The Sentiment Channel of Monetary Policy[†]

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Abstract

I study the role of sentiments in the transmission of monetary policy to economic activity. First, I present a simple theoretical model of diagnostic expectations that motivates my empirical analysis. In the theoretical model, I show that belief distortion interacts with monetary policy shocks to generate a sentiment channel of transmission in addition to the usually studied direct effects of monetary policy. Empirically, I test the existence and strength of this interaction effect between sentiments and high-frequency monetary policy surprises and document it is quantitatively important and operates *over and above* the usual channels examined in earlier studies. My results show that time variation in the sentiment channel can explain why the potency of monetary policy in influencing real activity varies over time.

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1 Introduction

Understanding the effects of monetary policy on the economy is a central theme of research in macroeconomics. Generally, there is consensus regarding the qualitative features of how monetary policy impacts economic activity (see, for instance, Christiano, Eichenbaum, and Evans (2005)); however, there is debate about whether and how the effectiveness of monetary policy varies over the business cycle. In this paper, I propose and examine the sentiment channel of monetary policy transmission to explain why the potency of monetary policy in stimulating (or restraining) economic activity varies over the business cycle.

The usual approach to quantifying the impact of monetary policy on the economy measures the percent change in economic activity (for e.g.industrial production) due to an exogenous change in the monetary policy. The sentiment channel I analyze in this paper stems from an interaction between the underlying optimism or pessimism in the economy and the exogenous change in monetary policy. I show that the sentiment channel co-exists with the first channel, and to differentiate between the two, I label the former as the direct effect of monetary policy and the latter as the sentiment channel or the interaction effect underlying monetary policy.

I first motivate the empirical specification used for estimating the different channels of monetary policy transmission by presenting a simple model of sentiments with risky debt, diagnostic agents, and monetary policy, building on the environment in Bordalo, Gennaioli, and Shleifer (2018).[1] Unlike rational agents who respond optimally to shocks in forming expectations, diagnostic agents overreact to current news or shocks and ex-

[1] In a standard model with rational expectations, sentiments do not have any first-order effects. To allow sentiments to be of first-order importance is therefore challenging while retaining the assumption of rational expectations. There are alternative approaches to model a departure from rational expectations, such as learning. In the standard behavioral model, where agents are not rational and learn about the laws of motion guiding the evolution of macro variables over time, changes in sentiment stem from exogenous shocks to the perceived laws of motion. However, a framework with diagnostic beliefs is elegant as sentiments in the model change endogenously in response to structural shocks in this environment. Additionally, studies such as Bordalo, Gennaioli, and Shleifer (2018), Bordalo, Gennaioli, Shleifer, and Terry (2022), Maxted (2023), and L'Huillier, Singh, and Yoo (Forthcoming), demonstrate in different environments, that diagnosticity is an empirically consistent feature.

trapolate these into future forecasts. Diagnosticity thus manifests as an overreaction, generating optimism or pessimism in the model. Time-varying sentiments in this environment thus stem from the assumption of diagnostic expectations.

In addition to diagnostic beliefs, the model features a continuum of firms that differ in riskiness. In period t, firms varying in riskiness borrow from risk-neutral financial intermediaries. A firm can either successfully repay debt (and produce) in period $t+1$ or default. Successful debt repayment (and production) in period $t+1$ is linked to the realized state in period $t+1$, unknown in t, and the underlying riskiness of the firm, which is known to financial intermediaries at t. In equilibrium, borrowing costs faced by risky firms in period t depend on expectations about future states; this forges a direct link between sentiments, borrowing costs, and real activity in the model. The average credit spread relative to the risk-free rate in the model is a function of the riskiness of borrowers, aggregate uncertainty in the economy, beliefs, and monetary policy. Moreover, it can be decomposed into a rational component and a component that is exclusively attributed to sentiments stemming from diagnosticity in belief formation.[2]

When agents are diagnostic, I show that the sentiment-driven component of the credit spread interacts with monetary policy shocks to generate an additional channel of monetary policy transmission that operates alongside the direct effect of monetary policy transmission. Investment by risky firms – a function of the credit spread – inherits this feature and likewise has a component that depends o the direct effects and a component driven purely by the overreaction stemming from the sentiment channel. The law of motion for investment generates testable implications, which I then take to the data.

In Section 3, I describe the empirical setup to examine the testable predictions implied by the theoretical framework. The main challenge in testing the existence and strength of

[2]The impact of diagnosticity-driven overreaction in response to monetary policy shocks can also be theoretically examined in the canonical New Keynesian model. However, taking the canonical New Keynesian model to data is challenging. The theoretical implications for credit spread in the model allow me to empirically measure diagnosticity in the data at a monthly level, which is critical to estimating local projections in quantifying the relative strengths of the direct effects and the sentiment-driven interaction effects. To illustrate the similarities in the theoretical predictions, I present the solution of the three-equation New Keynesian model with diagnostic expectations in Section E of the appendix.

the sentiment channel lies in obtaining an appropriate empirical measure of diagnosticity. In the theoretical model, the role of diagnosticity can be easily isolated; in the data, diagnosticity underlying belief formation is not directly observable. However, the extent of diagnosticity in the data can be inferred indirectly using the results from the theoretical model.

The theoretical model predicts that the average credit spread can be decomposed into two parts in the presence of diagnosticity. The first part captures the compensation demanded by a rational investor for bearing risk due to expected default and uncertainty in the economy. The second part captures the impact of sentiments on borrowing costs via the extent of diagnosticity. Furthermore, this second component (as per the theory) should be zero if the extent of diagnosticity is zero. Therefore, if it is possible to decompose the credit spread in the data into components that correspond to compensation for observable measures of risk (such as default risk, duration risk, and uncertainty in the economy) and compensation over and above these observable factors, then the latter can be interpreted to quantify compensation over and above what is demanded by a rational investor and driven by sentiments.

I use this intuition in the empirical analysis to quantify diagnosticity and measure it using a lagged value of the excess bond premium (EBP) from Gilchrist and Zakrajsek (2012). Gilchrist and Zakrajsek (2012) construct the EBP by purging their measure of credit spread for nonfinancial firms (Gilchrist-Zakrajsek spread)[3] of not only the risk due to expected default but any additional risks correlated with expected default as well, along with bond and firm-specific characteristics that can potentially influence yields via other channels. Given this approach, the empirical measure of EBP directly corresponds to the model-implied definition of the excess bond premium. It can be interpreted to capture the additional compensation for bearing risk over and above what a rational investor demands. Finally, the lagged value of the EBP as a stand-in for diagnosticity

[3]The Gilchrist-Zakrajsek credit spread is constructed by subtracting firm-specific yields from a synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate debt instrument.

also allows diagnosticity to exhibit potential time-variation over the business cycle in the empirical analysis.[4]

I measure monetary policy shocks in the empirical analysis using high-frequency changes in asset prices around a tight thirty-minute window bracketing FOMC announcements (along the lines of Gurkaynak, Sack, and Swanson (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), Swanson (2021) and Bauer and Swanson (2023)). In order to capture some of the effects of forward guidance as well as changes in the federal funds rate, I follow Nakamura and Steinsson (2018) and construct the monetary policy surprise measure as the first principal component of federal funds futures and Eurodollar futures out to a horizon of one year. This effectively summarizes the conduct of monetary policy throughout the sample that extends from July 1991 to June 2019.

To empirically test the existence and strength of the sentiment channel, Section 4 estimates local projections (Jordà (2005)) allowing for an interaction effect between sentiments and monetary policy surprises as well as the standard direct effect of monetary policy surprises. Estimating the coefficients of the latter over time is the usual approach to quantifying the effects of monetary policy on the economy. Examining the coefficients on the interaction term between sentiments and monetary policy surprises allows me to evaluate the existence and strength of this proposed interaction effect.

I find that the interaction effect – quantifying the strength of the sentiment channel – is not only significant and operational but quantitatively *as relevant as* the direct channel of monetary policy transmission usually examined in existing studies. Moreover, I show that the sentiment channel is independent of interactions between monetary policy surprises and measures capturing the real health of the economy. The sentiment channel thus operates over and above these features and does not stand in for cyclical fluctuations in real activity. Finally, the empirically estimated sentiment channel is robust to features

[4]This article is not the first to interpret the EBP as a measure of sentiment. Lopez-Salido, Stein, and Zakrajsek (2017) also use the EBP to measure credit-market sentiment to more generally examine the relation between time-varying credit market sentiment and real activity.

such as the 2008 financial crisis and the zero lower bound.

The results suggest the monetary policy more effectively stimulates real activity when sentiments are pessimistic. Additionally, when sentiments are optimistic, the central bank needs to tighten more to restrain an overheating economy. Therefore, an important takeaway from the results is that the direct effects of monetary policy can be amplified or diluted by the state of sentiments in the economy and explains why the effectiveness of monetary policy varies over the business cycle.

Related Literature This article is broadly related to four strands of literature. The first strand examines the real effects of monetary policy shocks, e.g., Christiano, Eichenbaum, and Evans (1999), Gertler and Karadi (2015), Jarociński and Karadi (2020), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), and Bauer and Swanson (2023). These articles quantify the usual "direct" effects of monetary policy surprises. I show that the sentiment channel operates over and above these direct effects and is quantitatively relevant and robust; additionally, in comparison to other studies (such as Gertler and Karadi (2015) and Jarociński and Karadi (2020)), I estimate direct effects that are bigger in magnitude.

The theoretical framework closely follows Bordalo, Gennaioli, and Shleifer (2018). Bordalo et al. (2018) provide the basis for diagnostic expectations arising from the representativeness heuristic introduced in Tversky and Kahneman (1983). Following Bordalo et al. (2018) and Bordalo et al. (2019), diagnostic expectations are increasingly gaining traction in the literature with studies such as Bordalo, Gennaioli, Shleifer, and Terry (2022), Maxted (2023), and L'Huillier, Singh, and Yoo (Forthcoming). These studies, however, do not focus on the sentiment channel underlying monetary policy transmission. The model in Section 2 provides the basis for my empirical analysis and demonstrates the impact of diagnosticity in the conduct of monetary policy.

In the present paper, I use the EBP to indirectly quantify the role of diagnosticity in the data. Since diagnosticity drives optimism or pessimism in the model, it can also be interpreted as a stand-in for the prevailing sentiment in the economy. This article, however, is not the first to interpret the EBP as a measure of sentiment. Lopez-Salido, Stein, and Zakrajsek (2017) also use the EBP to measure credit-market sentiment to more generally examine the relation between time-varying credit market sentiment and real activity.

Finally, the article is also related to studies that examine the role of financial conditions in assessing the real effects of monetary policy surprises. Earlier studies have examined the impact of time-varying financial frictions on the transmission of monetary policy shocks (e.g.: see Gertler and Karadi (2015) and Ottonello and Winberry (2020) among others). In this article, I show that time-varying sentiments, independent of time-varying financial frictions in credit markets, interact with monetary policy surprises to generate an additional channel for the propagation of monetary policy in the economy.

2 A Model of Sentiments with Monetary Policy

A simple model of sentiments helps motivate why we might expect the sentiment channel to amplify (or dampen) the effects of changes in monetary policy. I build off the basic model in Bordalo, Gennaioli, and Shleifer (2018), examining the impact of sentiments in a model featuring diagnostic expectations. The model features risky firms, risk-neutral financial intermediaries and the central bank conducting monetary policy.

2.1 Firms

There exists a continuum of firms of measure one. Each firm is indexed by ρ, capturing the underlying riskiness with $\rho \in \mathcal{R}$. A higher value of ρ implies a firm less likely to be productive in any given state ω_t since firm output for a given value of capital k evolves as

$$y(k|\rho, \omega_t) = \begin{cases} k^{\alpha} & \omega_t \geq \rho \\ 0 & \omega_t < \rho. \end{cases} \tag{1}$$

Here, $\alpha \in (0, 1)$. A firm indexed by riskiness ρ is productive as long as it is sufficiently safe with $\rho < \omega_t$. Note that as $\rho \to -\infty$, the firm will always choose to produce since $\rho \to -\infty$ corresponds to the safest firms. For two firms with different levels of riskiness, say ρ_1 and ρ_2, but same level of capital, as long as $\rho_1 < \omega_t$ and $\rho_2 < \omega_t$, both firms will produce and they will produce the same level of output. Riskiness ρ across the spectrum of firms is common knowledge and distributed across firms according to $f(\rho)$.

Capital installed in t becomes effective for production in $t + 1$. Additionally, capital depreciates fully at the end of each period. Thus, capital in period $t + 1$ and investment in period t can be used interchangeably in this model. To finance capital in period $t + 1$, firms raise debt from risk-neutral financial intermediaries in period t. A firm of riskiness ρ successfully produces and repays debt in $t + 1$ if $\omega_{t+1} \geq \rho$, otherwise the firm does not produce and defaults on its debt obligations. There is no record keeping in the model; therefore, if a firm of riskiness ρ defaults, it remains in the economy and can produce and borrow in subsequent periods.

2.2 Financial Intermediaries

To keep the framework analytically tractable and intuitive, I assume that firms in the model borrow from a perfectly competitive risk-neutral financial intermediary. The financial intermediary can be thought of as pooling the savings in the economy. Risk-neutral financial intermediaries face the option of investing in a one-period risk-free asset with a gross return of R_t or investing in debt issued by risky firms. The interest rate R_t on the risk-free asset is also the central bank's instrument for conducting monetary policy in this environment.

For a firm of riskiness ρ, productivity and successful debt repayment in $t + 1$ is tied to the state of the economy and the underlying riskiness of the firm ρ. Borrowing costs for funding capital in $t + 1$ by a firm indexed by riskiness ρ therefore depends on the perceived probability with which the firm will repay its debt. Let $\mu\Big(\rho, \mathcal{E}(t)\Big)$ denote the probability of successful debt repayment in $t + 1$ (hence production by a firm indexed by riskiness ρ). $\mathcal{E}(t)$ here governs how expectations are formed about the future state ω_{t+1} given the current state ω_t by financial intermediaries in this environment. Given the assumption of risk neutrality, the financial intermediary will require a return $r_{t+1}(\rho)$ from a firm of riskiness ρ such that

$$r_{t+1}(\rho)\mu\Big(\rho, \mathcal{E}(t)\Big) = R_t \quad \forall\rho. \tag{2}$$

This implies

$$\int_{-\infty}^{\infty} r_{t+1}(\rho)\mu\Big(\rho, \mathcal{E}(t)\Big)f(\rho)d\rho = R_t. \tag{3}$$

2.3 Evolution of expectations

The evolution of $\mathcal{E}(t)$ is critical to determining the credit spread faced by risky firms along with investment and output in this environment. When agents are rational, $\mathcal{E}(t) = E_t(\omega_{t+1})$ and when agents are diagnostic $\mathcal{E}(t) = E_t{}^{\theta}(\omega_{t+1})$. If agents are rational, then belief about the future state of the economy ω_{t+1} evolves according to the true Markovian distribution, that is

$$\omega_{t+1}|\omega_t \sim f(\omega_{t+1}|\omega_t).$$

Suppose, fundamentals ω_t evolve as an AR(1) process with iid Gaussian errors

$$\omega_t = (1-b_\omega)\overline{\omega} + b_\omega\omega_{t-1} + \epsilon_t^\omega; \text{ with } \epsilon_t^\omega \overset{iid}{\sim} N(0, \sigma_\omega^2), \tag{4}$$

then, $\omega_{t+1}|\omega_t \sim N(E_t\omega_{t+1}, \sigma_\omega^2)$, with $E_t\omega_{t+1} = (1-b_\omega)\overline{\omega} + b_\omega\omega_t$. The ex ante probability of successful debt repayment $\mu\Big(\rho, E_t\omega_{t+1}\Big)$ with rational expectations is

$$\mu\Big(\rho, E_t(\omega_{t+1})\Big) = \mathcal{P}(\omega_{t+1} \geq \rho|\omega_t) = \frac{1}{\sigma_\omega\sqrt{(2\pi)}}\int_\rho^\infty \exp - \frac{\Big(x - E_t(\omega_{t+1})\Big)^2}{2\sigma_\omega^2}dx$$

Now let us examine what happens if agents are not rational and beliefs are distorted relative to the rational benchmark. The key motivating assumption underlying diagnostic beliefs is – "an attribute is representative of a class if it is very diagnostic; that is, the relative frequency of this attribute is much higher in that class than in the relevant reference class" (see page 296 Tversky and Kahneman (1983)). Bordalo et al. (2018) implement belief distortion via this representativeness heuristic as "diagnostic belief" formation whereby agents overweight the realization of a random variable in period t in forming future forecasts of the same variable. Thus, when agents are diagnostic, belief about the future state of the economy ω_{t+1} evolve according to a distorted distribution given by

$$\omega_{t+1}|\omega_t \sim f^{\theta}(\omega_{t+1}|\omega_t) = f(\omega_{t+1}|\omega_t)\left[\frac{f(\omega_{t+1}|\omega_t)}{f(\omega_{t+1}|\omega_{t-1})}\right]^{\theta}\frac{1}{Z} \tag{5}$$

Here, $\theta > 0$ captures the extent of diagnosticity in beliefs and Z is a normalizing constant ensuring that $f^{\theta}(\omega_{t+1}|\omega_t)$ integrates to 1. The impact of diagnostic beliefs can be seen from equation (5). Equation (5) suggests that when $\theta > 0$, agents overweight news in period t ($\epsilon_t \neq 0$) relative to the "no news" baseline ($\epsilon_t = 0$): that is, agents overweight the importance of news about the current state ω_t when forming forecasts about future states. The term in the square brackets exactly captures this feature. If $\theta = 0$, as seen from equation (5), the model reverts to one with rational agents. Bordalo et al. (2018) further show that if fundamentals evolve as an AR(1) process with Gaussian errors, such as in, equation (4), then $f^{\theta}(\omega_{t+1}|\omega_t)$ is also Gaussian but with a distorted mean reflecting diagnosticity in belief formation.[5] Therefore,

$$f(\omega_{t+1}|\omega_t) \sim N(E_t\omega_{t+1}, \sigma_{\omega}^2) \text{ and } f^{\theta}(\omega_{t+1}|\omega_t) \sim N(E_t^{\theta}\omega_{t+1}, \sigma_{\omega}^2)$$

with

$$E_t^{\theta}\omega_{t+1} = E_t\omega_{t+1} + \theta(E_t\omega_{t+1} - E_{t-1}\omega_{t+1}). \tag{6}$$

The first term on the right-hand side of equation (6) is simply the forecast made by a rational agent. The second term on the right-hand side captures the extent of belief

[5] Proof can be found in Section A of the appendix.

distortion due to overweighting of current news. $\Big[E_t\omega_{t+1} - E_{t-1}\omega_{t+1}\Big]$ captures the differential between forecasts about ω_{t+1} between a scenario with news $\epsilon_t^\omega \neq 0$ and a scenario with no news, i.e. $\epsilon_t^\omega = 0$. The source of overreaction in a model with diagnostic beliefs stems from the extent agents overweight current news relative to a rational agent. Since a rational agent optimally updates beliefs about the state of the economy, the extent of belief distortion via θ thus generates optimism or pessimism in the economy. This way, the parameter θ and sentiments in the model can be used interchangeably.

While in this example, ω_t is a univariate AR(1) process, the result in equation (6) can also be applied to cases where the underlying state is a linear combination of nondegenerate normal random variables. That is, if $\omega_t = z_t + y_t$ where both z_t and y_t follow AR(1) processes with nondegenerate Gaussian distributions, then it is straightforward to show that

$$E_t^\theta\omega_{t+1} = E_t^\theta\Big[z_{t+1} + y_{t+1}\Big] = E_t^\theta z_{t+1} + E_t^\theta y_{t+1} =$$
$$E_t z_{t+1} + \theta(E_t z_{t+1} - E_{t-1}z_{t+1}) + E_t y_{t+1} + \theta(E_t y_{t+1} - E_{t-1}y_{t+1}). \quad (7)$$

2.4 Diagnostic expectations and borrowing costs

How does diagnosticity in belief formation (θ >0) impact the perceived probability of default by a firm of given riskiness ρ? When agents are diagnostic and $\theta > 0$, the ex ante probability of successful debt repayment and production in $t+1$ is

$$\mu\Big(\rho, E_t^\theta(\omega_{t+1})\Big) = \mathcal{P}^\theta(\omega_{t+1} \geq \rho|\omega_t) = \frac{1}{\sigma_\omega\sqrt{(2\pi)}}\int_\rho^\infty \exp -\frac{\Big(x - E_t^\theta(\omega_{t+1})\Big)^2}{2\sigma_\omega^2}dx \quad (8)$$

with equation (6) describing the expression for $E_t^\theta(\omega_{t+1})$. Thus as θ increases, the influence of current news on future forecasts increases; hence the role of sentiments increases as well. If agents observe positive news via $\epsilon_t^\omega > 0$, they will overweight this observation, and ceteris paribus, the perceived probability of debt repayment in $t+1$ will increase.

Likewise, when agents observe negative news via $\epsilon_t^\omega < 0$, they will overweight this observation, and ceteris paribus, the perceived probability of debt repayment in $t+1$ will decrease.

Given this structure underlying the perceived probability of debt repayment, note that a perfectly safe firm with $\rho \to -\infty$ will never default since $\lim_{\rho \to -\infty} \mu\Big(\rho, E_t^\theta(\omega_{t+1})\Big) = 1$. Additionally, in this setup there are no agency problems in the spirit of Bernanke et al. (1999), and there is no distinction between debt and equity financing. Both contracts are therefore contingent on the same outcome and promise the same rate of return. Following Bordalo et al. (2018) I assume that all capital is financed by debt.

2.5 Optimal capital choice and credit spreads

Given that risk-neutral financial intermediaries operate in a perfectly competitive environment, they are willing to lend to a firm of riskiness ρ as long as they are indifferent between lending to risky firms vis-à-vis investing in the risk-free asset. With diagnostic expectations, the incentive compatibility condition that achieves this is[6]

$$r_{t+1}(\rho)\mu\Big(\rho, E_t^\theta(\omega_{t+1})\Big) = R_t \quad \forall \rho, \tag{9}$$

with

$$\int_{-\infty}^{\infty} r_{t+1}(\rho)\mu\Big(\rho, E_t^\theta(\omega_{t+1})\Big) f(\rho) d\rho = R_t. \tag{10}$$

Given that R_t is the instrument for conducting monetary policy, equation (9) thus forges a direct link between borrowing costs faced by risky firms and monetary policy in the model. equation (9) also implies

$$r_{t+1}(\rho) = \frac{R_t}{\mu\Big(\rho, E_t^\theta(\omega_{t+1})\Big)}. \tag{11}$$

[6]In Bordalo et al. (2018), households are willing to supply any amount of capital to a firm with riskiness ρ as long as the interest rate makes the household indifferent between consuming and saving. Combined with no arbitrage on the rate of return on debt by a firm of riskiness ρ, this implies that the expected return on the risky firm debt has to be equal to $\frac{1}{\beta}$, $\forall \rho$.

A firm of riskiness ρ maximizes expected profits ($\pi^e_{t+1}(\rho)$)

$$\pi^e_{t+1} = \Big[k_{t+1}(\rho)^\alpha - r_{t+1}(\rho)k_{t+1}(\rho)\Big]\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big). \tag{12}$$

Using equation (11) to solve for $r_{t+1}(\rho)$ and plugging into the profit function of the firm in equation 12, implies that a firm of riskiness ρ solves

$$\max_{k_{t+1}(\rho)} \Bigg[k_{t+1}(\rho)^\alpha - \frac{R_t}{\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big)}k_{t+1}(\rho)\Bigg]\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big) \quad \forall\rho. \tag{13}$$

The optimal choice of capital, given R_t, ρ, and ${E_t}^\theta(\omega_{t+1})$ is

$$k_{t+1}(\rho) = \Bigg[\frac{R_t}{\alpha\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big)}\Bigg]^{\frac{1}{\alpha-1}}. \tag{14}$$

Using the expression for $r_{t+1}(\rho)$, the spread $S(\rho, {E_t}^\theta(\omega_{t+1}), R_t)$ on risky debt issued by a firm indexed by riskiness ρ relative to the risk-free rate R_t can be computed as

$$S(\rho, {E_t}^\theta(\omega_{t+1}), R_t) = \frac{R_t}{\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big)} - R_t = R_t\Bigg[\frac{1}{\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big)} - 1\Bigg]. \tag{15}$$

An improvement in expectations about the future state increases the probability of debt repayment $\mu\Big(\rho, {E_t}^\theta(\omega_{t+1})\Big)$ and thus dampens the credit spread. Likewise, given ${E_t}^\theta(\omega_{t+1})$, an increase in riskiness ρ reduces the probability of successful debt repayment and increases the credit spread. Integrating equation (15) with respect to ρ, we get the average credit spread in the economy, $S_t({E_t}^\theta(\omega_{t+1}), R_t)$ with

$$S_t({E_t}^\theta(\omega_{t+1}), R_t) = \int_{-\infty}^{\infty} S(\rho, {E_t}^\theta(\omega_{t+1}), R_t)f(\rho)d\rho \tag{16}$$

Solving for $\mu\Big(\rho, E_t^{\theta}(\omega_{t+1})\Big)$ as a function of $S(\rho, E_t^{\theta}(\omega_{t+1}))$, the optimal choice of capital in equation (14) can be expressed as

$$k_{t+1}(\rho) = \left[\frac{\alpha}{S(\rho, E_t^{\theta}(\omega_{t+1})) + R_t}\right]^{\frac{1}{1-\alpha}} \tag{17}$$

Thus for a given value of ρ, ceteris paribus, an increase in $E_t^{\theta}(\omega_{t+1})$ implies higher expected output produced by a firm of riskiness ρ. Likewise, ceteris paribus, an increase in $E_t^{\theta}(\omega_{t+1})$ implies the borrowing cost $(r_{t+1}(\rho))$ faced by a firm of riskiness ρ decreases. It is important to highlight here that ceteris paribus, both the credit spread and investment by a firm of riskiness ρ, would also change under the assumption of rationality; however, belief distortions via θ manifests as a component that now captures the overreaction relative to this rational baseline. equation (17) is key to understanding the dynamics of real activity in the model since it links expectations and monetary policy to credit spreads, investment, and hence output in the model. Since the paper focuses on isolating the sentiment channel of monetary policy transmission, I examine the supply side and pin down behavior of risky firms and risk-neutral financial intermediaries exclusively. The model can be closed along the lines of Smets and Wouters (2007). Here I just focus on equilibrium conditions above to motivate the empirical specification.

2.6 Monetary Policy

I assume that the central bank conducts monetary policy according to a simple rule that includes a systematic component as well as surprises to policy, with

$$R_t = \overline{R} + \alpha_x(\omega_t - \overline{\omega}) + \epsilon_t^i + \epsilon_{t-1}^{fg};\ \epsilon_t^i \overset{iid}{\sim} N(0, \sigma_i^2) \text{ and } \epsilon_t^{fg} \overset{iid}{\sim} N(0, \sigma_{fg}^2). \tag{18}$$

$\overline{R}$ is the interest rate in steady state. Here $\alpha_x > 0$ corresponds to the systematic component of policy that responds to deviations of ω_t from its steady state. ω_t in this environment can be interpreted to be a good indicator of the output gap in the economy.

I discuss this feature along with the evolution of the ω_t and in detail in Section 2.7 below. When the economy is weak with $(\omega_t - \overline{\omega}) < 0$, the central bank systematically eases policy by an amount $\alpha_x(\omega_t - \overline{\omega}) < 0$; likewise, in an overheating economy the central bank systematically tightens policy by an amount $\alpha_x(\omega_t - \overline{\omega}) > 0$.

Similar to the interpretation in Campbell, Fisher, Justiniano, and Melosi (2016), the surprise component of monetary policy consists of a shock to the interest rate ϵ_t^i and a shock to forward guidance ϵ_{t-1}^{fg}. The first term ϵ_t^i is the usual contemporaneous monetary policy disturbance (analogous to the policy surprise in the current federal funds rate), and the second term ϵ_{t-1}^{fg} can be interpreted as a forward guidance shock because they are revealed to the public before they are applied to the policy rule.[7]

2.7 Evolution of Expectations and the Underlying State of the Economy

I conclude the model description by specifying the evolution of the state of the economy ω_t. Specifying how ω_t evolves is the second point of departure from Bordalo et al. (2018). Bordalo et al. (2018) allow the state to evolve simply as an exogenous process which can be interpreted to be the source of cycles in their model. I deviate from Bordalo et al. (2018) and endogenize the evolution of ω_t and relate it to the output gap in the model economy. Aggregate output in the economy evolves as

$$y_t = \int_{-\infty}^{\infty} k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})^{\alpha} \mathcal{I}(\rho, \omega_t) f(\rho) d\rho \tag{19}$$

where

$$\mathcal{I}(\rho, \omega_t) = \begin{cases} 1 & \omega_t \geq \rho \\ 0 & \omega_t < \rho. \end{cases} \tag{20}$$

Given that $k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})$ is predetermined and unaffected by the realization of ω_t, an increase in ω_t relaxes the constraint $\omega_t \geq \rho$, implying that aggregate output is an increasing function of ω_t. Likewise, the output gap $y_t - y_{ss}$, defined relative to the steady

[7] The framework can be extended to allow for a sequence of forward guidance shocks. For simplicity, I define the forward guidance shock to contain a single surprise.

state output, is an increasing function of ω_t. Given the distribution of ρ, ω_t is therefore a sufficient statistic to describe the output gap in period t.[8]

Finally, I assume that ω_t evolves as

$$\omega_t = (1-b)\overline{\omega} + b\omega_{t-1} - c(R_t - \overline{R}) + \epsilon_t^x;\ \epsilon_t^x \overset{iid}{\sim} N(0, \sigma_x^2). \tag{21}$$

Here, $\overline{\omega}$ is steady state value of ω_t. Equation 21 can thought of as a simple backward looking IS curve.

Plugging in the interest rate rule, equation (18), in equation (21) yields

$$\omega_t - \overline{\omega} = \rho_1(\omega_{t-1} - \overline{\omega}) - \rho_2(\epsilon_t^i + \epsilon_{t-1}^{fg}) + \rho_3\epsilon_t^x \tag{22}$$

where $\rho_1 = \frac{b}{1+c\alpha_x}$, $\rho_2 = \frac{c}{1+c\alpha_x}$ and $\rho_3 = \frac{1}{1+c\alpha_x}$. An increase in ϵ_t^x in the model relaxes the constraint $\omega_t \geq \rho$, and the state of the economy becomes safer for riskier firms to produce. Equivalently, negative shocks to ϵ_t^x increase the level of slack in the economy as fewer firms are deemed sufficiently safe for production. The effect of shocks to monetary policy on ω_t operates similarly, with contractionary surprises increasing the slack and expansionary shocks relaxing the constraint and expanding production. Additionally, given this interpretation of ω_t, the idiosyncratic riskiness ρ underlying firms can also be interpreted as the idiosyncratic firm efficiency in the model environment, with more efficient firms remaining active in production as the economy worsens.

Optimal Forecast by Diagnostic Agents Given the specification for ω_t in equation (21), how do the forecasts of agents with diagnostic beliefs evolve in this economy? $E_t^\theta \omega_{t+1}$ is solved using equation (7) such that

$$E_t^\theta \omega_{t+1} = \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon_t^{fg} + \theta\Big(\rho_1\rho_3\epsilon_t^x - \rho_2\big(\epsilon_t^{fg} + \rho_1\epsilon_t^i\big)\Big) \tag{23}$$

[8]Section B of the appendix examines this in more detail.

As seen from equation (23), diagnostic agents extrapolate past shocks in the future forecast of ω_{t+1}.[9] To highlight the impact of diagnosticity more clearly equation (24) below summarizes the forecast by a rational agent

$$E_t\omega_{t+1} = \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon_t^{fg}. \tag{24}$$

Finally, equations (15), (17), (18), (21) and (23) summarize the nonlinear equilibrium conditions of the model.

2.8 Sentiments, Real Activity and the Interaction Effect

To explain the mechanism underlying the sentiment channel of monetary policy transmission and motivate the empirical model, I take a first-order approximation of the firm-level credit spread, $S(\rho, E_t{}^\theta(\omega_{t+1}), R_t)$, with respect to $E_t{}^\theta(\omega_{t+1})$ and R_t around the steady state of the model, yielding

$$S(\rho, E_t{}^\theta(\omega_{t+1}), R_t) - S_{ss}^\rho(\rho, \overline{\omega}, \overline{R}) = \left[\frac{1}{\mu\big(\rho, \overline{\omega}\big)} - 1\right](R_t - \overline{R}) - \overline{R}\frac{\mu_2'(\rho, \overline{\omega})}{\mu(\rho, \overline{\omega})^2}\Big(E_t{}^\theta\omega_{t+1} - \overline{\omega}\Big) \tag{25}$$

where

$$S_{ss}^\rho(\rho, \overline{\omega}, \overline{R}) = \left[\frac{1}{\mu\big(\rho, \overline{\omega}\big)} - 1\right]\overline{R}$$

is the credit spread faced by a firm of riskiness ρ in steady state and $\mu_2'(\rho, \overline{\omega})$ is the derivative of $\mu(.,.)$ with respect to the second argument. Integrating both sides of equation (25) with respect to ρ, we have

$$S_t - S_{ss} = \sigma_0(R_t - \overline{R}) - \sigma_1\Big(E_t{}^\theta(\omega_{t+1}) - \overline{\omega}\Big) \tag{26}$$

[9] The detailed derivation of equation (23) can be found in Section C of the appendix.

where $S_{ss} = \overline{R}\int_{-\infty}^{\infty}\left[\frac{1}{\mu\left(\rho,\overline{\omega}\right)} - 1\right] f(\rho)d\rho$ is the economywide credit spread in steady state, $\sigma_0 = \int_{-\infty}^{\infty}\left[\frac{1}{\mu\left(\rho,\overline{\omega}\right)} - 1\right] f(\rho)d\rho$ and $\sigma_1 = \overline{R}\int_{-\infty}^{\infty}\frac{\mu_2'(\rho,\overline{\omega})}{\mu(\rho,\overline{\omega})^2} f(\rho)d\rho$. Using equation (23), and substituting for $E_t^{\theta}\omega_{t+1}$ in equation (25) yields

$$S_t - S_{ss} = \sigma_0(R_t - \overline{R}) - \sigma_1\rho_1(\omega_t - \overline{\omega}) + \rho_2\epsilon_t^{fg} - \sigma_1\theta\Big(\rho_1\rho_3\epsilon_t^x - \rho_2\big(\epsilon_t^{fg} + \rho_1\epsilon_t^i\big)\Big) \tag{27}$$

If $\theta = 0$, we revert to the rational expectations paradigm with agents reacting optimally to news or shocks in the economy. Thus, by setting $\theta = 0$, in equation (27), we recover the compensation demanded by a rational agent for bearing default risk. Using this definition, the spread S_t^R demanded by a "rational" investor is

$$S_t^R - S_{ss} = \sigma_0(R_t - \overline{R}) - \sigma_1\rho_1(\omega_t - \overline{\omega}) + \rho_2\epsilon_t^{fg}. \tag{28}$$

Given S_t^R, the residual component of borrowing costs $(S_t - S_t^R)$

$$S_t - S_t^R = -\sigma_1\theta\Big(\rho_1\rho_3\epsilon_t^x - \rho_2\big(\epsilon_t^{fg} + \rho_1\epsilon_t^i\big)\Big) \tag{29}$$

quantifies the compensation in excess of what a rational investor demands due to optimism or pessimism in the economy. Similarly, up to first order, the firm-level capital choice $k_{t+1}(\rho)$ or investment,

$$\begin{aligned} &k_{t+1}(\rho, E_t{}^{\theta}(\omega_{t+1}), R_t) - k_{ss}(\rho, \overline{\omega}, \overline{R}) = \\ &\qquad -\frac{\alpha^{\frac{1}{1-\alpha}}}{1-\alpha}\left[\frac{1}{S(\rho,\overline{\omega},\overline{R}) + \overline{R}}\right]^{\frac{1}{1-\alpha}-1}\left[\big(S(\rho, E_t{}^{\theta}(\omega_{t+1})) - S(\rho,\overline{\omega},\overline{R})\big) + (R_t - \overline{R})\right]. \end{aligned} \tag{30}$$

where $k_{ss}(\rho,\overline{\omega},\overline{R}) = \left[\frac{\alpha}{S(\rho,\overline{\omega},\overline{R})+\overline{R}}\right]^{\frac{1}{1-\alpha}}$ is the capital owned by a firm of riskiness ρ at steady state. Integrating both sides of equation (30) with respect to ρ, up to a first-order approximation gives us

$$k_{t+1} - k_{ss} = -\sigma_1^k \left[\left(S_t - S_{ss} \right) + \left(R_t - \overline{R} \right) \right]. \tag{31}$$

Where, $k_{ss} = \int_{-\infty}^{\infty} \left[\frac{\alpha}{S(\rho,\overline{\omega},\overline{R})+\overline{R}} \right]^{\frac{1}{1-\alpha}} f(\rho) d\rho$ is the total capital stock in the economy at steady state, and $\sigma_1^k = \int_{-\infty}^{\infty} \frac{\alpha^{\frac{1}{1-\alpha}}}{1-\alpha} \left[\frac{1}{S(\rho,\overline{\omega},\overline{R})+\overline{R}} \right]^{\frac{1}{1-\alpha}-1} f(\rho) d\rho$. Using equations (28) and (29), k_{t+1} can be written as a sum of two parts, the first part (k_{t+1}^R) quantifying the relation between real activity and the rational component of credit spreads in the model and the second part ($k_{t+1} - k_{t+1}^R$) purely quantifying the effect of sentiments with

$$k_{t+1}^R - k_{ss} = -\sigma_1^k \left[\left(S_t^R - S_{ss} \right) + \left(R_t - \overline{R} \right) \right] \tag{32}$$

and

$$k_{t+1} - k_{t+1}^R = -\sigma_1^k \left[\left(S_t - S_t^R \right) \right] = \sigma_1^k \sigma_1 \theta \left[\rho_1 \rho_3 \epsilon_t^x - \rho_2 \left(\epsilon_t^{fg} + \rho_1 \epsilon_t^i \right) \right] \tag{33}$$

respectively. The law of motion of investment combining both these effects is

$$k_{t+1} - k_{ss} = \left[\underbrace{-\sigma_1^k \left(S_t^R - S_{ss} \right) + \left(R_t - \overline{R} \right)}_{Direct\ Effect} + \underbrace{\theta \sigma_1^k \sigma_1 \left[\rho_1 \rho_3 \epsilon_t^x - \rho_2 \left(\epsilon_t^{fg} + \rho_1 \epsilon_t^i \right) \right]}_{Sentiment\ Channel} \right] \tag{34}$$

There are two channels through which changes in monetary policy impact k_{t+1}. The first channel is the direct effect. So, what happens if the central bank conducts surprise tightening? Irrespective of whether the economy is experiencing other structural shocks (i.e. $\epsilon_t^x \neq 0$), through the equalization of returns channel quantified by the coefficient of $(R_t - \overline{R})$ in equation (28), a contractionary monetary policy surprise generates an increase in S_t^R. k_{t+1}^R decreases both due to direct effect of the surprise tightening, quantified by the coefficient of $(R_t - \overline{R})$ in equation (34), as well as through the impact of S_t^R on k_{t+1}^R. These impacts of a surprise monetary policy tightening on investment and the credit spread constitute the "direct effect" in the transmission of monetary policy shocks.

The second channel is the interaction effect quantifying the impact of diagnosticity-driven sentiments. Starting from an initial condition with $\epsilon_t^x = 0$, as predicted by equation (34), a surprise policy tightening (easing) endogenously generates pessimism (optimism) in the model. Consequently, the forecast for period $t+1$ is lower (higher) than what a rational agent predicts. Given the link between default and the future state of the economy, this excess pessimism (optimism) causes the credit spread to increase (decrease) and, in turn, investment to decrease (increase) by even more. Moreover, note that this channel co-exists simultaneously with the direct effect. If $\theta = 0$, the impact of surprise monetary policy tightening (easing) would correspond only to the direct effect. The model therefore generates the following testable implications.

Testable implication 1: If an econometrician regresses investment on monetary policy shocks, investment should decrease (increase) in response to a contractionary (expansionary) surprise in the policy instrument via the direct effect.

Testable implication 2: If an econometrician regresses investment on a measure of monetary policy shocks and the interaction between a measure monetary policy shocks and a measure of diagnosticity, then investment should decrease (increase) in response to the contractionary (expansionary) surprise, and by more than what is predicted by the "direct effect". That is, controlling for the direct effect, we can empirically test if the contribution of the sentiment channel is statistically significant and quantitatively important.

3 Empirical framework

In this section, I set up the empirical model that tests the model predictions summarized in the previous section. The usual approach to quantifying the dynamic impact of monetary policy shocks, using the method of local projections, involves estimating regression coefficients of the relevant dependent macroeconomic variable at $t+h$ on identified surprises along with controls and reporting the coefficient on the measure of monetary policy surprise as estimated impulse response at the desired horizon (Ramey, 2016). That is, following Jordà (2005) estimate

$$x_{t+h} = \alpha_h + \psi_h(L)z_t + \beta_h f_t + \epsilon_{t+h}. \tag{35}$$

Here, x is the macroeconomic variable of interest, z is a vector of control variables, $\psi_h(L)$ is a polynomial in the lag operator, and f_t is the empirical measure of the monetary policy surprise. The coefficient β_h thus characterizes the impact of a monetary policy shock at horizon h for the variable x. The vector of control variables usually contains lags of real activity, lags of a relevant price index, and lags of a policy instrument capturing the policy stance.

I test the coexistence of the sentiment channel, consistent with *Testable Implication 2* alongside the usual direct effect defined in equation (36) by augmenting equation (36) with an interaction term such that

$$x_{t+h} = \alpha_h + \psi_h(L)z_t + \beta_h f_t + \gamma_h f_t \theta_t + \epsilon_{t+h}. \tag{36}$$

The coefficient γ_h in equation (36) now captures the interaction effect between monetary policy surprises and sentiment induced by diagnosticity (θ_t) at horizon h. The main ingredients needed to test the existence and strength of the sentiment channel alongside the direct effect include a measure of monetary policy surprise (f_t) and an empirical measure of diagnosticity (θ_t).

Measuring Monetary Policy Surprises I measure monetary policy surprises (f_t) in equation (37) using high-frequency changes in the interest rate around a tight thirty-minute window bracketing FOMC announcements (along the lines of Gurkaynak et al. (2005), Gertler and Karadi (2015), Nakamura and Steinsson (2018), Miranda-Agrippino and Ricco (2021), Swanson (2021)). In particular, I identify surprises following the approach in Gurkaynak et al. (2005) and later extended in Swanson (2021) and use the one-dimensional measure of policy surprises consistent with Nakamura and Steinsson

(2018). In order to capture some of the effects of forward guidance as well as changes in the federal funds rate, I follow Nakamura and Steinsson (2018) and construct the monetary policy surprise measure as the first principal component of federal funds futures and Eurodollar futures out to a horizon of one year. This measure thus effectively quantifies the the conduct of monetary policy throughout the sample from 07/1991 to 06/2019.

In the theoretical model, monetary policy is conducted via changes in the real interest rate. In my empirical analysis, monetary policy shocks are identified as the surprise component of the nominal interest rate around a thirty minute window of FOMC announcements. However, high-frequency changes in the nominal interest rate correspond closely to surprises in the real interest rate as long as inflation expectations do not move as much as the nominal interest rate.

Measuring Diagnosticity In the data, diagnosticity underlying belief formation is not directly observable. However, the extent of diagnosticity in the data can be inferred indirectly using the results from the theoretical model. The theoretical model predicts that the average credit spread can be decomposed into two parts in the presence of diagnosticity. The first part captures the compensation demanded by a rational investor for bearing default risk and uncertainty in the economy. The second part captures the impact of sentiments on borrowing costs via the extent of diagnosticity. Furthermore, this second component (as per the theory) should be zero if the extent of diagnosticity is zero.[10]

Therefore, if it is possible to decompose the credit spread in the data into components that correspond to a compensation for observable measures of risk (such as default risk, duration risk, and uncertainty in the economy) and a compensation over and above these observable factors, then the latter can be interpreted to quantify compensation over and above what is demanded by a rational investor. Consistent with the theoretical model, this latter component depends on the extent agents overreact to news or shocks

[10] This component can also be zero if there are no structural shocks in the economy at that point; however, if the extent of diagnosticity is zero, then this component should always be zero.

in the economy and, therefore, a function of diagnosticity in belief formation along with structural shocks.

I use this intuition in the empirical analysis to quantify diagnosticity and measure it using the excess bond premium (EBP) constructed in Gilchrist and Zakrajsek (2012). Gilchrist and Zakrajsek (2012) construct the EBP measure in two steps. In the first step, Gilchrist and Zakrajsek (2012) construct their measure of the credit spread (Gilchrist-Zakrajsek spread) for nonfinancial firms by subtracting firm-specific yields from a synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate debt instrument. Next, Gilchrist and Zakrajsek (2012) construct the EBP by purging their measure of the credit spread for nonfinancial firms of not only the risk due to expected default but also any risk or rsk premium that is correlated with expected default as well. Furthermore, in removing default risk in constructing the EBP, Gilchrist and Zakrajsek (2012) additionally control for bond-specific characteristics that could potentially influence bond yields through a term premium or a liquidity premium channel.

A more direct approach to quantifying diagnosticity-driven sentiment is constructing an empirical measure following Maxted (2023). Maxted (2023) constructs an empirical measure of sentiment using forecast errors for GDP growth rate. In the context of the present article, I construct a similar measure using forecast errors underlying the high-yield credit spread for the US using proprietary data provided by Moody's. However, this data on forecast errors is only available between 07/2007 and 12/2019. With the caveat of the restricted sample, the correlation between the empirically constructed measure following Maxted (2023) and the lagged EBP is about 0.6. Moreover, to further check the validity of the lagged EBP as a suitable empirical proxy for diagnosticity-driven sentiments, I estimate local projections quantifying the magnitude of the interaction effect on the subsample where these two overlap. The two measures provide very similar results; if anything, the results with the lagged EBP as a measure of sentiment are more conservative. These results are presented in detail in Section D.1 of the appendix.

I thus use the EBP in $t-1$ to quantify the state of diagnosticity in period t. Using a lagged value of EBP to measure diagnosticity also makes the measure exogenous to shocks realized in period t. Furthermore, the EBP fluctuates in the data, with positive (negative) values denoting a higher (lower) price of bearing risk controlling for expected default and uncertainty. Given this range, the EBP can be zero or very close to zero in the data. The empirical analysis in this way considers periods where the extent of overreaction to shocks is close to zero. With this measure, the empirical specification can be expressed as

$$x_{t+h} = \alpha_h + \psi_h(L)z_{t-j} + \beta_h f_t + \gamma_h f_t EBP_{t-1} + \epsilon_{t+h}. \tag{37}$$

Controls and Estimation The baseline set of controls z_t comprises the logarithm of the Index of Industrial production, the logarithm of the CPI, the Gilchrist and Zakrajsek (2012) Excess Bond Premium, and the market yield on U.S. Treasury Securities at 1-Year Constant Maturity, i.e., $z_t = [IP_t, CPI_t, EBP_t, TBill_{1,t}]$.[11] Equation (37) is estimated using monthly data between 07/1991 and 06/2019 and a lag-length of 12. The monthly measure of monetary policy surprises is constructed by summing all of the high-frequency surprises each month. To account for the serial correlation in the error terms, I use the Newey-West correction for calculating standard errors.

Impulse Responses, the Role of Sentiments The general definition of an impulse response function $IRF(x_{t+h}|d_t = d; Z_t)$, for a variable x_t, to a shock d_t at time t, at horizon h is given by

$$IRF(x_{t+h}|d_t = d; Z_t) = E_t(x_{t+h}|d_t = d; Z_t) - E_t(x_{t+h}|d_t = 0; Z_t).$$

[11] Data used for constructing local projections can be accessed as follows: IP_t– https://fred.stlouisfed.org/series/INDPRO CPI_t– https://fred.stlouisfed.org/series/CPILFESL, EBP_t – https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/recession-risk-and-the-excess-bond-premium-accessible-20160408.html, $TBill_{1,t}$ https://fred.stlouisfed.org/series/DGS1

Applying this definition, the total effect of a 1-unit surprise tightening in f_t, at horizon h on variable x, is given by

$$IRF(x_{t+h}|f_t = 1; Z_t) = \Big(\beta_h f_t + \gamma_h EBP_{t-1} f_t | f_t = 1\Big) = \Big(\beta_h + \gamma_h EBP_{t-1}\Big). \tag{38}$$

β_h, therefore, quantifies the strength of the direct effect at horizon h and, given EBP_{t-1}, γ_h quantifies the interaction effect via the sentiment channel at horizon h. Thus, given EBP_{t-1}, if the estimate of γ_h is insignificant, this eliminates the role of the sentiment channel. However, if γ_h is estimated to be significantly different from zero, the total effect of a 1-unit surprise tightening at horizon h, depends on both the direct effect and interaction effect.

To put the scale of the prevailing sentiment in the economy, EBP_{t-1}, in perspective to, Figure 1 plots the time variation in the excess bond premium. Figure 1 shows that the EBP fluctuates significantly and frequently breaches the one-standard-deviation threshold. More importantly, there are several episodes when the EBP is much larger (both positive and negative). Considering this evidence, when graphing impulse response

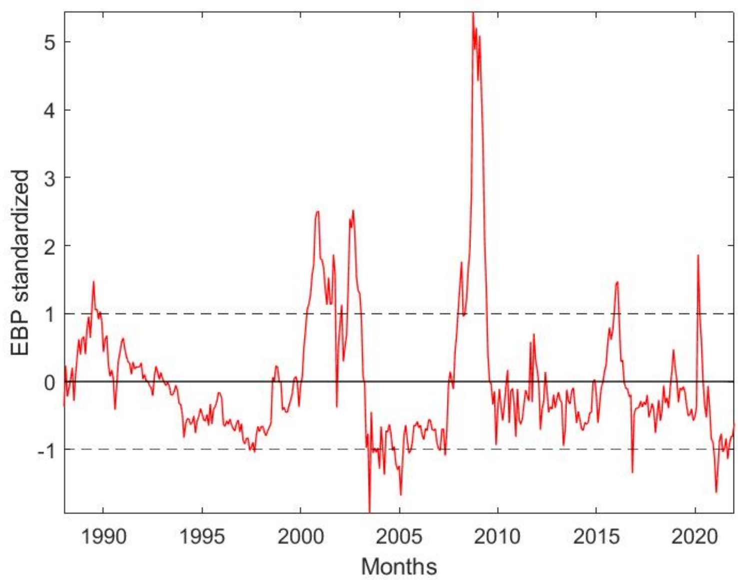

Figure 1: Time variation in the standardized excess bond premium (EBP). Dashed lines denote 1-standard-deviation bands.

functions, I fix the value of $EBP_{t-1} = 1$ to interpret the quantitative importance of the sentiment-driven interaction effects. Fixing the value of $EBP_{t-1} = 1$ allows me to compare the relative strength of the direct effect vis-$\grave{a}$-vis the sentiment-driven interaction effect. The total effect, on impact for a 1-unit surprise to monetary policy, with $EBP_{t-1} = 1$ is given by

$$IRF(x_{t+h}|f_t = 1; Z_t, EBP_{t-1} = 1) = \beta_h + \gamma_h. \tag{39}$$

Quantifying the Scale of Monetary Policy Surprises Finally, before reporting the results, I discuss how to interpret the scale of monetary policy surprises. To quantify the scale of a one-unit increase in the one-dimensional measure of monetary policy surprise, the Eurodollar futures of different maturities (the first four quarterly Eurodollar futures – ED1-ED4 respectively) is regressed on the estimated high-frequency measure of surprises along with a constant. Table 1 shows that when the measure of monetary policy surprises increases by 1-unit, this generates a 7.91 basis point increase in the yield of a Eurodollar future in the very short run (maturity of one quarter), and 10.54 basis point increase in the Eurodollar futures maturing at a longer horizon (maturity of 4 quarters).

Eurodollar Future	1	2	3	4
Effects of monetary policy surprise				
Baseline Surprises	7.91	9.44	10.28	10.54

Table 1: Effect of a one-unit change in my high-frequency measure of monetary policy surprises on Eurodollar futures of different maturities (1 through 4 quarters ahead)

4 Results

The baseline results are obtained by estimating equation (37) with monetary policy surprises identified using the one-dimensional measure in Nakamura and Steinsson (2018) and Bauer and Swanson (2023).

4.1 Local Projections with the Baseline Measure of Monetary Policy Surprises

According to *Testable Implication 1*, β_h should be less than zero for a 1-unit surprise tightening. According to *Testable Implication 2*, given $EBP_{t-1} > 0$, and controlling for the direct effect given by β_h, γ_h should be less than zero for a 1-unit surprise tightening.

To investigate these implications, Figure 2 plots the response of Industrial Production to a one-unit surprise monetary policy tightening. The left column of Figure 2 presents the usual direct effect of quantifying the effects of monetary policy surprises (β_h), and the right column plots the interaction effect (γ_h). For simplicity, I report results here using the raw high-frequency instrument for monetary policy discussed above; later, in Section 4.2, I consider orthogonalizing this instrument with respect to relevant economic news, as recommended by Bauer and Swanson (2023).

The direct effect is contractionary and qualitatively consistent with earlier studies examining the impact of exogenous tightening in monetary policy. I estimate that industrial production declines gradually, hitting a trough of about -0.7% after about 18 months. These estimates are somewhat larger than Gertler and Karadi (2015), but consistent with Bauer and Swanson (2023).[12]

Let us now examine if the interaction effect works over and above the direct effect to generate additional quantitative implications for real effects related to monetary policy surprises. The right column of Figure 2 plots the estimated interaction effect γ_h, assuming a 1-unit positive value of the EBP in $t-1$, which is consistent with moderately pessimistic market sentiment. Figure 2 shows that, γ_h is negative and significant at a confidence level of 90%. Thus, the interaction effect between sentiments and monetary policy surprises contributes to the decline in industrial production in response to a 1-unit surprise tightening. Note, that much of the decline in activity attributed to the inter-

[12]Gertler and Karadi (2015) consider a 25bp tightening in the one-year government bond rate and estimate contractionary effects in IP with a maximum decline of about -0.4%. A one-unit tightening in the measure I use corresponds to a 10.54 bp increase in the four-quarter ahead Eurodollar future. After adjusting for the shock size, the direct effects are consistent with Bauer and Swanson (2023). Bauer and Swanson (2023) consider a surprise 25 bp tightening to the one-year T-Bill rate.

Response of Industrial Production

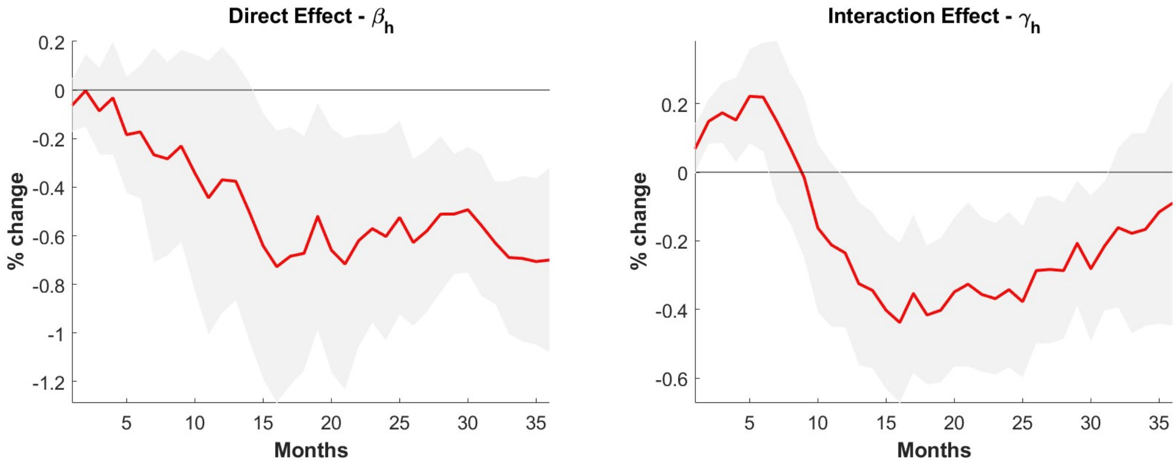

Figure 2: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Shaded areas denote 90% confidence bands (Newey-West). A one-unit surprise monetary policy tightening corresponds to approximately a 10.5 basis point increase in four quarters ahead Eurodollar future. The interaction effect in the right column is plotted, assuming a one-unit positive value of the EBP in the initial period.

action effect appears in the medium term, at around six months. The initial increase attributed to the sentiment channel in the first 5 months of transmission goes away once I control for predictability of monetary policy surprises to relevant macroeconomic news. Section 4.2 examines these results.

Relative to the direct effect, what is the magnitude attributed to the interaction effect quantifying the sentiment channel? The direct effect of a 1-unit surprise tightening is contractionary; however if we examine the interaction effect (right panel of Figure 2), we observe that at each horizon, it is almost as big as the direct effect. Moreover, the effects are estimated more precisely.

Figure 2 plots the percent change in industrial production estimated directly using data underlying macro variables and sentiments (and thus might be driven by the scale). For comparison, Figure 3 now plots the impulse responses estimated using standardized data to isolate better the quantitative contribution of the direct and the interaction effects. Figure 3 plots the response of industrial production for a one-unit surprise tightening via the direct effect and the interaction effect on the same axes, given a one-standard-deviation positive value of the EBP in $t-1$. Note that, Figure 3 compares the strength of the two channels assuming a one standard deviation positive value of the EBP in $t-1$; however, sentiments are time-varying and when sentiments are extremely pessimistic, the real effects via the sentiment channel can exceed the direct effect and in the process increase the impact of monetary policy on real activity.

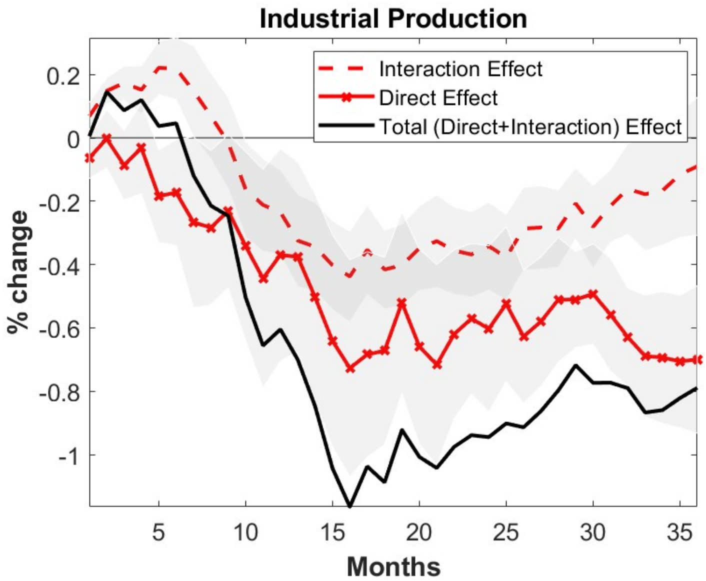

Figure 3: Comparing the direct effect (crossed red line), interaction effect (dashed red line), and total effect (black line) of a one-unit surprise monetary policy tightening on $\log(IP)$ using standardized data. Shaded areas denote 90% confidence bands (Newey-West). The solid black line plots the total effect given by $\beta_h + \gamma_h EBP_{t-1}$, assuming a one std. deviation positive value of EBP in $t-1$. A one-unit surprise monetary policy tightening corresponds to approximately a 10.5 basis point increase in four-quarter-ahead Eurodollar future.

Equivalently, the results in Figures 2 and 3 suggest that surprise monetary policy easing is significantly more effective in stimulating the economy when credit-market sentiments are particularly pessimistic. Likewise, when sentiments are particularly optimistic, the tightening necessary to restrain the economy is larger.[13]

Figure 4, plots the impulse response functions for the EBP to a 1-unit monetary

[13] Although the sample for the empirical analysis ends at 07/2019, during the episode of recent tightening through 2022 and 2023, the EBP was negative for a substantial part of the sample, indicating optimism in the economy. Consistent with my empirical results, the realized tightening dampened real activity less than perhaps expected. The average value of the EBP during 2022 was around -16 basis points or equivalently, -0.4 standard deviations below the average.

policy shock. The left column, as before, presents the direct effects. Consistent with other studies such as Gertler and Karadi (2015) and Bauer and Swanson (2023), on impact, credit-market sentiment measured using the excess bond premium increases, and the effect is somewhat persistent. The right column studies the interaction effect. What stands out is the gradual increases in the excess bond premium followed by a decline. The increase due to the interaction effect is significant a few periods after the shock. Similar to the response of industrial production, the strength of the interaction effect is not only stronger but more precisely estimated relative to the direct effect. The presence of the interaction term thus potentially creates a feedback mechanism that reinforces the impact of initial tightening when sentiments are pessimistic and dilutes the same when sentiments are optimistic. Section G in the appendix plots the response of CPI and the yield on the one-year Treasury bill. These results are discussed in greater detail when I examine the impact of orthogonalizing monetary policy surprises in Section 4.2.

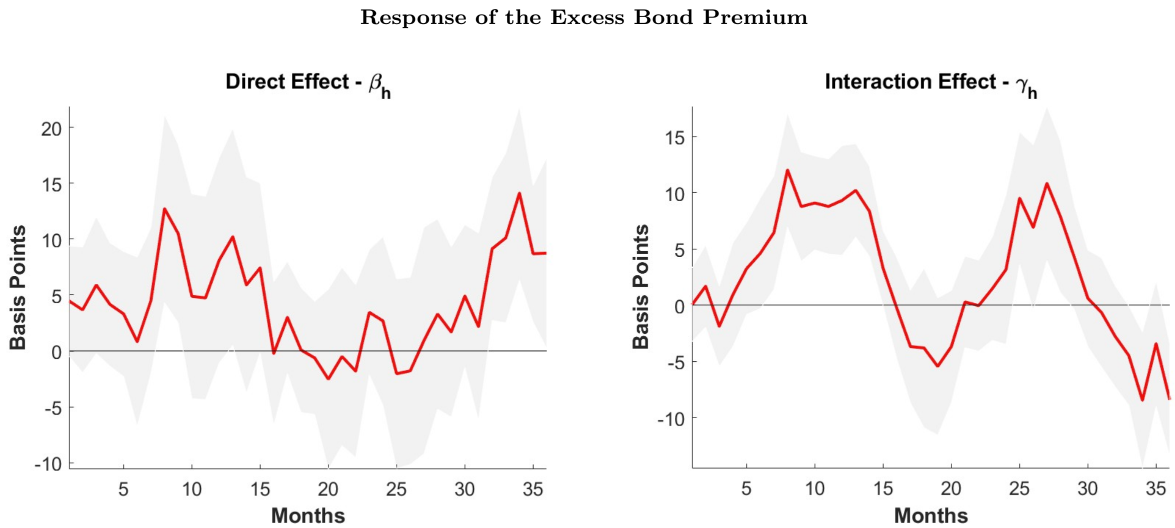

Figure 4: Left column: Direct effect of a one-unit surprise monetary policy tightening on the EBP. Right column: Interaction effect of a one-unit surprise monetary policy tightening on EBP. Shaded areas denote 90% confidence bands (Newey-West). A one-unit surprise monetary policy tightening corresponds to approximately a 10.5 basis point increase in four-quarter-ahead Eurodollar future. The interaction effect in the right column is plotted assuming a one-unit positive value of the EBP in the initial period.

4.2 Controlling High Frequency Surprises for Other Macroeconomic Announcements

The analysis in the previous section uses high-frequency identification to identify surprises in monetary policy. This approach usually allows the identification of a "true surprise" since the possibility of the release of relevant non-monetary news around this window is small. However, Ramey (2016), Miranda-Agrippino and Ricco (2021), and Bauer and Swanson (2023) suggest that even for a tight thirty-minute window surrounding FOMC announcements, the extracted surprises might not be truly exogenous and contain a predictable component (especially when daily surprises are cumulated at a monthly level). This predictability may bias the estimated impulse response functions of macroeconomic variables to a monetary policy shock, because part of the estimated effects could be due to the correlated economic and financial news rather than to monetary policy itself. To check the robustness of the sentiment channel stemming from the interaction between the lagged EBP and monetary policy surprises to this possible bias, I next construct local projections using an "orthogonalized measure" of surprises.

This orthogonalized measure is constructed by orthogonalizing the baseline high-frequency measure of surprises (f_t) introduced in Section 3 to relevant macroeconomic and financial news around the announcement window. The choice of variables for orthogonalization follows Bauer and Swanson (2023) and consists of nonfarm payroll surprise,[14], employment growth,[15] the S&P 500,[16] the slope of the yield curve,[17] commodity prices[18] and the treasury skewness.[19] To orthogonalize the baseline measure of surprises to these

[14]The surprise component of the most recent nonfarm payrolls release prior to the FOMC announcement measured as the difference between the released value of the statistic minus the median expectation for that release obtained from the Money Market Services survey.

[15]The log change in nonfarm payroll employment from one year earlier to the most recent release before the FOMC announcement

[16]The log change in the S&P500 stock price index from three months (65 trading days) before the FOMC announcement to the day before the FOMC announcement.

[17]Measured as the change in the slope of the yield curve from three months before the FOMC announcement to the day before the FOMC announcement, measured as the second principal component of one-to ten-year zero-coupon Treasury yields from Gurkaynak et al. (2007).

[18]Measured as the log change in the Bloomberg Commodity Spot Price index (BCOMSP) from three months before the FOMC announcement to the day before the FOMC announcement

[19]Measured by the implied skewness of the ten-year Treasury yield, measured using options on 10-year

macroeconomic and financial variables, I estimate a regression of the form

$$f_t = \alpha + \beta X_t + \epsilon_t \tag{40}$$

I denote the orthogonalized measure of monetary policy surprises by $\hat{f}_t = \epsilon_t$. I next use this measure of monetary policy surprise, orthogonal to relevant macroeconomic and financial news, to estimate local projections of the form

$$x_{t+h} = \alpha_h + \psi_h(L)z_t + \beta_h \hat{f}_t + \gamma_h \hat{f}_t EBP_{t-1} + \epsilon_{t+h}. \tag{41}$$

Eurodollar Future	1	2	3	4
Effects of 1-unit monetary policy surprise				
Baseline Surprises	7.906	9.4455	10.2775	10.5445
Orthogonalized surprises	7.8983	9.3333	10.1204	10.4433

Table 2: Effect of a one-unit change in my high-frequency measure of monetary policy surprises on Eurodollar futures of different maturities (1 through 4 quarters ahead). Orthogonalized surprises are constructed by removing the correlation of relevant macroeconomic and financial news that predate the monetary policy announcements from the baseline measure.

Table 2 summarizes the scale of a one-unit increase in the measure of monetary policy surprise orthogonalized to relevant macroeconomic and financial news that predate monetary policy announcements. Figures 5-8 compare the responses of macro variables to orthogonalized (blue line) surprises relative to the baseline surprises (red line) presented in the earlier section.

Orthogonalizing the monetary policy surprises with respect to macroeconomic and financial news amplifies the magnitude and precision of both the estimated direct effects of monetary policy and the interaction effects with sentiments. The right column of Figure 5 shows that orthogonalizing surprises to macroeconomic and financial news dampens the increase in activity in the first five months of propagation while amplifying

Treasury note futures with expirations in 1–3 months, averaged over the preceding month, from Bauer and Chernov (2021).

the contractionary effects in the short to medium run. Table 3 below summarizes the trough response of industrial production, highlighting the direct, interaction, and total effect for both the baseline measure of monetary policy surprise and the orthogonalized measure of surprise.

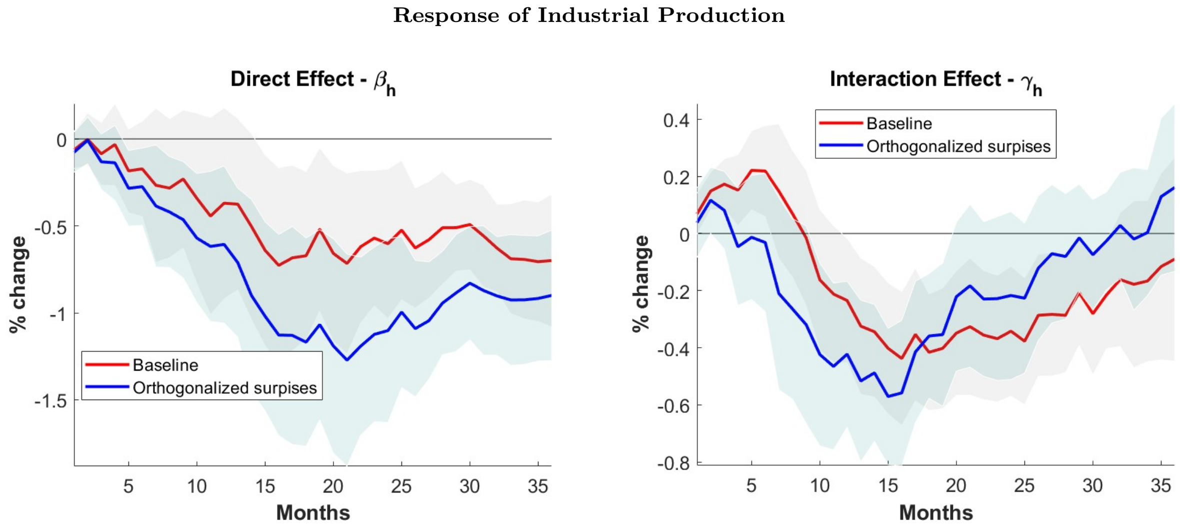

Figure 5: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Shaded areas denote 90% confidence bands (Newey-West). A one-unit surprise monetary policy tightening for the baseline measure corresponds to approximately a 10.5 basis point increase in four-quarter-ahead Eurodollar future. A one-unit surprise monetary policy tightening for the orthogonalized measure corresponds to approximately a 10.4 basis point increase in four-quarter-ahead Eurodollar future. The interaction effect in the right column is plotted assuming a 1-unit positive value of of the EBP in the initial period.

Baseline measure of monetary policy surprise	**Direct effect**	**Interaction effect**	**Total effect**
Month of hitting trough response	21	16	16
Trough response in %	-0.70	-0.65	-1.35
Orthogonalized measure of monetary policy surprise			
Month of hitting trough response	21	15	16
Trough response in %	-1.26	-0.87	-1.94

Table 3: Summarizing the trough response (calculated as the maximum decline) in $\log(IP)$ in response to a one-unit surprise tightening via both the baseline and the orthogonalized measure of monetary policy surprise when EBP has a one-unit positive value in $t-1$.

Figure 6 report analogous results for the EBP. Similar to the response of Industrial

Response of Excess Bond Premium

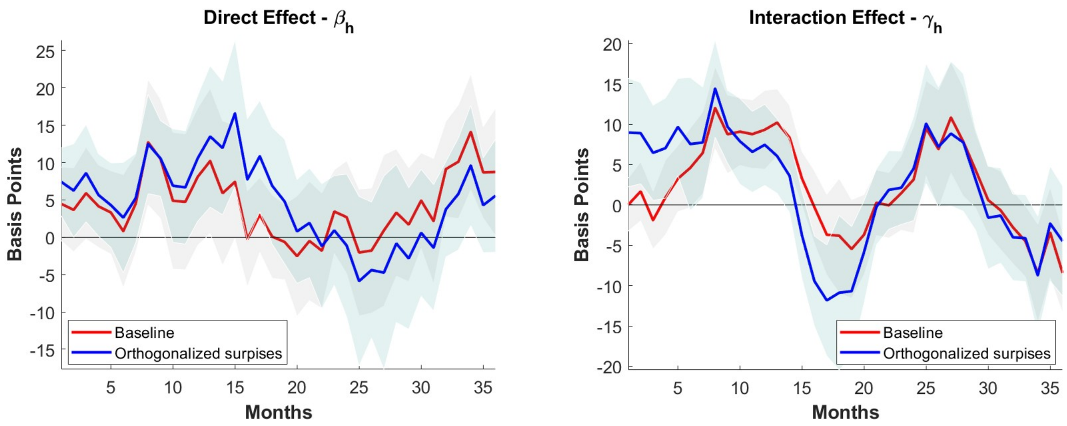

Figure 6: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Shaded areas denote 90% confidence bands (Newey-West). See notes to Figure 5 and text for details.

Production, orthogonalization amplifies the response of the EBP on impact via the interaction effect (right column of Figure 6). The direct effect of monetary tightening on the EBP is comparable for both specifications.

Figure 7 plots the impact on the CPI across both measures of monetary policy surprises. Figure 7 demonstrates that while the baseline specification fails to generate a significant impact on the CPI, the interaction effect with orthogonalized monetary policy surprises now generates a persistent decline. Put differently; an expansionary policy can stimulate inflation when sentiments are pessimistic. Relative to industrial production, the overall effect on the CPI is modest; the finding is intuitive nonetheless. The direct effect is comparable across both specifications.[20]

Finally, Figure 8 plots the response of the yield on the one-year Treasury security, and the responses are broadly comparable across both measures of surprises to monetary policy.

[20] Gertler and Karadi (2015) examine the impact of a surprise monetary policy tightening and find that the impact on inflation is modest. While their approach to identification using external instruments solves the price puzzle, the impact on inflation for a 25 basis point suprise tightening, while negative on average, is quantitatively small and significant only in the longer run. However, Bauer and Swanson (2023), using their orthogonalized measure of monetary policy surprises in a structural VAR with external instruments, find a bigger and more significant decline in the CPI.

Response of CPI

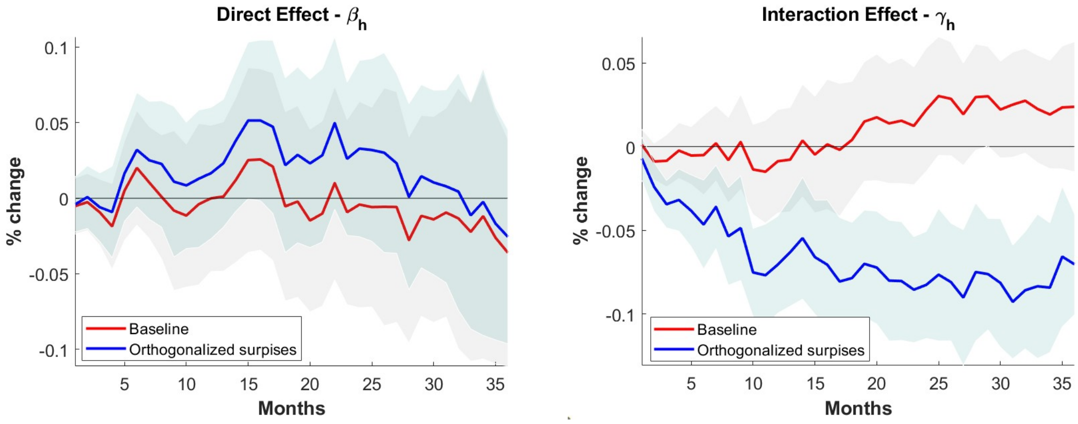

Figure 7: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Shaded areas denote 90% confidence bands (Newey-West). See notes to Figure 5 and text for details.

Response of 1 year T-bill market yield

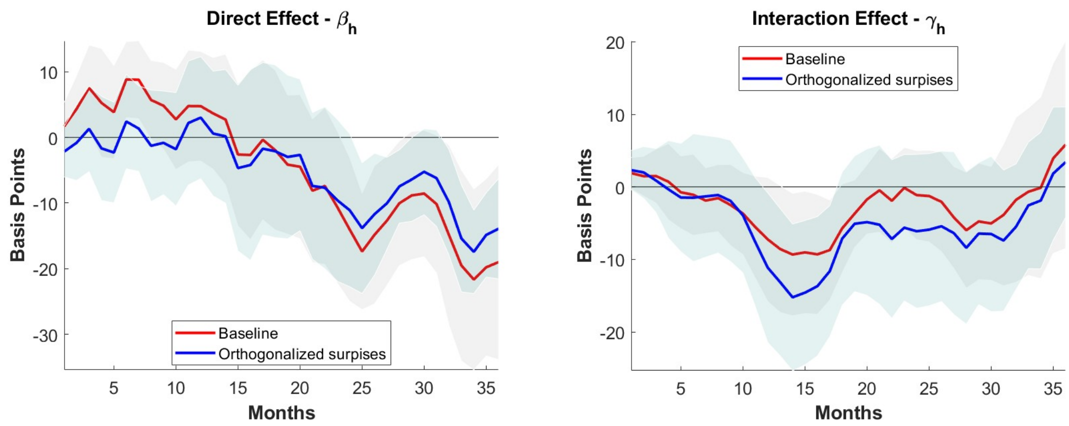

Figure 8: Left column: Direct effect of a one-unit surprise monetary policy tightening on the one-year Treasury security. Right column: Interaction effect of a one-unit surprise monetary policy tightening on the one-year Treasury security. Shaded areas denote 90% confidence bands (Newey-West). See notes to Figure 5 and text for details.

Figures 5 - 8 thus illustrate that, even if we control for macroeconomic news that might predict monetary policy surprises, the contribution of the "interaction effect" via the sentiment channel is preserved and in many cases amplified. Moreover, to isolate the impact on the CPI, controlling for the predictable component of policy surprises is critical.

4.3 Is the Interaction Effect Independent of the Cycle?

The results in the earlier section demonstrate the existence and strength of the interaction effect quantifying the role of sentiments. However, what if the empirically estimated interaction effect is simply standing in for the health of the economy and tied to the state of the business cycle? This section checks the validity and strength of the interaction effect while simultaneously allowing for a real-activity-driven interaction effect. If the strength of policy transmission is more related to interactions stemming from the "real" health of the economy, then accounting for this additional channel should eliminate or dampen the contribution of the sentiment channel. I now test for this feature. To measure the health of "real" activity in the economy, I use the unemployment rate.[21] I carry out this exercise by augmenting equation (42)

$$x_{t+h} = \alpha_h + \sum_{j=1}^{p} \psi_h(L) z_{t-j} + \beta_h \hat{f}_t + \gamma_h \hat{f}_t EBP_{t-1} + \epsilon_{t+h}. \tag{42}$$

with an additional channel stemming from the interaction between the unemployment rate (u_t) and monetary policy surprises

$$x_{t+h} = \alpha_h \psi_h(L) z_t + \beta_h \hat{f}_t + \gamma_h \hat{f}_t EBP_{t-1} + \delta_h \hat{f}_t u_{t-1} + \epsilon_{t+h}. \tag{43}$$

I also include the unemployment rate in the set of controls z in equations 42 and 43. In estimating equation 43, I use the measure of orthogonalized surprises $-\hat{f}_t$ introduced in Section 4.2 and use standardized variables to compare the contribution of each channel independent of scale with an additional channel stemming from the interaction between the unemployment rate and monetary policy surprises.

[21] The unemployment rate is a commonly used variable to quantify the state of the economy and distinguish between periods of high activity vis-*à*-vis low activity (see Ramey and Zubairy (2018) and Sahm (2019), for instance).

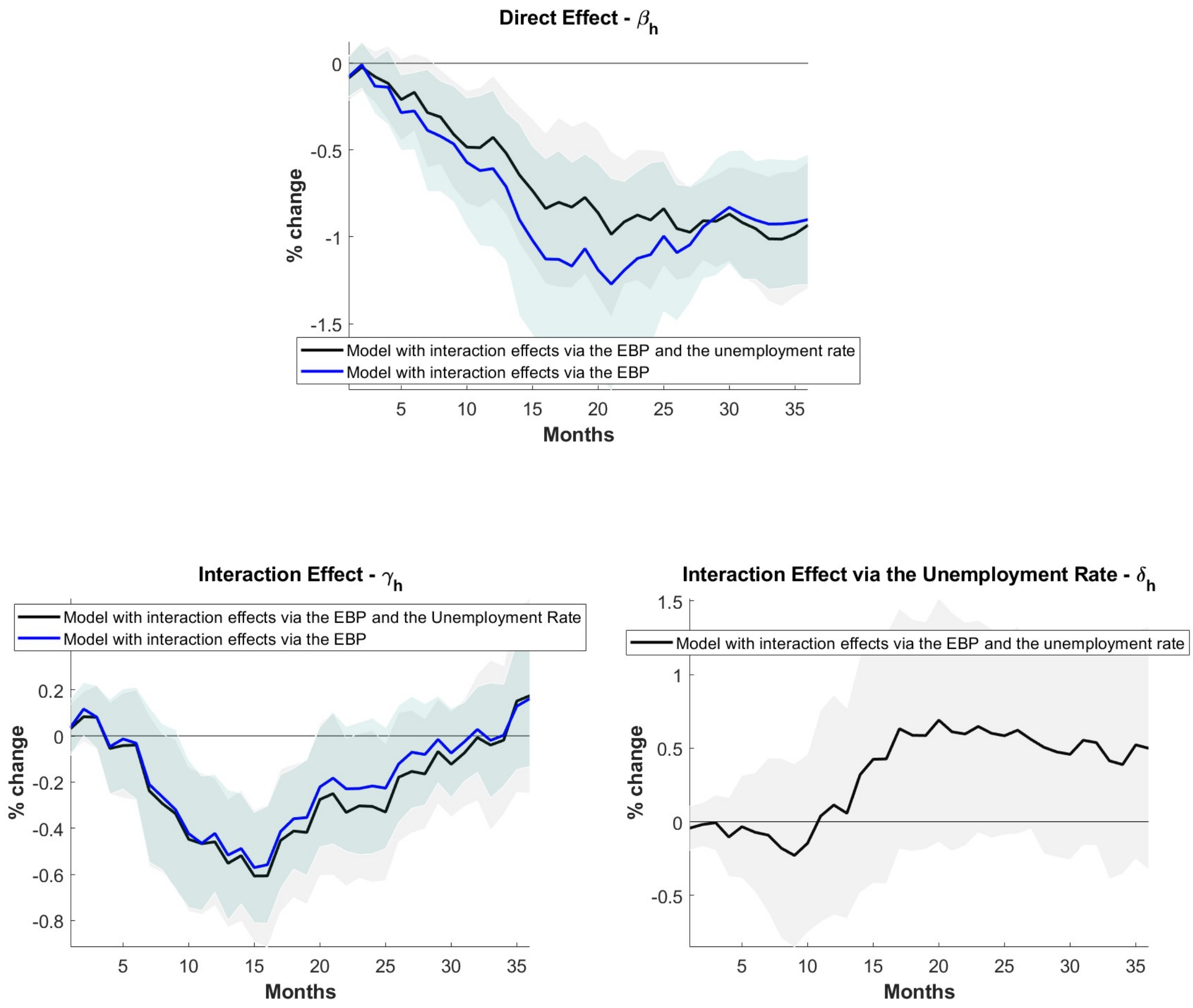

Figure 9: Top panel: Direct effect (in standard deviations) of a one-unit surprise monetary policy tightening on $\log(IP)$. Bottom left panel: Interaction effect (in standard deviations) of a one-unit surprise monetary policy tightening on $\log(IP)$ due to credit-market sentiment. Bottom right panel: Interaction effect of a one-unit surprise monetary policy tightening on $\log(IP)$ due to "real activity" channel. Light-shaded areas denote 90% confidence bands, and dark-shaded areas denote 68% confidence bands (Newey-West). Interaction effects plotted assuming a one standard deviation positive value of EBP and the Unemployment Rate.

Figure 9 plots estimated coefficients β_h quantifying the direct effect, γ_h quantifying the interaction effect stemming from the sentiment channel, and δ_h quantifying the interaction effect stemming from the "real activity" channel. Figure 9 shows that even at a confidence level of 68%, the interaction between real activity, quantified by the unemployment rate, and monetary policy surprises is insignificant. Figure 9 also compares the direct and the interaction effect via the credit-market sentiment channel estimated in equation (42) to emphasize that neither strength nor the significance of the sentiment channel is diluted if I allow for interaction between monetary policy surprises and the unemployment rate. The strength of the interaction effect thus continues to remain relevant. The exercise thus shows that the interaction effect is not simply capturing the cyclical fluctuations in real activity.

5 Robustness Checks

The analysis in Section 4 demonstrates that the interaction effect plays a key role in the transmission of monetary policy surprises. It operates over and above the usual direct effects through which monetary policy impacts real activity. This section further tests the robustness of this interaction effect by controlling for important features such as the zero lower bound, periods of financial turbulence, and aggregate measures of financial risk. I describe each of these additional controls below. Figure 10 (and Figures 15-17 in

Response of Industrial Production

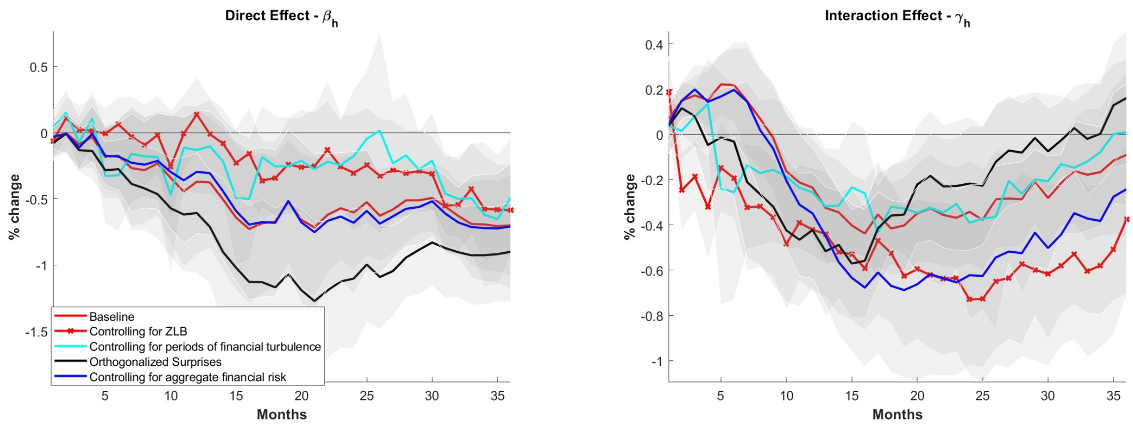

Figure 10: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(IP)$. Shaded areas denote 90% confidence bands (Newey-West).

Section H of the Appendix) compares the estimated direct effect and sentiment channel via the interaction effect relative to the baseline (red) and relative to estimated effects after removing predictability in monetary policy surprises (black). For each robustness check, the baseline measure of monetary policy surprises (described in Section 4.1) has been used.

Zero Lower Bound I check the robustness of my results to the zero lower bound (ZLB) on the nominal interest rate by dropping the periods in which the ZLB constraint binds (01/2009 – 11/2015) and re-estimate equation (36). Figure 10 (and Figures 15-17 in Section H of the Appendix) plots the results corresponding to the direct effect and the interaction effect in crossed-red lines.

Dropping periods of financial turbulence An obvious concern in the empirical exercise might be that the strength of the sentiment channel captured by the coefficient between the interaction of one-period lagged excess bond premium and contemporaneous policy surprises is driven by elevated pessimism in credit markets during the financial crisis. To control for this feature, I drop periods of financial turbulence and re-estimate equation (36) by dropping the sample between 07/2008 and 06/2009.[22] Figure 10 (and Figures 15-17 in Section H of the Appendix) plots these results in light-blue.

Controlling for Aggregate Risk in Financial Markets Gilchrist and Zakrajsek (2012) construct the measure of excess bond premium to control for expected default along with bond-specific characteristics and the term premium. By using the excess bond premium as a measure of credit-market sentiment, I assume that once I control for these measures commonly used to quantify financial frictions, what is left is a measure of sentiment.

However, the results may be driven by aggregate risk in financial markets that stem from sources different from the corporate bond markets. To check the robustness of results to this feature, I re-estimate 37 by including a measure of aggregate financial risk. Financial risk is being measured by the risk sub-index used for constructing the National Financial Condition Index (Brave and Butters, 2012). The risk subindex[23] captures

[22]This makes the estimated direct effects comparable with the analysis in Gertler and Karadi (2015), who also evaluate the robustness of their results by dropping this period.

[23]The financial risk sub-index of the NFCI is constructed using data on 34 risk indicators. For details,

volatility and funding risk in the financial sector. Like the EBP, a positive value of the NFCI risk sub-index indicates tighter-than-average conditions implying that the readiness of markets to bear financial risk is lower, while negative values indicate the opposite. The set of controls z_t in equation 41 now, along with lags of industrial production, the CPI, the excess bond premium, and the yield on one-year Treasury security, includes the NFCI financial risk sub-index. Figure 10 (and Figures 15-17 in Section H of the Appendix) plots these results in dark blue.

6 Conclusion

I motivate a role for sentiments in the transmission of monetary policy to the economy using a model of diagnosticity in belief formation. I then empirically analyze the existence and strength of the proposed sentiment channel in the data. To measure diagnosticity in the data, I use intuition from the model and quantify unobserved diagnosticity using the lagged value of the excess bond premium, which forges a connection between sentiments in the data and diagnosticity in the model. My empirical results show that the interaction effect stemming from sentiments is quantitatively significant. In particular, monetary policy's impact on the economy is significantly more powerful when credit market sentiments are pessimistic than optimistic. When direct effects are combined with sentiment-driven interaction effects, the results can explain why the potency of monetary policy in influencing real activity varies over time.

My results have important implications for researchers in monetary economics and monetary policymakers. For researchers, I find evidence of a new and important channel for the transmission of monetary policy to the real economy. It would be interesting to investigate whether a similar sentiment channel exists in other economies, such as the Euro area, and whether a sentiment channel exists for the effects of monetary policy on other variables. Researchers might also want to take the sentiment channel of monetary policy into account in their own estimates of the effects of monetary policy to avoid getting

refer to https://www.chicagofed.org/research/data/nfci/background.

biased results that depend on the state of the economy. For monetary policymakers, my results imply that monetary policy is generally more potent in recessions and other times when sentiments are pessimistic.

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Appendix

A Deriving the distribution under diagnostic expectations

$$\omega_{t+1}|\omega_t \sim f^\theta(\omega_{t+1}|\omega_t) = f(\omega_{t+1}|\omega_t)\Big[\frac{f(\omega_{t+1}|\omega_t)}{f(\omega_{t+1}|\omega_{t-1})}\Big]^\theta \frac{1}{Z} \tag{44}$$

The true Markovian distribution of fundamentals is given by

$$f(\omega_{t+1}|\omega_t) \sim N(E_t\omega_{t+1}, \sigma_\omega^2).$$

Applying this to equation (44),

$$\begin{aligned}
f^\theta(\omega_{t+1}|\omega_t) &= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]\left[\frac{\frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]}{\frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_{t-1}\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]}\right]^\theta \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]\left[\frac{\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]}{\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_{t-1}\omega_{t+1}}{\sigma_\omega}\Big)^2\Big]}\right]^\theta \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2-\theta\frac{1}{2}\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2+\theta\frac{1}{2}\Big(\frac{\omega_{t+1}-E_{t-1}\omega_{t+1}}{\sigma_\omega}\Big)^2\Big] \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big((1+\theta)\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2-\theta\Big(\frac{\omega_{t+1}-E_{t-1}\omega_{t+1}}{\sigma_\omega}\Big)^2\Big)\Big] \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big((1+\theta)\Big(\frac{\omega_{t+1}-E_t\omega_{t+1}}{\sigma_\omega}\Big)^2-\theta\Big(\frac{\omega_{t+1}-E_{t-1}\omega_{t+1}}{\sigma_\omega}\Big)^2\Big)\Big] \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big((1+\theta)\Big(\frac{\omega_{t+1}^2+(E_t\omega_{t+1})^2-2\omega_{t+1}E_t\omega_{t+1})}{\sigma_\omega^2} \\
&\quad -\theta\Big(\frac{(\omega_{t+1}^2+(E_{t-1}\omega_{t+1})^2-2\omega_{t+1}E_{t-1}\omega_{t+1})}{\sigma_\omega^2}\Big)\Big] \\
&= \frac{1}{\sigma_\omega\sqrt{2\pi}}\exp\Big[-\frac{1}{2}\Big(\frac{(1+\theta)((E_t\omega_{t+1})^2-2\omega_{t+1}E_t\omega_{t+1})+\omega_{t+1}^2-\theta(E_{t-1}\omega_{t+1})^2+\theta 2\omega_{t+1}E_{t-1}\omega_{t+1}}{\sigma_\omega^2}\Big)\Big]
\end{aligned} \tag{45}$$

Simplifying the expression by collecting the linear and quadratic terms in ω_{t+1}

$$f^{\theta}(\omega_{t+1}|\omega_t) \propto \frac{1}{\sigma_\omega\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left[\frac{\omega_{t+1}^2 - 2\omega_{t+1}[E_t\omega_{t+1} + \theta(E_t\omega_{t+1} - E_{t-1}\omega_{t+1})]}{\sigma_\omega^2}\right]\right]$$

$$f^{\theta}(\omega_{t+1}|\omega_t) = \frac{1}{Z}\frac{1}{\sigma_\omega\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left[\frac{\omega_{t+1} - [E_t\omega_{t+1} + \theta(E_t\omega_{t+1} - E_{t-1}\omega_{t+1})]}{\sigma_\omega}\right]^2\right]. \quad (46)$$

Here Z is the normalizing constant, with $Z = \exp\left[-\frac{1}{2}\frac{\theta(1+\theta)(E_t\omega_{t+1} - E_{t-1}\omega_{t+1})^2}{\sigma_\omega^2}\right]$.

B Microfounding the state of the economy

Output – $y_t(\rho)$ produced by a firm of riskiness ρ in period t depends on capital chosen in period $t-$ and the realized state ω_t in period t and given by

$$y_t(\rho) = k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})^{\alpha}\mathcal{I}(\rho, \omega_t). \quad (47)$$

where

$$\mathcal{I}(\rho, \omega_t) = \begin{cases} 1 & \omega_t \geq \rho \\ 0 & \omega_t < \rho. \end{cases} \quad (48)$$

Note that $k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})$ is predetermined and unaffected by the realization of ω_t. The realization of ω_t determines whether a firm of riskiness ρ with capital $k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})$ is able to produce and successfully repay it's debt from period $t-1$. A higher value of ω_t means it is more likely that a firm of riskiness ρ produces since it relaxes the constraint $\omega_t \geq \rho$. This implies that $y_t(\rho)$ is an increasing function of ω_t $\forall \rho$. Given this relation, it can be concluded that aggregate output (y_t) given by

$$y_t = \int_{-\infty}^{\infty} k_t(\rho, E_{t-1}^{\theta}(\omega_t), R_{t-1})^{\alpha}\mathcal{I}(\rho, \omega_t)f(\rho)d\rho \quad (49)$$

is an increasing function of ω_t. In this environment, the output in steady state y_{ss} evolves as

$$y_{ss} = \int_{-\infty}^{\infty} k_{ss}(\rho, \overline{\omega}, \overline{R})^{\alpha}\mathcal{I}(\rho, \overline{\omega})f(\rho)d\rho \quad (50)$$

In the absence of shocks, $E^{\theta}_{t-1}(\omega_t) = \overline{\omega}$, and the steady state interest rate $\overline{R} = \frac{1}{\beta}$. Defining, the output gap with respect to steady state output in the economy $(y_t - y_{ss})$, and applying equation (49), implies $(y_t - y_{ss})$ is an increasing function of ω_t. In this way, ω_t is a good indicator of the of output gap in the economy. Finally, I close the model, by specifying ω_t to evolve as a backward looking IS curve with

$$\omega_t = (1-b)\overline{\omega} + b\omega_{t-1} - c(R_t - \overline{R}) + \epsilon^x_t;\ \epsilon^x_t \sim N(0, \sigma^2_x),\ c > 0. \tag{51}$$

C Deriving expression for diagnostic beliefs

The output gap in the economy, ω_t, evolves as

$$\omega_t = (1-b)\overline{\omega} + b\omega_{t-1} - c(R_t - \overline{R}) + \epsilon^x_t;\ \epsilon^x_{t+1} \overset{iid}{\sim} N(0, \sigma^2_x). \tag{52}$$

The central bank conducts monetary policy with

$$R_t = \overline{R} + \alpha_x(\omega_t - \overline{\omega}) + \epsilon^i_t + \epsilon^{fg}_{t-1};\ \epsilon^i_t \overset{iid}{\sim} N(0, \sigma^2_i) \text{ and } \epsilon^{fg}_t \overset{iid}{\sim} N(0, \sigma^2_{fg}).$$

Iterating one period forward and plugging in the value of R_t in the expression for the output gap implies

$$\omega_{t+1} - \overline{\omega} = \rho_1(\omega_t - \overline{\omega}) - \rho_2(\epsilon^i_{t+1} + \epsilon^{fg}_t) + \rho_3\epsilon^x_{t+1} \tag{53}$$

where $\rho_1 = \frac{b}{1+c\alpha_x}$, $\rho_2 = \frac{c}{1+c\alpha_x}$ and $\rho_2 = \frac{1}{1+c\alpha_x}$.

$$E_t\omega_{t+1} = E_t\Big[\overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2(\epsilon^i_{t+1} + \epsilon^{fg}_t) + \rho_3\epsilon^x_{t+1}\Big] = \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon^{fg}_t \tag{54}$$

Plugging in the expression for ω_t

$$E_t\omega_{t+1} = \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon_t^{fg} = \overline{\omega} + \rho_1\Big[\rho_1(\omega_{t-1} - \overline{\omega}) - \rho_2(\epsilon_t^i + \epsilon_{t-1}^{fg}) + \rho_3\epsilon_t^x\Big] - \rho_2\epsilon_t^{fg}$$
$$= \overline{\omega} + \rho_1^2(\omega_{t-1} - \overline{\omega}) - \rho_1\rho_2(\epsilon_t^i + \epsilon_{t-1}^{fg}) + \rho_1\rho_3\epsilon_t^x - \rho_2\epsilon_t^{fg}. \quad (55)$$

and

$$E_{t-1}\omega_{t+1} = \overline{\omega} + \rho_1^2(\omega_{t-1} - \overline{\omega}) - \rho_1\rho_2\epsilon_{t-1}^{fg} \quad (56)$$

Plugging on the values of $E_t\omega_{t+1}$ and $E_{t-1}\omega_{t+1}$, from equations 54, 55 and 56,

$$E_t^{\theta}\omega_{t+1} = E_t\omega_{t+1} + \theta\Big[E_t\omega_{t+1} - E_{t-1}\omega_{t+1}\Big] = \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon_t^{fg}$$
$$+\,\theta\Big[\overline{\omega} + \rho_1^2(\omega_{t-1} - \overline{\omega}) - \rho_1\rho_2(\epsilon_t^i + \epsilon_{t-1}^{fg}) + \rho_1\rho_3\epsilon_t^x - \rho_2\epsilon_t^{fg} - \overline{\omega} - \rho_1^2(\omega_{t-1} - \overline{\omega}) + \rho_1\rho_2\epsilon_{t-1}^{fg}\Big]$$
$$= \overline{\omega} + \rho_1(\omega_t - \overline{\omega}) - \rho_2\epsilon_t^{fg} + \theta\Big[\rho_1\rho_3\epsilon_t^x - \rho_1(\epsilon_t^{fg} + \rho_2\epsilon_t^i)\Big] \quad (57)$$

D Constructing an empirical measure of sentiment

To check the robustness of the EBP as a suitable measure of sentiment, I construct an empirical measure of sentiment using 3 month ahead forecast for the high-yield spread and the actual high-yield spread constructed by Moody's. The empirical measure of sentiment is constructed following Maxted (2023).

I briefly outline the construction of this empirical measure of sentiment below. For a more detailed examination, refer to Section A.2 of the appendix to Maxted (2023). Following Maxted (2023), in discrete time the information measure $\mathcal{I}_t$ quantifying a weighted measure of current and past shocks evolves as

$$\mathcal{I}_t = \sum_{j=0}^{\infty}\mathcal{K}^j\sigma\epsilon_{t-j} = \sigma\Big[\epsilon_t + \sum_{j=1}^{\infty}\mathcal{K}^j\epsilon_{t-j}\Big]. \quad (58)$$

Here, $\mathcal{K}$ is the discount factor governing the speed of information decay. If the model is at a monthly frequency, $\mathcal{K} = \exp(-\kappa/12)$. In contrast to Maxted (2023), the underlying information structure in this article is consistent with Bordalo et al. (2018) with the information measure containing only the most recent shock. This corresponds to the case of $\mathcal{K} = 0$.

Under diagnosticity, agents forecast the credit-spread in $t+1$ as

$$E_t^\theta S_{t+1} = E_t S_{t+1} + \frac{\theta}{12}\mathcal{I}_t \tag{59}$$

Subjective shocks, $\sigma\hat{\epsilon}_{t+1}$ are defined as the difference between the actual value of the credit spread realized in $t+1$ and the prediction made under diagnosticity in period t with

$$\sigma\hat{\epsilon}_{t+1} = S_{t+1} - E_t^\theta S_{t+1}. \tag{60}$$

Applying equation (59), and substituting the value of $E_t^\theta S_{t+1}$ in equation (60) yields

$$\underbrace{\sigma\hat{\epsilon}_{t+1}}_{Subjective\ Shocks} = \underbrace{S_{t+1} - E_t S_{t+1}}_{Objective\ Shocks} - \frac{\theta}{12}\mathcal{I}_t = \sigma\epsilon_{t+1} - \frac{\theta}{12}\mathcal{I}_t. \tag{61}$$

Equation 61 in conjunction with equation 58 and $\mathcal{K} = 0$ implies

$$\mathcal{I}_t = \sigma\hat{\epsilon}_t + \frac{\theta}{12}\mathcal{I}_{t-1} \tag{62}$$

Iterating backwards and using initial condition $\mathcal{I}_0 = 1$,

$$\mathcal{I}_t = \sum_{j=0}^{t-1}\left(\frac{\theta}{12}\right)^j \sigma\hat{\epsilon}_{t-j}. \tag{63}$$

Consistent with Maxted (2023), subjective shocks are measured using forecaster errors, with

$$\mathcal{I}_t = \sum_{j=0}^{t-1}\left(\frac{\theta}{12}\right)^j FE_{t-j}^{HY Moodys} \tag{64}$$

Forecast errors in the data are measured as the difference between the actual high-yield credit spread minus the predicted credit spread, three months ago. Ideally, we would like to have one-step ahead forecast errors. However, I am constrained by the availability of data here since Moody's only provides three step ahead monthly forecasts. Given a calibration of θ, equation 64 can then be used to generate an empirical measure of sentiment. To calibrate, θ I follow Bordalo et al. (2018). I first use data on annualized credit spread between 07/2007 and 12/2019 to estimate an AR(1) process with

$$HYSpread_t = \overline{HYSpread} + \rho_{hyspread} HYSpread_{t-1} + \epsilon_t^{hyspread}; \text{ with } \epsilon_t^{hyspread} \sim N(0, \sigma^2) \tag{65}$$

Estimating equation 65 yields $\rho = 0.844$ and $\sigma = 0.698$. If θ quantifies the extent of diagnosticity, then the forecast in $t+1$ is biased by $\theta \times \rho_{hyspread} \times \sigma$. In constructing the empirical measure of sentiment, θ is calibrated such that a one standard deviation in $\mathcal{I}$ corresponds to a 1% bias in the credit spread forecast, i.e.,

$$1 = \theta \rho_{hyspread} \sigma = \theta \times 0.844 \times 0.698 \implies \theta = \frac{1}{0.844 \times 0.698} = 1.699 \tag{66}$$

Using this calibration and using the forecast errors in equation 65, we can obtain a measure of credit-market sentiment underlying high-yield bonds issued by Moody's between 07/2007 and 12/2019. Table 4 below reports the correlation of this constructed measure iof sentiment with different lags of EBP.

	h=0	h=1	h=2	h=3
corr($\mathcal{I}_t, EBP_{t-h}$)	0.47	0.58	0.68	0.73

Table 4: Reporting the coefficient between the empirically constructed measure of sentiment $\mathcal{I}_t$ with the contemporaneous value of the EBP and different lags of EBP.

The subjective errors are measured using forecast errors using the difference between the actual high-yield spread in t and the forecast made 3 months ago in $t-3$. This feature attenuates the correlation between $\mathcal{I}_\sqcup$ and the one-period lagged value of the

EBP. However, as I increase the lags underlying EBP the strength of the co movement increases with the correlation being 0.73 for a thrice lagged value of the EBP. Irrespective of this feature, overall Table 4 suggests that the lagged value of EBP is a good empirical proxy to quantify diagnosticity implied sentiment.

D.1 Comparing predictions using different measures of sentiments

Next, I use the empirically constructed measure of sentiment and construct impulse responses to a 1-unit monetary policy tightening. I compare the strength of the estimated sentiment channel with what is obtained with the EBP as the measure of sentiment.

The empirically constructed measure of sentiment is constructed using forecast errors for Moody's high yield credit spread between 07/2007 and 12/2019, and the measure of monetary policy surprises are available between 07/1991 and 06/2019. Given the data availability, the sample for estimating impulse responses using local projections is restricted to 07/2007 - 06/2019.

The available sample overlaps with the Great Recession with periods of extreme financial turbulence (between 07/2008 and 06/2009). Additionally, the ZLB constraint binds between 01/2009 and 11/2015. Given the extended sample size, I can check the robustness of the results by dropping these periods from the sample in the main text. However, given that the data on forecast errors underlying credit spread is available only between 07/2007 - 06/2019, I control for these episodes by modifying equation (36) stated below

$$x_{t+h} = \alpha_h + \psi_h(L)z_t + \beta_h f_t + \gamma_h f_t EBP_{t-1} + \epsilon_{t+h}. \tag{67}$$

as

$$\begin{aligned} x_{t+h} = \alpha_h + \psi_h(L)z_t + \beta_h^1 f_t(1 - ZLB_t) + \gamma_h^1 f_t Sent_t(1 - ZLB_t) \\ + \beta_h^2 f_t ZLB_t + \gamma_h^2 f_t Sent_t ZLB_t + \epsilon_{t+h}. \end{aligned} \tag{68}$$

Here, ZLB_t is a dummy variable that equals 1 in periods where the zero lower bound on the nominal interest rate binds. The dummy variable takes the value 1 between (01/2009 - 11/2015). The coefficients β_h^1 and γ_h^1 now quantify the magnitude of the direct and interaction effects after controlling for the periods over which the ZLB binds and controls for most of the sample with periods of financial turbulence.

I estimate equation (68) using the empirically constructed measure of sentiment following Maxted (2023) and the lagged value of the EBP using the baseline measure of monetary policy surprises. Figure 11 plots these results.

Response of Industrial Production

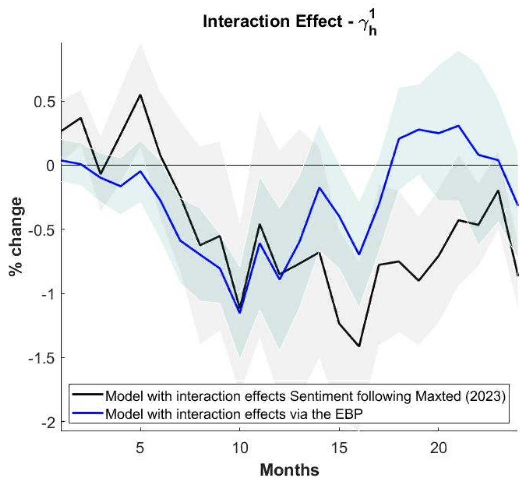

Figure 11: Interaction effect of a one-unit surprise monetary policy tightening on $\log(IP)$ with different measures of sentiment using the baseline measure of monetary policy surprises. Blue line: Interaction effect when sentiment is measured using a lagged value of EBP. Black line: Interaction effect when sentiment is measured using the empirical measure following Maxted (2023). Impulse responses constructed assuming a 1-standard deviation-positive value of the relevant measure of sentiment. Shaded areas denote 90% confidence bands (Newey-West).

Figure 11 shows that both sentiment measures generate similar interaction effects after controlling for periods over which the ZLB binds and controls for most of the sample with periods of financial turbulence. An important point to note here is that the empirically constructed measure of sentiment is 0 when θ is 0. I use a similar intuition in the main text when using the lagged value of the EBP. Figure 11 thus confirms that the lagged value of the EBP is indeed a good measure of the underlying sentiment. Moreover, given data availability, I use this measure for the empirical analysis in the main text.

E Diagnostic expectations in a canonical three equation New Keynesian Model

To derive the predictions under diagnosticity in belief formation I use the model and notation in L'Huillier et al. (Forthcoming). The framework in L'Huillier et al. (Forthcoming) introduce nominal rigidities via quadratic adjustment costs in terms of the final goods consistent with Rotemberg (1982). The log-linearized equilibrium conditions are given by

$$\hat{y}_t = E_t[\hat{y}_{t+1}] + \theta[E_t\hat{y}_{t+1} - E_{t-1}\hat{y}_{t+1}] - \left(\hat{i}_t - [E_t\hat{\pi}_{t+1} + \theta(E_t\hat{\pi}_{t+1} - E_{t-1}\hat{\pi}_{t+1})]\right) + \theta[\pi_t - E_{t-1}\pi_t] \tag{69}$$

$$\pi_t = \beta[E_t\hat{\pi}_{t+1} + \theta(E_t\hat{\pi}_{t+1} - E_{t-1}\hat{\pi}_{t+1})] + \kappa(\hat{y}_t - \hat{a}_t) \tag{70}$$

$$\hat{i}_t = \phi_\pi\hat{\pi}_t + \phi_x(\hat{y}_t - \hat{a}_t) + \epsilon^i_t + \epsilon^{fg}_{t-1} \tag{71}$$

$$\hat{a}_t = \rho_a\hat{a}_{t-1} + \epsilon^x_t. \tag{72}$$

The framework in L'Huillier et al. (Forthcoming) does not include shocks to forward guidance and surprises to monetary policy consist of a shock to the nominal interest rate ϵ^i_t. Note that setting $\theta = 0$, in equations 69 and 70, reverts the model back to the environment with rational expectations. I guess a solution for output ($\hat{y}_t$) and inflation ($\hat{\pi}_t$) of the form

$$\hat{y}_t = P^{y,\theta}_1\epsilon^{fg}_{t-1} + P^{y,\theta}_2 a_{t-1} + P^{y,\theta}_3\epsilon^i_t + P^{y,\theta}_4\epsilon^{fg}_t + P^{y,\theta}_5\epsilon^x_t \tag{73}$$

and

$$\hat{\pi}_t = P^{\pi,\theta}_1\epsilon^{fg}_{t-1} + P^{\pi,\theta}_2 a_{t-1} + P^{\pi,\theta}_3\epsilon^i_t + P^{\pi,\theta}_4\epsilon^{fg}_t + P^{\pi,\theta}_5\epsilon^x_t. \tag{74}$$

Following the solution technique outlined in L'Huillier et al. (Forthcoming), the system of equations in (69-72) is solved using the minimum state variable solution such that

$$P^{y,\theta}_1 = \frac{-1}{1 + \phi_x + \kappa\phi_\pi}; \;\; P^{\pi,\theta}_1 = \kappa P^{y,\theta}_1 \tag{75}$$

$$P_2^{y,\theta} = \frac{\rho_a(1-\beta\rho_a)\phi_x + \kappa\rho_a(\phi_\pi - \rho_a)}{(1-\beta\rho_a)(1+\phi_x-\rho_a)+\kappa(\phi_\pi-\rho_a)};\ P_2^{\pi,\theta} = \frac{\kappa P_2^{y,\theta}}{1-\beta\rho_a} - \frac{\kappa\rho_a}{1-\beta\rho_a} \tag{76}$$

$$P_3^{y,\theta} = \frac{-1}{1+\phi_x+\kappa(\phi_\pi-\theta)};\ P_3^{\pi,\theta} = \kappa P_3^{y,\theta} \tag{77}$$

$$P_4^{y,\theta} = \frac{(1+\theta)P_1^{y,\theta} + (1+\theta)P_1^{\pi,\theta}[1-\beta(\phi_\pi-\theta)]}{1+\phi_x+\kappa(\phi_\pi-\theta)}; P_4^{\pi,\theta} = \beta P_1^{\pi,\theta}(1+\theta) + \kappa P_4^{y,\theta} \tag{78}$$

$$P_5^{y,\theta} = \frac{(1+\theta)P_2^{y,\theta} + (1+\theta)P_2^{\pi,\theta}[1-\beta(\phi_\pi-\theta)] + \kappa(\phi_\pi-\theta)}{1+\phi_x+\kappa(\phi_\pi-\theta)}; P_5^{\pi,\theta} = \beta P_2^{\pi,\theta}(1+\theta)+\kappa(P_5^{y,\theta}-1) \tag{79}$$

By setting $\theta = 0$, we recover the coefficients for solution in the model with rational expectations

$$P_1^{y,0} = \frac{-1}{1+\phi_x+\kappa\phi_\pi};\ P_1^{\pi,0} = \kappa P_1^{y,0} \tag{80}$$

$$P_2^{y,0} = \frac{\rho_a(1-\beta\rho_a)\phi_x + \kappa\rho_a(\phi_\pi - \rho_a)}{(1-\beta\rho_a)(1+\phi_x-\rho_a)+\kappa(\phi_\pi-\rho_a)};\ P_2^{\pi,0} = \frac{\kappa P_2^{y,0}}{1-\beta\rho_a} - \frac{\kappa\rho_a}{1-\beta\rho_a} \tag{81}$$

$$P_3^{y,0} = \frac{-1}{1+\phi_x+\kappa\phi_\pi};\ P_3^{\pi,0} = \kappa P_3^{y,0} \tag{82}$$

$$P_4^{y,0} = \frac{\left(P_1^{y,0} + P_1^{\pi,0} - P_1^{\pi,0}\phi_\pi\beta\right)}{1+\phi_x+\kappa\phi_\pi}; P_4^{\pi,0} = \beta P_1^{\pi,0} + \kappa P_4^{y,0} \tag{83}$$

$$P_5^{y,0} = \frac{\left(P_2^{y,0} + P_2^{\pi,0} - P_2^{\pi,0}\phi_\pi\beta + \kappa\phi_\pi\right)}{1+\phi_x+\kappa\phi_\pi}; P_5^{\pi,0} = \beta P_2^{\pi,0} + \kappa(P_5^{y,0}-1) \tag{84}$$

Note, that the coefficients quantifying the role of state variables in the models with diagnostic agents and rational expectations are identical, with $P_1^{y,\theta} = P_1^{y,0}$, $P_2^{y,\theta} = P_2^{y,0}$, $P_1^{\pi,\theta} = P_1^{\pi,0}$, and $P_2^{\pi,\theta} = P_2^{\pi,0}$ as evident from equations 75, 80, 76, and 81 respectively.

Now, to understand the impact of diagnosticity, on macroeconomic variables, consider the impact of a shock to forward guidance in period t, ϵ_t^{fg} on output gap $\hat{y}_t$. The model under rational expectations predicts, on impact, the response of output is

$$P_4^{y,0} = \frac{\left(P_1^{x,0} + P_1^{\pi,0} - P_1^{\pi,0}\phi_\pi\beta\right)}{1+\phi_x+\kappa\phi_\pi} \tag{85}$$

whereas in an environment with diagnostic agents,

$$P_4^{y,\theta} = \frac{(1+\theta)P_1^{y,\theta} + (1+\theta)P_1^{\pi,\theta}[1-\beta(\phi_\pi-\theta)]}{1+\phi_x+\kappa(\phi_\pi-\theta)}. \tag{86}$$

Note, that $P_1^{y,\theta} = P_1^{y,0}$ and $P_1^{\pi,\theta} = P_1^{\pi,0}$ from equations 75 and 80. Evaluating the incremental contribution owing to diagnosticity-driven overreaction

$$\begin{aligned}
P_4^{y,\theta} - P_4^{y,0} &= \frac{(1+\theta)\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} - \frac{\Big(P_1^{y,0} + P_1^{\pi,0} - P_1^{\pi,0}\phi_\pi\beta\Big)}{1+\phi_x+\kappa\phi_\pi} \\
&= \frac{(1+\theta)\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} - \frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}\phi_\pi\beta\Big)}{1+\phi_x+\kappa\phi_\pi} \\
&= \frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} - \frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}\phi_\pi\beta\Big)}{1+\phi_x+\kappa\phi_\pi} \\
&\quad + \theta\frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} \\
&= \Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}\phi_\pi\beta\Big)\Big[\frac{1}{1+\phi_x+\kappa(\phi_\pi-\theta)} - \frac{1}{1+\phi_x+\kappa\phi_\pi}\Big] + \frac{\theta\beta P_1^{\pi,\theta}}{1+\phi_x+\kappa(\phi_\pi-\theta)} \\
&\quad + \theta\frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} \\
&= \Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}\phi_\pi\beta\Big)\Big[\frac{\kappa\theta}{\Big(1+\phi_x+\kappa(\phi_\pi-\theta)\Big)\Big(1+\phi_x+\kappa\phi_\pi\Big)}\Big] + \theta\frac{\Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta\Big)}{1+\phi_x+\kappa(\phi_\pi-\theta)} \\
&\quad + \frac{\theta\beta P_1^{\pi,\theta}}{1+\phi_x+\kappa(\phi_\pi-\theta)} \\
&= \Big(P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}\phi_\pi\beta\Big)\Big[\frac{\kappa\theta}{\Big(1+\phi_x+\kappa(\phi_\pi-\theta)\Big)\Big(1+\phi_x+\kappa\phi_\pi\Big)}\Big] + \\
&\quad \theta\Big[\frac{P_1^{y,\theta} + P_1^{\pi,\theta} - P_1^{\pi,\theta}(\phi_\pi-\theta)\beta + \beta P_1^{\pi,\theta}}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]
\end{aligned} \tag{87}$$

Plugging in $P_1^{\pi,\theta} = \kappa P_1^{y,\theta}$ from equations 75 and 80.

$$P_4^{y,\theta} - P_4^{y,0} = \Big(P_1^{y,\theta} + \kappa P_1^{y,\theta} - \kappa P_1^{y,\theta}\phi_\pi\beta\Big)\Big[\frac{\kappa\theta}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big]+ \theta\Big[\frac{P_1^{y,\theta} + \kappa P_1^{y,\theta} - \kappa P_1^{y,\theta}(\phi_\pi-\theta)\beta + \beta\kappa P_1^{y,\theta}}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]$$

$$P_4^{y,\theta} - P_4^{y,0} = P_1^{y,\theta}\Big[\frac{\kappa\theta[1+\kappa-\kappa\phi_\pi\beta]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big]+\theta P_1^{y,\theta}\Big[\frac{1+\kappa-\kappa(\phi_\pi-\theta)\beta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]$$

$$P_4^{y,\theta} - P_4^{y,0} = P_1^{y,\theta}\Big[\frac{\kappa\theta[1+\kappa-\kappa\phi_\pi\beta]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big]+\theta P_1^{y,\theta}\Big[\frac{1+\kappa-\beta\kappa\phi_\pi+\beta\kappa\theta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]$$

$$P_4^{y,\theta} - P_4^{y,0} = \theta P_1^{y,\theta}\Big[\frac{\kappa[1+\kappa(1-\phi_\pi\beta)]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big]+\theta P_1^{y,\theta}\Big[\frac{1+\kappa(1-\phi_\pi\beta)+\beta\kappa\theta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]. \tag{88}$$

The overreaction in output due to diagnosticity in belief formation in the canonical New Keynesian model is therefore given by

$$P_4^{y,\theta} - P_4^{y,0} = \theta P_1^{y,\theta}\Big[\frac{\kappa[1+\kappa(1-\phi_\pi\beta)]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big]+\theta P_1^{y,\theta}\Big[\frac{1+\kappa(1-\phi_\pi\beta)+\beta\kappa\theta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]$$

$$P_4^{y,\theta} - P_4^{y,0} = \theta P_1^{y,\theta}\Big[\frac{\kappa[1+\kappa(1-\phi_\pi\beta)]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}+\frac{1+\kappa(1-\phi_\pi\beta)+\beta\kappa\theta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]. \tag{89}$$

If θ is set to zero, the sentiment-driven overreaction component is eliminated with $P_4^{y,\theta} - P_4^{y,0} = 0$. $P_1^{y,\theta} = \frac{-1}{1+\phi_x+\kappa\phi_\pi} < 0$ given that the parameters are positive. Allowing diagnosticity in the New Keynesian model thus generates a similar additional component as generated in the model presented in Section 2. Finally, following equation (89) $P_4^{y,\theta}$, can be expressed as

$$P_4^{y,\theta} = \underbrace{P_4^{y,0}}_{Direct\ Effect} \underbrace{+\theta P_1^{y,\theta}\Big[\frac{\kappa[1+\kappa(1-\phi_\pi\beta)]}{\big(1+\phi_x+\kappa(\phi_\pi-\theta)\big)\big(1+\phi_x+\kappa\phi_\pi\big)}\Big] + \theta P_1^{y,\theta}\Big[\frac{1+\kappa(1-\phi_\pi\beta)+\beta\kappa\theta+\beta\kappa}{1+\phi_x+\kappa(\phi_\pi-\theta)}\Big]}_{Interaction\ Effect} \tag{90}$$

equation (90) thus generates theoretically similar predictions for real activity as demonstrated in Section 2.

F Other measures of economic activity

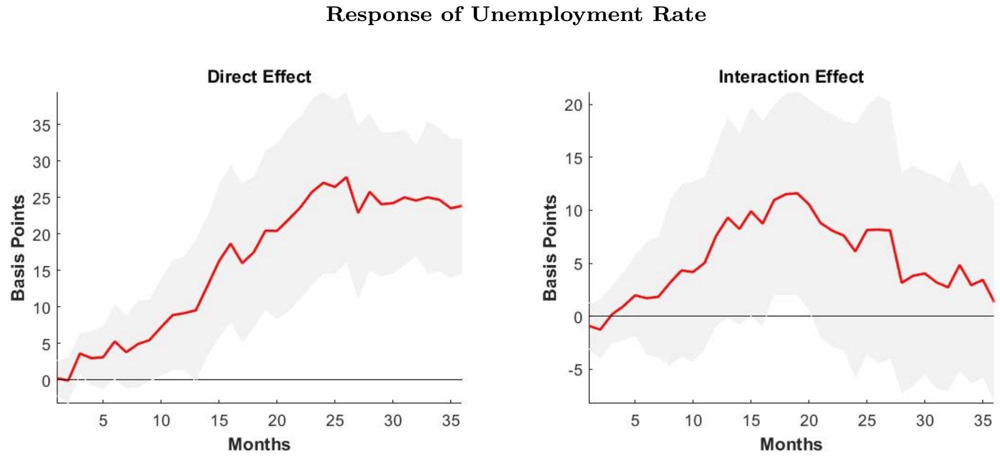

Figure 12: Left column: Direct effect of a one-unit surprise monetary policy tightening on the unemployment rate. Right column: Interaction effect of a one-unit surprise monetary policy tightening on the unemployment rate. Shaded areas denote 90% confidence bands (Newey-West).

G Response of CPI and 1 year T-Bill rate to a 1-unit increase in the baseline measure of monetary policy surprise

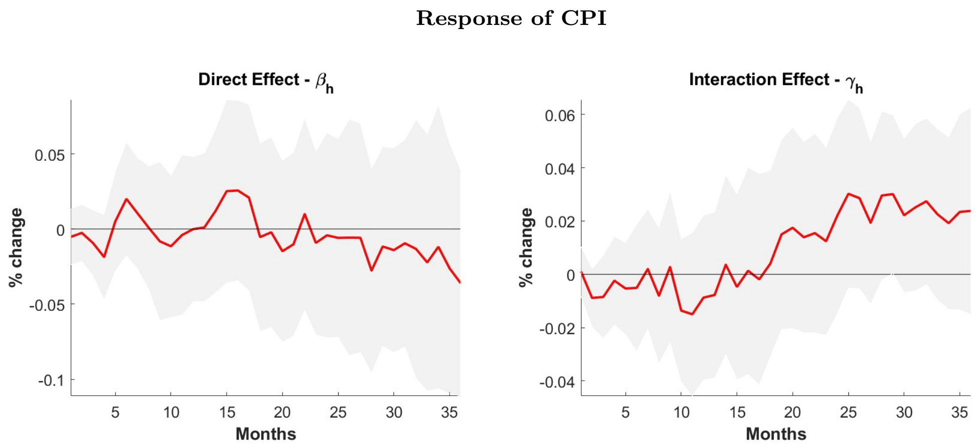

Figure 13: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Shaded areas denote 90% confidence bands (Newey-West). A one-unit surprise monetary policy tightening corresponds to approximately a 10.5 basis point increase in 4 quarter ahead Euro-dollar future. The interaction effect in the right column is plotted assuming a 1-unit positive value of credit-market sentiment in the initial period.

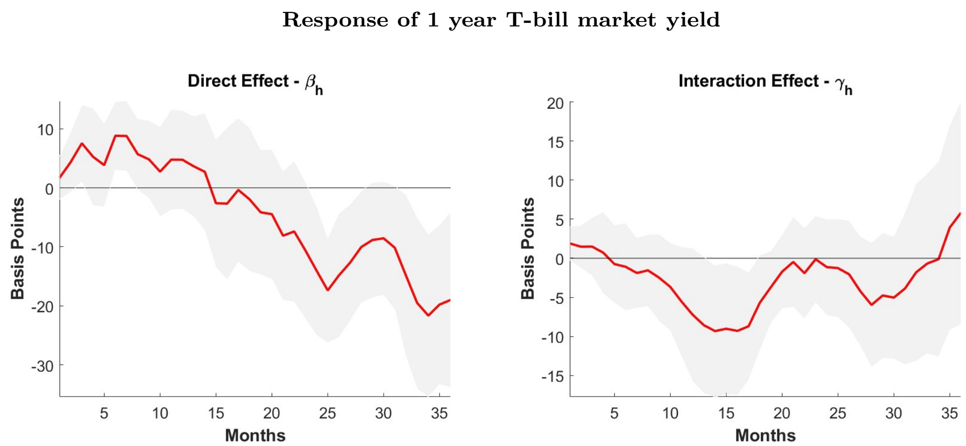

Figure 14: Left column: Direct effect of a one-unit surprise monetary policy tightening on the one year Treasury security. Right column: Interaction effect of a one-unit surprise monetary policy tightening on the one year Treasury security. Shaded areas denote 90% confidence bands (Newey-West). A one-unit surprise monetary policy tightening corresponds to approximately a 10.5 basis point increase in 4 quarter ahead Euro-dollar future. The interaction effect in the right column is plotted assuming a 1-unit positive value of credit-market sentiment in the initial period.

H Other robustness checks

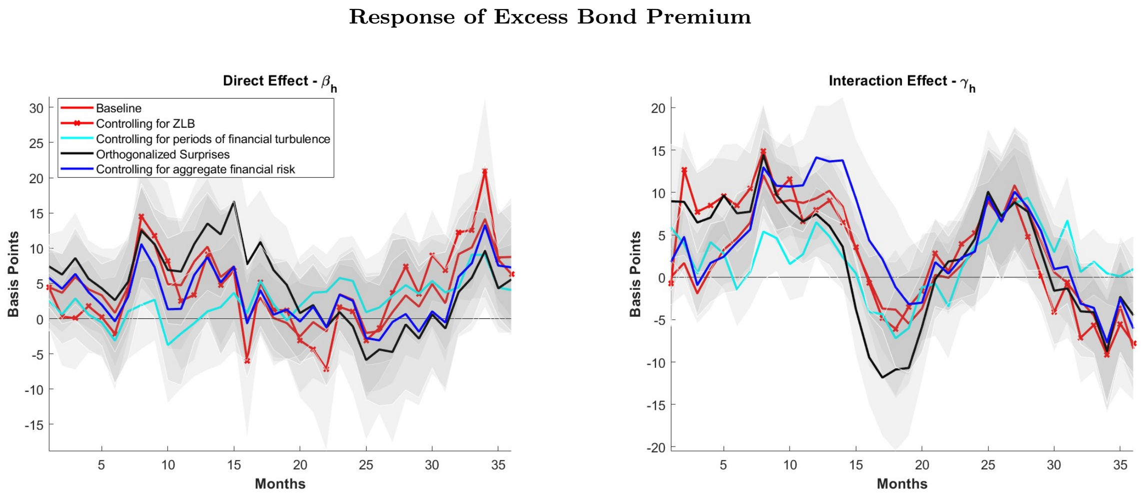

Figure 15: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Shaded areas denote 90% confidence bands (Newey-West).

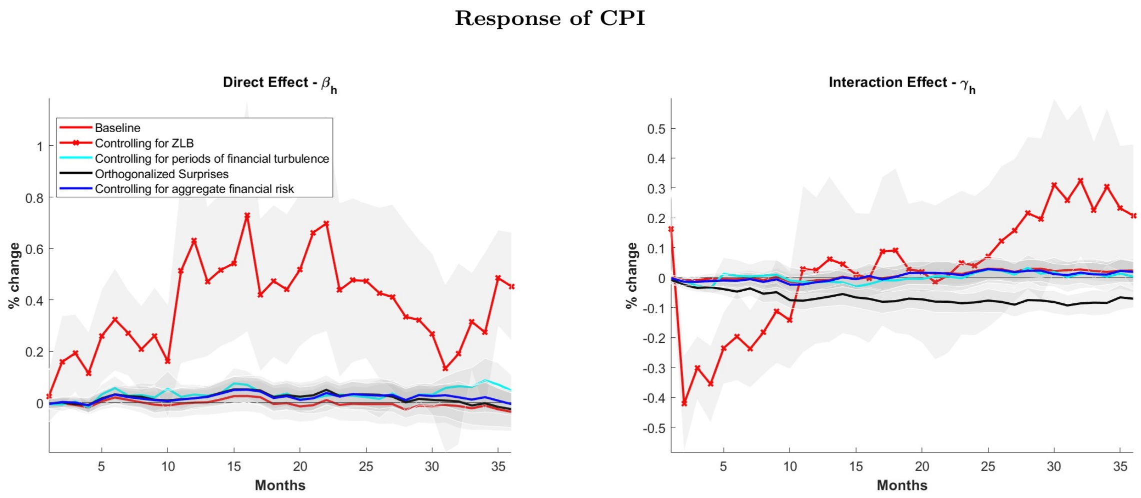

Figure 16: Left column: Direct effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Right column: Interaction effect of a one-unit surprise monetary policy tightening on $\log(CPI)$. Shaded areas denote 90% confidence bands (Newey-West).

Response of 1 year T-bill market yield

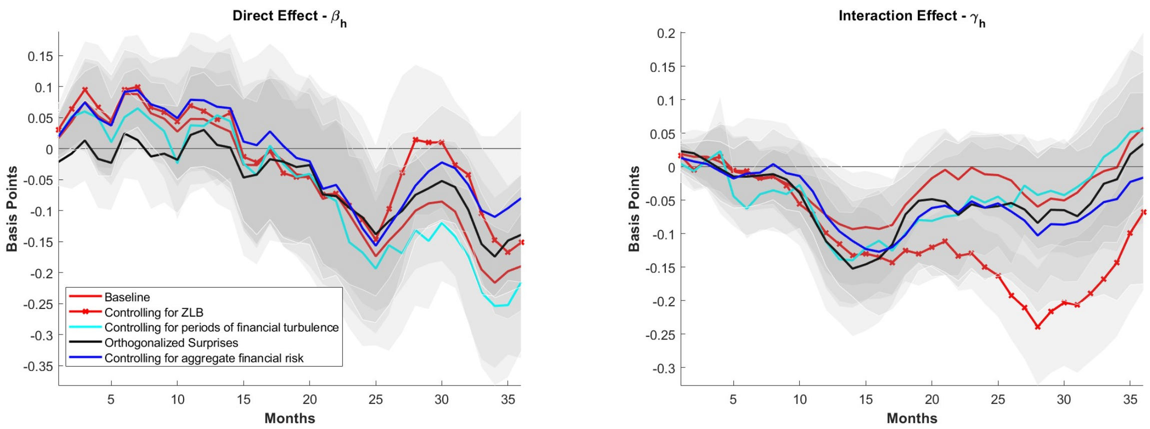

Figure 17: Left column: Direct effect of a one-unit surprise monetary policy tightening on the one year Treasury security. Right column: Interaction effect of a one-unit surprise monetary policy tightening on the one year Treasury security. Shaded areas denote 90% confidence bands (Newey-West).