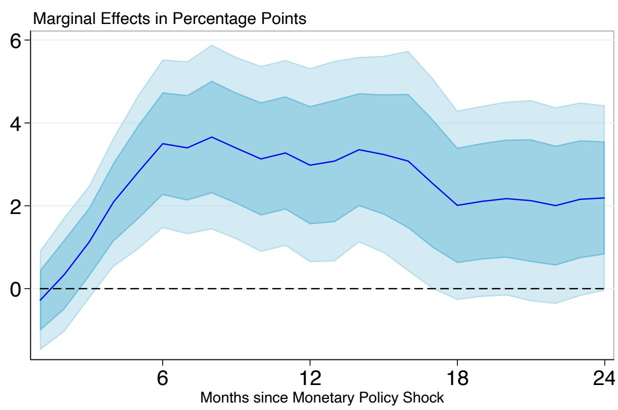
In this section, we discuss our second set of empirical findings, which relate to monetary policy's effects on firm-level investment. We again uncover three main results. First, monetary easings increase firm-level investment in a hump-shaped fashion. Second, investment rises more for firms with *looser* financial conditions (*lower* EBPs) following a monetary easing, the opposite direction from what we documented for credit spreads in the previous

[16] This stands in contrast to the findings in Ottonello and Winberry (2020), who document that the *average* borrowing cost of firms with lower default risk are more responsive to monetary policy.

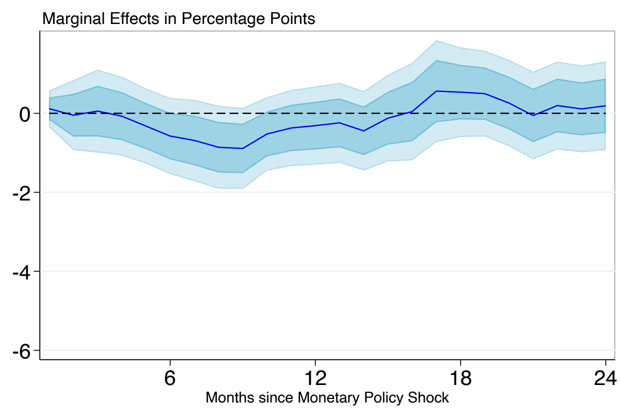
FIGURE 5

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

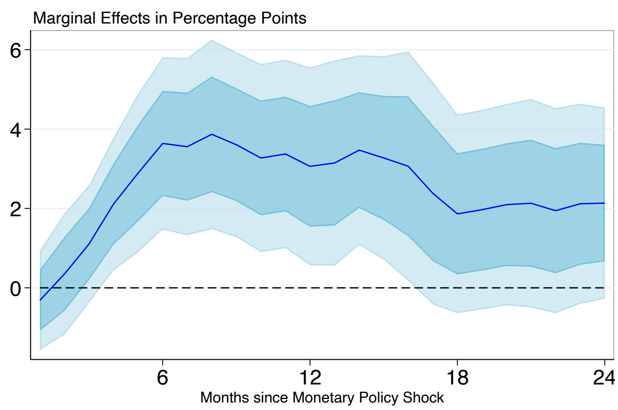
(A) Conditional on EBP



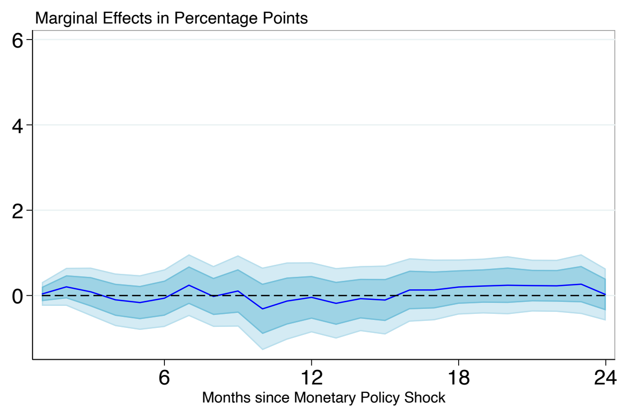

(B) Conditional on Distance to Default




(C) Conditional on EBP




(D) Conditional on Leverage

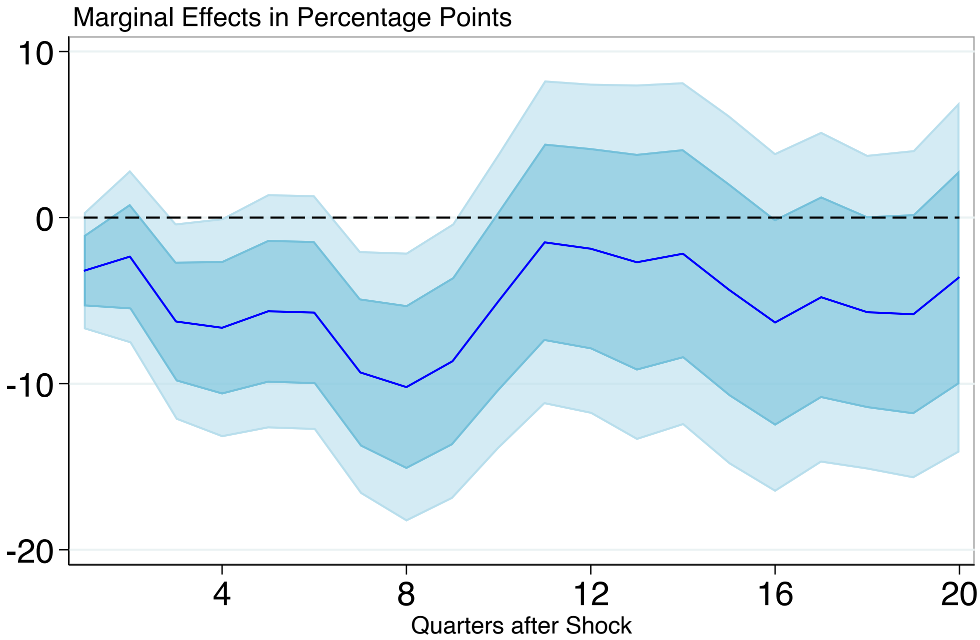



*Note.* Figure 5 reports dynamic interaction coefficients from a horserace between the monetary policy shock $\varepsilon_t^m$ interacted with (A) the $EBP_{i,t-1}[k]$ and (B) a measure of firms' default-risk $x_{i,t-1}$. Panels 5a and 5b report the interaction coefficients $\beta_2$ and $\beta_3$, respectively, from estimating equation (6) with $x_{i,t} = dd_{i,t}$, while Panels 5c and 5d report the interaction coefficients $\beta_2$ and $\beta_3$, respectively, from estimating equation (6) 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.

section. And third, the EBP tends to supersede default risk in regulating the sensitivity of firms' investment to monetary shocks. We discuss robustness at the end of the section.

We begin by using quarterly firm-level balance sheet data from Compustat 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 the end of period $t-1$, as in Ottonello and Winberry (2020). With this in hand, our first specification in this section looks to estimate the

Figure 6
Monetary Policy's Effect on Firm-Level Investment




*Note.* Figure 6 traces the dynamic effects effects ($\beta_1^h$) of a Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) on 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.

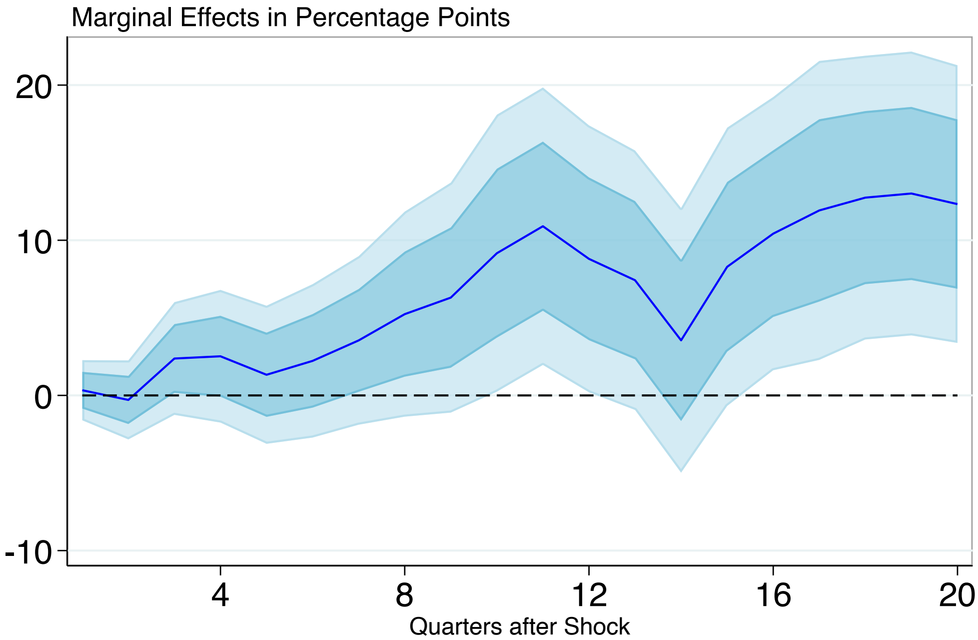
average dynamic response of firm-level investment to a monetary policy shock at a quarterly frequency. We do so using the following local projection:

$$\log K_{it+h} - \log K_{it} = \alpha_i^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \gamma^h \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}, \tag{7}$$

where our control variables are the same as in the previous section, except we replace our bond fixed effect with a firm fixed effect $\alpha_i$ and substitute the monthly Chicago Fed's national activity index for quarterly U.S. GDP growth.

Figure 6 displays the average response of firm-level investment to a monetary policy shock ($\beta_1^h$) at different horizons $h$. The negative marginal effects highlight that a monetary policy easing predicts a significant increase in firm-level investment, on-average. Specifically, at its its peak 8 quarters after the shock, a 1 percentage point monetary easing is associated with about a 10 percentage point increase in investment for the average firm, which is

Figure 7
Monetary Policy's Effect on Firm-Level Investment Depending on EBP




*Note.* Figure 7 traces the effects of the dynamic interaction ($\beta_2^h$) between $EBP_{i,t-1}$ and a Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (8), 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.

comfortably in line with existing estimates.

Next, we investigate how the sensitivty of a firm's investment to monetary policy depends on its EBP. To do so, we first aggregate our EBP state variable across bonds to the firm level, and from a monthly to a quarterly frequency, and estimate the following:

$$\log K_{it+h} - \log K_{it} = \alpha_i^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times EBP_{it-1} + \beta_3^h EBP_{it-l} + \gamma^h \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}, \tag{8}$$

where, relative to (7), we additionally include the interaction between our EBP state and the monetary policy shock, as well as the EBP state in levels.

Figure 7 traces the dynamic interaction effects ($\beta_2^h$) between the monetary policy shock and a firm's EBP on their investment. In light of our findings from the previous section, where a monetary easing led to a larger fall in the marginal borrowing rate for high-EBP firms, one might expect that the investment of these firms with tighter financial conditions would rise more, relative to firms with looser financial conditions. Instead, the positive marginal effect in Figure 7 indicate the opposite: firms with *looser* financial conditions (*lower* EBPs) increase investment relative to firms with tighter financial conditions following a monetary easing. In the subsequent section, we provide a model to rationalize this puzzle.

Finally, Ottonello and Winberry (2020) document that monetary policy's influence over firm investment depends on firms' default risk, which we confirm holds in our sample as well in Appendix ??. In line with their findings, we show that investment by firms with lower default risk is more sensitive to monetary policy. To investigate whether default risk or financial conditions is most responsible the sensitivity of firms' investment to monetary policy, we proceed as in the previous section by running a horserace between the monetary policy shock $\varepsilon_t^m$ interacted with (A) the $EBP_{i,t-1}[k]$ ($\beta_2^h$) and (B) a measure of firms' default-risk $x_{i,t-1}$ ($\beta_3^h$), either leverage or distance-to-default, using the following specification:

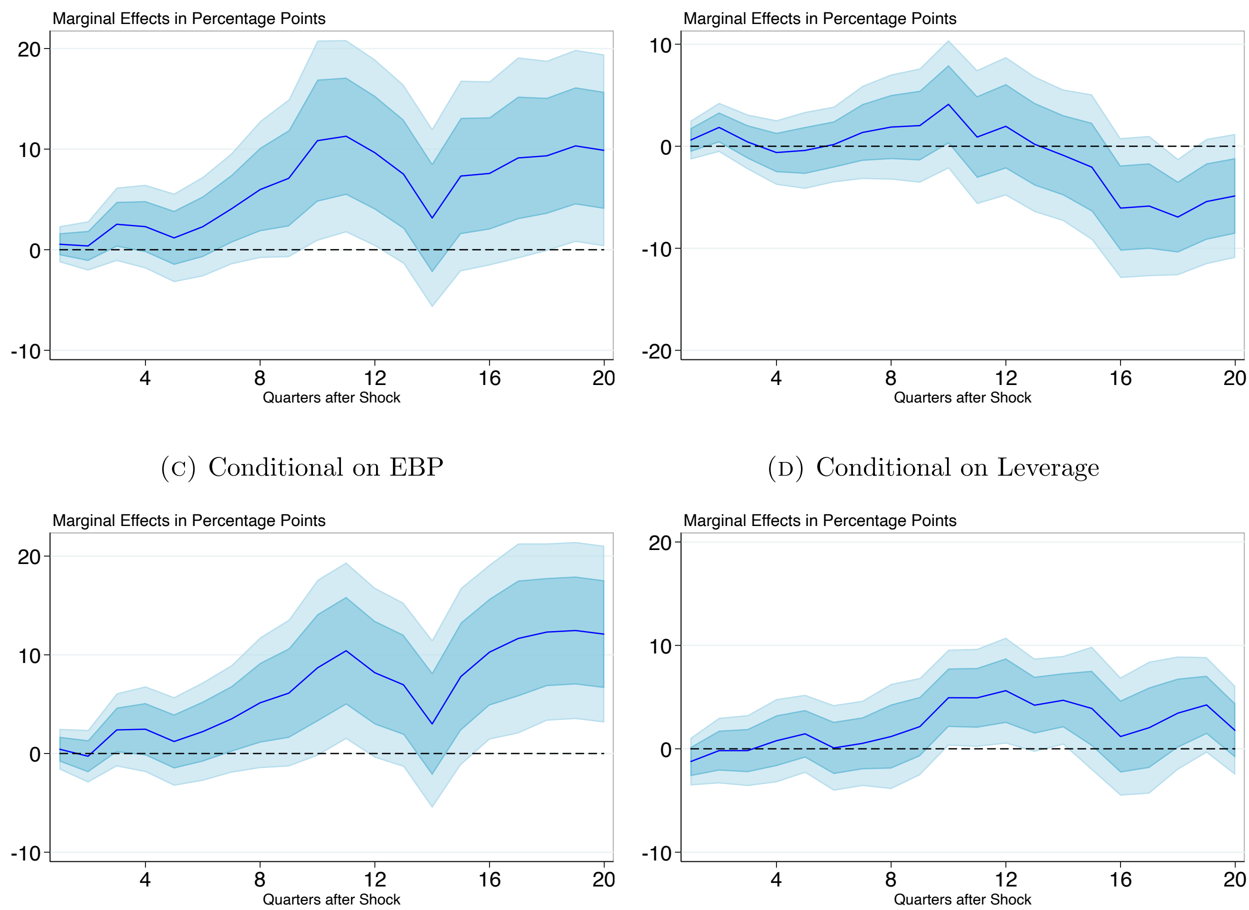
$$\log K_{it+h} - \log K_{it} = \alpha_i^h + \beta_0^h + \beta_1^h \varepsilon_t^m + \beta_2^h \varepsilon_t^m \times EBP_{it-1} + \beta_3^h \varepsilon_t^m \times x_{it-1} \\ + \beta_4^h EBP_{it-l} + \gamma^h \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^h \mathbf{Y}_{t-l} + e_{ith}, \qquad (9)$$

where $x_{it-1}$ here refers to a measure of the idiosyncratic component of firm's default risk, as in Ottonello and Winberry (2020). The interaction effects ($\beta_2^h$) and ($\beta_3^h$) are displayed in Figure 8. The results indicate that default risk's regulation, whether using distance-to-default (Panel 8b) or leverage (Panel 8d), of monetary policy's effects of firm level spreads, is attenuated when jointly conditioning on EBP, while the EBP's effect is largely unchanged.

**Robustness:** Our results are robust to a wide array of variations to our empirical approach, namely: (i) alternative monetary policy shocks, (ii) including additional macro controls, (iii) horseraces between the EBP and other state variables (age, size, liquidity and credit rating), and (iv) alternative functional forms for the EBP and other candidate state variables.

Figure 8
Monetary Policy's Effect on Firm-Level Investment by EBP vs. Default-Risk

(A) Conditional on EBP — (B) Conditional on Distance to Default — (C) Conditional on EBP — (D) Conditional on Leverage




*Note.* Figure 8 reports the dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's default-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 8b and is $lev_{i,t}$ in Panel 8d, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (7). 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.

# 5 Interpretation

In this section, we interpret our empirical findings through the lens of a general equilibrium financial accelerator model, similar to those of Bernanke and Gertler (1989) and Bernanke et al. (1999). The model features entrepreneurs who combine their net worth with external financing from households to invest in risky capital. This investment process is subject to the standard costly state verification financial friction, which leads to an upward sloping cost of external funds (supply of capital) curve.[17] Coupled with firms' downward sloping demand for capital, due to decreasing returns to scale, we can solve for firm's credit spread and capital investment in equilibrium.

We use this framework to document three theoretical results related to our empirical findings. First, in the model, the premium on external finance faced by firms, their credit spread, is a function both of their net worth, which determines their default risk for a given level of investment and hence the slope of the capital supply curve, and the curvature of their production technology, which determines the slope of their capital demand curve. Under a standard calibration, we show firms with more convex production functions, for a given net worth, have lower credit spreads in equilibrium—that is, a lower EBP component of spreads—because their demand curves are initially steep before flattening near equilibrium. Thus, while existing work has focused on the slope of the capital supply curve and hence the default component of spreads, we show that our model provides a natural mapping between the slope of the capital demand curve and the component of spreads unrelated to firm's intrinsic riskiness (net worth), their EBP.

Second, because low-EBP firms have capital demand curves that are relatively flat near equilibrium, a monetary policy loosening that shifts the supply of capital outward along the demand curve elicits a large increase in investment but only a mild decrease in firms' cost of funds. This is consistent with our empirical findings and rationalizes our puzzle result by shifting our focus from the slope of the capital supply curve to the slope of the capital demand curve. An implication of this is that low-EBP firms invest more out of changes in their credit spreads, regardless of whether the change in spreads is due to a monetary shock. We test this prediction empirically in the following section.

Third, we show that heterogeneity by net worth or default risk itself, as emphasized in Ottonello and Winberry (2020) and Anderson and Cesa-Bianchi (2021), delivers results at odds with our empirical findings. Low net-worth (high default-risk) firms face a relatively steep capital supply curve such that, for a fixed demand for capital, a monetary policy loosening elicits a relatively mild adjustment both in investment and borrowing costs. That

[17] see also Townsend (1979), Williamson (1987), Kiyotaki and Moore (1997).

is, high net-worth firms experience a large increase in the investment *precisely because* their marginal borrowing rates fall considerably. This suggests that default risk is unlikely to be the driver of heterogeneity in the investment channel, but rather that net worth is correlated with a firm's EBP, with high net worth firms having a low EBP.

## 5.1 Model

Consider a 2-period overlapping generations model with households (lenders) and entrepreneurs, who manage firms. Each period, $\eta$ households and $1-\eta$ entrepreneurs are "born" endowed with 1 unit of labor and with the following preferences over consumption when young ($c_1$) and when old ($c_2$):

$$\text{Households: } u(c_1)+\beta\mathbb{E}[c_2] \qquad \text{Entrepreneurs: } \mathbb{E}[c_2]. \tag{10}$$

Since entrepreneurs have no dis-utility over labor and do not consume in the first period, their net worth (n) is equal to their wage rate (w).

Entrepreneurs manage firms that have access to Cobb Douglas production technology:

$$y_t=\theta_t k_t^{\alpha} h_t^{1-\alpha}=\theta_t k_t^{\alpha} \tag{11}$$

where $\theta_t \sim \phi$ is an i.i.d. technology shock and the second equality comes from both types of agents having no dis-utility for labor such that $h_t=1$. Thus, this technology exhibits decreasing returns to scale. In addition, capital fully depreciates every period ($\delta=1$).

Young households and entrepreneurs have access to a safe storage technology that converts 1 unit of period t output to $R$ units of output in the following period, where $R$ denotes the gross risk-free rate. Alternatively, agents can save using entrepreneurs' risky technology that converts $i$ units of period t output to $\omega i$ units of capital in the subsequent period where $\omega \sim G(-\frac{1}{2}\sigma^2,\sigma)$, with G denoting the cdf of the lognormal distribution such that $\mathbb{E}[\omega]=1$. Importantly, only entrepreneurs can directly view the realization of $\omega$, while households must pay a monitoring cost proportional to the amount invested $\gamma i$.

Entrepreneurs can borrow funds $i-n$ from households to raise more capital for production. However, without monitoring, they have an incentive to deceive households regarding the realization of $\omega$ to keep a greater share for themselves. Given this costly state verification (CSV) financial friction, entrepreneurs and households enter into a contract that specifies how they split the returns to the capital invested $\omega ir$, where $r$ is the marginal return capital, as well as the conditions under which the household monitors the entrepreneur, as a function of the state $\omega$. As shown in Bernanke et al. (1999), the optimal contract is a debt contract that incentives truth-telling about the state $\omega$, where the lender's monitoring rule $M(\omega)$ and the fraction of $\omega$ the lender earns $R(\omega)$ take the form:

$$M(\omega) = \begin{cases} 0 & \omega > \overline{\omega} \\ 1 & \omega \leq \overline{\omega} \end{cases} \qquad R(\omega) = \begin{cases} \overline{\omega} & \omega > \overline{\omega} \\ \omega & \omega \leq \overline{\omega} \end{cases}$$

where $\overline{\omega}$ denotes the threshold realization of $\omega$ such that if realized $\omega$ lies below this threshold, households monitor and earn the entire project "pie"—akin to entrepreneur default—, while if $\omega$ lies above this threshold households do not monitor and earn the threshold itself—the fixed income. We can then use these state-contingent rules to derive the expected payoffs of entrepreneurs and households, respectively, for an initial investment i as a function of the threshold $\overline{\omega}$:

$$\mathbb{E}[\Pi^E(i,\overline{\omega})] = ir[\int_{\overline{\omega}}^{\infty} \omega g(\omega) d\omega - \overline{\omega}(1 - G(\overline{\omega}))] \equiv irE[\overline{\omega}] \tag{12}$$

$$\mathbb{E}[\Pi^L(i,\overline{\omega})] = ir[\int_{0}^{\overline{\omega}} \omega g(\omega) d\omega - G(\overline{\omega})\gamma + \overline{\omega}(1 - G(\overline{\omega}))] \equiv irL[\overline{\omega}] \tag{13}$$

Finally, the entrepreneur looks to maximize the size of their expected share such that the household's expected share is at least as great as their outside option, the risk-free storage technology:

$$\max_{i,\overline{\omega}} irE[\overline{\omega}] \;\; \text{s.t.} \;\; irL[\overline{\omega}] \geq R(i-n) \;\; \text{and} \;\; E[\overline{\omega}] + L[\overline{\omega}] = 1 - G(\overline{\omega})\gamma \tag{14}$$

which gives two equations that jointly determine the optimal $\overline{\omega}^*$ and $i^*$:

$$\frac{R}{r} = 1 - G(\overline{\omega}^*)\gamma + \frac{E[\overline{\omega}^*]}{E'[\overline{\omega}^*]} g(\overline{\omega}^*]\gamma \tag{15}$$

$$i^* = \frac{nR}{R - r(1 - G(\overline{\omega}^*)\gamma - E[\overline{\omega}^*]}) ) \tag{16}$$

## 5.2 Capital Demand and Supply

In this subsection, we define a recursive competitive equilibrium, $\{V^L(K,\theta), V^E(K,\theta), w(K,\theta), r(K,\theta), K^{'}(K,\theta)\}$, and use it to trace the demand and supply of capital curves. The equilibrium satisfies:

1. Household optimization: given $w(K,\theta)$, $r(K,\theta)$ and $K^{'}(K,\theta)$, households solve

$$V^L(K,\theta) = \max_{i,\overline{\omega}} u(w(K,\theta) - (i-n)) + \beta \int \overbrace{ir(K^{'},\theta^{'})L(\overline{\omega})}^{R(i-n)} \phi(\theta^{'})d\theta^{'} \tag{17}$$

The solution to the household problem is given by the solution to the optimal contracting problem in (14), with $i^*$ and $\overline{\omega}^*$ from equation (16) and (15), respectively.

2. Firm optimization: given $w(K,\theta)$ and $r(K,\theta)$, firms solve

$$V^E(K,\theta) = \max_{K,H} \theta K^{\alpha} H^{1-\alpha} - r(K,\theta)K - w(K,\theta)H, \tag{18}$$

where, since $H = 1$, we see that

$$w(K,\theta) = (1-\alpha)\theta K^{\alpha} \tag{19}$$

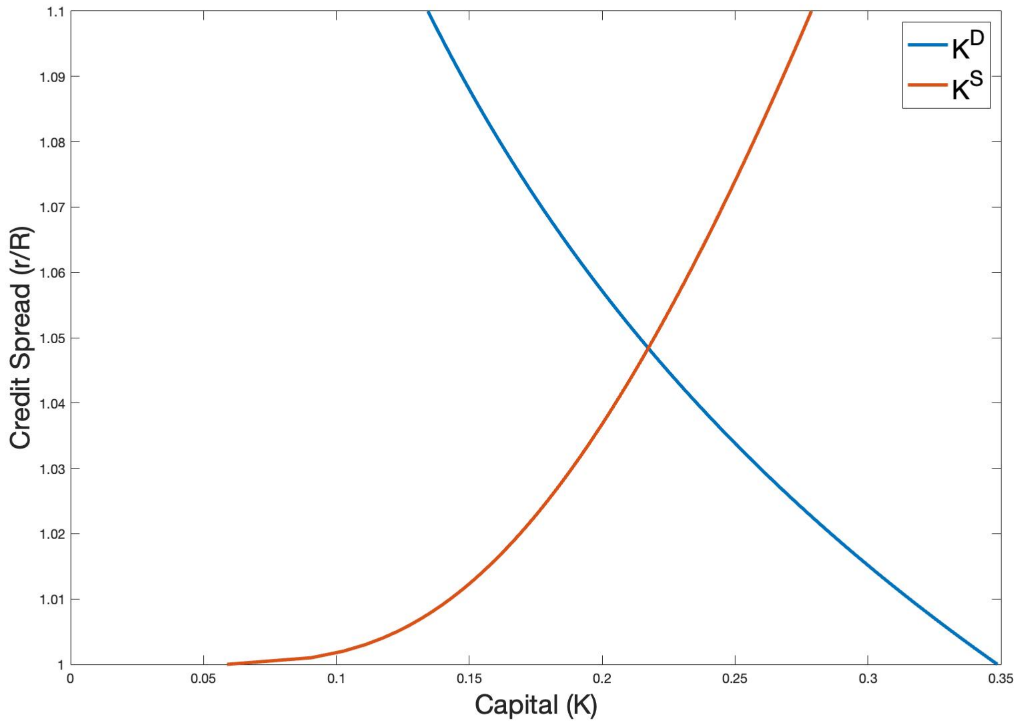
$$r(K,\theta) = \alpha\theta K^{\alpha-1}. \tag{20}$$

Equation (20) is firm's demand for capital, $K^D(r)$. It sets the marginal product of capital (MPK) equal to the marginal return to capital.

3. Law of Motion for the aggregate capital stock:

$$K^{'}(K,\theta) = i(1 - G(\overline{\omega})\gamma) \tag{21}$$

FIGURE 9
Capital Market Equilibrium




*Note.* Figure 9

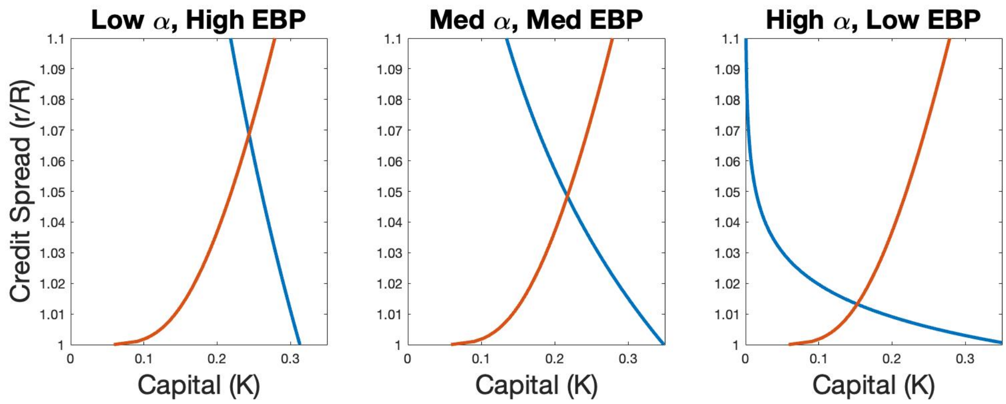
Equation (21) is the capital supply curve, $K^S(r)$, with optimal $i$ and $\overline{\omega}$ defined in equations (15) and (16). It states that capital in the next period is equal to investment net of monitoring costs.

4. Market Clearing: $H = \eta h^L + (1-\eta)h^E = 1$ and $K^D = K^S$

Figure 9 plots the demand and supply schedules for capital under a standard calibration (see Appendix for details). The capital supply curve is upward sloping since, as the marginal return to capital $r$ increases, households are willing to supply more funds to firms to invest in capital. Conversely, the demand for capital is downward sloping due to decreasing returns to scale in the firm's production function. Capital market equilibrium occurs at the intersection of the two schedules, with $K = 0.22$ and $r/R = 1.05$.

FIGURE 10

Convexity in Production and the EBP Component of Credit Spreads




*Note.* Figure 10

## 5.3 Convexity of Production and the EBP

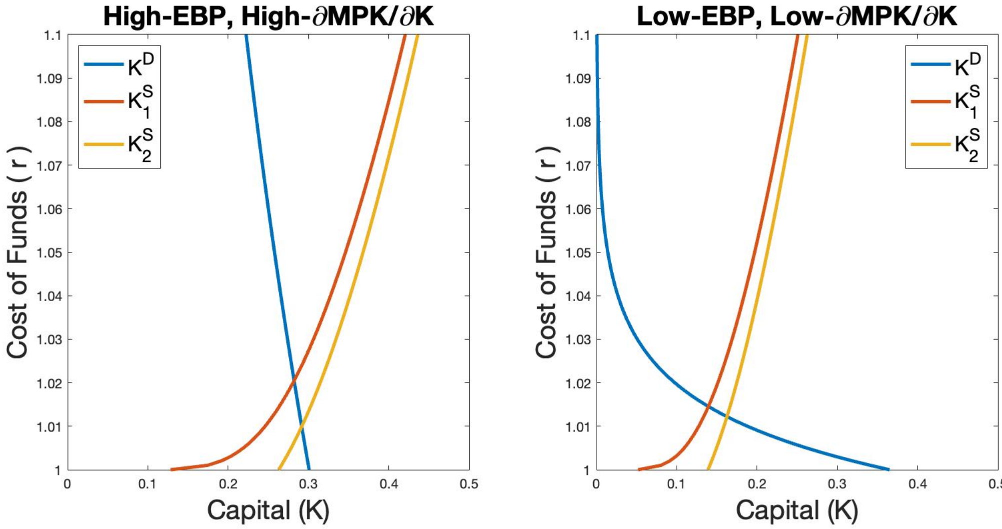
In this section, we highlight the link between the slope of a firm's demand curve, $\frac{\partial MPK}{\partial K}$, and the component of a firm's credit spread unrelated to its net worth—an EBP-like quantity.

In our model, the curvature of a firm's production technology affects both the slope of the demand curve, its marginal product of capital, and the slope of the supply curve, since firm net worth—and hence firm default risk for a given level of capital stock—is equal to the marginal product of labor. Since we are interested in the link between the marginal product of capital and the EBP—the component of credit spreads above firm default risk—we consider in Figure 10 a comparative statics exercises where firms have the same net worth, that is, they face the same capital supply curve, but differ in their demand for capital. Specifically, we vary the parameter $\alpha$, which parameterizes the slope of the capital demand curve, and consider three cases: $\alpha_{low} = 0.735$, $\alpha_{med} = 0.9$, and $\alpha_{high} = 0.985$. These three cases are displayed in the three panels of Figure 10.

Figure 10 demonstrates that, holding constant firm net-worth, firms with higher $\alpha$ have lower credit spreads. Since these differences in spreads are unrelated to default-risk compensation due to firm net worth, our model demonstrates a link between the curvature of a firm's production function and their EBP. This link arises because as capital invested increases, high-$\alpha$/low-EBP firms' MPK initially falls quickly before flattening out

FIGURE 11

Monetary Policy on Spreads and Investment by Firm EBP




*Note.* Figure 11

near equilibrium. That is, near equilibrium, low-EBP firms have a relatively low $\frac{\partial MPK}{\partial K}$, their investment decisions become increasingly borrowing-rate sensitive.[18] We explore this borrowing-rate sensitivity of investment in the context of monetary policy in the next section.

## 5.4 Monetary Policy, Borrowing Costs and Investment

### 5.4.1 Heterogeneity by EBP

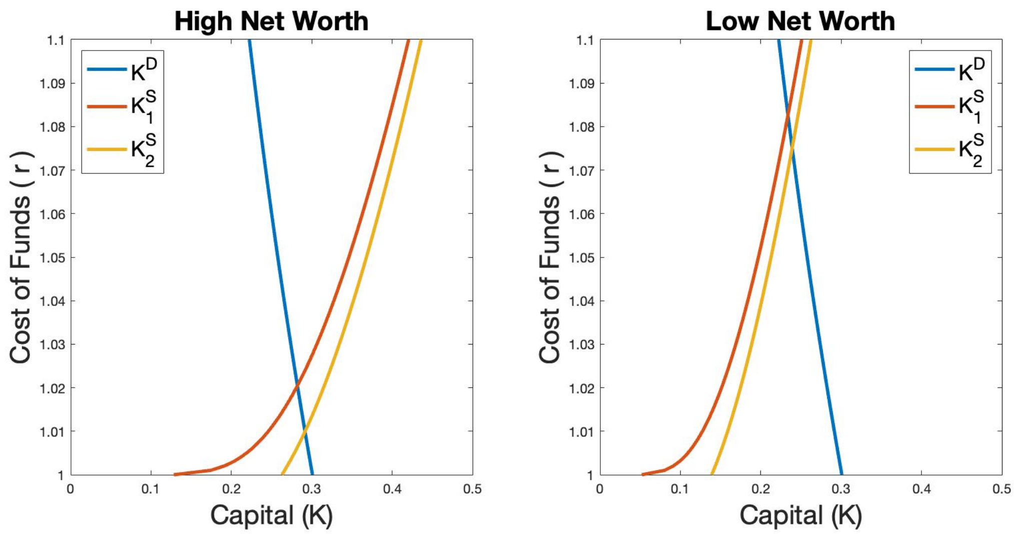
In this subsection, we study how monetary policy differentially affects the marginal borrowing rate ($r$) and investment ($K$) of firms with different EBPs. We capture these differences in EBPs, as in the previous section, through differences in the convexity of firms' production functions (parameterized by $\alpha$), which leads to differences in firms' $\frac{\partial MPK}{\partial K}$. Firms with low-EBP have flatter demand curves, lower $\frac{\partial MPK}{\partial K}$, near equilibrium.

Figure 11 studies the comparative statics to a monetary policy easing, that is, a de-

[18]It is worth noting that when K is sufficiently low, high $\alpha$ firms have *steeper* capital demand curves/high $\frac{\partial MPK}{\partial K}$. If capital market equilibrium occurred in these low-K regions, high $\alpha$ firms would have high EBPs. This shows that firm EBPs move around as the capital supply moves around—consistent with the fact that EBPs are time-varying in the data but display some persistence.

FIGURE 12

Monetary Policy on Spreads and Investment by Firm Net Worth




*Note.* Figure 12

crease in the risk-free rate $R$, for two firms with different EBPs.[19] In both panels, we see that by lowering the value of household's outside option, a decrease in R shifts the supply of capital curve outward. For the low-EBP firm with a flat demand curve near equilibrium, displayed in Panel B, this shift along the demand curve elicits a large increase in investment $K$, but only a mild fall in their marginal borrowing rate $r$. Conversely, for the high-EBP firm with steep demand curve in Panel A, the shift leads to a small increase in investment accompanied by a large fall in their marginal borrowing rate. These results are consistent with our empirical findings from the previous sections and rationalize our puzzle result by shifting focus to the slope of the capital demand curve.

#### 5.4.2 Heterogeneity by Net Worth

In this section, we show that considering heterogeneity by firm net worth, which manifests as differences in the slope of the capital supply curve faced by firms, leads to results at odds with our empirical findings. Empirically, we showed that following a monetary policy shock, firms with low default risk, which map to high net-worth firms in our model, experience mild

[19] Unlike in the previous section, these firms face different capital supply curves due to differences in their net worth/wage rate. The results are even more pronounced if firm's face the same capital supply curve.

changes in their spreads but large movements in their investment. These effects, however, are crowded out by our EBP state.

Figure 12 shows the response to an easing of monetary policy, $R\downarrow$, for both high net worth (Panel A) and low net worth (Panel B) firms. Contrary to our empirical results, we see that high net worth (low default risk) firms experience both a large increase in their investment and a large increase in their spreads. This occurs because differences in net worth lead to differences in the slope and intercept of the capital supply curve. Instead, our empirics and theory suggest that net worth, and hence default risk, of firms may simply be correlated with the EBP.

# 6 Firm-Level Spreads and Investment

Our results thus far point to a puzzle: monetary policy loosenings generate only a small easing in credit spreads of low-EBP firms but trigger a large increase in these firm's investment. This cannot simultaneously hold in models where investment responds uniformly across firms to changes in borrowing costs. In this section, we first show that much of the observed heterogeneity in monetary policy's effects on investment works *through* firm financial conditions (the EBP). Next, we document that investment done by left-tail EBP firms is the most responsive to changes in EBP. This helps rationalize the disconnect between monetary policy's effects on spreads and investment.

To begin, we augment our investment local projection (7) estimated in Section 4 with firm credit spreads decomposed into its constituent parts: EBP and predicted spread $\hat{S}$:[20]

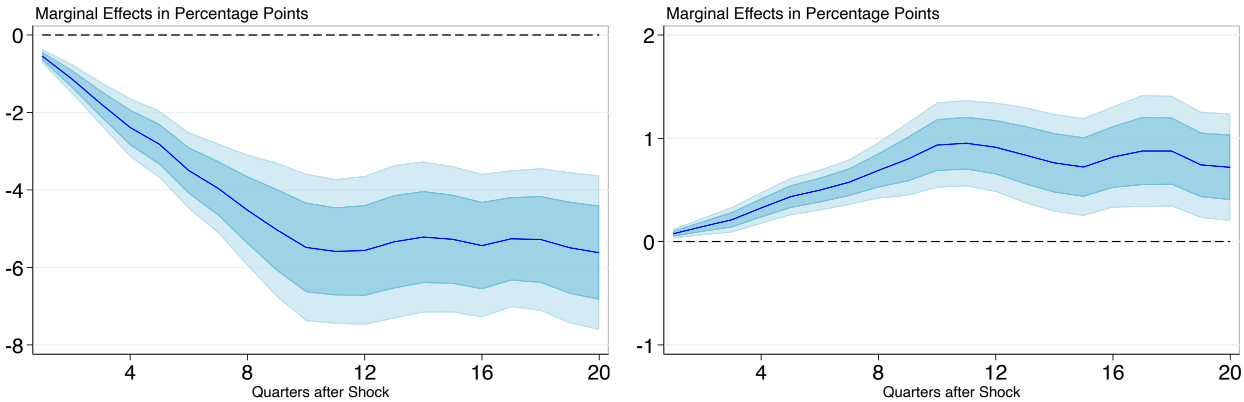
$$\log K_{it+h} - \log K_{it} = \alpha_i + \beta_0 + \beta_1 \Delta S_{i,t} + \beta_2 \Delta S_{i,t} \times EBP_{it-1} + \beta_3 EBP_{it-1} + \gamma' \mathbf{Z}_{it-1} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + e_{ith}. \tag{22}$$

Figure **??** plots estimates of the marginal effect ($\beta_3$) of $EBP_{it}$ on firm investment at different horizons. The results indicate that a rise in $EBP_{it}$, a deterioration in firm

[20] $\mathbf{Z}_{it-l}$ and $\mathbf{Y}_{t-l}$ include the same controls as in section 4.

FIGURE 13
Credit Spread Shocks and Firm-Level Investment by EBP

(A) Unconditional (B) Conditional on EBP




*Note.*

$i$'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 1 percentage point increase in firm $i$'s EBP is associated with a nearly 2.5 percentage point drop in its investment. Importantly, Figure D.6 in Appendix D shows that the significance and magnitude of the monetary policy interaction term $[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$, estimated from (22), fall considerably relative to estimates from Section 4, for each $x_{it-1}$.[21] This suggests that much of the observed heterogeneity in monetary policy's effects on investment is working *through* the excess bond premium component of credit spreads.[22]

Next, to assess the heterogeneous effects of EBP on investment, we estimate an augmented version of (22):

This specification crucially adds the interaction between the within-firm variation in a firm's financial position and the $EBP$, $[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it}$.[23] Figure D.2 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 D.2a and D.2b respectively, the results suggest that investment done by both low default-risk and low-EBP firms—safe firms—is substantially

[21] The same is also true if $EBP_{it-1}$, rather than $EBP_{it}$, is included in regression 22, as noted above.

[22] Figure D.7 plots the dynamic effect 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 little influence over $\hat{S}$.

[23] It also controls for lags of EBP, consistent with the other measures of firm financial positions.

more responsive to movements in funding costs, as captured by their EBP, as compared to firms at the other end of the distribution. In contrast, we find little evidence of heterogeneity based on leverage, though the point estimate has the correct sign. Appendix Figure D.8 indicates that the default-risk interaction effects become more muted in magnitude and significance when a variant of specification (**??**) with both an EBP interaction and a default-risk interaction is estimated, although not by as much as in sections 3 and 4.

The findings in this section help settle the disconnect between monetary policy's effects on credit spreads versus investment. Our finding stands in contrast to the Ottonello and Winberry (2020) model, where monetary easings lead low default-risk firms' investment to rise more because their credit spreads remain relatively low. Crucially, because credit spreads are driven solely by default risk in their model, spreads *increase* in response to monetary easings as firms take on more debt to finance new investment. Instead, in section 3, we show that monetary policy only affects the risk premium component of spreads and that spreads *decrease* in response to monetary easings, with high-EBP (riskier) firms' spreads falling by more. Instead, it is low-EBP (safer) firms whose investment is more responsive to changes in marginal borrowing costs (the EBP component of credit spreads) that rationalizes the greater elasticity of low-EBP firms investment to monetary policy shocks. This may be due to low-EBP firms having access to more productive investment opportunities (Cavalcanti et al. (2021)).

The results here and from Section 3 imply a challenge for policymakers: while monetary policy is most effective at influencing the financial conditions of right-tail EBP firms, it is movements in the financial conditions of left-tail EBP firms that generate larger investment responses. To effectively influence real business activity, policymakers may need to adopt policies that specifically target these latter firms who are relatively more responsive.

# 7 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 EBP firms' investment responds more than high-EBP firms'. This helps rationalize the puzzle that risky firms' spreads but safe firms' investment is more responsive to monetary policy.

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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). 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).[24] Figure A.1 plots the time series of our mean credit spread and that of Gilchrist and Zakrajšek (2012) and highlights that the correlation is 92%.

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:

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

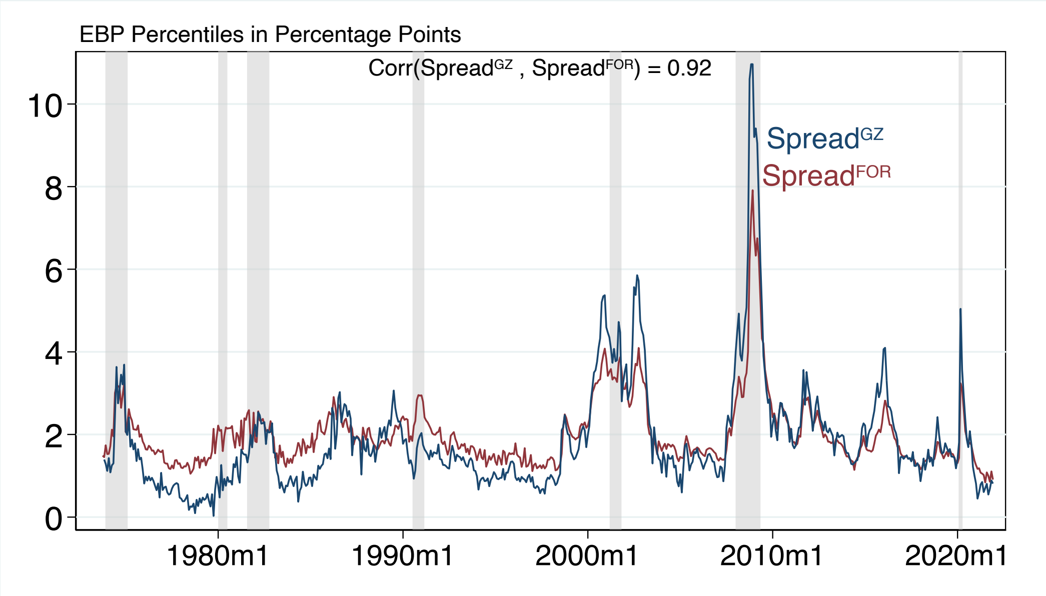
in which the log of the credit spread $S_{it}[k]$ is a linear function of (i) firm $i$'s distance-to-default $DD_{it}$ (Merton, 1974), capturing firm $i$'s expected default probability, (ii) a vector of bond characteristics $\mathbf{Z}_{it}[k]$, which includes the bond's duration, coupon rate and age, and (iii) an error term $\upsilon_{it}[k]$. $\mathbf{Z}_{it}[k]$ includes the bond's duration, amount outstanding, coupon rate and age.[25] Further, we include both industry and credit rating fixed effects. Table A.1 provides the results from estimating (A.1) by OLS.

Assuming the error term is normally distributed, the predicted spread of bond $k$ issued

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

[25] 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.

FIGURE A.1
Credit Spreads: Comparison with Gilchrist and Zakrajšek (2012)




*Note.* Figure A.1 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.

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

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

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 monthly EBPs for 11,319 bonds from 1,913 firms, which we term the bond-level EBP distribution. Figure A.2 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 our credit spread model from above is the firm's Merton (1974)

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

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

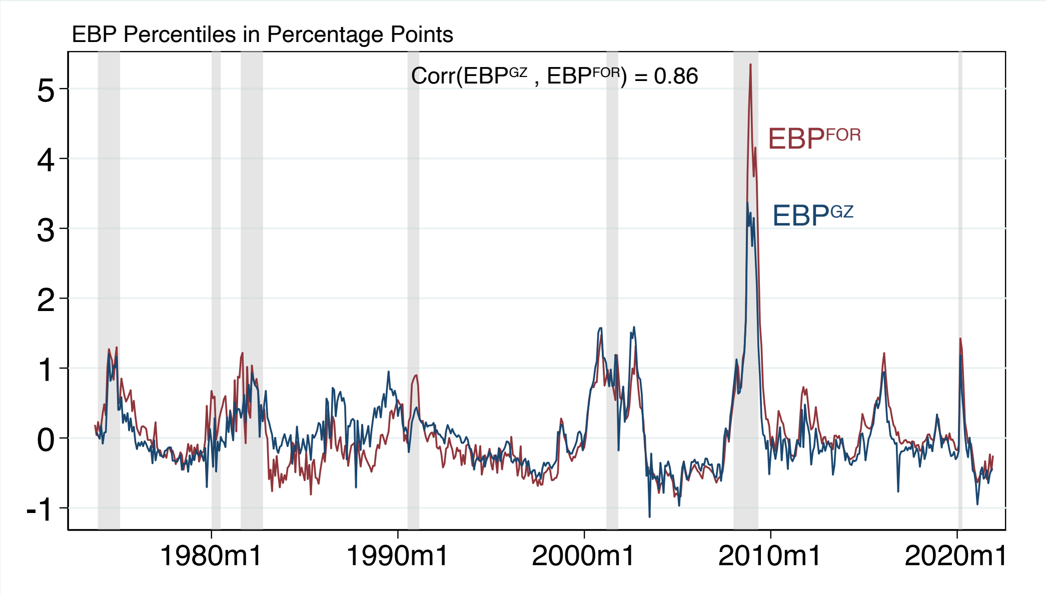
*Note.* Table A.1 present the estimated coefficients, standard errors and T-statistics from estimating (A.1) by OLS. The sample period is October 1973 to December 2021 and includes 682,316 observations. $LEV_t$, $SLP_t$, $CRV_t$ refer to the level, slope and curvature (first three principal components) 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 i and month t (Cameron et al. (2011)).

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

Figure A.2
Excess Bond Premium: Comparison with Gilchrist and Zakrajšek (2012)




*Note.* Figure A.2 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.

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 $\sigma_V$.[26] 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 $\mu_V$.[27]. We then iterate on $\sigma_V$ until convergence.

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

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

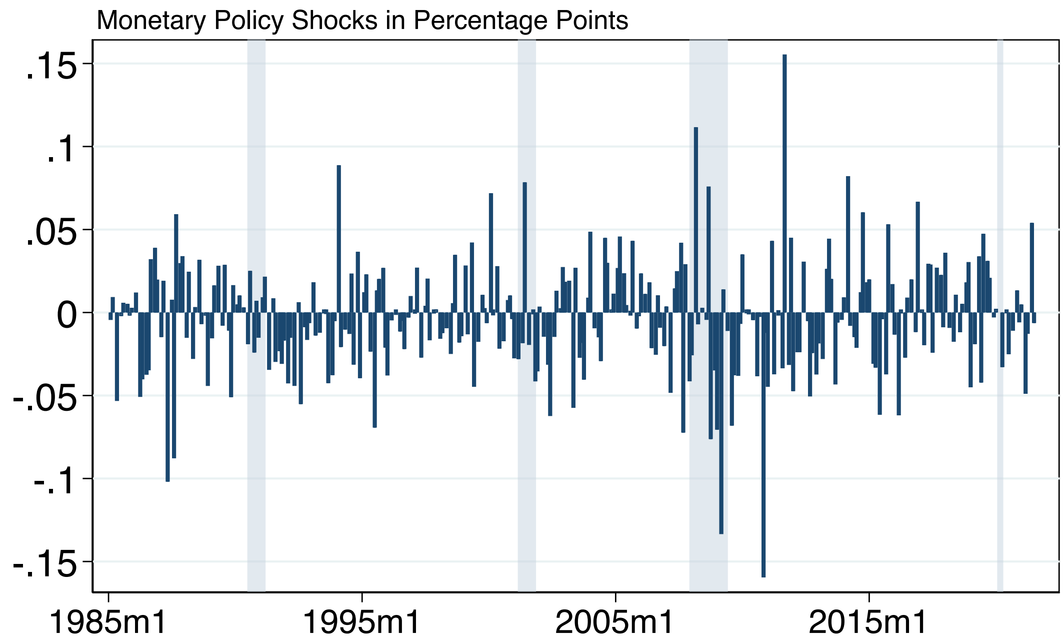
Since default at T occurs when a firm's value falls below the value of its debt ($\log(V/D) < 0$), the DD captures the distance a firm is above default, given an expected asset growth rate $\mu_V$ and volatility $\sigma_V$ until T, in units of standard deviations.

[26] 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.

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

# B Appendix: Bu, Rogers and Wu (2021) Monetary Policy Shock

FIGURE B.1
Bu, Rogers and Wu (2021) Monetary Policy Shock

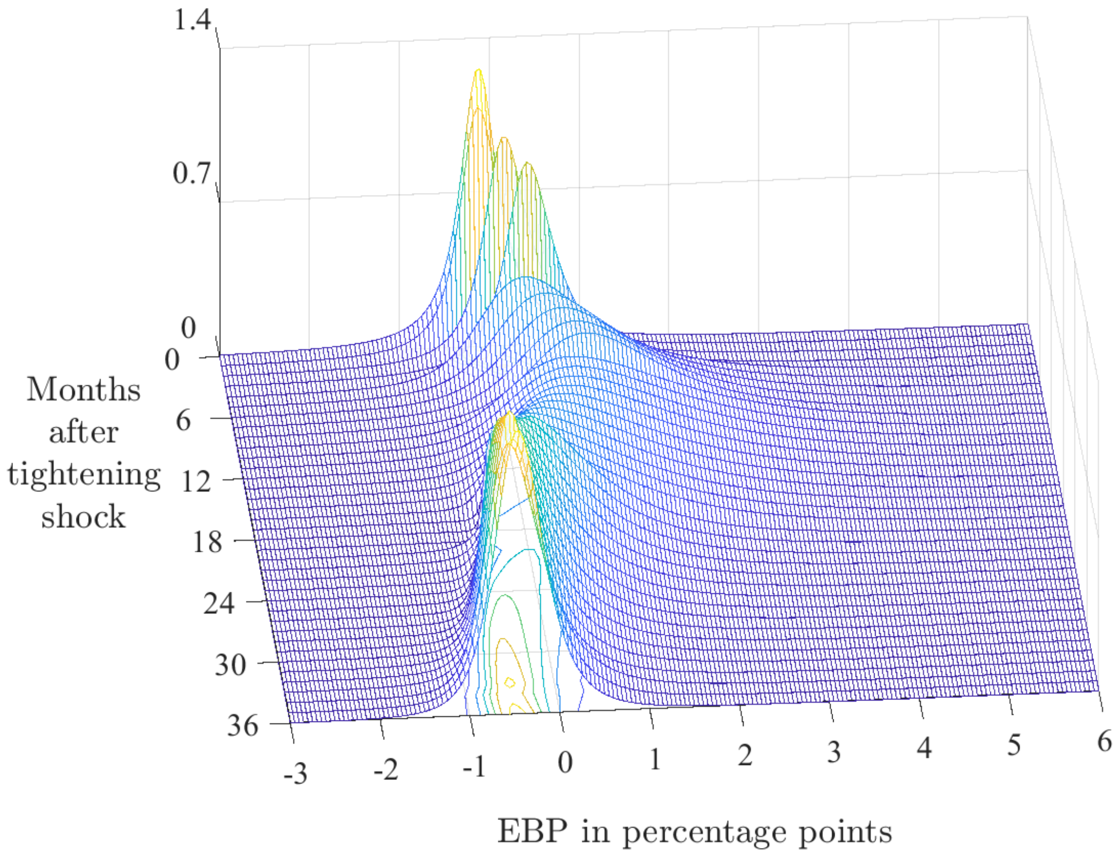



*Note. Figure B.1 plots the time series of the extended Bu et al. (2021) monetary policy shock from January 1985 to July 2021. Shaded columns represent periods classified as recessions by the National Bureau of Economic Research.*

# C Appendix: Aggregate Effects of EBP Heterogeneity

FIGURE C.1

Monetary Policy's Effect on Cross-Sectional Distribution of EBP




*Note.* Figure C.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 C. 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.

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. [28] Second, we approximate the probability density function at each

[28]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 C.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:

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

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).[29]

Tables C.1a and C.1b report the regression coefficients from estimating (C.1) using the $25^{th}$ and $75^{th}$ percentiles of the EBP distribution, respectively. Table C.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 C.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.

[29]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 C.1
The Cross-Sectional EBP Distribution and One-Year-Ahead Economic Activity

(a) $25^{th}$ Percentile

| Variables | GDP | INV | IP |
|---|---|---|---|
| $\mathrm{EBP}_t^{\mathrm{mean}}$ | 0.37 | 0.71 | 0.76* |
| | (0.25) | (1.26) | (0.42) |
| $\mathrm{EBP}_t^{25}$ | -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 |
|---|---|---|---|
| $\mathrm{EBP}_t^{\mathrm{mean}}$ | -1.09*** | -3.72* | -4.39*** |
| | (0.40) | (2.01) | (0.69) |
| $\mathrm{EBP}_t^{75}$ | 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 C.1 reports the marginal effects of $EBP_t^{mean}$ and $EBP_t^{\tau}$ for $\tau \in \{25, 75\}$ in Panels C.1a, and C.1b, respectively, from estimating regression (C.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.

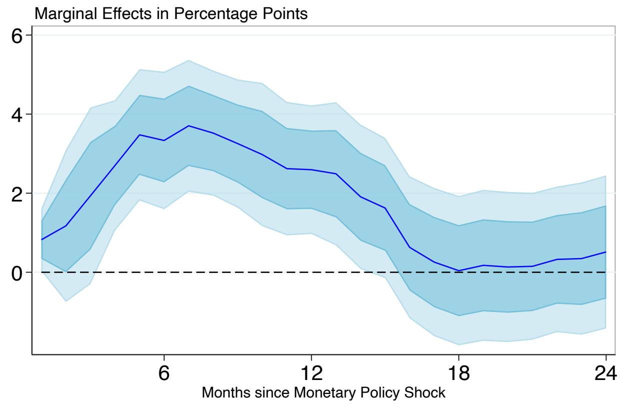
# D Appendix: Additional Results

## D.1 Additional Results from Main Body

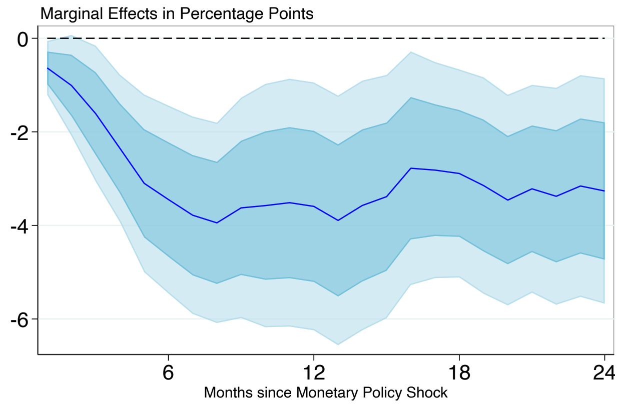
Figure D.1

Heterogeneous Effects of Monetary Policy on Bond-Level EBP

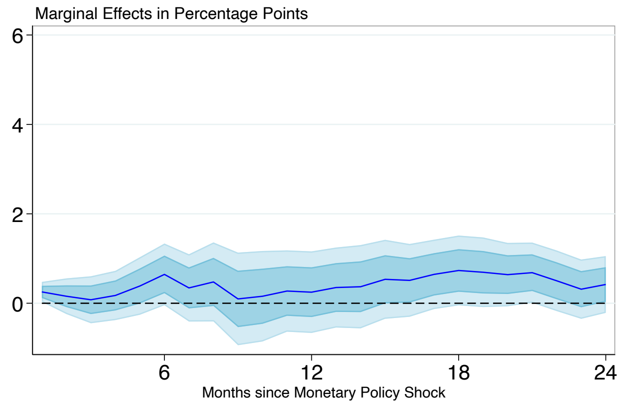
(A) Conditional on EBP




(B) Conditional on Distance to Default




(C) Conditional on Leverage



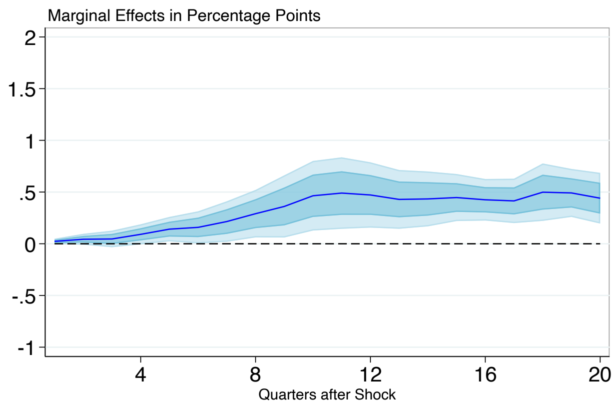

*Note.* Figure D.1 reports the dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's financial position $x_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$), where $x_{i,t}$ is $EBP_{i,t}[k]$ in Panel D.1a, is $dd_{i,t}$ in Panel D.1b and is $lev_{i,t}$ in Panel D.1c, on the h-period change in EBP, $EBP_{it+h}[k] - EBP_{i,t}[k]$, from regression (**??**). 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.

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

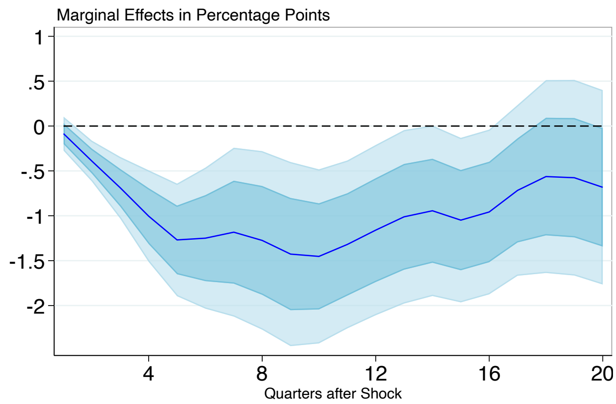
Figure D.2

Heterogeneous Effects of Firm EBP on Firm Investment

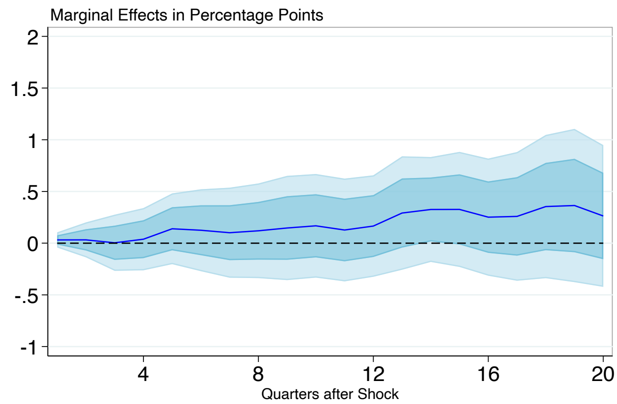
(A) Conditional on EBP




(B) Conditional on Distance-to-Default



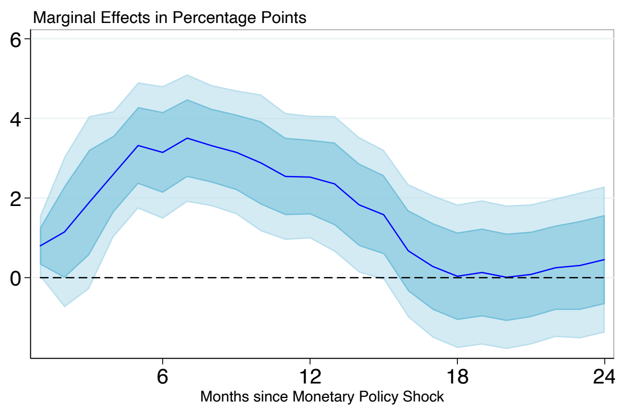

(C) Conditional on Leverage



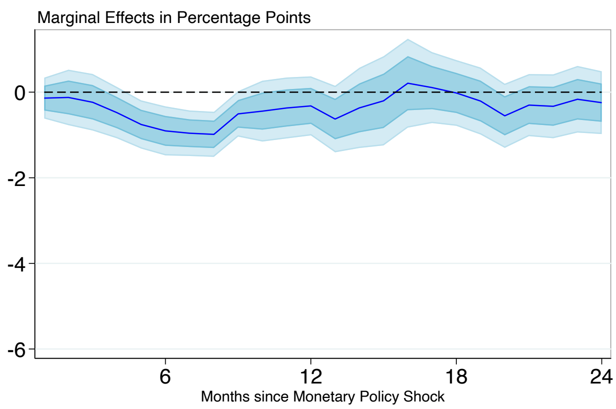

*Note.* Figure D.2 reports the dynamic effects ($\beta_4$) of the interaction between within-firm variation in a firm's financial position $x_{i,t}$ and the EBP, $[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m$, where $x_{i,t}$ is the EBP in Panel D.2a, the distance to default $dd_{i,t}$ in Panel D.2b and leverage $lev_{i,t}$ in Panel D.2c, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$, from regression (**??**). 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.

## Figure D.3
Monetary Policy on EBP: Double Interaction by EBP and Default-Risk

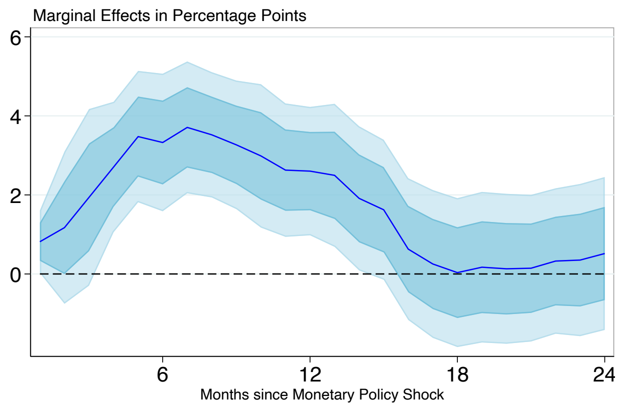
(A) $\hat{\beta}_3$: EBP Interaction



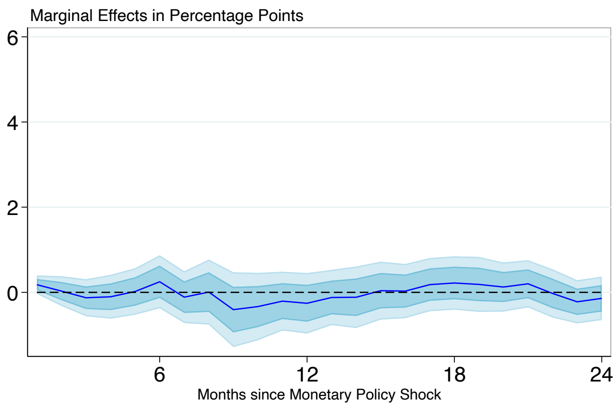

(B) $\hat{\beta}_2$: Distance to Default Interaction




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

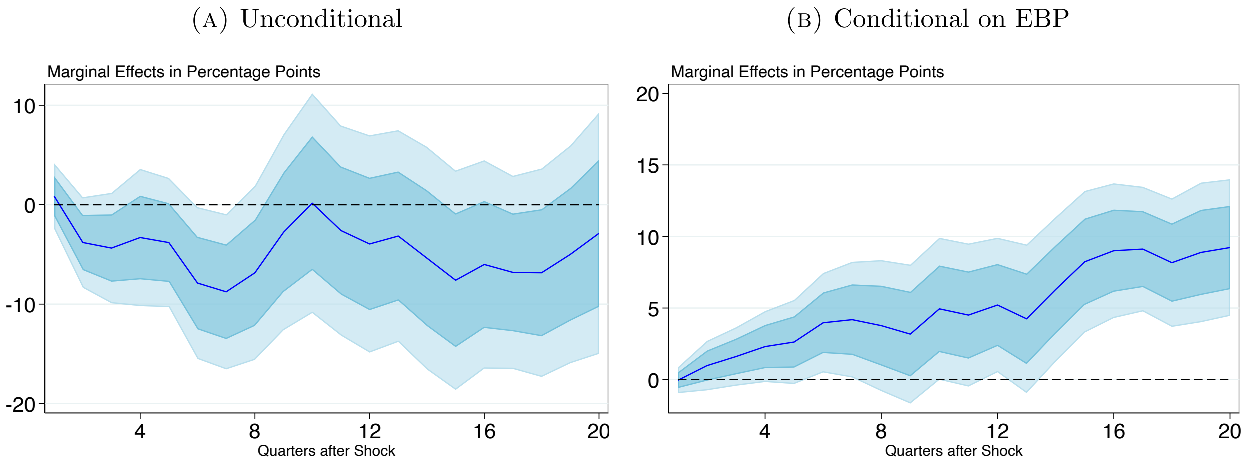



(D) $\hat{\beta}_2$: Leverage Interaction




*Note*. Figure D.3 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's $EBP_{i,t}$ 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 default-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, $EBP_{it+h}[k] - EBP_{i,t}[k]$. Panels D.3a and D.3b report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation D.1 with $x_{i,t} = dd_{i,t}$, while Panels D.3c and D.3d report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation D.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.

FIGURE D.4
Monetary Policy's Effect on Firm-Level Investment

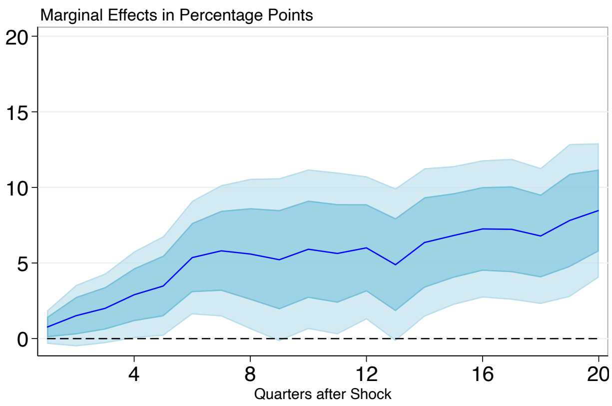



*Note.* Figure D.4 reports the dynamic effects of a Bu et al. (2021) monetary policy shock ($\beta_1$) in Panel D.4a and of the interaction ($\beta_2$) between within-firm variation in a firm's $EBP_{i,t}$ and the monetary shock, $[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$, in Panel D.4b, on the h-period Investment of firm i, $\log K_{it+h} - \log K_{it}$ , from regression (D.2). 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.

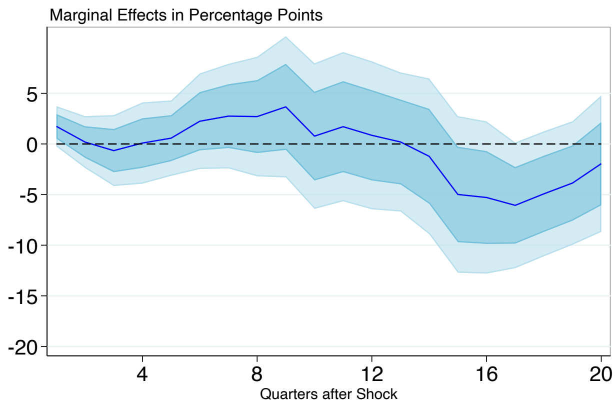
$$\begin{aligned}\log K_{it+h} - \log K_{it} =& \beta_0 + \beta_1\varepsilon_t^m + \beta_2[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m + \beta_3 EBP_{it-2} \\ &+ \sum_{l=1}^{3}\gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3}\delta_l' \mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith}, \qquad \text{(D.2)}\end{aligned}$$

Figure D.5
Monetary Policy on Investment: Double Interaction by EBP and Default-Risk

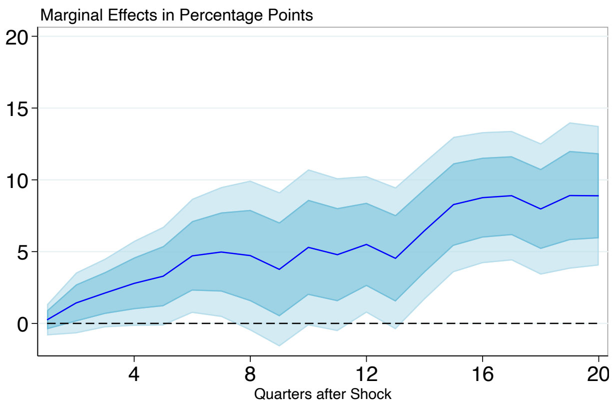
(a) $\hat{\beta}_3$: EBP Interaction



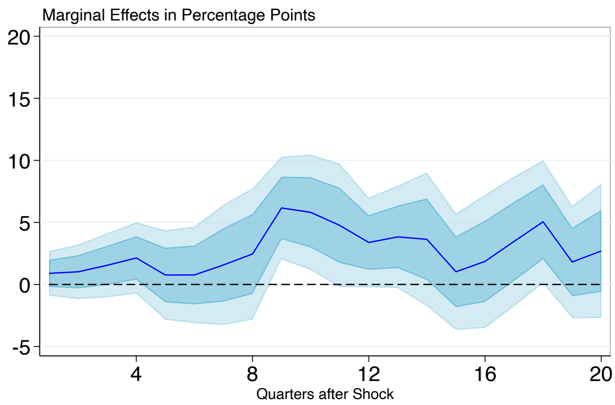

(b) $\hat{\beta}_2$: Distance to Default Interaction




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




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



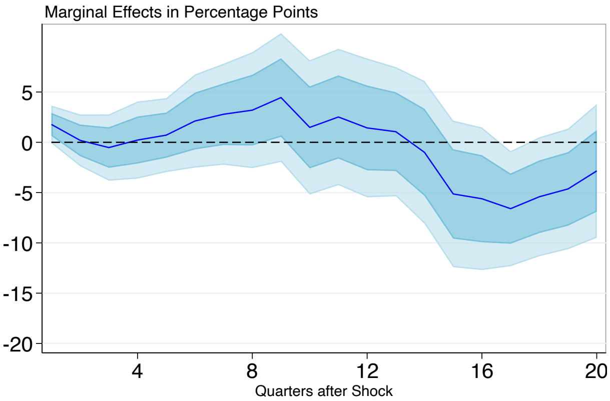

*Note.* Figure D.5 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's $EBP_{i,t}$ and a Bu et al. (2021) monetary policy shocks ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$) and (B) the interaction of within-firm variation in a firm's default-risk $x_{i,t}$ 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 D.5a and D.5b report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation D.3 with $x_{i,t} = dd_{i,t}$, while Panels D.5c and D.5d report the interaction coefficients $\beta_3$ and $\beta_2$, respectively, from estimating equation D.3 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.

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

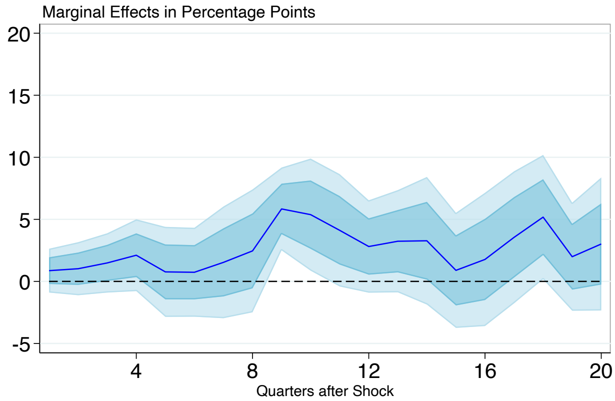
Figure D.6

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

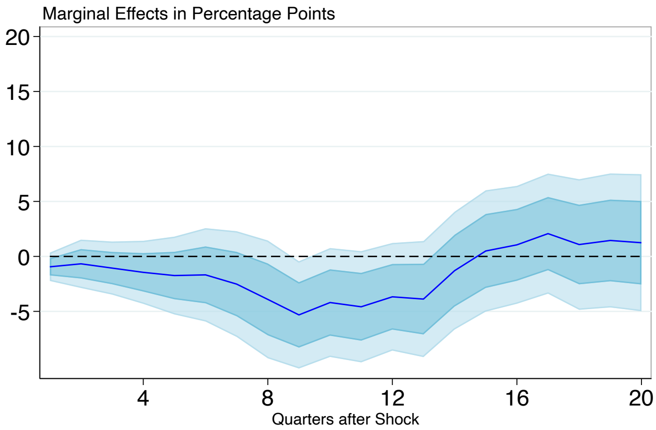
(a) $\hat{\beta}_2$: Distance to Default Interaction




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



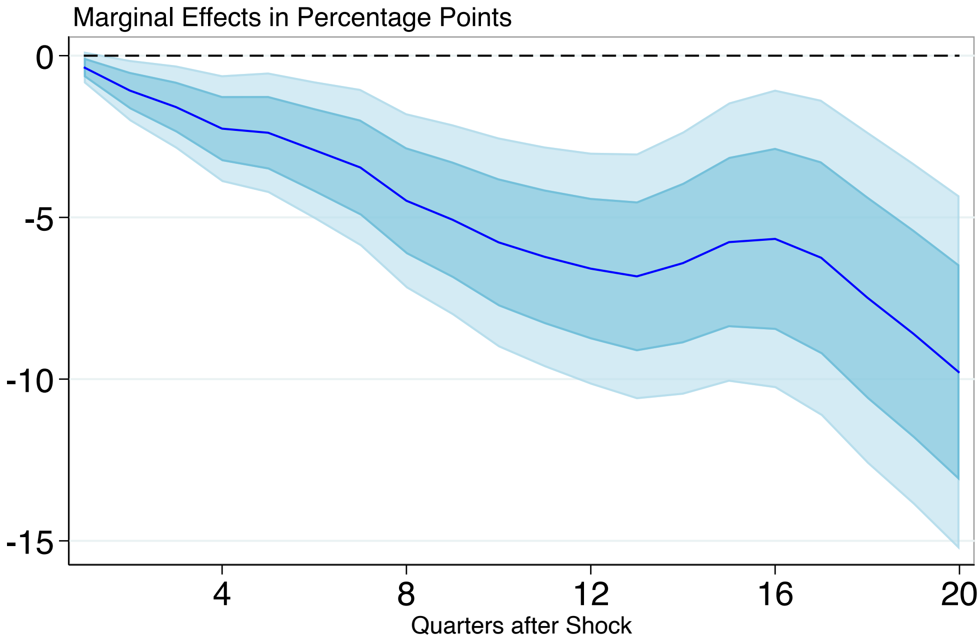

(c) $\hat{\beta}_2$: EBP Interaction




*Note.* Figure D.6 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 (D.4), which includes the $EBP_{i,t}$. $x_{i,t}$ is distance to default in Panel D.6a, leverage in Panel D.6b, and the EBP in Panel D.6c. 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.

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

Figure D.7
Firm-Level Effects of $\hat{S}$ on Investment



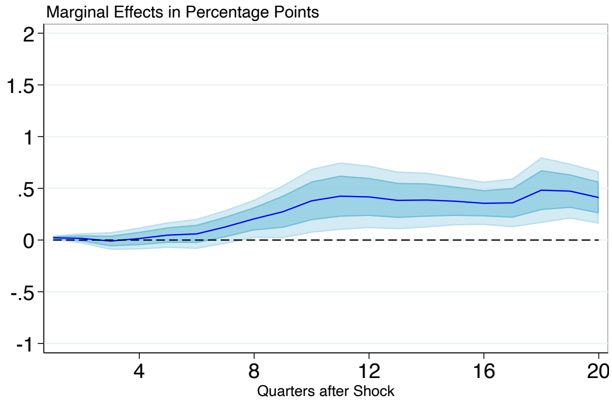

*Note.* Figure D.7 reports the dynamic effects ($\beta_4$) of the Predicted Spread ($\hat{S}$) on the h-period Investment of firm i $\log K_{it+h} - \log K_{it}$ from regression (D.5), where the frequency of the data is quarterly. The inner and outer shaded areas correspond to the 68% and 90% confidence intervals constructed using two-way clustered standard errors by firm i and quarter t (Cameron et al., 2011), respectively.

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_3 EBP_{it} + \beta_4 \hat{S}_{it} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith}, \tag{D.5}$$

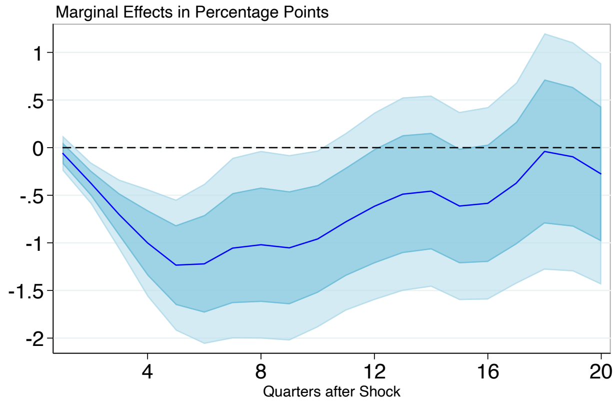
FIGURE D.8

EBP on Investment: Double Interaction with EBP and Default-Risk

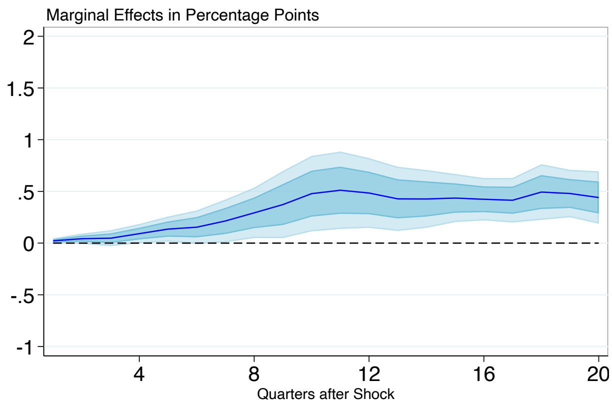
(A) $\hat{\beta}_3$: EBP Interaction



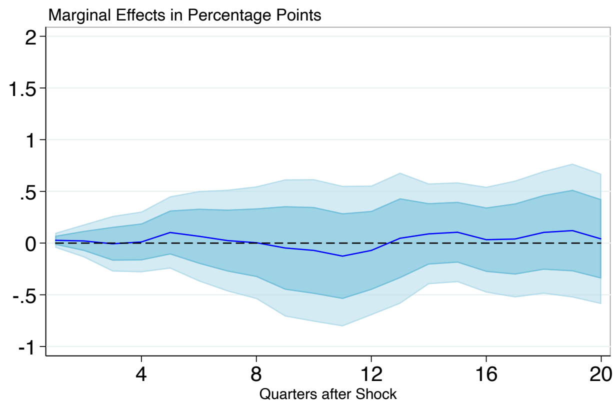

(B) $\hat{\beta}_4$: Distance to Default Interaction




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




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

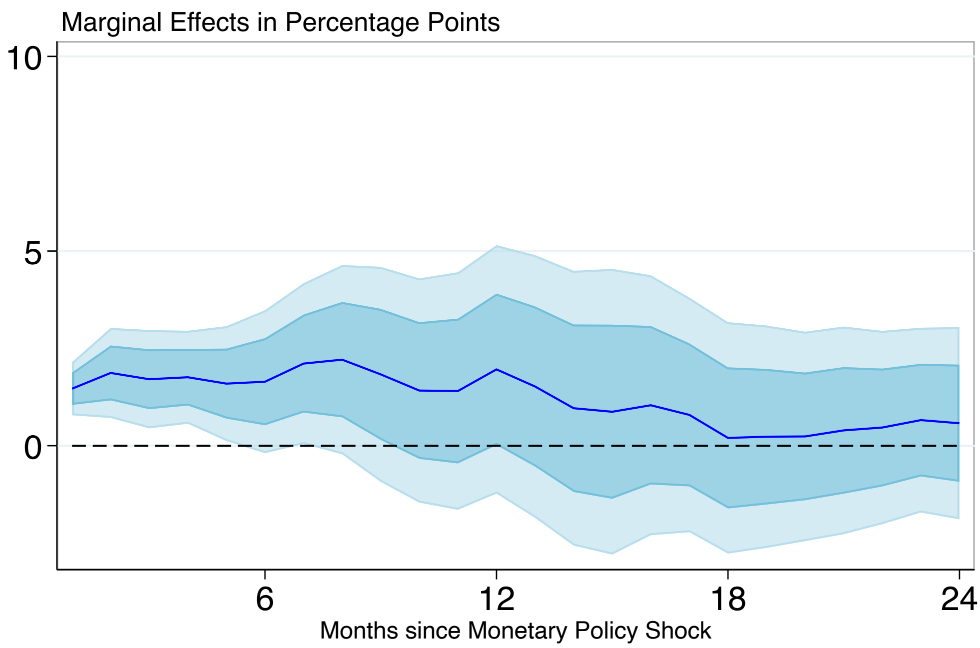



*Note.* Figure D.8 reports the results for a horserace between (A) the interaction of within-firm variation in a firm's lagged EBP and the EBP ($[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]EBP_{it}$) and (B) the interaction of within-firm variation in a firm's default-risk $x_{i,t}$ and the EBP ($[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it}$), on the h-period change firm i's Investment, $\log K_{it+h} - \log K_{it}$. Panels D.8a and D.8b report the interaction coefficients $\beta_3$ and $\beta_4$, respectively, from estimating equation D.6 with $x_{i,t} = dd_{i,t}$, while Panels D.8c and D.8d report the interaction coefficients $\beta_3$ and $\beta_4$, respectively, from estimating equation D.6 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.

$$
\begin{aligned}
\log K_{it+h} - \log K_{it} = & \beta_1 \varepsilon_t^m + \beta_2 EBP_{it} + \beta_3[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]EBP_{it} + \beta_4[x_{it-1} - \mathbb{E}_i(x_{it})]EBP_{it} \\
& + \beta_5[x_{it-1} - \mathbb{E}_i(x_{it})]\varepsilon_t^m + \beta_6[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\
& + \beta_7 \hat{S}_{it} + \sum_{l=1}^{3} \theta_l' EBP_{it-l} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \beta_0 + \alpha_i + \alpha_{cr} + e_{ith}
\end{aligned}
\tag{D.6}
$$

## D.2 Robustness to Jarociński and Karadi (2020) Monetary Policy Shock

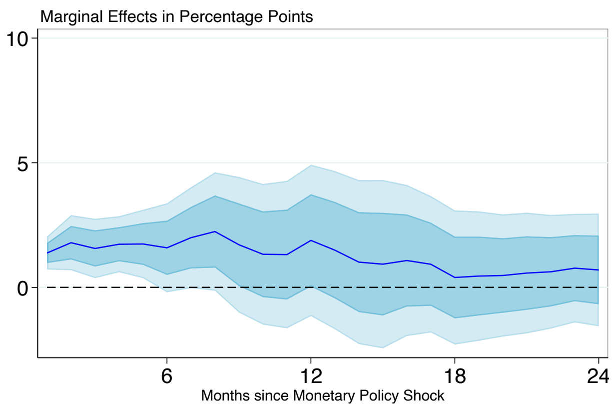
FIGURE D.9
Monetary Policy's Effect on Bond-Level Credit Spreads



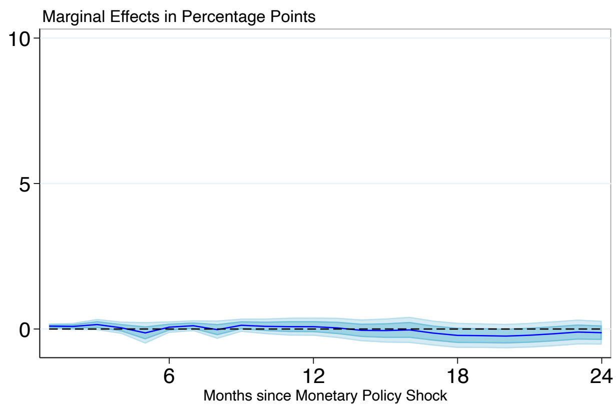

*Note.* The analogue of Figure 3 with a Jarociński and Karadi (2020) monetary policy shock.

FIGURE D.10
Monetary Policy's Effect on Bond-Level Credit Spreads

(A) EBP

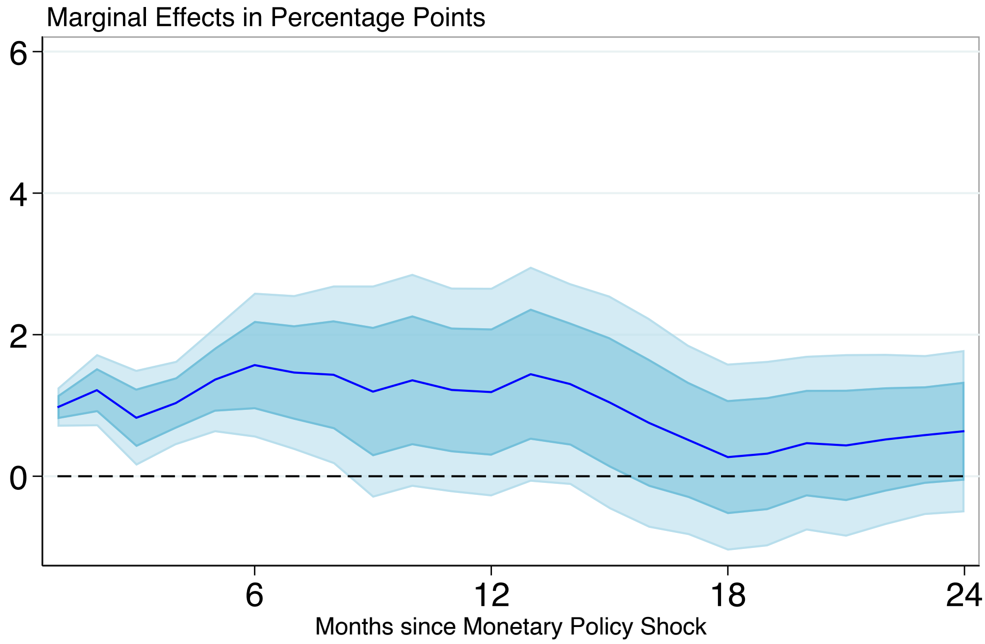



(B) Predicted Spread




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

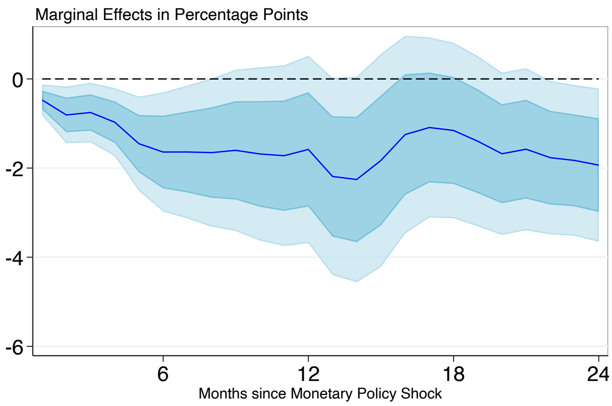
Figure D.11
Monetary Policy's Effect on Bond-Level EBP by Firm EBP



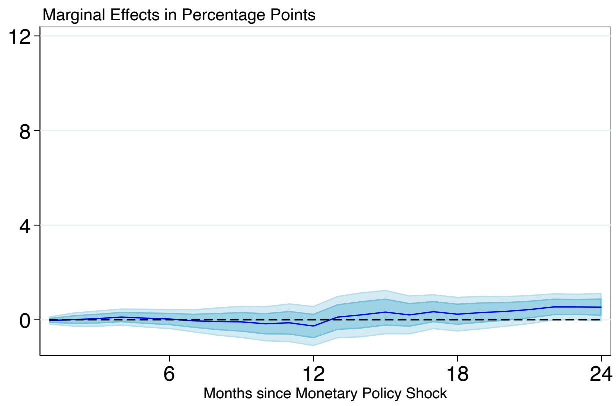

*Note.* The analogue of Figure D.1a with a Jarociński and Karadi (2020) monetary policy shock.

Figure D.12
Monetary Policy's Effect on Bond-Level EBP by Firm Default-Risk

(a) Distance to Default



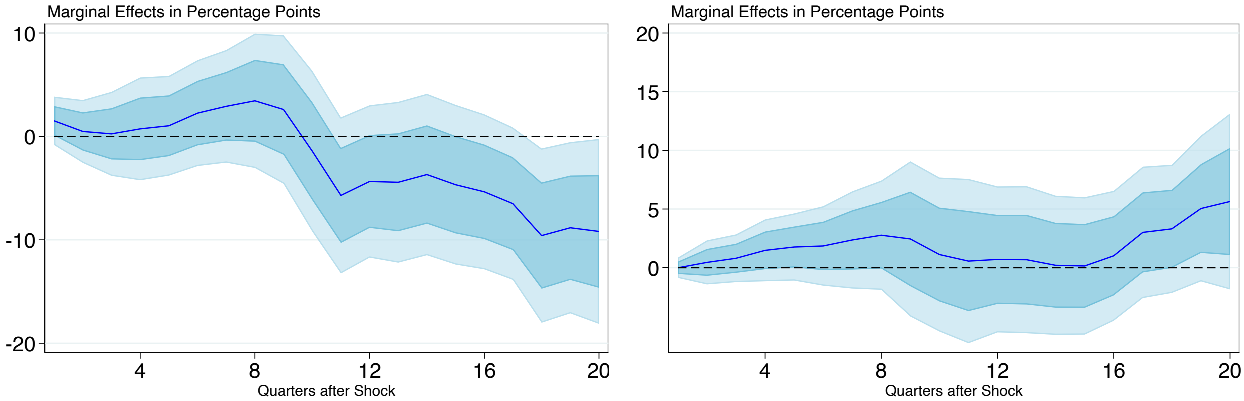

(b) Leverage




*Note.* The analogue of Figure D.1 with a Jarociński and Karadi (2020) monetary policy shock.

FIGURE D.13
Monetary Policy's Effect on Firm-Level Investment

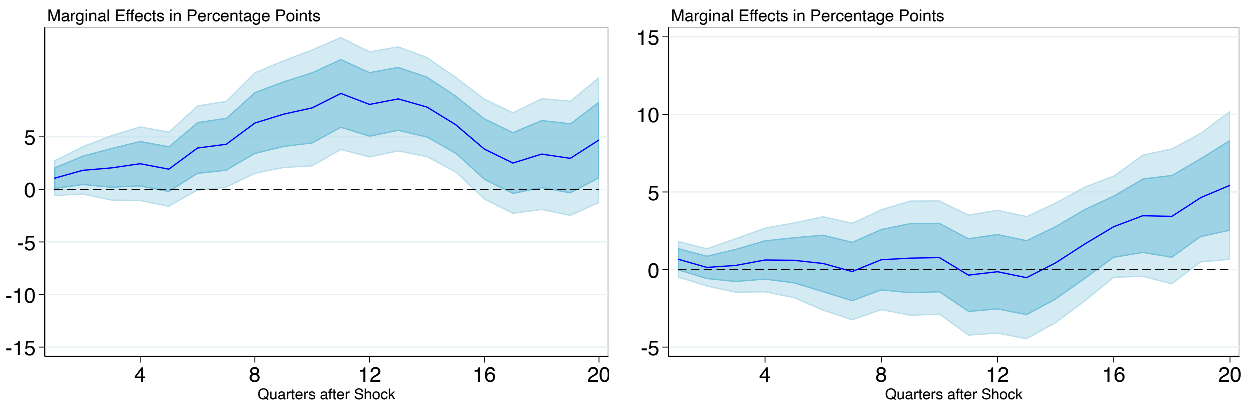
(A) $\hat{\beta}_1$: Unconditional (B) $\hat{\beta}_2$: EBP Interaction




*Note.* The analogue of Figure 13 with a Jarociński and Karadi (2020) monetary policy shock. .

FIGURE D.14
Monetary Policy's Effect on Firm-Level Investment by Firm Default-Risk

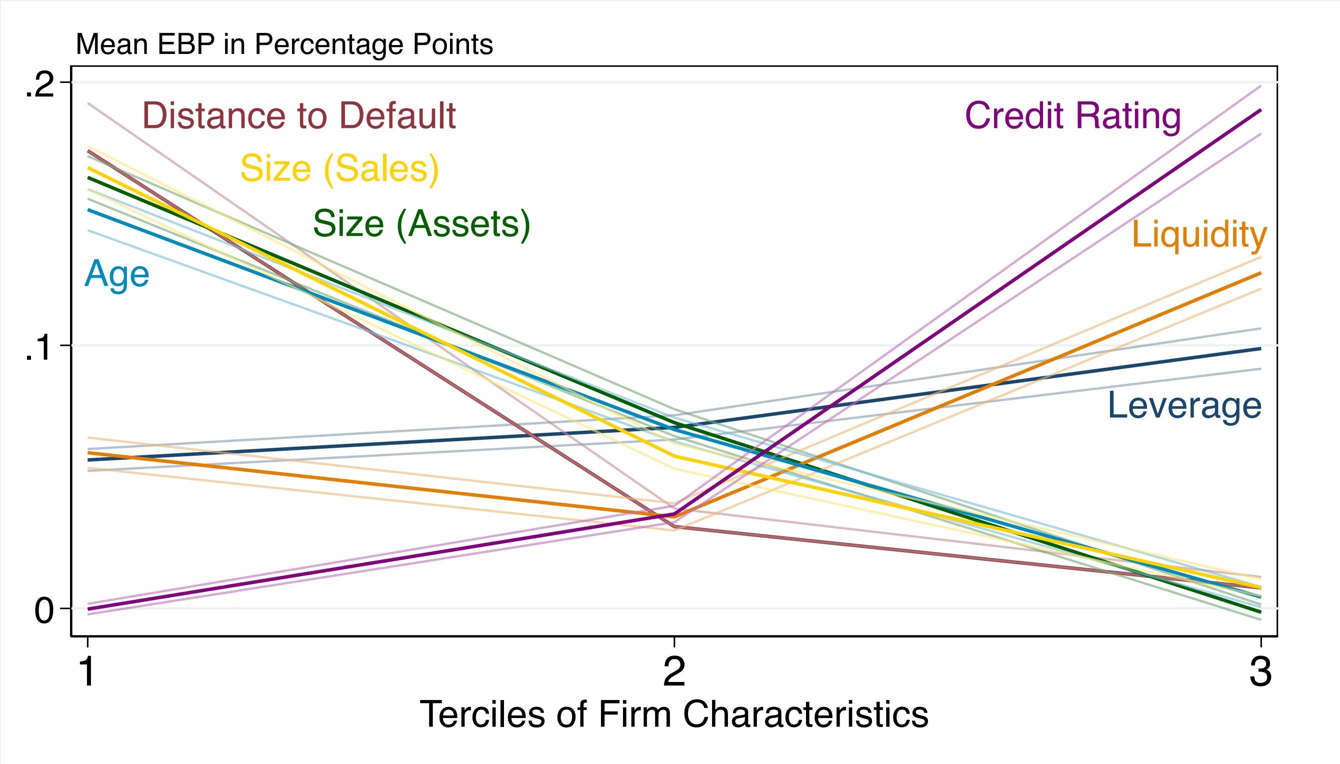
(A) $\hat{\beta}_2$: Distance to Default Interaction (B) $\hat{\beta}_2$: Leverage Interaction




*Note.* The analogue of Figure 8 with a Jarociński and Karadi (2020) monetary policy shock. .

## D.3 Robustness to Heterogeneity in the Literature

Figure D.15
Average EBP per Tercile of Firm Characteristics

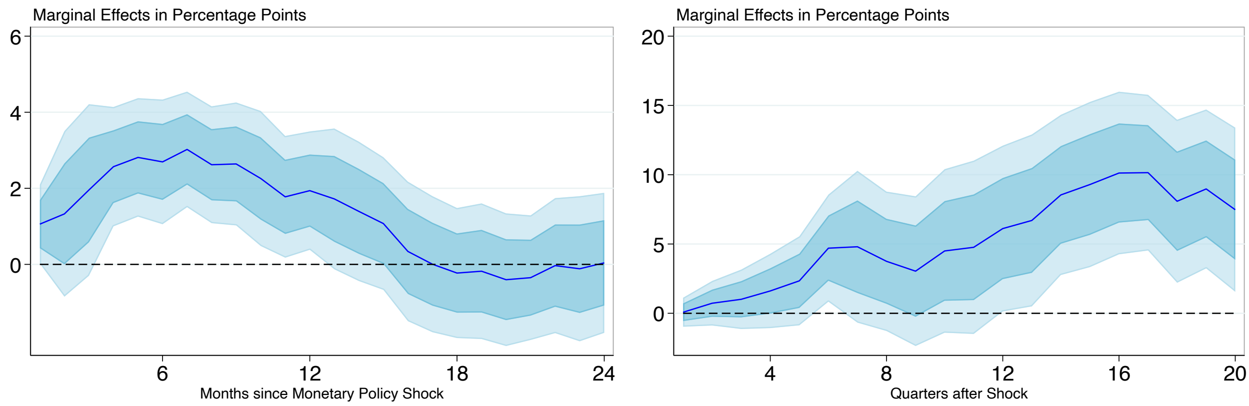



*Note.* Figure D.15 reports the average EBP, and 90% confidence intervals, for each tercile of firm distance-to-default, leverage, age, liquidity, size (assets), size (sales), and credit rating. Bond EBPs and firm characteristics are calculated as the within-firm average over the sample. EBPs are then averaged for each tercile.

In what follows, we run horse-races between (1) interactions between monetary policy shocks with the within-firm variation in EBP; (2) interactions between monetary policy shocks with various other firm-level variables. In each case, we show that interactions using within-firm variation of EBP "survive" the horserace, demonstrating that our results of heterogeneity by risk-premium is robust to all other variables identified in the literature.

FIGURE D.16
Monetary Policy on EBP and Investment: Double Interaction by EBP and Size (sales)

(A) $\hat{\beta}_3$ from (D.7): Interaction on EBP (B) $\hat{\beta}_3$ from (D.8): Interaction on Investment




*Note*. Figure D.16 reports

### D.3.1 Robustness to Size, measured by sales (Gertler and Gilchrist (1994))

$$\begin{aligned} EBP_{it+h}[k] - EBP_{it}[k] =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{size_{it-1}}] \varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})] \varepsilon_t^m \\ & + \beta_4 EBP_{it-1} + \beta_5 \mathbf{1}_{size_{it-1}} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^{'} \Delta \mathbf{Y}_{t-l} + \alpha_k + \alpha_{cr} + e_{ikth} \end{aligned} \tag{D.7}$$

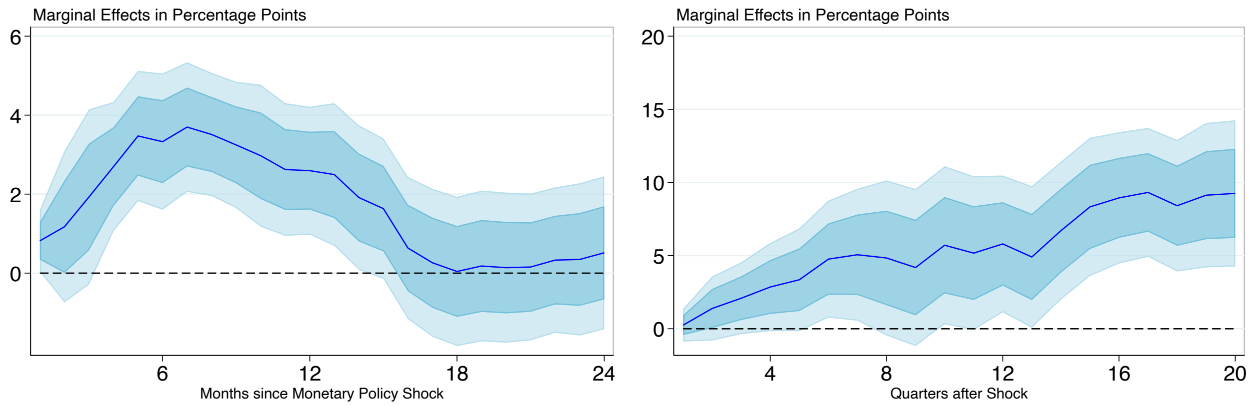
$$\begin{aligned} \log K_{it+h} - \log K_{it} =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{size_{it-1}}] \varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})] \varepsilon_t^m \\ & + \beta_4 \mathbf{1}_{size_{it-1}} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3}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

Similar to Gertler and Gilchrist (1994) and Ottonello and Winberry (2020), $\mathbf{1}_{size_{it-1}}$ is an indicator function taking the value of 1 if a firm's average sales over the past 5 years are in the top 2/3s of the distribution, and 0 otherwise.

FIGURE D.17

Monetary Policy on EBP and Investment: Double Interaction by EBP and Age

(A) $\hat{\beta}_4$ from (D.9): Interaction on EBP (B) $\hat{\beta}_4$ from (D.10): Interaction on Investment




*Note.* Figure D.17 reports

### D.3.2 Robustness to Age (Cloyne et al. (2019))

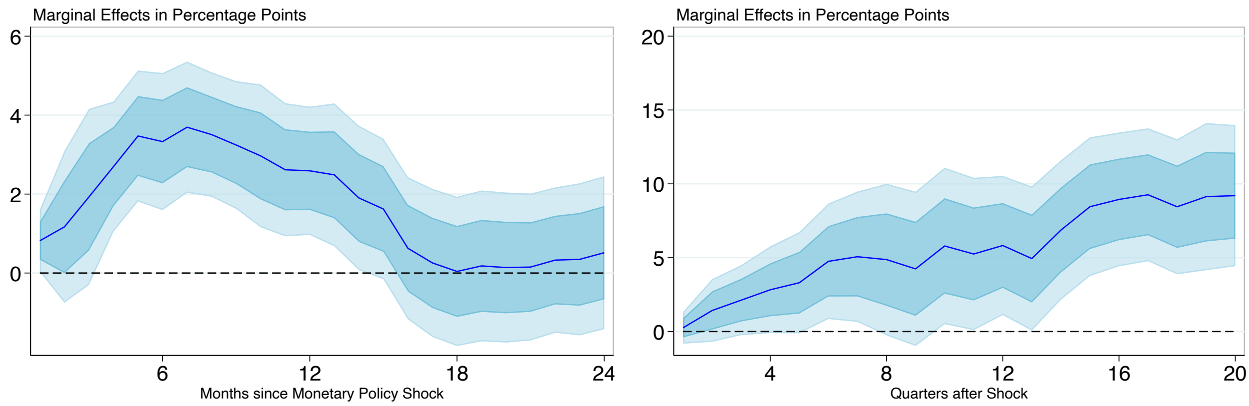
$$EBP_{it+h}[k] - EBP_{it}[k] = \beta_0 + \beta_1\varepsilon_t^m + \beta_2[\mathbf{1}_{old_{it-1}}]\varepsilon_t^m + \beta_3[\mathbf{1}_{med_{it-1}}]\varepsilon_t^m + \beta_4[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$$
$$+ \beta_5 EBP_{it-1} + \beta_6\mathbf{1}_{old_{it-1}} + \beta_7\mathbf{1}_{med_{it-1}} + \sum_{l=1}^{3}\gamma_l^{'}\mathbf{Z}_{it-l} + \sum_{l=1}^{3}\delta_l^{'}\Delta\mathbf{Y}_{t-l} + \alpha_k + \alpha_{cr} + e \tag{D.9}$$

$$\log K_{it+h} - \log K_{it} = \beta_0 + \beta_1\varepsilon_t^m + \beta_2[\mathbf{1}_{old_{it-1}}]\varepsilon_t^m + \beta_3[\mathbf{1}_{med_{it-1}}]\varepsilon_t^m + \beta_4[EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m$$
$$+ \beta_5\mathbf{1}_{old_{it-1}} + \beta_6\mathbf{1}_{med_{it-1}} + \sum_{l=1}^{3}\gamma_l^{'}\mathbf{Z}_{it-l} + \sum_{l=1}^{3}\delta_l^{'}\mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith}, \tag{D.10}$$

As in Cloyne et al. (2019), $\mathbf{1}_{old_{it}}$ is an indicator function taking the value of 1 if a firm is more than 50 years removed from its IPO, and 0 otherwise, and $\mathbf{1}_{med_{it}}$ is an indicator function taking the value of 1 if a firm is between 15 and 50 years removed from its IPO, and 0 otherwise.

FIGURE D.18
Monetary Policy on EBP and Investment: Double Interaction by EBP and Liquidity

(A) $\hat{\beta}_3$ from (D.11): Interaction on EBP (B) $\hat{\beta}_3$ from (D.12): Interaction on Investment




*Note*. Figure D.18 reports

### D.3.3 Robustness to Liquidity (Jeenas (2019))

$$
\begin{aligned}
EBP_{it+h}[k] - EBP_{it}[k] = &\beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [liq_{it-1}]\varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\
&+ \beta_4 EBP_{it-1} + \beta_5 liq_{it-1} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \Delta \mathbf{Y}_{t-l} + \alpha_k + \alpha_{cr} + e_{ikth}
\end{aligned} \tag{D.11}
$$

$$
\begin{aligned}
\log K_{it+h} - \log K_{it} = &\beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [liq_{it-1}]\varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\
&+ \beta_4 liq_{it-1} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith},
\end{aligned} \tag{D.12}
$$

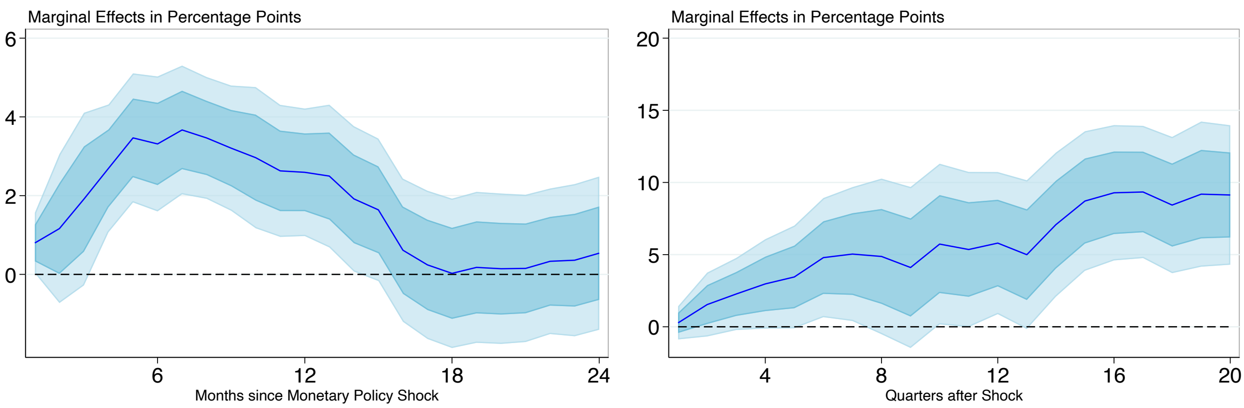
As in Jeenas (2019), the variable $liq_{it}$ is the liquidity ratio i.e. the ratio of cash and short-term investments to total assets.

Figure D.19

Monetary Policy on EBP and Investment: Double Interaction by EBP and Credit Rating

(A) $\hat{\beta}_3$ from (D.13): Interaction on EBP

(B) $\hat{\beta}_3$ from (D.14): Interaction on Investment




*Note.* Figure D.19 reports

### D.3.4 Robustness to Credit Rating (Ottonello and Winberry (2020))

$$
\begin{aligned}
EBP_{it+h}[k] - EBP_{it}[k] =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{cr_{it-1}}] \varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})] \varepsilon_t^m \\
& + \beta_4 EBP_{it-1} + \beta_5 \mathbf{1}_{cr_{it-1}} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^{'} \Delta \mathbf{Y}_{t-l} + \alpha_k + \alpha_{cr} + e_{ikth}
\end{aligned}
\tag{D.13}
$$

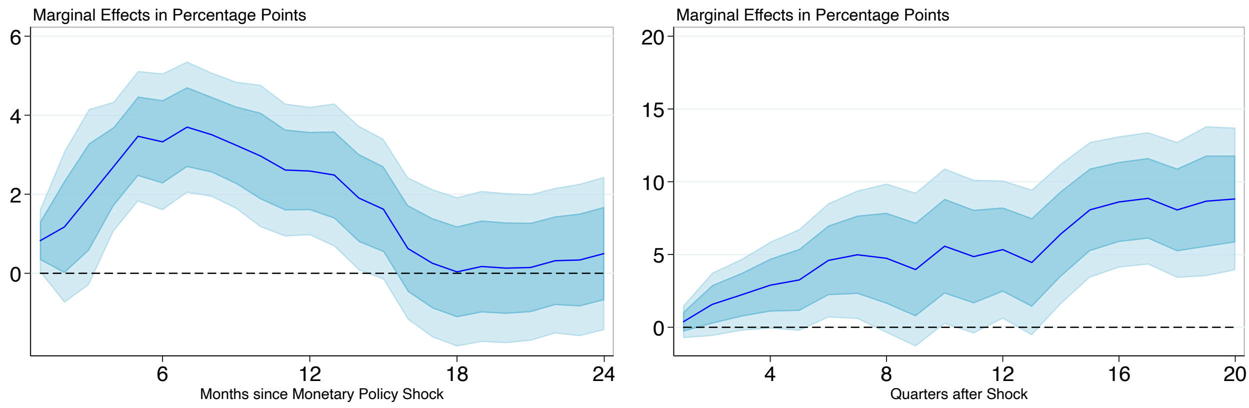
$$
\begin{aligned}
\log K_{it+h} - \log K_{it} =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{cr_{it-1}}] \varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})] \varepsilon_t^m \\
& + \beta_4 \mathbf{1}_{cr_{it-1}} + \sum_{l=1}^{3} \gamma_l^{'} \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l^{'} \mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith},
\end{aligned}
\tag{D.14}
$$

As in Ottonello and Winberry (2020), $\mathbf{1}_{cr_{it}}$ is an indicator variable taking the value of 1 if a firm's credit rating is in the top half of the credit rating distribution and 0 otherwise.

Figure D.20

Monetary Policy on EBP and Investment: Double Interaction by EBP and Size (assets)

(A) $\hat{\beta}_3$ from (D.15): Interaction on EBP (B) $\hat{\beta}_3$ from (D.16): Interaction on Investment




*Note*. Figure D.20 reports

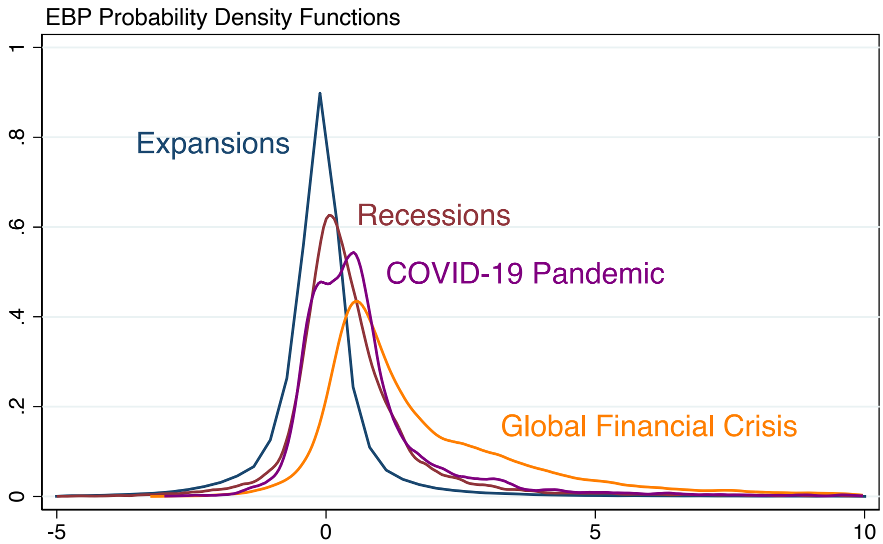
### D.3.5 Robustness to Size measured by assets

$$\begin{aligned} EBP_{it+h}[k] - EBP_{it}[k] =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{size_{it-1}}]\varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\ &+ \beta_4 EBP_{it-1} + \beta_5 \mathbf{1}_{size_{it-1}} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \Delta \mathbf{Y}_{t-l} + \alpha_k + \alpha_{cr} + e_{ikth} \end{aligned} \tag{D.15}$$

$$\begin{aligned} \log K_{it+h} - \log K_{it} =& \beta_0 + \beta_1 \varepsilon_t^m + \beta_2 [\mathbf{1}_{size_{it-1}}]\varepsilon_t^m + \beta_3 [EBP_{it-1} - \mathbb{E}_i(EBP_{it})]\varepsilon_t^m \\ &+ \beta_4 \mathbf{1}_{size_{it-1}} + \sum_{l=1}^{3} \gamma_l' \mathbf{Z}_{it-l} + \sum_{l=1}^{3} \delta_l' \mathbf{Y}_{t-l} + \alpha_i + \alpha_{cr} + e_{ith}, \end{aligned} \tag{D.16}$$

$\mathbf{1}_{size_{it-1}}$ is an indicator function taking the value of 1 if a firm's size, measured by assets, is in the top 2/3s of the distribution, and 0 otherwise.

Figure E.1
Cross-Sectional EBP Distribution in COVID-19, the GFC, Recessions and Expansions




*Note.* Figure E.1 plot the EBP's estimated cross-sectional probability density functions during expansions, recessions excluding the GFC and COVID-19, the Global Financial Crisis and the COVID-19 pandemic, respectively, as defined by the National Bureau of Economic Research.

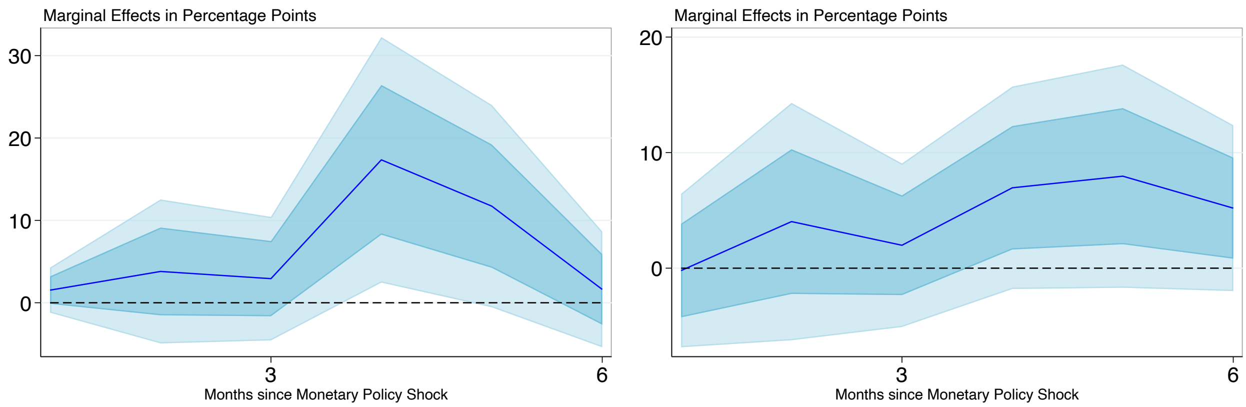
# E Appendix: U.S. Monetary Policy and the EBP in COVID-19

As is well known, the U.S. Fedeal Reserve responded to COVID-19 by lowering the policy rate to zero and reinvigorated its asset purchases. The Bu et al. (2021) monetary policy shock series displayed in Figure B.1 highlights that monetary shocks during the COVID-19 period were overwhelmingly easings. At the same time, the time series of EBP percentiles displayed in Figure 2 indicates that the deterioration of firms' financial conditions at the onset of the pandemic occurred with unprecedented speed, reaching a peak one month into the recession, far faster than in any previous U.S. recession. Despite this, firm EBPs during the recession did not come close to reaching the levels seen during the GFC; they also returned to normal rather quickly. Figure E.1 reveals that, in its totality, the cross-sectional EBP distribution during the COVID-19 recession closely resembled the EBP distribution during "vanilla" recessions, and exhibited a considerably lower mean, variance and right-skew than did the EBP distribution during the GFC.

Figure E.2

Monetary Policy's Effect on Bond-Level Excess Bond Premia During COVID-19

(a) Unconditional (b) Conditional on EBP




*Note.* Panel E.2a of Figure E.2 reports the dynamic effects ($\beta_1$) of Bu et al. (2021) monetary policy shocks ($\varepsilon_t^m$) on the h-period change in credit spreads $EBP_{it+h}[k] - EBP_{i,t}[k]$ from regression (4), during the COVID-19 period (January 2020–December 2021) at a monthly frequency. Panel E.2b dynamic effects ($\beta_2$) of the interaction between within-firm variation in a firm's $EBP_{i,t}$ 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 (**??**), during the COVID-19 period (January 2020–December 2021) at a monthly frequency. 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.

In this section, we demonstrate the effectiveness of U.S. monetary policy at taming the rise of credit spreads in the COVID-19 period (January 2020 until December 2021), and argue that this may have helped keep firms afloat during the great lockdown.[30] We re-estimate our baseline local projection for the effects of monetary policy shocks on credit spreads, equation (4), for the COVID-19 period. The results are displayed in Figure E.2. Relative to our findings from Section 3 (Figure **??**), the magnitude of the EBP response to monetary policy shocks during the COVID-19 period is nearly *five* times as large. At the peak response 4-months ahead, a 1 percentage point monetary easing during COVID-19 predicts a nearly 20 percentage point fall in a firm's EBP. This implies that the U.S. monetary policy response during the pandemic was particularly effective at easing the financial conditions of the average U.S. firm.

Furthermore, by re-estimating specification (**??**) for the COVID-19 period, we show

[30] These findings complement Gilchrist et al. (2020) who find that the Federal Reserve's more targeted Secondary Market Corporate Credit Facility helped lower spreads in the wake of the COVID-19 pandemic.

that high EBP firms' financial conditions were particularly sensitive to monetary policy (Figure E.2b). Thus, the monetary easings at the onset of the pandemic would have contributed to a steep decline in EBPs for right-tail firms in particular, leading to a more-symmetric COVID-19 EBP distribution. This is consistent with the findings from Figure E.1.

Altogether, these results demonstrate the efficacy with which U.S. monetary policy corralled the fast-deteriorating financial conditions of U.S. firms during the COVID-19 pandemic. Unfortunately, we are unable to trace the effects of changes in firm financial conditions to firm investment due to insufficient observations.[31] It is possible, even likely, that rather than taking advantage of easier financial conditions to invest, firms during COVID-19 used easier credit conditions to continue to pay workers and roll-over existing debt in an effort to keep their businesses afloat as revenues dried up. This would imply a limited pass-through of monetary stimulus to firm investment and wider economic activity, consistent with Tenreyro and Thwaites (2016). Our findings shed new light on *why* monetary policy is less-effective in recessions: it is not due to the (in)effectiveness of monetary policy at stimulating firms' credit spreads, at least during the COVID-19 recession. Nevertheless, by keeping businesses afloat, this monetary policy response likely helped the U.S. economy rebound quickly once lockdown restrictions eased.

[31] For our monthly frequency regressions, the COVID-19 sample affords us about 42,000 observations. For quarterly frequency investment regressions, we are left with only about 2000 observations, which is insufficient to draw meaningful conclusions.