EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

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Firms' risk and monetary transmission: revisiting the excess bond premium

No 3118

Abstract

This paper examines whether firm-specific cyclical and idiosyncratic risk profiles influence corporate bond spreads and the transmission of monetary policy. I extend the standard excess bond premium (EBP) framework of Gilchrist & Zakrajšek (2012) to allow investors' required compensation for default risk to vary with firm-level risks. Incorporating these effects reveals that a significantly larger share of a monetary policy shock's impact on credit spreads is driven by changes in default risk compensation (as opposed to the EBP). In particular, for firms with more cyclical risk, up to one-fourth of the additional spread widening following a contractionary monetary policy shock reflects higher expected default compensation, substantially more than implied by the traditional EBP. By contrast, firms with high idiosyncratic risk show no strong differential response to monetary policy shocks relative to other firms.

JEL Classification: D22, E43, E44, E52, G12

Keywords: excess bond premium, cyclicality, risk, monetary policy, sentiment

Non-technical summary

This paper explores how corporate bond yields rise when the central bank tightens policy and, in particular, whether the increase reflects a higher risk of default or broader market conditions such as investor risk appetite and liquidity. A large recent literature shows that most of the immediate rise in spreads following a monetary policy tightening shock comes from the "excess bond premium" (EBP), that is, the part of the spread not explained by default risk. The EBP is commonly viewed as a barometer of the financial sector's risk-bearing capacity and prevailing liquidity conditions. This paper explores whether the way in which firms' risk profiles differ matters for how monetary policy passes through to credit costs.

To study this, the paper extends the standard EBP framework in order to allow for compensation for default risk to vary with two firm characteristics that investors observe and price: how sensitive a firm is to the business cycle (its cyclicality) and how volatile it is for firm-specific reasons (its idiosyncratic risk). The analysis brings this idea to the data by combining a large weekly panel of US corporate bonds since 2016 with firm-level stock market data and high-frequency measures of monetary policy surprises around Federal Reserve announcements. I find that firm risk profiles are important drivers of credit spreads and of how default risk is compensated.

Three additional findings emerge. First, at the aggregate level, monetary tightening still raises corporate spreads mainly by increasing the EBP rather than by sharply boosting compensation for expected default risk. However, under the new formulation, a larger fraction of the credit spread response to monetary policy shocks is explained by changes in compensation for default risk, although most of the average effect still goes through the EBP. Second, once the pricing of default risk is allowed to differ depending on firms risk profiles, fundamentals play a noticeably larger role for companies that are highly cyclical: for these firms, up to about one quarter of the additional spread widening after a contractionary policy surprise reflects higher compensation for default risk, compared with roughly eight percent under the traditional EBP calculation. In other words, using the augmented EBP reveals that fundamentals (default risk) play a bigger role in the heterogeneous transmission to these firms' spreads than previously thought. Third, firms with high idiosyncratic risk do not display a significantly larger sensitivity of spreads to monetary shocks beyond what their default risk would already imply. This result intuitively aligns with the notion that a monetary shock is an aggregate disturbance: firms facing primarily idiosyncratic volatility are not disproportionately affected by macro shocks beyond what their default risk would suggest.

1 Introduction

How does monetary policy transmit to corporate bond spreads, and what is the role of firm-specific risks in determining the relative importance of these? A growing body of evidence shows that much of the impact of monetary tightening on corporate bond spreads operates through increases in the portion of spread that is not explained by compensation for default risks, that is, the excess bond premium (EBP), rather than through higher expected default losses (see, for example, Anderson & Cesa-Bianchi (2024), Chiţu et al. (2023) or Ferreira et al. (2023)). This contrasts with traditional theory (see Bernanke & Gertler (1995)), which predicts that a monetary tightening raises default risk and thus widens spreads via higher default compensation.

The EBP, first introduced by Gilchrist & Zakrajšek (2012), is typically interpreted as a measure of the risk-bearing capacity of the financial sector and should therefore go beyond compensation for risks associated with interest rate expectations or credit risk. It captures factors like market sentiment, liquidity conditions, and other macroeconomic uncertainties that affect bond prices. For that, an increase in the EBP reflects a reduction in the risk-bearing capacity of the financial sector.[1] The pricing of corporate bonds is influenced by a variety of factors beyond traditional credit risk metrics. Bonds with similar credit ratings or default probabilities can trade at significantly different yields, suggesting that factors beyond fundamental default risk are at work. Indeed, non-fundamental factors, such as noise trading or behavioral biases, can substantially influence bond prices, causing them to deviate from their intrinsic values. Other considerations include market segmentation (see, for example, Holm-Hadulla & Leombroni (2022)) or differences in liquidity.

In this paper, I investigate the role of two concrete firm-level risk measures (a firm's cyclicality and its idiosyncratic risk) in shaping credit spreads and the heterogeneous response to monetary policy shocks. These risks are observable to investors to some extent, and investors may price

[1] This induces a contraction in the supply of credit and a deterioration in macroeconomic conditions, and has been shown to have predictive power over economic activity. In particular, Gilchrist & Zakrajšek (2012) show that positive shocks to the EBP that are orthogonal to the current state of the economy lead to declines in economic activity and asset prices. They show that the excess bond premia provides a timely and useful gauge of credit supply conditions and that a reduction in the supply of credit (an increase in the excess bond premium) causes a drop in asset prices and a contraction in economic activity through the financial accelerator mechanisms (see Bemanke & Gertler (1989), Kiyotaki & Moore (1997), Bernanke et al. (1999), Hall (2011)).

bonds differently *ex ante* depending on a firm's risk profile. The central hypothesis is that the standard EBP calculation, which assumes a linear relationship between default risk and spreads, may overlook nonlinearities: investors could demand different compensation for a given change in default risk depending on the firm's risk profile. In particular, the premium required for a rise in default risk might be higher for firms that are already very sensitive to the business cycle, compared to more stable firms.

The contribution of the paper is twofold: first, after estimating firm-level exposure to cyclical and idiosyncratic risks, I reformulate the EBP to account for these and, second, I test how this affects the heterogeneous transmission of monetary policy shocks into credit spreads components. I reformulate the EBP computation to allow for, first, heterogeneity in default-risk pricing across firms and, second, for changes in default risk to translate into changes in compensation for default risks that depend on firm-level cyclical and idiosyncratic risks. Intuitively, this means that, for example, a change in a firm's default probability can have a larger impact on its corporate bond spread if the firm is highly cyclical. I find that these two types of risks are important determinants of credit spreads.

Second, I empirically evaluate how accounting for these nonlinear effects alters the transmission of monetary policy shocks through credit spreads. In particular, I examine whether the share of the impact of a monetary policy shock that is attributed to default-risk compensation vs. the EBP differs when firm risk profiles are taken into account, relative to the traditional approach in the literature. I find that under the new formulation, a larger fraction of the credit spread response to monetary policy shocks is explained by changes in compensation for default risk, although a large proportion of the transmission still goes through the EBP. Moreover, for firms with more cyclical risk profiles, up to one fourth of the additional increase in spreads that follow a contractionary monetary shock is driven by higher compensation for default risk, whereas only roughly 8% is attributed to default risk under the traditional EBP computation. In other words, using the augmented EBP reveals that fundamentals (default risk) play a bigger role in the heterogeneous transmission to these firms' spreads than previously thought. Second, there is a stark heterogeneity across risk dimensions: cyclical risk emerges as an important driver of differential spread responses, while idiosyncratic risk does not. Bonds of firms with high idiosyncratic risk do not exhibit any excess sensitivity to monetary policy shocks: their spreads move in line with those of other firms. This result intuitively aligns with the notion that a monetary shock is an aggregate disturbance: firms facing primarily idiosyncratic volatility are not disproportionately affected by macro shocks beyond what their default risk would suggest.

These findings contribute to the literature on the credit channel of monetary policy by highlighting the importance of firm heterogeneity. They show that the formulation of default-risk compensation plays a crucial role in shaping the EBP, and in measuring how monetary shocks transmit through credit markets. Finally, they show that cyclical risk, and not idiosyncratic risk, drives heterogeneous responses to monetary policy shocks.

The paper is organised as follows. Section 2 reviews the literature; Section 3 presents the data sources; Section 4 presents the methodology to compute firm-level cyclical and idiosyncratic risks; Section 5 computes and presents the reformulated excess bond premia; Section 6 studies the heterogeneous response of corporate bond spreads to monetary policy shocks; and Section 7 concludes.

2 Related Literature

This paper is, first, related to the strand of the literature that focuses on understanding the drivers of corporate bond prices and, in particular, on the so-called credit spread puzzle, that is, the finding that less than one-half of the variation in corporate bond spreads can be attributed to the financial health of the issuer (see for example Elton et al. (2001), Collin-Dufresne et al. (2001), Houweling et al. (2005), and Driessen (2005). The seminal paper Gilchrist & Zakrajšek (2012) decomposes the credit spreads into a component capturing the countercyclical movements of spreads in expected defaults, and a component representing the cyclical changes in the relationship between the measured default risk and credit spreads, that is, the EBP. From a European perpective, De Santis (2016) focuses on corporate bonds in the euro area and distinguishes between credit risk, systematic risk, and a "pricing error"; and Bleaney et al. (2016) shows that bond spreads are a robust predictor of economic activty across European countries.

A large group of studies have focused on understanding the drivers of cross-sectional heterogeneities in corporate bond prices. Bonds with similar credit ratings or default probabilities can trade at significantly different yields, suggesting that factors beyond fundamental default risk are at work. Empirical evidence supports this view: for example, Collin-Dufresne et al. (2001) find that the majority of monthly credit spread changes cannot be explained by firm-specific variables, and instead appear to be principally driven by local supply/demand shocks unrelated to credit risk or liquidity. Another key consideration is market segmentation and investor heterogeneity. Differences in who holds a bond can lead to differences in how it is priced and how it reacts to shocks. As a result, if the corporate bond market is segmented, similar bonds may carry different premia depending on their investor base.[2] Holm-Hadulla & Leombroni (2022) study the corporate bond yields response to European Central Bank policy announcements depending on the type of investors, and find that corporate bonds with higher mutual fund shares exhibit larger reactions to announcements. In a similar line, Kirti & Singh (2024) focus on the role of insurers. A further driver of cross-sectional heterogeneity is liquidity differences across bonds. Bao et al. (2011) show that the illiquidity in corporate bonds is substantial, significantly greater than what can be explained by bid–ask spreads, and establish a strong link between bond illiquidity and bond prices. Calomiris et al. (2022) study the role of indexation in driving increased demand. While all these factors drive cross-sectional heterogeneities in corporate bond spreads, what drivers the cross-sectional heterogeneity of the bond-level excess bond premia has remained understudied.

Firm risks have indeed been shown to reflect in corporate bond spreads. Campbell & Taksler (2003) uses panel data for the late 1990s to show that idiosyncratic firm-level volatility can explain as much cross-sectional variation in yields as can credit rating. Crouzet & Mehrotra (2020) compare corporate bond spreads for small and large firms over the business cycle. Finally, Gabaix et al. (2025) propose upgrading credit pricing and risk assessment through embeddings. In this paper I aim at complementing those findings by showing how firms' risk profiles are important drivers of compensation for default risk and, therefore, of the resulting EBP computation.

An separate strand of the literature is one that focuses on the heterogeneous transmission of monetary policy shocks to corporate bonds. Palazzo & Yamarthy (2022) find a positive relation between corporate credit risk and unexpected monetary policy shocks during FOMC announcement days. Moreover, Anderson & Cesa-Bianchi (2024) examine how heterogeneity in firm leverage influences the sensitivity of the EBP to monetary policy shocks. Extisting research has documented a heterogeneous response of the EBP to monetary and global risk shocks (see Chiţu et al. (2023)), and to monetary policy shocks across risk-aversion regimes (see Domenech Palacios & Jančoková (2025)). Similarly, Ferreira et al. (2023) posit that firms with

[2] For example, if traditional long-term investors (e.g. pension funds, banks, insurance firms) avoid certain securities entirely (such as high-yield bonds or bonds that are just above the investment-grade cut-off and therefore assessed to be at risk of being downgraded), those bonds can end up concentrated in the hands of specialized investors who require higher excess returns.

high cyclicality of default risk experience a substantially larger rise in the EBP when market returns fall, and interpret the EBP as a measure the compensation investors require for the cyclicality of default risk. In this paper I pursue three goals: (i) quantify more generally how firms' risk profiles shape credit spreads; (ii) incorporate this channel into the measurement of compensation for default risk; and (iii) assess the heterogeneous transmission of monetary policy to credit spreads once heterogeneity in firms' risk compensation is taken into account.

3 Data

3.1 Bond-level credit spreads, equity prices, and additional firm-level information

I use Moodys' Analytics Credit Edge for corporate bond market data. The data tracks secondary market prices of corporate bonds of US listed firms and information of the issuing firm. I retrieve US data for non-financial firms, which is available since 2016. I keep senior unsecured bonds as in Gilchrist & Zakrajšek (2012) and keep only those bonds with maturity longer than one year. The Moody's CreditEdge dataset provides secondary-market option-adjusted spreads for publicly listed firms, resulting in 1,592 U.S. companies and 21,654 bonds. The data are at a weekly frequency, with observations recorded each Friday.

The data contains information on bond characteristics, such as maturity date, coupon, duration, yield to maturity, amount outstanding, and rating, among others. It also contains firm-level information and balance sheet data, including total book assets, total current liabilities, current debt, asset value, asset volatility, and default point.

I obtain stock price data from Datastream. After merging the two sources, the final sample includes 1,361 firms (19,978 bonds) for which both credit spreads and stock price data are available.

3.2 Monetary policy surprises

To address endogeneity issues related to the fact that variations in the federal funds rate are driven by the Federal Reserve's endogenous response to aggregate economic conditions, it is common to use high frequency identification techniques. That implies using the change in the federal funds rate implied from a federal funds futures contract computed using a narrow 30-minute window of time around a monetary policy announcement by the FOMC, as pioneered by

Kuttner (2001) and followed by Gurkaynak et al. (2005) and Swanson (2021). The underlying idea is that, because futures contracts provide a measure of market participants' expectations of future interest rates, the high frequency reaction is interpreted as a noisy proxy for an exogenous monetary policy shock. Because of the short time horizon, the measure is not contaminated by other unrelated news.

However, it is possible that the monetary policy event not only contains information about monetary policy but also about the central bank's assessment of the economic outlook, as shown in Jarociński & Karadi (2020). I use shocks constructed following their methodology to isolate pure monetary policy news from other contemporaneous non-monetary information embedded in interest rate surprises.[3] Figure A.1 plots the obtained series of shocks, and Table A.1 summarises the statistical properties of the obtained shocks.[4]

4 Cyclical and idiosyncratic risks

4.1 Measuring cyclical and idiosyncratic risks

Using firm-level stock return data for U.S. listed firms and an aggregate market index at daily frequency, I first compute firm-level measures of cyclical and idiosyncratic risks by analysing each firm's sensitivity to aggregate market fluctuations, as well as the volatility of its returns unexplained by market movements.

Specifically, I calculate log returns for the aggregate market index and for each firm i at a monthly frequency as:

$$r_t^m = (\ln(p_t^m) - \ln(p_{t-1}^m)) \times 100, \qquad r_t^i = (\ln(p_t^i) - \ln(p_{t-1}^i)) \times 100$$

where p_t^m and p_t^i denote the prices at time t. I proxy market movements with the SP500 index. The sample covers the period from 2000 to 2024, comprising 1361 publicly traded U.S. firms drawn from Datastream, consistent with the coverage available in Moody's as described

[3]The decomposition is achieved by a simple rotation of the covariance matrix of high-frequency movements in interest rates and stock market prices in a narrow window around the policy announcement. The identifying restriction is based on the following assumption: shocks that lead to a negative comovement of interest rate and equity prices are interpreted as driven by monetary policy news, while shocks that lead to a positive comovement of interest rates and equity prices are interpreted as driven by nonmonetary news.

[4]Due to the outlier event on 20 March 2020, I replace the corresponding shock with zero. This adjustment does not affect the results in the following sections, as either COVID-related dummies are included or the period is excluded from the analysis.

in Section 3.

In a second stage, for each firm i, I estimate the following linear factor model:

$$r_t^i = \alpha^i + \beta^i r_t^m + \varepsilon_t^i \tag{1}$$

where β^i represents the firm's return sensitivity to market movements and ε_t^i is the residual return component. This framework closely follows the standard market model, consistent with the Capital Asset Pricing Model (CAPM), in which β^i serves as the measure of systematic risk, and the variance of the residuals captures firm-specific idiosyncratic risk. The coefficients are estimated using ordinary least squares (OLS).[5]

I interpret the estimated β^i as follows:

$$\begin{cases} \beta^i > 1, & \text{highly cyclical: firm } i \text{ is more sensitive than the market,} \\ 0 < \beta^i < 1, & \text{pro-cyclical: firm } i \text{ moves with the market, but less so,} \\ \beta^i < 0, & \text{counter-cyclical: firm } i \text{ moves opposite to the market.} \end{cases}$$

To quantify idiosyncratic risk, I calculate the variance of the regression residuals ε_t^i, which measures the extent of variation of the return unexplained by market movements and thus indicates how much firm i returns are driven by idiosyncratic factors rather than systematic co-movement with the market. I therefore proxy cyclical risk with the firm-level beta coefficient and idiosyncratic risk with the variance of the regression residuals from the market model. This approach corresponds to an *ex-post*, realized estimation of systematic and idiosyncratic risk exposures based on historical returns. This simple method is standard in the literature (see, for example, Bekaert et al. (2012) or Bartram et al. (2018)).

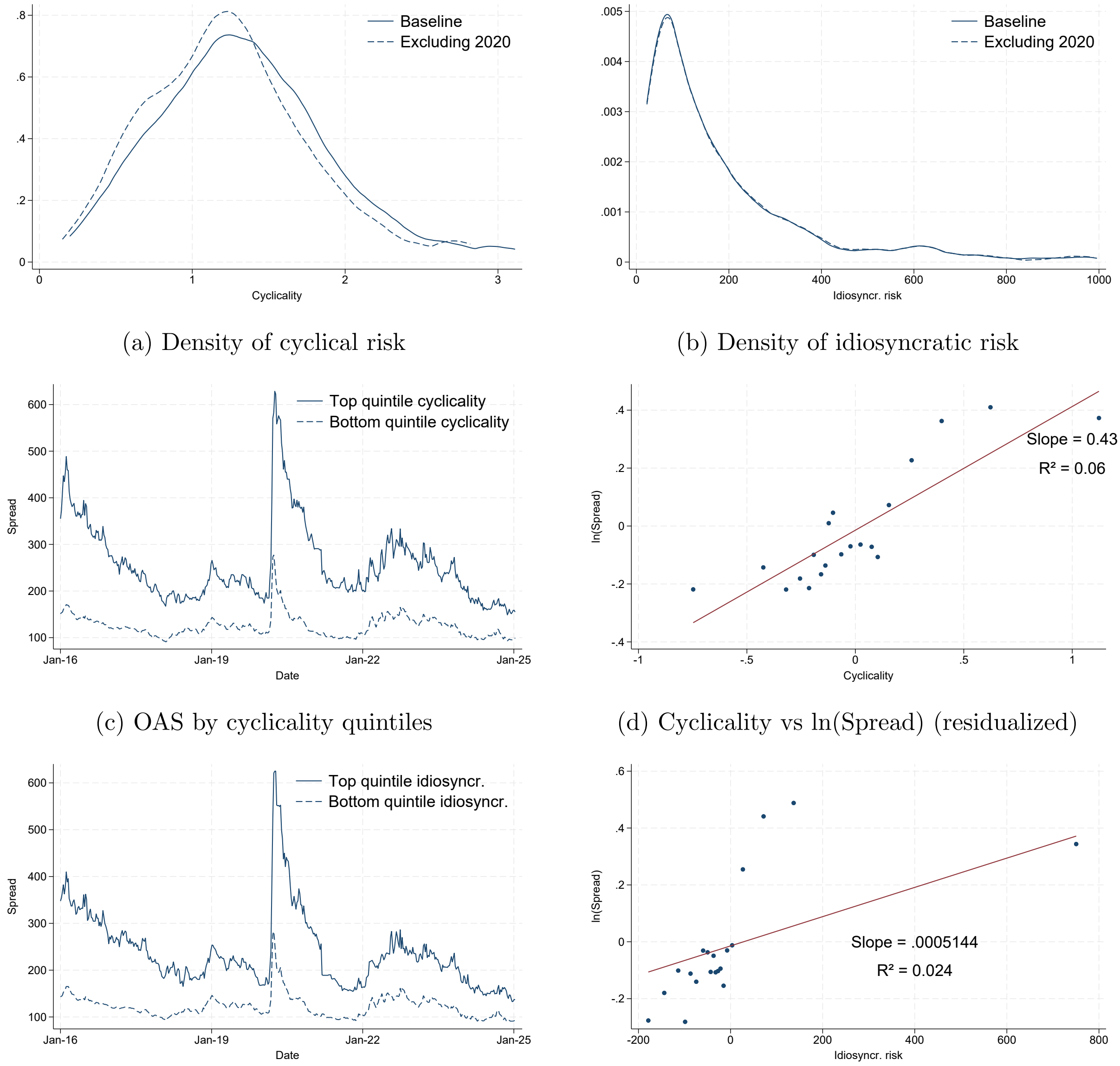
Figures 1a and 1b display the density distributions of computed cyclical and idiosyncratic firm-level risks.[6] , [7] To assess the role of Covid-related disruptions, and the potential introduction of atypical dynamics, in the computation I repeat the analysis excluding 2020 (dashed line).

[5] Note that, since the focus is on the co-movement between a firm's returns and that of the market, rather than on the co-movement of compensation for risk, the risk-free rate is not subtracted. In contrast, the CAPM model typically emphasizes compensation for risk above the risk-free rate (systematic risk), thereby isolating excess returns. For reference, Figure A.2 displays the distribution obtained when computing cyclical and idiosncratic risks as excess returns compared to the baseline and shows a similar distribution of firm-level betas.

[6] Tables A.2 and A.3 report key moments and percentiles of the resulting distributions of cyclicality and idiosyncratic risks, where the rightmost column shows the results excluding the year 2020.

[7] To mitigate the influence of extreme values, I winsorize firm-level betas at the 1st and 99th percentiles.

Figure 1: Distribution of risk and bond spread relationships by firm-level risks



(a) Density of cyclical risk

(b) Density of idiosyncratic risk

(c) OAS by cyclicality quintiles

(d) Cyclicality vs ln(Spread) (residualized)

(e) OAS by idiosyncratic risk quintiles

(f) Idiosyncratic risk vs ln(Spread) (residualized)

Notes: Top row: density distributions of cyclical (left) and idiosyncratic (right) risks (2000–2024; "Excl. 2020" excludes 2020 observations). Middle row: median OAS by cyclicality quintiles (left) and vinned scatterplot for cyclicality vs ln(Spread), residualized for date and industry fixed effects (right). Bottom row: median OAS by idiosyncratic risk quintiles (left) and binned scatterplot for idosyncratic vs ln(Spread), residualized for date and industry fixed effects (right).

4.2 Cyclical and idiosyncratic risks, and credit spreads

Figures 1c and 1e illustrate that bonds issued by firms in the highest quaintile of cyclicality or idosyncratic risks exhibit a systematically higher median option-adjusted spreads compared to those in the lowest quantile. Indeed, the simple correlation between the measure of firm-level cyclicality and option-adjusted spreads is 23%, while the correlation between firm-level idiosyncratic risk and spreads is 17%. Figures 1d and 1f show that this relationship remains statistically significant even after controlling for time and industry fixed effects.[8]

5 Augmented Excess Bond Premia

5.1 Measuring default risk

The distance to default (DD) measure is grounded in the structural credit risk model of Merton (1974). In this framework, a firm's equity can be viewed as a call option on the firm's assets, with a strike price equal to a critical default threshold (the "default point"). Intuitively, shareholders will choose to default (and let equity become worthless) if the market value of assets falls below the promised debt obligations, since equity has limited liability. Conversely, if asset value exceeds the debt at maturity, shareholders pay off the debt and retain the residual value. This option-theoretic view implies that the probability of default is determined by three key inputs.

Under Merton's model, the distance to default (DD) summarizes how far the firm's asset value is from the default threshold in units of asset volatility. The firm's assets are modeled to follow a stochastic process (e.g. geometric Brownian motion) with drift μ and volatility σ_V. In continuous-time form, for a given time horizon T, the distance to default is defined as the number of standard deviations that the asset value at horizon is above the default point. Mathematically, if V_t is the current asset value and F is the default point (debt face value due at T), Merton's model implies:

$$\mathrm{DD}_t = \frac{\ln\left(\frac{V_t}{F}\right) + \left(\mu - \frac{1}{2}\sigma_V^2\right) T}{\sigma_V \sqrt{T}}$$

This expression is derived from the distribution of V_T under log-normal dynamics. It represents the distance (in standard deviation units) between the expected log-asset value at time T and the log-default threshold. A larger DD indicates that the firm's assets would have to drop by many σ_V shocks before hitting F, hence a lower default risk, whereas a small or negative DD indicates proximity to distress.

In practice, I use the methodology implemented by Moody's KMV/CreditEdge to construct a one-year horizon distance to default. T is set at $T = 1$ (one year), and the default point F is defined based on the firm's liabilities. Rather than using the total book value of debt as F (as in

[8] Figures A.3 and A.4 present analogous results when using the alternative risk measures excluding 2020.

the simplest Merton formulation), Moody's defines the default point empirically as short-term liabilities plus one-half of long-term liabilities. This adjustment reflects the observation that most firms default when asset values fall to roughly that level of obligations (short-term debt and about half of long-term debt) rather than the full face value of long-term debt (see Banerjee et al. (2020)).

Given these inputs, a firms's distance to default on any date t is calculated as:

$$\text{DD}_t = \frac{V_t - F_t}{V_t\,\sigma_V}$$

which is algebraically equivalent to the one-year version of the Merton DD formula above under the simplifying assumption of zero drift.[9] This ratio measures the buffer (in asset value terms) between the firm's assets and its default point, relative to asset volatility. Intuitively, it informs of how many standard deviation moves in V_t would erase the buffer and lead to default. [10]

5.2 The excess bond premia

The EBP is obtained first by regressing the log of option-adjusted credit spreads (the difference between the return of a given bond j issued by firm i at time t and the risk-free rate at the same maturity) on the computed firm-specific measure of expected default (distance to default DD_t^i) and a vector of bond-specific characteristics Z_{jt}^i:[11]

$$\ln S_{jt}^i = \delta\,\text{DD}_t^i + \gamma' Z_{jt}^i + \varepsilon_{jt}^i \tag{2}$$

where the zero-mean disturbance ε_{jt}^i represents a "pricing error." The vector Z_{jt}^i includes duration, amount outstanding, coupon rate, and an indicator variable that equals one if the bond is callable; industry (NAICS3) and rating fixed effects are included as controls.

Two minor deviations from the baseline specifications in the literature arise. First, because the bond issuance dates are unavailable, I cannot include age as a control. Given that age is not

[9] See Jessen & Lando (2015).

[10] Figure A.5 plots the evolution of the cross-sectional median and interquartile range of the resulting distance to default. The data suggest that the distance to default of firms varies over time and over the economic cycle.

[11] Note that the spreads are computed over a hypothetical Treasury security with the same cash flows as the underlying corporate bond. It is calculated discounting the cashflow sequence of the bond by continuously-compounded zero-coupon Treasury yields obtained from the US Treasury yield curve estimated by Gürkaynak et al. (2007).

a statistically significant determinant of option-adjusted spreads in Anderson & Cesa-Bianchi (2024), I assume that omitting it does not materially affect the results. Second, Gilchrist & Zakrajšek (2012) augment their baseline by interacting dummy variable indicating whether a bond is callable with the control variables and including the three yield-curve factors (level, slope, and curvature). By contrast, and consistent with Anderson & Cesa-Bianchi (2024), I rely directly on the option-adjusted spread supplied by the data provider instead of constructing those interaction terms.

Assuming normally distributed disturbances, the predicted level of the spread for bond j issued by firm i at time t is given by:

$$\hat{S}^i_{jt} = \exp\left[\hat{\delta}\,\mathrm{DD}^i_t + \hat{\gamma}' Z^i_{jt} + \tfrac{1}{2}\hat{\sigma}^2\right] \tag{3}$$

where $\hat{\delta}$ and $\hat{\gamma}$ are the OLS estimates and $\hat{\sigma}^2$ is the estimated variance of the disturbance ε^i_{jt}. This represents the expected spread given the fundamentals.

The EBP is then defined as the difference between the observed spread and the predicted spread:

$$\mathrm{EBP}^i_{jt} = S^i_{jt} - \hat{S}^i_{jt} \tag{4}$$

This difference captures how much the market prices firm-specific risks above and beyond fundamentals. The aggregate EBP is computed as the cross-sectional average across bonds.

5.3 Augmenting the bond-level excess bond premia

Using the estimated firm-level measures of cyclical risk $Cycl^i$ and idiosyncratic risk IS^i outlined in Section 4, I augment the standard EBP regression to capture this additional sources of variation. The underlying rationale is that investors can *ex ante* account for these characteristics, thereby adjusting both the risk compensation they demand and their response to changes in default risk accordingly. The dependent variable, $\ln S^i_{jt}$ is the log of the option adjusted spread of a bond:

$$\ln S^i_{jt} = \beta_1\,\mathrm{DD}^i_t + \beta_2\,Cycl^i + \beta_3\,(Cycl^i \times \mathrm{DD}^i_t) + \beta_4 \mathrm{IS}^i + \beta_5\,(\mathrm{IS}^i \times \mathrm{DD}^i_t) + \gamma' Z^i_{jt} + \varepsilon^i_{jt} \tag{5}$$

where DD^i_t is the firm's distance-to-default, $Cycl^i$ measures the cyclicality of firm i's equity returns, IS_t^i is firm i's idiosyncratic risk, Z_{jt}^i is the vector of bond-level controls (in particular, I include the log of duration, log of amount outstanding, the log of coupon, and an indicator variable indicating whether the bond is callable), β_2 and β_4 capture the sensitivity of spreads to firm cyclical and idiosyncratic risks, respectively; and β_3 and β_5 capture the differential sensitivity of changes in default risk to spreads depending on firms' risks. ε_{jt}^i is the residual capturing the unexplained component: the bond-level the EBP. As in Gilchrist & Zakrajšek (2012), the regression is estimated by OLS, and the standard errors are double clustered at the firm and date dimensions, and are therefore robust to both cross-sectional dependence and serial correlation (see, for example, Cameron et al. (2011)).

Table 1 presents the results. The first column reports the baseline results with the specification as in Equation 2. The magnitude of the coefficient for distance to default is similar than that in Gilchrist & Zakrajšek (2012), which suggests that a one percent increase in the measure (that is, a decreased risk of default) is associated with a 9.2% decrease in (option-adjusted) bond spread. The R-squared is also similar to the 0.649 that is obtained in the baseline specification in Gilchrist & Zakrajšek (2012), which shows that default risk and bond-specific controls capture a large majority of the unconditional variation in credit spreads.

In Column 2, I introduce two additional variables: one measuring the firm's cyclicality of risk, and another capturing the interaction between default risk and cyclicality. The positive coefficient on the former indicates that investors demand higher compensation, on average, to finance firms whose risk profiles are more cyclical. The significant interaction term with distance to default suggests that investor sensitivity to changes in default risk intensifies when firms exhibit greater cyclicality of risk.

In Column 3 I replicate this approach using idiosyncratic risk. The results echo those for cyclical risks: *ceteris paribus*, investors demand higher premiums to hold bonds issued by firms with greater exposure to idiosyncratic shocks. Moreover, the interaction effect indicates that investor responsiveness to shifts in default risk intensifies when idiosyncratic risk is higher.

In Columns 4 and 5, I allow for a more flexible approach, where different effects for increased cyclicality of risk (Column 4) and idiosyncratic risk (Column 5) are allowed for each different industry. For that, I introduce two industry-level interaction terms: Industry fixed effects $\times$ cyclicality of risk, and Industry fixed effects $\times$ idiosyncratic risks, respectively. These terms capture the idea that firms within certain industries may be penalized differently (e.g., bonds issued by firms with an average level of cyclicality might be more in demand if their industry

Table 1: EBP regression models

	(1) Baseline	(2) Cyclicality	(3) Idios. risk	(4) Cyclicality	(5) Idios. risk	(6) Cyclicality idiosincr. risk
Cyclicality × DD		-0.020***		-0.037***		-0.024**
		(0.008)		(0.011)		(0.012)
Idiosyncratic × DD			-0.029***		-0.057***	-0.042***
			(0.006)		(0.012)	(0.012)
Distance to default (DD)	-0.092***	-0.094***	-0.095***	-0.096***	-0.097***	-0.097***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)
Cyclicality		0.086***				
		(0.031)				
Idiosyncratic risk			0.113***			
			(0.023)			
Duration	0.337***	0.337***	0.338***	0.340***	0.340***	0.342***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
Par value	-0.047***	-0.047***	-0.047***	-0.046***	-0.047***	-0.044***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Coupon	0.470***	0.467***	0.467***	0.464***	0.463***	0.461***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Callable	-0.040	-0.041	-0.039	-0.045*	-0.038	-0.045*
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)
Observations	2,754,288	2,754,288	2,754,288	2,754,288	2,754,288	2,754,288
Rating FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Industry FE × Cycl.	NO	NO	NO	YES	NO	YES
Industry FE × Idios.	NO	NO	NO	NO	YES	YES
Adjusted R^2	0.686	0.687	0.688	0.692	0.692	0.696
Within R^2	0.397	0.399	0.401	0.408	0.408	0.416

Notes: The table presents the results of the estimation specification in Equation 5 and its variants described in the text. Firm cyclical and idiosyncratic risks are computed as described in Section 4. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Idiosyncratic and cyclical risk variables have been standardised such that a unit increase is a one-standard deviation increase of the distribution. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

is highly cyclical). A similar mechanism applies for idiosyncratic risks. The results remain consistent: both interaction coefficients are strongly significant, reinforcing the idea that the impact of default risk on spreads is amplified when firm-specific cyclicality and idiosyncratic risks are high. Finally, Column 6 combines both cyclical and idiosyncratic risks.

Overall, the results indicate that accounting for firm exposure to cyclical and idiosyncratic risks and, especially, their dynamic interactions with default risk, is crucial in explaining bond spreads. Including these controls improves explanatory power: across Columns 1 to 6, the within R^2 increases from 0.397 to 0.416, signaling that these additional characteristics account for part of the variation in spreads beyond what is usually controlled for. Omitting these additional controls could result in mistakenly attributing the unexplained component in Column 1 solely to shifts in investors' risk-bearing capacity.

Table A.4 displays the results when cyclical and idiosyncratic risks are computed excluding 2020. Table A.5 replicates the baseline results, now including an extra set of controls: a separate dummy for each observation in 2020, with the aim of capturing with these the abnormal dynamics during the COVID-19 period—driven by large market volatility and Fed interventions.[12] By doing so, the unusual cross-sectional average fluctuations in corporate bond spreads are absorbed in the analysis, shielding the core model estimates from distortion.[13]

5.4 Comparing the measures of EBP

I define the bond-level EBP as the difference between the observed bond spread and its predicted value from Equation (5) (computed analogously to Equation 3), isolating the portion of credit spreads not explained by compensation for default risk, or bond characteristics. In what follows, I compare the EBP that results from computing the residuals in Column 1 in Table 1 ("Traditional EBP") and those from Column 6 in the same table ("New EBP").

Figure 2a shows the distribution density resulting from the two different computations. Both Traditional and New EBPs are asymmetrical, with a longer right tail, indicating that extreme positive values of EBP are more common than extreme negative ones. Both distributions are centered around a similar level.[14] Differences lie in dispersion and tail behavior: the Traditional

[12] For example, Carriero et al. (2024) add a dummy for each month from March 2020 onward to absorb the COVID shock.

[13] These dummies effectively remove pandemic data from influencing residuals, preserving the estimation of underlying dynamics. The result is a model that treats each cross-section in 2020 as its own outlier mitigating their impact on parameter estimates.

[14] Note that, because of the correction resulting from Equation 3, the resulting bond-level EBP can be negative.

EBP captures more extreme positive premia, driving up the right tail, while the New EBP smooths or dampens these outliers, producing a more symmetric distribution. The left tail of the new EBP is wider, as the density declines more gradually than that of the traditional EBP. The cross-sectional distribution of the excess bond premia can be explained by a number of reasons, including differences in the liquidity of the bonds (see, for example, Calomiris et al. (2022), Goldberg & Nozawa (2021) and Galliani et al. (2014)), market segmentation (see Chen et al. (2014) and Holm-Hadulla & Leombroni (2022)), or pure noise.

Figure 2b shows the time series of the cross-sectional average of the bond-level EBP. Although both series share a broadly similar trajectory, notable differences emerge in their dynamic behavior. Figure 2c illustrates the evolution of the cross-sectional tails. Notably, much of the difference in cross-sectional heterogeneity arises from the dynamics of the left tail. An interesting exception is the COVID period, during which both series moved similarly in the left tail, while the divergence became more pronounced in the right tail. This pattern is intuitive: the new formulation captures the additional compensation investors may demand for riskier firms, likely concentrated in the right tail, thereby increasing the compensation for risk *ex ante* and dampening the rise in EBP for those firms.

Figure 2d shows the dispersion of the cross-sectional EBP (measured as the distance between the 90th and the 10th percentiles) and Figure 2e the skewness of the EBP (measured as the Kelly skewness).[15] While the difference in dispersion in EBP appears more evident in times where the average EBP is lower, this could be due to increased compensation for risk that investors might require for certain firms. In times where the EBP is higher, the difference in dispersion is dampened.

6 Monetary policy transmission through credit spreads

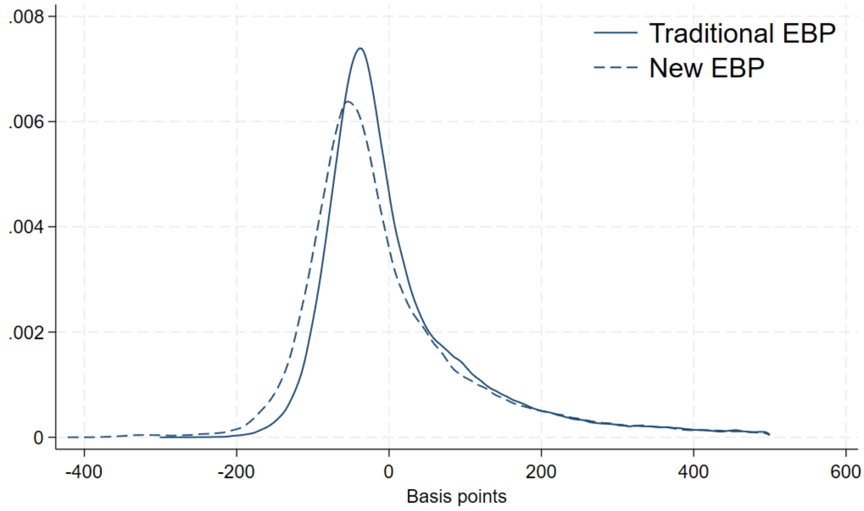
6.1 Average effects of monetary policy across credit spreads components

I analyse how monetary policy transmits to credit costs by components (compensation for default risk vs EBP) with a particular interest in understanding whether there are differences in how monetary policy is transmitted depending on the approach taken to compute the EBP. Decomposing bond spreads into a fitted value ($\hat{\nu}_{j,t}$) and the residual, that is, the bond-level

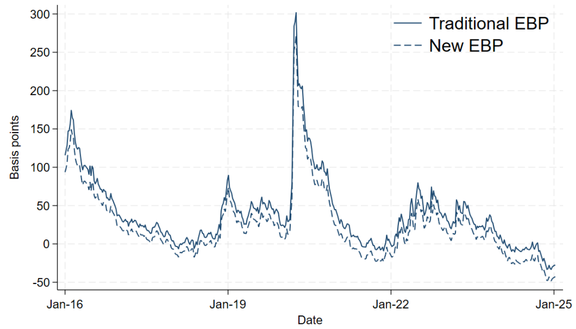
Moreover, because of the fixed effects, residuals from Equation 5 are demeaned within each group, and therefore the center of both distributions can differ slightly.

[15]Figure A.6 depicts the distribution patterns when comparing the 75th and 25th percentiles instead.

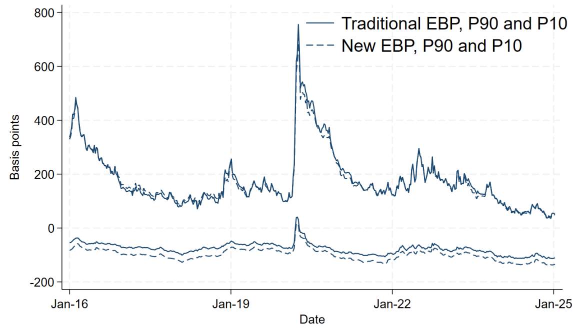
Figure 2: EBP: distribution, time series, and moments



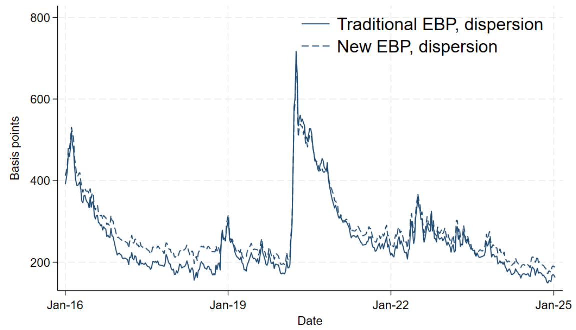
(a) Distribution density of EBP



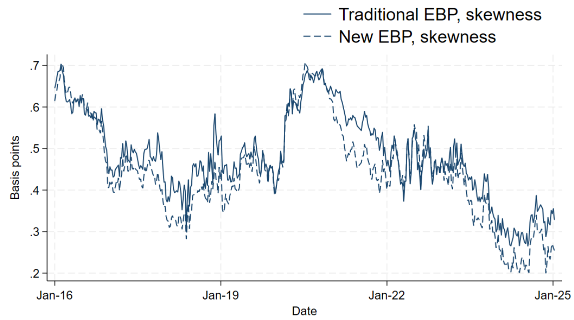
(b) EBP: a time series comparison — Average EBP



(c) EBP: a time series comparison — Percentiles



(d) EBP: moments — Dispersion



(e) EBP: moments — Kelly skewness

Notes: "Traditional EBP" ("New EBP") refers to the bond-level EBP resulting from specifications in Column 1 (Column 6) in Table 1. Density distribution of bond-level EBP. The left chart in second row compares the average bond-level EBP over time. The right chart compares the 90th and 10th percentiles of the cross-sectional distributions.The left chart in third row depicts the difference between the 90th and the 10th cross-sectional percentiles. The right chart compares the cross-sectional Kelly skewness.

EBP ($ebp_{j,t}$), I estimate how each of the components of credit spreads respond to monetary policy shocks. Although corporate bond spreads are observed at a weekly frequency, the data reflect prices as of Fridays. Since FOMC policy decision and statement release typically occur on Wednesdays, the measured response captures the effect of the monetary policy shock two business days after its announcement.

The window used is slightly larger than that of other high-frequency studies in the literature. As Anderson & Cesa-Bianchi (2024) note, corporate bonds, particularly high-yield bonds, tend to be less liquid than other assets such as equities and Treasuries. Allowing for a longer time window enables a more complete absorption of the shock. This approach is more conservative than that of other studies in the literature, such as Gertler & Karadi (2015) and Gilchrist et al. (2024), which use a two-week window to analyze how corporate bond spreads respond to monetary policy surprises.

I start with a specification which aims at estimating the average effect of monetary policy shocks on each component. To this end, I follow Jarociński & Karadi (2020) in defining US monetary policy shocks as explained in Section 3. I normalise the size of the shock so that it corresponds to a 25 basis points increase in the one year Treasury bill. In particular I estimate the following specification:

$$\mathrm{y}^i_{j,t} = \alpha^i_j + \beta\varepsilon^m_t + e^i_{j,t} \tag{6}$$

where: $y^i_{j,t} = [\Delta cs^i_{j,t}; \Delta\hat{\nu}^i_{j,t}; \Delta ebp^i_{j,t}]$ for bond j issued by firm i; α_j are bond fixed effects, ε^m_t denotes the monetary policy shock.

Table 2: Credit spreads, expected default, EBP: average effect

	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
Monetary policy surprise	9.929**	0.754**	0.925**	9.160**	8.461**
	(4.518)	(0.293)	(0.359)	(4.379)	(4.115)
Observations	2,878,495	2,874,153	2,719,461	2,874,153	2,719,461
R-squared	0.087	0.085	0.080	0.083	0.081
Covid dummies	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

Notes: The table presents the results of the estimation specification in Equation 6. Columns 2 and 4 have as dependent variable the fitted values and the residual resulting from the specification in Column 1 in Table 1. Columns 3 and 5 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Covid dummies refer to a separate dummy for every weekly observation from March 2020 until end of 2020. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. *** p<0.01, ** p<0.05, * p<0.1

Table 2 presents the baseline results. Column 1 shows that, on average, a 25 basis point monetary policy tightening causes an increase in corporate bond spreads of almost 10 basis points. The remaining columns decompose this effect. Specifically, Columns 2–3 isolate the portion of the spread change explained by compensation to default risk and bond characteristics, that is, the fitted values from Equation 2, while Columns 4–5 examine the contribution of changes in the EBP. Columns 2 and 4 use the "traditional" computation of the EBP, whereas Columns 3 and 5 apply the "new" approach introduced in Column 6 of Table 1. Two key findings emerge. First, under the new decomposition, a larger share of the transmission operates through firm and bond fundamentals, and a smaller share through investors' risk-bearing capacity. Second, even after accounting for these fundamentals and their interaction with firm-level risk of default, the bulk of the variation in spreads is still attributable to changes in the EBP.

The results in Columns 2 and 4 are consistent with Anderson & Cesa-Bianchi (2024), in that the coefficient on the EBP is substantially larger than that on the fitted values. A difference in the magnitude of all coefficients emerges, but this is likely due to the fact that the time window in my analysis is shorter, *i.e.* around 2 days after the announcement (compared to 5 in their study). However, unlike their findings, I do detect a statistically significant effect of monetary policy shocks on the fitted values for both measures of the EBP.[16] While a very large proportion of the transmission goes through increased excess bond premia, this reflects a lower risk bearing capacity of the financial sector as monetary policy moves tend to transmit via intermediation rather than directly pushing up expected default probabilities overnight. This could respond to firms typically reacting slowly and ratings not changing in lock-step with rate moves, while market liquidity (see for example Adrian & Shin (2009) and, for the case of quantitative easing, Boneva et al. (2022)), inventory space and sentiment can react quickly, pushing upwards the EBP in a short window.

Table A.7 presents the decomposition of credit spreads based on the estimates from Column 5 of Table 1, where only cyclical-risk compensation is incorporated. In contrast, Table A.6 reports the results corresponding to Column 4, which isolates idiosyncratic-risk compensation. Strikingly, substantial deviations from the traditional EBP framework emerge only when cyclical risks are considered.

[16]The authors note that, although they do not find a statistically significant effect, default risk does respond to monetary policy shocks.

6.2 Heterogeneous effects of monetary policy across credit spreads components

Exploiting the cross-sectional dimension of the dataset, I ask: does monetary policy transmit in a heterogeneous manner across firms that are assessed as riskier? I consider how the response of credit spreads and its components vary across groups of firms: first, those that are considered highly cyclical compared with the rest of firms; and second, those considered highly exposed to idiosyncratic risks compared with the rest of firms. I estimate a specification with bond and sector-time fixed effects as follows:

$$\mathrm{y}^i_{j,t} = \alpha^i_j + \alpha^i_{s,t} + \beta_1\big(\varepsilon^m_t \times 1\{\mathrm{Risk}^i\}\ \big) + \beta_3 1\{\mathrm{Risk}^i\} + e^i_{j,t} \tag{7}$$

where, as before, $y^i_{j,t} = [\Delta cs^i_{j,t}; \Delta\hat{\nu}^i_{j,t}; \Delta ebp^i_{j,t}]$ for bond j issued by firm i; α_j are bond fixed effects, $\alpha^i_{s,t}$ are sector $\times$ time fixed effects, ε^m_t denotes the monetary policy shock, and $1\{\mathrm{Risk}^i\} = [1\{\mathrm{Cycl}^i\}; 1\{\mathrm{IS}^i\}]$ are indicator variables for whether the firm issuing the bond is highly cyclical and exposed highly to idiosyncratic shocks, respectively. I define high cyclicality as those firms that are above the median across the sample, and I consider a firm to be exposed highly to idiosyncratic shocks when its measure or risk lies above the median of the sample distribution. Additionally, I alternatively classify firms as risky when their measure lies above the median *within* their sector. I drop observations between March 2020 and December 2020 to avoid contamination from Covid-specific dynamics. As before, I use the two alternative decompositions of spreads into the fitted values and the EBP.

The baseline results are presented in Table 3a, which examines heterogeneous transmission to more cyclical firms, and in Table 3b, which focuses on heterogeneity in the transmission of monetary policy shocks among firms with greater idiosyncratic risk. Columns 2 and 4 decompose the effect shown in Column 1 into fitted values and EBP using the traditional approach. Columns 3 and 5 present the decomposition using the new approach, derived from Column 6 in Table 1, which incorporates additional fundamental factors in the calculation of the compensation for risk and the EBP.

In Table 3a, Column 1 shows that following a tightening monetary policy shock, corporate bond spreads of more cyclical firms increase by approximately 3.8 basis points more than those of less cyclical firms, suggesting heterogeneous transmission of monetary policy along this dimension. Examining the components, the new computation of the EBP indicates that a much

Table 3: Credit spreads, expected default, EBP: heterogeneity
(a) High cyclicality

	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × high cycl.	3.778**	0.297**	0.958***	3.447**	2.782*
	(1.662)	(0.145)	(0.301)	(1.675)	(1.629)
Observations	2,464,857	2,461,062	2,461,032	2,461,062	2,461,032
R-squared	0.205	0.407	0.377	0.202	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

(b) High idiosyncratic

	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × high idiosyncr.	5.871	-0.001	0.859*	5.909	4.930
	(3.911)	(0.182)	(0.450)	(3.832)	(3.488)
Observations	2,464,857	2,461,062	2,461,032	2,461,062	2,461,032
R-squared	0.205	0.407	0.377	0.202	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

(c) Credit spreads, expected default EBP: heterogeneity

	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × Q4 cycl.	0.405	-0.073	0.810*	0.583	0.625
	(2.537)	(0.187)	(0.427)	(2.471)	(2.577)
MP surprise × Q1 cycl.	-4.165*	-0.384**	-0.778***	-3.591*	-1.908
	(2.272)	(0.180)	(0.234)	(2.168)	(1.708)
Observations	2,605,560	2,601,511	2,461,032	2,601,511	2,461,032
R-squared	0.205	0.396	0.377	0.202	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

Notes: The table presents the results of the estimation specification in Equation 7. Columns 2 and 4 have as dependent variable the fitted values and the residual resulting from the specification in Column 1 in Table 1. Columns 3 and 5 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Data between March 2020 and December 2020 are excluded. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25-basis-points increase in the one-year Treasury bill. High cyclicality and idiosyncratic risks are indicator variables equal to one for those firms that are above the median across the sample distribution. *** p<0.01, ** p<0.05, * p<0.1

larger share of the pass-through operates through compensation for default risk than with the traditional computation. Specifically, around one-fourth of the increase in spreads is driven by higher compensation for default risk, compared with only about 8% when using the traditional EBP calculation.

In contrast, Table 3b shows that, while spreads of the firms with higher idiosyncratic risk tend to increase by more when hit by a tightening shock, the difference is not statistically significant. Intuitively, a monetary policy shock, being an aggregate disturbance, does not necessarily trigger a sharper increase in financing costs for firms more exposed to idiosyncratic risk. This could be both because investors already demand higher compensation for bearing those risks and because increases in default risk for such firms may be more closely tied to firm-specific rather than aggregate factors. However, the new decomposition of the spreads suggests that a larger proportion of this increase is explained by increased compensation for default risks.[17]

Table 3c further investigates heterogeneities in monetary policy transmission by examining whether bonds issued by firms in the tails of the distributions of cyclicality of risk experience differential transmission of monetary policy shocks. To this end, I incorporate indicator variables identifying whether the issuing firm falls into the top or bottom quartile of each distribution, along with interaction terms between these indicators and the monetary policy shock. The table shows that firms in the lowest quartile (i.e., the left tail of the cyclical risk distribution) benefit from a smaller pass-through of monetary policy shocks to corporate bond spreads. An opposite effect, albeit less strongly significant, is observed for firms in the highest quartile compared with the rest. As in earlier results, the new EBP decomposition suggests that a greater proportion of the spread increase operates through compensation for default risks than under the traditional EBP calculation.

Table A.10, meanwhile, confirms the weakness of heterogeneous monetary policy transmission to firms based on their exposure to idiosyncratic risk. This is consistent with earlier findings, and intuitive given the aggregate nature of monetary policy shocks. However, firms in the highest quartile of firm idiosyncratic risks experience larger compensation for default risks in the aftermath of a tightening shock.

[17] Tables A.8 and Table A.9 replicate the analysis with a within-industry classification of high cyclical and idiosyncratic risks. In particular, the results based on an alternative classification, where firms are defined as highly cyclical (exposed to high idiosyncratic risks) if they are above the median within their industry. The results suggest that the baseline classification offers stronger heterogeneous effects as in both the heterogeneous effect is much weaker when the risk profiles are defined within each industry.

7 Conclusions

In this paper, I investigate whether nonlinearities in compensation for default risk should be explicitly included when calculating the EBP. I demonstrate that firm-level idiosyncratic and cyclical risks are significant determinants of credit spreads, and I adapt the EBP computation to capture these effects. When these risk-based adjustments are incorporated, a larger share of the impact of a monetary policy shock on credit spreads is transmitted via increased compensation for credit risk.

I then analyze whether monetary policy shocks transmit heterogeneously depending on firm risk profiles, and I show that around one quarter of the additional effect of the shock on more cyclical firms is driven by compensation for default risks. In contrast, firms with high idiosyncratic risk do not exhibit any differential response: monetary shocks affect their bond spreads similarly to other firms. Overall, these findings highlight the importance of accounting for adjusted default-risk compensation for firm-level idiosyncratic and cyclical risks.

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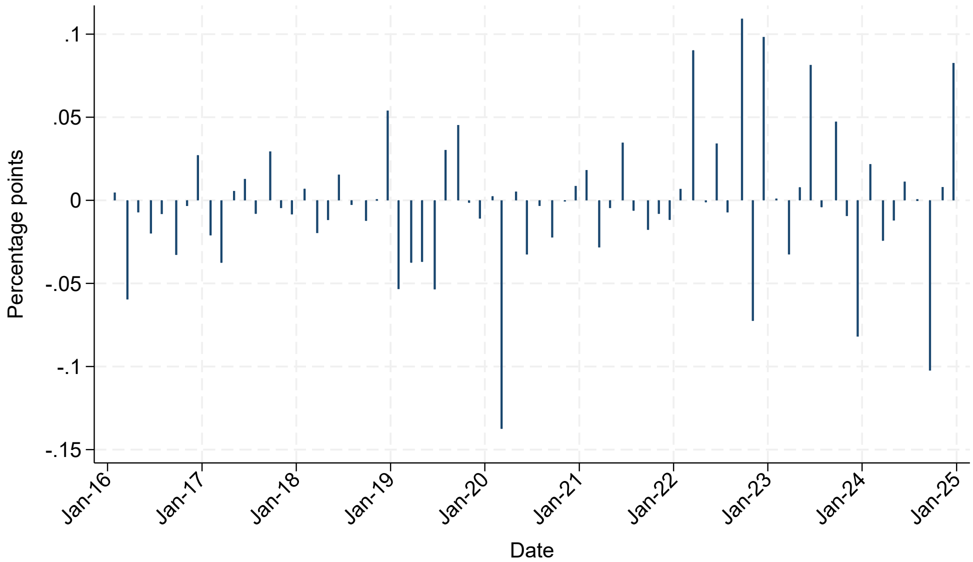
A Supplemental appendix

Figure A.1: Monetary policy shocks



Notes: The figure plots the monetary policy shocks that drive interest rate surprises. The shocks are computed following the methodology of Jarociński & Karadi (2020) and cover 73 FOMC announcements from January 2016 until December 2024.

Table A.1: Summary Statistics of Monetary Policy Surprises

Group	Mean	Median	Std. Dev.	Min	Max	N. obs.
MP surprise	-0.002	-0.003	0.041	-0.138	0.109	73
Contractionary MP surprise	0.030	0.017	0.032	0.000	0.109	30
Expansionary MP surprise	-0.026	-0.012	0.029	-0.138	-0.001	42

Note: This table reports summary statistics for pure monetary policy shocks following the methodology of Jarociński & Karadi (2020) covering 73 FOMC announcements from January 2016 until December 2024. ”Contractionary” and ”Expansionary” shocks are defined based on whether the shock value is greater or less than zero, respectively.

Table A.2: Summary Statistics of Firm-Level Cyclicality

Statistic	Cyclicality	Cyclicality, excl. 2020
Mean	1.343	1.236
Std. Dev.	.576	.538
Skewness	.551	.526
Kurtosis	3.388	3.274
P1	.199	.15
P25	.945	.843
Median	1.307	1.207
P75	1.681	1.548
P99	3.112	2.819
N	1361	1361

Table A.3: Summary Statistics of Firm-Level idiosyncratic risk

Statistic	Idiosyncratic risk	Idiosyncratic risk, excl. 2020
Mean	227.191	229.745
Std. Dev.	306.643	308.824
Skewness	3.403	3.361
Kurtosis	16.806	16.449
P1	22.755	22.755
P25	62.478	62.626
Median	125.523	126.472
P75	250.344	255.359
P99	1954.998	1957.702
N	1361	1361

Table A.4: EBP with Covid dummies

VARIABLES	(1) Cyclicality	(2) Idiosyncr. risk	(3) Cyclicality	(4) Idiosyncr. risk
Cyclicality (ex. 2020)	0.078**		0.054*	
	(0.032)		(0.032)	
Cyclicality (ex. 2020) × DD	-0.018**		-0.011	
	(0.008)		(0.008)	
Idiosyncratic (ex. 2020) × DD		-0.030***		-0.026***
		(0.006)		(0.006)
Idiosyncratic (ex. 2020)		0.114***		0.099***
		(0.023)		(0.023)
Distance to default (DD)	-0.094***	-0.095***	-0.092***	-0.094***
	(0.012)	(0.011)	(0.012)	(0.011)
Duration	0.337***	0.338***	0.336***	0.337***
	(0.015)	(0.016)	(0.016)	(0.016)
Par value	-0.047***	-0.047***	-0.047***	-0.047***
	(0.011)	(0.011)	(0.011)	(0.011)
Coupon	0.467***	0.467***	0.466***	0.465***
	(0.040)	(0.040)	(0.039)	(0.040)
Callable	-0.041	-0.039	-0.042	-0.041
	(0.027)	(0.027)	(0.027)	(0.027)
Observations	2,754,288	2,754,288	2,754,288	2,754,288
Rating FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Covid dummies	NO	NO	YES	YES
Adjusted R^2	0.687	0.688	0.711	0.712
Within R^2	0.399	0.401	0.444	0.446

Notes: The table presents the results of the estimation specification in Equation 5 and its variants described in the text. Firm cyclical and idiosyncratic risks are computed as described in Section 4. The regression includes one separate dummy for every observation in 2020. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Idiosyncratic and cyclical risk variables have been standardised such that a unit increase is a one-standard deviation increase of the distribution. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. *** p<0.01, ** p<0.05, * p<0.1

Table A.5: EBP with Covid dummies

VARIABLES	(1) Baseline	(2) Cyclicality	(3) Idios. risk	(4) Cyclicality (2)	(5) Idios. risk (2)	(6) Cyclicality idiosincr. risk
Cyclicality × DD		-0.013*		-0.027**		-0.015
		(0.008)		(0.011)		(0.012)
Idiosyncratic × DD			-0.026***		-0.047***	-0.036***
			(0.006)		(0.014)	(0.014)
Distance to default (DD)	-0.091***	-0.092***	-0.094***	-0.094***	-0.094***	-0.093***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)
Cyclicality		0.061*				
		(0.031)				
Idiosyncratic risk			0.098***			
			(0.023)			
Duration	0.336***	0.336***	0.337***	0.339***	0.339***	0.341***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Par value	-0.047***	-0.047***	-0.047***	-0.046***	-0.047***	-0.043***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Coupon	0.468***	0.466***	0.465***	0.463***	0.462***	0.460***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)
Callable	-0.042	-0.043	-0.041	-0.046*	-0.039	-0.047*
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.026)
Observations	2,754,288	2,754,288	2,754,288	2,754,288	2,754,288	2,754,288
Rating FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Industry FE × Cycl.	NO	NO	NO	YES	NO	YES
Industry FE × Idios.	NO	NO	NO	NO	YES	YES
Covid dummies	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.710	0.711	0.712	0.714	0.715	0.719
Within R^2	0.444	0.444	0.446	0.452	0.452	0.460

Notes: The table presents the results of the estimation specification in Equation 5 and its variants described in the text. Firm cyclical and idiosyncratic risks are computed as described in Section 4. The regression includes one separate dummy for every observation in 2020. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Idiosyncratic and cyclical risk variables have been standardised such that a unit increase is a one-standard deviation increase of the distribution. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Credit spreads, expected default, EBP: average effect

VARIABLES	(1) Spread	(2) Fitted Col. 4	(3) EBP Col. 4
Monetary policy surprise	9.929**	0.926***	8.460**
	(4.518)	(0.352)	(4.133)
Observations	2,878,495	2,719,461	2,719,461
R-squared	0.087	0.084	0.083
Covid dummies	YES	YES	YES
Bond FE	YES	YES	YES

Notes: The table presents the results of the estimation specification in Equation 6. Columns 2 and 3 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Covid dummies refer to a separate dummy for every weekly observation from March 2020 until end of 2020. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. *** p<0.01, ** p<0.05, * p<0.1

Table A.7: Credit spreads, expected default, EBP: average effect

VARIABLES	(1) Spread	(2) Fitted Col.5	(3) EBP Col. 5
Monetary policy surprise	9.929**	0.764**	8.632**
	(4.518)	(0.310)	(4.144)
Observations	2,878,495	2,719,461	2,719,461
R-squared	0.087	0.080	0.083
Covid dummies	YES	YES	YES
Bond FE	YES	YES	YES

Notes: The table presents the results of the estimation specification in Equation 6. Columns 2 and 3 have as dependent variable the fitted values and the residual resulting from the specification in Column 5 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Covid dummies refer to a separate dummy for every weekly observation from March 2020 until end of 2020. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. *** p<0.01, ** p<0.05, * p<0.1

Table A.8: Credit spreads, expected default, EBP: heterogeneity

VARIABLES	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × high cycl. (within)	3.058	0.132	0.701*	2.843	1.027
	(2.407)	(0.230)	(0.409)	(2.303)	(2.121)
Observations	2,605,560	2,601,511	2,461,032	2,601,511	2,461,032
R-squared	0.205	0.396	0.377	0.201	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

Notes: The table presents the results of the estimation specification in Equation 7. Columns 2 and 4 have as dependent variable the fitted values and the residual resulting from the specification in Column 1 in Table 1. Columns 3 and 5 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Data between March 2020 and December 2020 are excluded. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. High cyclicality and idiosyncratic risks are indicator variables equal to one for those firms that are above the median across the sample distribution. *** p<0.01, ** p<0.05, * p<0.1

Table A.9: Credit spreads, expected default, EBP: heterogeneity

VARIABLES	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × high idiosyncr. (within)	4.025	0.115	0.728	3.883	2.079
	(3.350)	(0.236)	(0.450)	(3.260)	(2.965)
Observations	2,605,560	2,601,511	2,461,032	2,601,511	2,461,032
R-squared	0.205	0.396	0.377	0.202	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

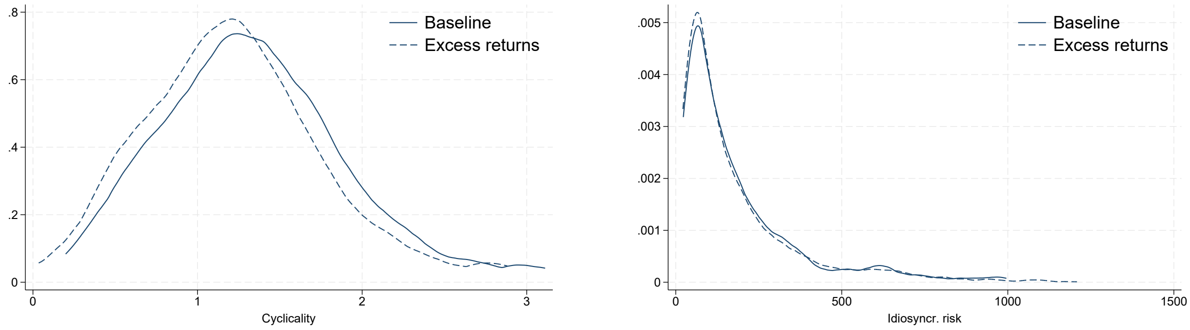
Notes: The table presents the results of the estimation specification in Equation 7. Columns 2 and 4 have as dependent variable the fitted values and the residual resulting from the specification in Column 1 in Table 1. Columns 3 and 5 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Data between March 2020 and December 2020 are excluded. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. High cyclicality and idiosyncratic risks are indicator variables equal to one for those firms that are above the median across the sample distribution. *** p<0.01, ** p<0.05, * p<0.1

Table A.10: Credit spreads, expected default, EBP: heterogeneity

VARIABLES	(1) Spread	(2) Fitted traditional	(3) Fitted new	(4) EBP traditional	(5) EBP new
MP surprise × Q4 idiosyncr.	0.368	-0.082	0.906**	0.411	0.281
	(2.430)	(0.087)	(0.459)	(2.317)	(2.463)
MP surprise × Q1 idiosyncr.	-4.706	-0.056	-0.461	-4.619	-3.012
	(3.808)	(0.248)	(0.351)	(3.678)	(3.477)
Observations	2,605,560	2,601,511	2,461,032	2,601,511	2,461,032
R-squared	0.205	0.396	0.377	0.202	0.201
Time × sector FE	YES	YES	YES	YES	YES
Bond FE	YES	YES	YES	YES	YES

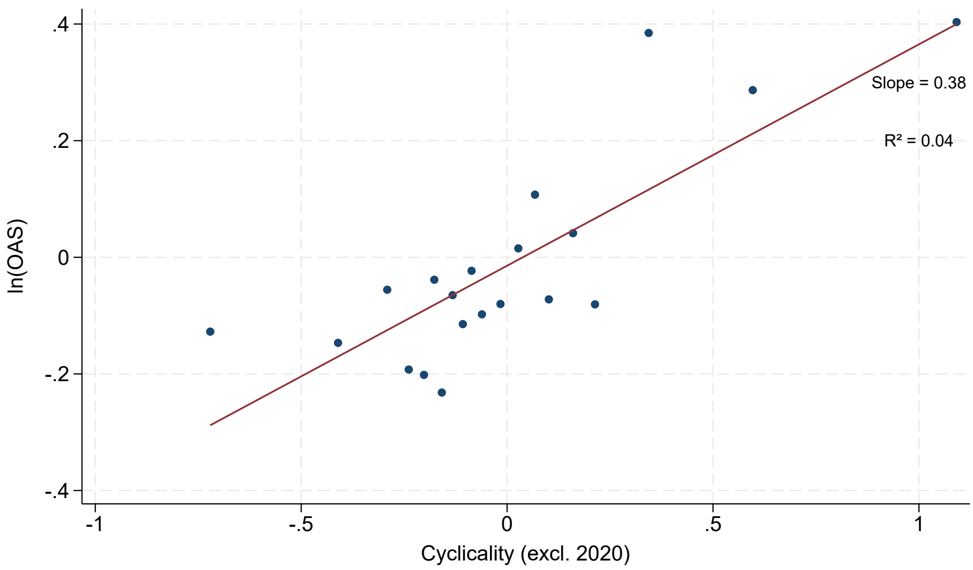
Notes: The table presents the results of the estimation specification in Equation 7. Columns 2 and 4 have as dependent variable the fitted values and the residual resulting from the specification in Column 1 in Table 1. Columns 3 and 5 have as dependent variable the fitted values and the residual resulting from the specification in Column 6 in Table 1. Standard errors (reported in parentheses) are clustered two-way, at the firm and time level. Data between March 2020 and December 2020 are excluded. The frequency of the data is weekly and the sample period covers from January 2016 to end of 2024. Credit spreads are measured in basis points and the size of the surprise is normalised so that it corresponds to a 25 basis points increase in the one-year Treasury bill. High cyclicality and idiosyncratic risks are indicator variables equal to one for those firms that are above the median across the sample distribution. *** p<0.01, ** p<0.05, * p<0.1

Figure A.2: Density of firms' cyclical and idiosyncratic risks



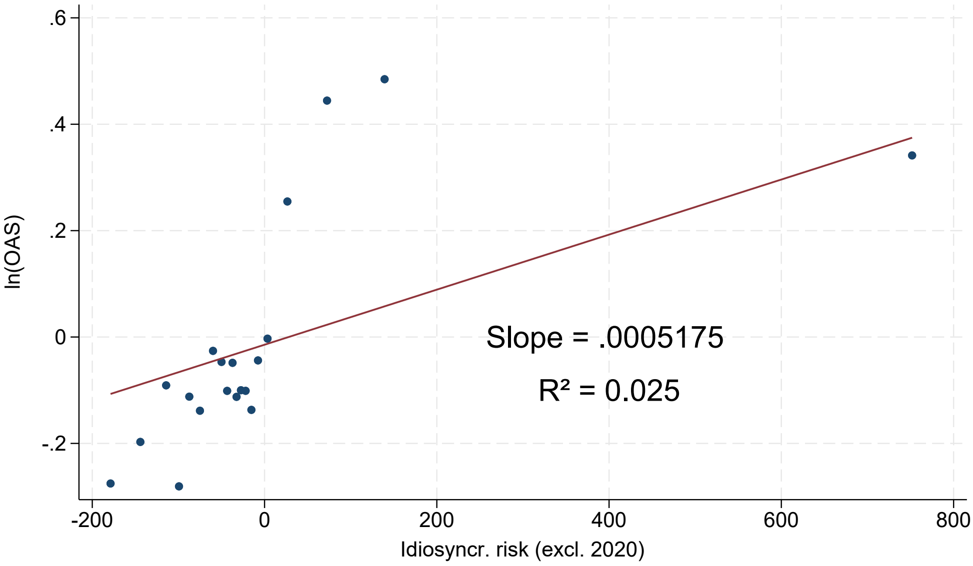
Notes: The figure displays the density distribution of the computed firm-level cyclical (left chart) and idiosyncratic (right chart) risks across listed US firms and following the methodology presented in Section 4. The data used for the computation is monthly and spans from 2000 to end of 2024. "Excess returns" refers to the results obtained when cleaning equity returns from the risk-free rate.

Figure A.3: Cyclicality of risk (excl. 2020) and spreads



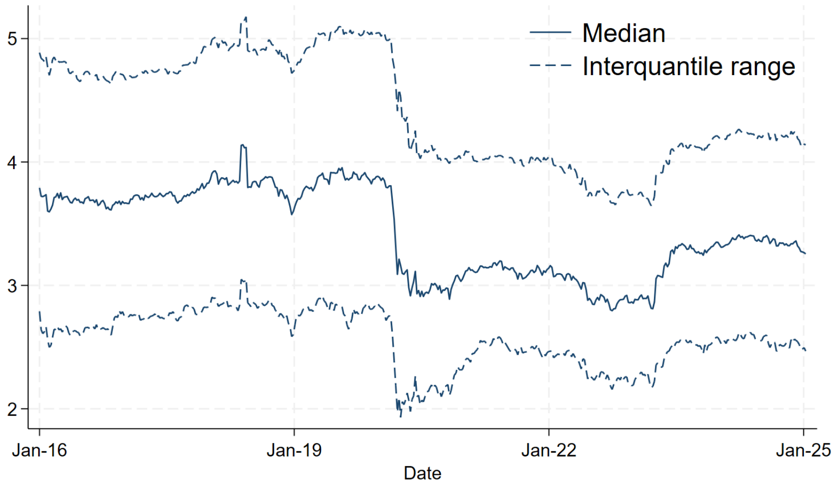
Notes: The figure presents a binned scatterplot where cyclicality and ln(OAS) are residualised with date and industry fixed effects.

Figure A.4: Idiosyncratic risk (excl. 2020) and spreads



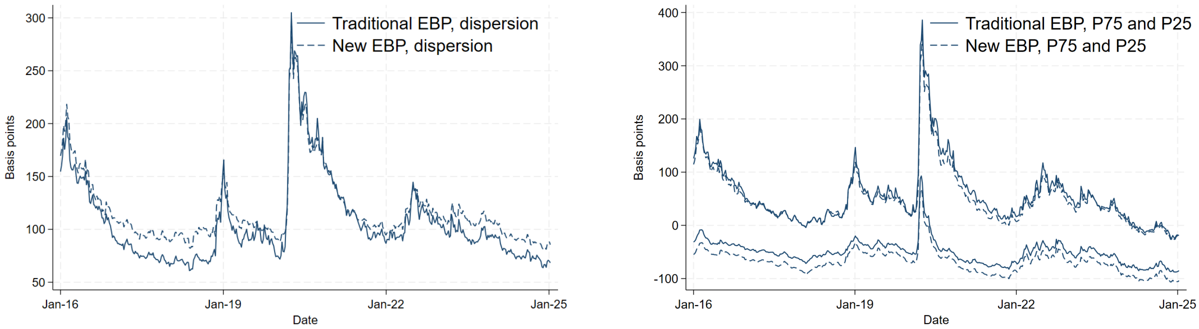
Notes: The figure presents a binned scatterplot where idiosyncratic risk and ln(OAS) are residualised with date and industry fixed effects.

Figure A.5: The cross section evolution of the distance to default



Notes: The figure plots the weekly-distance to default from January 2016 to December 2024. The solid line depicts the cross-sectional median of the distance to default; while the dashed lines show the 25th and 75th cross-sectional percentiles. For more details on construction see main text.

Figure A.6: EBP: distribution



Notes: "Traditional EBP" ("New EBP") refers to the bond-level EBP resulting from specifications in Column 1 (Column 6) in Table 1. The left chart compares the cross-sectional difference between the 75th and 25th percentiles. The right chart compares the 75th and 25th percentiles of the cross-sectional distributions.

Acknowledgements

I thank Björn Fischer, Magdalena Grothe, Marta Guasch, Fédéric Holm-Hadulla, Peter McAdam, Ana-Simona Manu, Arnaud Mehl, Ine Van Robays and Motohiro Yogo, for helpful comments and discussions. I am thankful to Martina Jančoková and DG-I/IPA division for help with data preparation and for the sharing of monetary policy shocks. I am responsible for any remaining errors.
Note: The views expressed are mine and do not represent those of the ECB or the Eurosystem.

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PDF 978-92-899-7441-7 ISSN 1725-2806 doi: 10.2866/8211946 QB-01-25-213-EN-N