Cautious Monetary Policy*

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Abstract

I show that when uncertainty about economic conditions is higher, the Federal Reserve adjusts interest rates less aggressively to changes in inflation and economic activity. Moreover, under higher uncertainty, interest rates are less sensitive to demand shocks, which generate larger fluctuations in inflation and unemployment. To account for these findings, I develop a simple New Keynesian model where the monetary authority receives a noisy signal of the demand shock. Consequently, it adjusts interest rates less aggressively than if it observed the actual shock. Since the shock remains unchanged while the policy response weakens, inflation and economic activity experience larger fluctuations.

Keywords: Monetary Policy, Taylor Rule, Uncertainty, New Keynesian

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1 Introduction

Monetary authorities make decisions under uncertainty about current and future economic conditions. The literature offers conflicting views on how this uncertainty influences interest rate policy. Some authors, such as Brainard (1967); Svensson (1999); Estrella and Mishkin (2007), argue that policymakers should act more cautiously under higher uncertainty, adjusting interest rates less in response to observed shocks. In contrast, others, including Giannoni (2002, 2007); Wieland (2000a,b); Beck and Wieland (2002), argue for a more aggressive response. However, there is limited empirical evidence on how uncertainty affects monetary policy decisions.

This paper addresses the following questions: How does the level of uncertainty in the economy affect monetary policy? What are the implications of this effect for inflation and economic activity? I provide empirical evidence that the Federal Reserve adjusts interest rates more cautiously when uncertainty is higher—that is, for a given change in inflation or economic activity, the interest rate response is smaller in magnitude. Moreover, I find that demand shocks generate larger fluctuations in inflation and unemployment under higher uncertainty.

To explain these findings, I develop a simple New Keynesian model, following Aoki (2003, 2006); Svensson and Woodford (2003a, 2004), in which the monetary authority receives a noisy signal about the underlying demand shock. The less precise the signal, the greater the uncertainty faced by the policymaker. In the model, higher uncertainty leads the monetary authority to optimally respond less aggressively to the observed signal, as a smaller fraction of it is attributed to the underlying shock. As a result, a given demand shock propagates more strongly through the economy under higher uncertainty. With a weaker interest rate response, larger adjustments in prices and output are required to clear the market in equilibrium, amplifying fluctuations in inflation and economic activity.

I model uncertainty as the precision of the signal that the policymaker receives about the underlying demand shock.[1] Greater uncertainty reduces the ability of the monetary authority to accurately assess current conditions and, consequently, to predict future economic outcomes. For this reason, I use the Jurado, Ludvigson, and Ng (2015) measure of uncertainty in the empirical analysis, which captures the average width of confidence intervals around forecasts of various economic variables. This measure is well-suited to the analysis, as it aligns closely with the model's concept of uncertainty: a more precise

[1] Notice that, in the model, a more precise signal can arise either from a reduction in the variance of the noise component or from an increase in the variance of the demand shock.

signal corresponds to narrower forecast intervals. Intuitively, when the current state of the economy is better understood (uncertainty lower), it becomes easier to forecast future economic conditions because the initial conditions are more accurately known. Importantly, this measure captures aggregate economic uncertainty in a broad sense, without isolating uncertainty about a single source, instead it reflects the combined effects of variations in the variances of different shocks and other sources of forecast uncertainty, including the presence of noisy signals.

My empirical analysis shows that the Federal Reserve responds less aggressively to changes in economic activity and inflation when uncertainty is higher. I reach this conclusion using two complementary approaches. In the first approach, I estimate a Taylor rule[2] that includes interaction terms between inflation and the output gap with my uncertainty measure. These interaction terms capture how the Federal Reserve's response varies with the level of uncertainty, which is the central focus of my analysis. In the second approach, I use local projections à la Jordà (2005) to estimate the federal funds rate response to a demand shock, again allowing for an interaction term with my uncertainty measure. In both cases, uncertainty is treated as a state variable that conditions monetary policy behavior, not as an exogenous shock. The objective is not to estimate the effects of uncertainty shocks per se, but rather to study how uncertainty shapes the conduct of monetary policy, motivating my focus on interaction terms.

For the first approach, I estimate this Taylor rule in three ways. First, following Clarida, Gali, and Gertler (2000), I use lagged economic variables as instruments. Second, I use expectations data from the Greenbook, as proposed by Orphanides (2001). Third, I apply ordinary least squares, following Carvalho, Nechio, and Tristao (2021)'s argument that monetary policy shocks account for only a small fraction of business cycle fluctuations, making endogeneity less of a concern.

All three methods show that the interaction terms in the Taylor rule for inflation and the output gap are negative and statistically significant. Based on this evidence, I conclude that the Federal Reserve adjusts interest rates less aggressively in response to changes in inflation and economic activity when uncertainty is higher.

I now turn to the second approach in more detail, in which I use local projections à la Jordà (2005) to estimate the federal funds rate response to a demand shock, allowing for an interaction term with my uncertainty measure. This method has the advantage of not requiring any assumption about the

[2] A Taylor rule describes how interest rates respond to changes in inflation and the output gap. See Taylor (1993), Clarida, Gali, and Gertler (2000), and Orphanides (2001).

specific policy rule followed by the Federal Reserve. My benchmark measure of a demand shock is the business cycle shock identified by Angeletos, Collard, and Dellas (2020).[3] This shock is interpreted as a demand shock because it causes inflation and output to move in the same direction. Furthermore, it leads to a sharp rise in interest rates.[4] I again find a negative and statistically significant interaction term, supporting the view that the Federal Reserve adopts a more cautious stance during periods of higher uncertainty.

Next, I examine how the response of inflation and unemployment to demand shocks varies with the level of uncertainty in the economy. To do this, I estimate local projections of both variables in response to the Angeletos, Collard, and Dellas (2020) business cycle shock, including an interaction term with my uncertainty measure. I find that higher uncertainty amplifies the effects of a given demand shock on inflation and unemployment.

To interpret my empirical findings, I modify the standard three-equation New Keynesian model[5] by assuming that the monetary authority receives only a noisy signal of the fundamental demand shock, and cannot observe inflation or the output gap.[6] A noisier signal, or a smaller variance of the demand shock, corresponds to higher uncertainty, leading the monetary authority to attribute a larger portion of the signal to the noise. As a result, higher uncertainty causes the optimal monetary policy to respond less aggressively to the shock. This weaker response amplifies the effects of a given demand shock on inflation and economic activity as markets must clear in equilibrium. Importantly, these dynamics arise regardless of whether policy is conducted under discretion or commitment.[7]

In the model, certainty equivalence and the separation principle apply.[8] These principles imply that uncertainty affects policy only through the signal extraction problem, not by altering the policymaker's

[3] This shock is identified using a max-share approach in a VAR, which consists in finding the linear combination of fundamental shocks that maximizes unemployment fluctuations over the business cycle. See Barsky and Sims (2011) and Francis et al. (2014) for details on this identification method.

[4] Shocks that do not cause substantial movements in interest rates are unsuitable for this analysis because they would not generate enough variation to identify the estimated coefficients, resulting in statistically insignificant estimates.

[5] See, for example, Galí (2015).

[6] Section 6.5 relaxes this assumption by allowing the monetary authority to observe inflation and the output gap, albeit with noise. If these variables were perfectly observed, the monetary authority could directly infer the underlying demand shock.

[7] Optimal monetary policy can be formulated under two main frameworks: commitment or discretion. Under commitment, the monetary authority follows a predetermined, state-contingent plan and cannot deviate from it. Under discretion, policy decisions are made period by period, allowing for adjustments based on current conditions without being constrained by past commitments.

[8] Certainty equivalence implies that optimal policy under partial information mirrors the policy under full information, except that the monetary authority responds to an efficient estimate of the state variables rather than their true values. The separation principle allows the optimization and estimation problems to be solved independently.

reaction function. The monetary authority sets interest rates optimally based on its estimate of the underlying economic shock. When uncertainty is higher, this estimate becomes less precise. As a result, the weaker interest rate response observed under higher uncertainty is entirely driven by the fact that a noisier signal leads the policymaker to perceive a smaller fundamental shock. The more cautious policy response thus reflects optimal behavior under partial information—not a change in the coefficients governing the response to observed variables.

Optimal monetary policy in my model differs from that in the standard New Keynesian framework. In the standard model, optimal policy perfectly offsets demand shocks, keeping the output gap and inflation at their steady-state levels — a result known as divine coincidence.[9] In contrast, divine coincidence does not hold in my model because the monetary authority observes only a noisy signal of the demand shock. This informational friction prevents full stabilization.[10] As a result, my model aligns with empirical evidence showing that demand shocks, such as those identified by Angeletos, Collard, and Dellas (2020) and Gilchrist and Zakrajšek (2012), cause movements in both inflation and output, contradicting the implications of divine coincidence.

I also examine the effects of a cost-push shock for different level of uncertainty. As with the demand shock, the model predicts that the monetary authority reacts more cautiously to a cost-push shock when uncertainty is higher. However, the macroeconomic implications differ: the response of output is smaller, and the effect on inflation does not vary significantly with uncertainty. The inflation response reflects two opposing forces operating through the New Keynesian Phillips Curve. First, under a cost-push shock, the output gap is directly determined by the interest rate via the Euler equation. When uncertainty is higher, the monetary authority raises interest rates less aggressively, which leads to a smaller contraction in output and thus less downward pressure on inflation. Second, higher uncertainty leads agents to expect lower future inflation, as they perceive the cost-push shock to be smaller. Through the expectations channel in the Phillips Curve, this lowers current inflation. These two forces—higher inflation due to reduced output contraction, and lower inflation due to more muted expectations—offset each other, resulting in relatively little variation in inflation across different levels of uncertainty.

[9] A simple way to break divine coincidence is interest rate smoothing, as developed in Woodford (1999). In this approach, the monetary authority's loss function includes a preference for gradual adjustments in interest rates

[10] This result is related to Aoki (2003, 2006), who also highlight how informational frictions can prevent full stabilization. However, their framework assumes that agents and the central bank observe all underlying variables perfectly but with a delay, whereas in my model, these variables are never perfectly observed. A similar point is also made by Svensson and Woodford (2004).

The results discussed above motivate my focus on the interaction between demand shocks and uncertainty in the empirical analysis. Furthermore, demand shocks generate co-movements in inflation and the output gap, providing a clear theoretical counterpart to the Taylor rule specification with interaction terms. In particular, both interaction terms in the Taylor rule are estimated to be negative, indicating that the monetary authority responds less aggressively to inflation and the output gap under higher uncertainty. To maintain consistency between the Taylor rule estimation and the local projection approach, it is essential to use a shock that generates a co-movement in inflation and output—precisely the pattern observed with demand shocks.

Two final comments are worth noting. First, in the model, the variance of the demand shock affects only the signal extraction problem and has no direct impact on the equilibrium allocation. As a result, changes in the level of uncertainty—absent any other fundamental shock—do not alter equilibrium outcomes. In other words, uncertainty shocks, interpreted as changes in the variance of the demand shock or the measurement error, do not directly influence the equilibrium. This modeling choice is intentional and aligns with the empirical focus of the paper. The analysis does not aim to study the direct effects of uncertainty shocks but rather to examine how uncertainty conditions the economy's response to fundamental shocks.

Second, the theoretical model is used both to guide the empirical analysis and to provide a structural interpretation of the findings. Nonetheless, the main contribution of this paper lies in its empirical results. I provide novel evidence that the Federal Reserve adjusts interest rates more cautiously when uncertainty is higher and that demand shocks lead to larger fluctuations in inflation and unemployment under such conditions. These findings offer new insights into how uncertainty shapes the conduct and effectiveness of monetary policy in practice, distinguishing this work from prior research that has focused primarily on theoretical predictions.

Literature review. My theoretical contribution relates to the literature examining how uncertainty shapes monetary policy decisions, which can be broadly divided into three strands.

The first strand focuses on parameter uncertainty, beginning with the seminal work of Brainard (1967), who showed that, in a static setting, greater uncertainty about the effectiveness of monetary policy leads the policymaker to respond more cautiously. The key insight is that the monetary authority allows deviations of the target variables from their mean in order to reduce their overall volatility—achieved through a more muted policy response. This result extends to dynamic settings in, for example, Svensson (1999) and Estrella and Mishkin (2007).

However, the prediction of a more cautious stance under higher uncertainty does not always hold. When multiple parameters are uncertain, the stronger or weaker policy response with respect to the full-information benchmark depends on which source of uncertainty dominates. For instance, Craine (1979) shows that if uncertainty about the dynamics of the control variable outweighs uncertainty about the strength of monetary policy, then the optimal response may be more aggressive. Similarly, Kimura and Kurozumi (2007) find that when the central bank is uncertain about the probability that firms can adjust prices à la Calvo, the optimal policy response becomes more aggressive.

Relatedly, Wieland (2000a,b); Beck and Wieland (2002) show that in dynamic models with uncertainty about the strength of policy transmission, the central bank may optimally respond more aggressively when it internalizes how its actions affect future information. In this case, higher uncertainty increases the value of information, making experimentation through larger interest rate movements desirable.

The second strand builds on robust control theory, pioneered by Hansen and Sargent (2001). In this framework, the policymaker seeks to guard against worst-case outcomes that may arise from model misspecification, typically by minimizing a max-regret loss function. As in the parameter uncertainty literature, the predicted policy response depends on the nature of the uncertainty. Some specifications imply a more aggressive stance, as in Giannoni (2002, 2007), while others suggest caution. For example, Tetlow and Von zur Muehlen (2001) presents scenarios in which the optimal policy is either more or less aggressive, depending on which model features are assumed to be misspecified.

I contribute to these two strands of the literature by analyzing the business cycle implications of noisy information. In contrast to the models discussed above, my framework predicts that greater uncertainty always leads to a more cautious policy response. This behavior does not result from changes in the policymaker's preferences or structural parameters but emerges endogenously from the signal extraction problem: under partial information, the policymaker perceives the shock to be smaller as uncertainty increases. Furthermore, the model provides clear predictions for how the propagation of different types of shocks—such as demand and cost-push shocks—depends on the level of uncertainty.

The third strand, closely related to my approach, examines how partial information about economic indicators affects the responsiveness of monetary policy. This literature shows that noisier indicators should receive less weight in policy decisions. My contribution differs by studying how aggregate uncertainty in the economy affects the monetary policy response and the propagation of demand and supply shocks. For example, Kuttner (1992), Ehrmann and Smets (2003), Svensson and Woodford (2003a), and Cukierman and Lippi (2005) analyze how the unobservability of potential output shapes monetary policy. However, these papers do not examine how changes in the level of uncertainty affect optimal policy behavior over time, which is the central question in my analysis.

My model is also closely related to Rudebusch (2001), Smets (2002), Swanson (2004), Aoki (2003, 2006), and Boehm and House (2019), who show that noise in economic indicators can induce policy caution. However, these studies focus primarily on how uncertainty affects the interest rate response and do not examine how it shapes the transmission of demand shocks to output and inflation. By contrast, I explicitly analyze how the propagation of demand shocks depends on the level of uncertainty—an analysis that is central for interpreting the empirical results of this paper.

My work is also related to Lippi and Neri (2007), who estimate a small-scale New Keynesian model under partial information. Their focus, however, is on identifying which observable variables are most informative for the central bank, rather than on how changes in overall uncertainty in the economy affect policy behavior over time. In contrast, my analysis centers on how changes in the precision of information systematically affect the monetary authority's response.

My paper also connects to the empirical literature estimating monetary policy rules, including Clarida, Gali, and Gertler (2000), Orphanides (2001), and Carvalho, Nechio, and Tristao (2021). I extend this line of research by introducing interaction terms between inflation, the output gap, and my measure of uncertainty, allowing me to test whether the Federal Reserve's policy rule becomes more or less responsive as uncertainty changes. My findings are consistent with those of Bauer, Pflueger, and Sunderam (2024), who document that professional forecasters perceive the policy rule to become more cautious when uncertainty rises. However, while Bauer, Pflueger, and Sunderam (2024) focus on the perceived rule by profession forecasters, I provide evidence that the actual rule followed by the Federal Reserve varies with uncertainty.

Finally, this paper contributes to the broader literature on economic uncertainty, including the influential work of Bloom (2009), which examines the direct effects of uncertainty on macroeconomic outcomes. In contrast, my focus is on how uncertainty shapes the monetary authority's reaction function and the propagation of demand and supply shocks. For example, Cieslak et al. (2023) estimate a Taylor rule that includes uncertainty as a level effect, but do not examine how the policy response to inflation and the output gap varies with uncertainty, as I do. Cho et al. (2021) studies the effects of uncertainty shocks within a New Keynesian framework. My approach differs: I do not model uncertainty as a shock, but rather as a state variable that conditions the transmission of fundamental shocks. The key contribution of my work is to show how the effects of both demand and supply shocks depend on the prevailing level of uncertainty, thereby highlighting the state-dependency of monetary policy effectiveness.

Outline. The paper is organized as follows. Section 2 frames the empirical question and motivates my empirical strategy. Section 3 presents evidence that the monetary authority is more cautious when uncertainty is higher in the economy. Section 4 examines how demand shocks propagate through the economy as uncertainty increases. Section 5 investigates the robustness of the empirical findings. Section 6 develops a simple linearized New Keynesian model to interpret the empirical results. Section 7 briefly discusses alternative interpretations of the uncertainty measure. Section 8 concludes.

2 Framework

I examine how uncertainty influences the monetary authority's interest rate decisions. Specifically, I investigate whether the monetary authority adjusts its policy response when uncertainty varies. To this end, I use the following "reduced form" equation:

$$r_t = \alpha + \beta \epsilon_t + \gamma \, Uncertainty_t \times \epsilon_t + controls_t + u_t \tag{1}$$

where r_t is the interest rate, ϵ_t represents a shock affecting the interest rate, $Uncertainty_t$ is a measure of economic uncertainty, $controls_t$ denotes a set of relevant control variables, and u_t is an error term orthogonal to the independent variables.

The key parameter of interest is γ, which captures how uncertainty affects the monetary authority's response to economic shocks. Without loss of generality, I normalize the shock ϵ_t so that it leads to an increase in the interest rate, implying $\beta > 0$. Under this normalization, a positive interaction term ($\gamma > 0$) indicates that the monetary authority reacts more aggressively to the shock as uncertainty rises. Conversely, a negative interaction term ($\gamma < 0$) implies a more cautious response.

Note that the specification in equation (1) does not examine the direct effects of uncertainty shocks.

Instead, it treats $Uncertainty_t$ as a state variable reflecting the prevailing level of uncertainty in the economy, rather than as an exogenous shock.

Equation (1) admits a structural interpretation. Suppose the monetary authority minimizes the discounted sum of a quadratic loss function subject to linear constraints and sets the interest rate under discretion.[11] Additionally, assume that the monetary authority and private agents have the same information set.[12] Under these assumptions, as shown by Pearlman, Currie, and Levine (1986) and Svensson and Woodford (2003b), certainty equivalence and the separation principle apply.[13] As a result, the monetary authority sets the optimal time-t interest rate, r_t^*, according to:

$$r_t^* = F\mathbb{E}\left(X_t|\mathcal{I}_t\right) \tag{2}$$

where X_t is a vector of exogenous (state) variables, and $\mathbb{E}(.|\mathcal{I}_t)$ denote the expectation operator conditional on the monetary authority's time t information set, $\mathcal{I}_t$. The matrix F can be obtained solving the model under full information. Thus, uncertainty, in this case defined as a less informative information set, affects only the estimates of the underlying state variables, $\mathbb{E}\left(X_t|\mathcal{I}_t\right)$, but not the responsiveness of the monetary authority, F. This happens because, as discussed above, certainty equivalence and the separation principle apply. Finally, if the monetary authority sets the interest rate under commitment, equation (2) becomes $r_t^* = \tilde{F}\mathbb{E}\left(X_t|\mathcal{I}_t\right) + \Phi\Gamma_{t-1}$, where Γ_{t-1} is the vector of Lagrange multipliers, representing the past commitments of the monetary authority. The difference between F and $\tilde{F}$ reflects how the policy response to expected state variables differs under commitment versus discretion. However, this distinction is not central to the paper's objective, as I do not attempt to estimate either F or $\tilde{F}$. Importantly, the key argument supporting equation (1) holds under both commitment or discretion. A detailed description of this model is provided in Appendix C.

Notably, the optimal policy prescribed by equation (2) hold for a broad class of linearized models

[11] Optimal monetary policy can be formulated under two main frameworks: commitment or discretion. Under commitment, the monetary authority follows a predetermined, state-contingent plan and cannot deviate from it. Under discretion, policy decisions are made period by period, allowing for adjustments based on current conditions without being constrained by past commitments.

[12] This assumption can be relaxed; it suffices to assume that the monetary authority has less information than private agents. However, for simplicity, I assume symmetric information. See Svensson and Woodford (2004) for a detailed analysis of asymmetric information scenarios.

[13] Certainty equivalence implies that optimal policy under partial information mirrors the policy under full information, except that the monetary authority responds to an efficient estimate of the state variables rather than their true values. The separation principle allows the optimization problem and the estimation problem of the state variables to be solved independently.

with different information structures. For example, both the canonical New Keynesian model and its various modifications[14] yield solutions consistent with equation (2).

For simplicity, consider now a special case where there is only one state variable representing a fundamental shock, such as a demand shock. Furthermore, for simplicity, assume that the other endogenous variables in the model—such as the output gap—are not observable to the monetary authority.[15] Suppose also that the state variable follows a normal distribution, i.e., $X_t \sim N(\mu, \sigma^2_{X_t})$, and that the monetary authority observes a noisy signal, ϵ_t, given by $\epsilon_t = X_t + \nu_t$, where $\nu_t \sim N(0, \sigma^2_{\nu_t})$ represents the noise. Under these assumptions, the monetary authority's expectation of X_t is given by:

$$\mathbb{E}\left(X_t|\mathcal{I}_t\right) = \mathbb{E}\left(X_t|\epsilon_t\right) = \frac{\lambda_t}{1+\lambda_t}\epsilon_t \tag{3}$$

where $\lambda_t \equiv \frac{\sigma^2_{X_t}}{\sigma^2_{\nu_t}}$ denotes the signal-to-noise ratio. A lower signal-to-noise ratio reflects higher uncertainty, as the monetary authority attributes a larger share of the observed signal to noise rather than to the true underlying shock.

Finally, applying a first-order Taylor expansion of $\frac{\lambda_t}{1+\lambda_t}$ around $\bar{\lambda}$ and using equation (2), I obtain:

$$r^*_t \approx \bar{\beta}\epsilon_t + \bar{\gamma}(\epsilon_t \times \lambda_t) \tag{4}$$

The derivation of equation (4), along with the result that $\bar{\beta}$ and $\bar{\gamma}$ must have the same sign, is provided in Appendix F.1.[16] Crucially, equation (4) illustrates how the signal-to-noise ratio, λ_t, influences the monetary authority's behavior. As λ_t decreases—indicating a less precise signal, and thus more uncertainty—the monetary authority reacts less aggressively, attributing a larger share of the observed signal, ϵ_t, to noise.

This mechanism provides a structural interpretation of equation (1): as uncertainty rises, the monetary authority underestimates the magnitude of the shock and therefore adjusts the interest rate more cautiously, seeking to avoid overreacting to the noise embedded in the signal. This relationship implies that the coefficient γ in equation (1) has the opposite sign of $\bar{\gamma}$ in equation (4). Section 7 discusses

[14] See, for instance, Svensson (1997) and Clarida, Gali, and Gertler (1999).

[15] Observing endogenous variables—such as inflation or the ouput gap—would complicate the filtering problem without altering the main insight. Section 6.5 explores the case in which these variables are observed with noise in a standard New Keynesian model.

[16] The sign of $\bar{\beta}$ and $\bar{\gamma}$ depends on the sign of F.

alternative structural interpretations of equation (1), including the classic framework of Brainard (1967), in which parameter uncertainty leads to more cautious policymaking, and a nonlinear model in which the monetary authority exhibits risk aversion.

The benchmark empirical measure of uncertainty used in this paper is the one proposed by Jurado, Ludvigson, and Ng (2015), which captures the average width of the confidence intervals of forecasts of various economic variables. This measure is well-suited for the analysis, as it provides a comprehensive time-series representation of economic uncertainty and directly corresponds to the type of uncertainty modeled above. Intuitively, when uncertainty about the current state of the economy is low—corresponding in the model to a high signal-to-noise ratio—it becomes easier to predict the future path of the economy. Accurate knowledge of initial conditions improves the precision of forecasts about future economic conditions. Appendix D details the mapping between the model-implied measure of uncertainty and its empirical counterpart, showing that a more precise signal enables the monetary authority to form more accurate forecasts, leading to lower measured uncertainty—that is, narrower confidence intervals of the forecasts of economic variables.

3 Empirical Strategy and Results

In this section, I provide empirical evidence that the Federal Reserve tends to react more cautiously during periods of higher uncertainty. To test this hypothesis, I employ two distinct methodologies, both grounded in the intuition behind equation (1). The central objective is to estimate the interaction term, γ, in equation (1), which captures how the responsiveness of monetary policy varies with the level of uncertainty.

First, I estimate a Taylor rule in which inflation and the output gap are interacted with the Jurado, Ludvigson, and Ng (2015) measure of uncertainty. This methodology and its empirical results are discussed in Section 3.1. Second, I use local projections à la Jordà (2005) to estimate the federal funds rate response to a demand shock, allowing for an interaction term with my uncertainty measure. This approach closely mirrors equation (1), and its results are presented in Section 3.2.

3.1 Estimating a Taylor rule that accounts for the effect of uncertainty

A Taylor rule is a relationship that describes how the interest rate adjusts in response to variations in inflation and the output gap. Since the seminal work of Taylor (1993), this framework has served as a benchmark for understanding how monetary authorities set interest rates. For instance, Carvalho, Nechio, and Tristao (2021) estimated the following specification:

$$r_t = \alpha + \beta_1 \pi_t + \gamma_1 y_t + \rho_1 r_{t-1} + \rho_2 r_{t-2} + u_t \tag{5}$$

where r_t is the federal funds rate, π_t is inflation, y_t is the output gap, and u_t is the error term, which can be interpreted as monetary shock. Since the independent variables may be correlated with the monetary shock, the regressors are endogenous. For instance, inflation at time t is affected by the realization of the monetary shock, leading to biased estimates under ordinary least squares (OLS). However, Carvalho, Nechio, and Tristao (2021) show that endogeneity introduces only a small bias, as monetary policy shocks account for a limited share of business cycle fluctuations. Accordingly, they estimate equation (5) using both OLS and, following Clarida, Gali, and Gertler (2000), the generalized method of moments (GMM). To address endogeneity directly, Orphanides (2001) replaced the realized values of inflation and the output gap with their expectations as contained in the Greenbook data. In this section, I employ all three approaches—OLS, GMM, and the Greenbook data—to estimate the Taylor rule.

However, equation (5), referred as the "benchmark" Taylor rule, does not account for how uncertainty influences the monetary authority's interest rate decisions. Building on the insight from equation (1), I introduce interaction terms of inflation and the output gap with uncertainty. Specifically, the signal about the fundamental shock, ϵ_t, in equation (1) can be reinterpreted as a vector comprising inflation and the output gap. Movements in these variables are informative about the underlying shocks affecting the economy, so inflation and the output gap can be interpreted as signals of those shocks. I therefore estimate a Taylor rule that incorporates the effect of uncertainty using the following specification:

$$r_t = \alpha + \beta_1 \pi_t + \beta_2 (\pi_t \times JLN_{t-1}) + \gamma_1 y_t + \gamma_2 (y_t \times JLN_{t-1}) + \delta_1 JLN_{t-1} + \rho_1 r_{t-1} + \rho_2 r_{t-2} + u_t \tag{6}$$

where r_t is the federal funds rate, π_t is annual CPI inflation, y_t is the output gap, JLN_{t-1} is the Jurado, Ludvigson, and Ng (2015) measure of uncertainty.[17] For simplicity, I refer to this specification as the "Taylor rule considering uncertainty". The coefficients of interest are β_1, γ_1, β_2 and γ_2. The coefficients β_1 and γ_1 capture the level effects of inflation and the output gap on the interest rate, respectively. Both are expected to be positive, as higher inflation or a higher output gap typically leads the monetary authority to raise interest rates to cool the economy—a standard prediction supported by empirical evidence.

The variable JLN_{t-1} enters equation (6) in levels as a control, following standard practice in the empirical literature when including interaction terms. However, its estimated coefficient, δ_1, is not central to the analysis, as the focus of this paper is on the state-dependency of monetary policy on uncertainty—specifically, whether and how uncertainty modifies the responsiveness of monetary policy, rather than whether uncertainty itself directly affects policy levels.

The primary contribution of my analysis lies in estimating the interaction terms, β_2 and γ_2. Negative values for these coefficients indicate that the Federal Reserve responds more cautiously during periods of elevated uncertainty: for a given level of inflation and output gap, the monetary authority adjusts the interest rate less aggressively when uncertainty is higher. This result is consistent with the model in Section 2, which shows that under greater uncertainty, the monetary authority perceives shocks to be smaller than under full information, leading to more measured interest rate adjustments.

The objective of my paper is not to develop a novel methodology for estimating the Taylor rule. Accordingly, I follow the approach of Carvalho, Nechio, and Tristao (2021), and estimate equation (6) using OLS and GMM for the US economy. Additionally, building on the insight of Orphanides (2001), I also estimate equation (6) by replacing π_t and y_t with their expected values, $E_t\pi_{t+4}$ and $E_t y_{t+1}$, obtained from the Greenbooks data. The sample period spans from the first quarter of 1983 to the last quarter of 2018. The set of instruments used in the GMM estimation is consistent with those employed by Clarida, Gali, and Gertler (2000) and Carvalho, Nechio, and Tristao (2021). A detailed description of the data is provided in Appendix A.

Table 1 reports the estimates of equation (5), the "benchmark" Taylor rule, in columns (1), (3), and (5) and of equation (6), the Taylor rule considering uncertainty, in columns (2), (4), and (6). Columns (1) and (2) present the estimates obtained using OLS; columns (3) and (4) report the estimates using

[17] This variable is lagged by one period to mitigate potential endogeneity issues that arise when uncertainty moves contemporaneously with the monetary shock.

GMM; columns (5) and (6) display the estimates based on the Greenbook data. All coefficients in the table, except the coefficient on JLN, are divided by $1-\rho \equiv 1-\rho_1-\rho_2$. Thus, the reported coefficients correspond to$\pi^{cpi} \equiv \frac{\beta_1}{1-\rho}$, $\pi^{cpi} \times JLN \equiv \frac{\beta_2}{1-\rho}$, $y^* \equiv \frac{\gamma_1}{1-\rho}$, $y^* \times JLN \equiv \frac{\gamma_2}{1-\rho}$, $JLN \equiv \delta_1$ and $\rho \equiv \rho_1+\rho_2$. This scaling allows for interpretation of the coefficients as long-run effects, following standard practice in the literature. I also standardize the JLN measure so that the interaction terms capture the effect of a one-standard-deviation increase in uncertainty. Column (1) presents the "benchmark" Taylor rule estimates using OLS. This specification confirms that the results using my sample period and data are consistent with the literature, which reports the estimated coefficients on inflation ranging from 1.5 to 2 and the estimated coefficients on output gap between 0.8 and 1. Similar consistency is observed in columns (3) and (5), where I employ GMM and Greenbook data, respectively. Column (2) provides the OLS estimates of equation (6) and indicates that both interaction terms are negative and statistically significant different from zero. This implies that the Federal Reserve moderates interest rate adjustments during periods of elevated uncertainty. Furthermore, the coefficients on inflation and the output gap remain close to those in the "benchmark" Taylor rule, suggesting that uncertainty introduces an additional and distinct channel not previously examined in the literature. Column (4) reports the GMM estimates of equation (6), again yielding negative interaction terms, while the coefficients on inflation and the output gap align with those in column (3). Finally, column (6) presents the estimates based on Greenbook data. Again, the interaction terms are negative, and the coefficients on inflation and the output gap align with those in the "benchmark" Taylor rule estimated using Greenbook data in column (5). Overall, Table 1 provides evidence that the Federal Reserve responds more cautiously to inflation and output fluctuations during periods of heightened uncertainty.

3.2 Local projections of the interest rate

Building on equation (1), and to further examine whether the Federal Reserve reacts more cautiously during periods of heightened uncertainty, I estimate the following local projection for different horizons j:

$$\Delta r_{t+j,t-1} = \alpha + \beta_{1,j} Shock_t + \beta_{2,j}(JLN_{t-1} \times Shock_t) + \beta_{3,j} JLN_{t-1} + \delta_j X_{t-1} + u_t \tag{7}$$

where $\Delta r_{t+j,t-1} \equiv r_{t+j} - r_{t-1}$ is the variation of the federal funds rate between time $t-1$ and $t+j$, $Shock_t$ is the standardized business cycle unemployment shock estimated by Angeletos, Collard, and

Dellas (2020), JLN_{t-1} is the JLN measure of uncertainty and X_{t-1} is a set of controls containing two lags of GDP, investment, inflation, and unemployment.[18] Equation (7) closely resembles equation (1) once the variable $Shock_t$ is interpreted as a signal of the fundamental shock affecting the economy, rather than the shock itself. In practice, shocks cannot be observed or estimated perfectly from the data; only proxy measures are available. For this reason, the business cycle unemployment shock can be interpreted as the signal that the monetary authority observes.

Equation (7) is estimated using OLS because the variable $Shock_t$ is exogenous, and the primary focus is on the coefficient of the interaction term, $\beta_{2,j}$. As shown by Bun and Harrison (2019), in a specification like equation (7), the coefficient on interaction term is unbiased as long as at least one of the two variables in the interaction—here, $Shock_t$—is exogenous. For interpretability, I normalize the variable $Shock_t$ so that it leads to an increase in the federal funds rate. This normalization ensures that the level effect of the shock is positive, i.e., $\beta_{1,j} > 0$ for all j. The key contribution of this specification lies in the interaction term, $\beta_{2,j}$, which captures the influence of uncertainty on the Federal Reserve's reaction function. A negative $\beta_{2,j}$, consistent with the model discussed in Section 2, implies that, in response to the same observed signal about the fundamental shock, the Federal Reserve adjusts the interest rate by a smaller amount when uncertainty is higher.

If the variable JLN_{t-1} were exogenous, the coefficient $\beta_{3,j}$ could be interpreted as capturing the direct effect of an uncertainty shock. However, even under this interpretation, the objective of this paper is not to study uncertainty shocks, but rather to examine the interaction term between demand shocks and uncertainty, $\beta_{2,j}$, which captures how uncertainty affects the responsiveness of monetary policy.

Equation (7) can also be interpreted as a "reduced form" Taylor rule because it replaces inflation and the output gap with a well-identified shock—the business cycle unemployment shock estimated by Angeletos, Collard, and Dellas (2020). I use this specific shock for three key reasons: (i) it is constructed as a linear combination of fundamental shocks that maximizes unemployment fluctuations at the business cycle frequency. As such, it captures the most important shock affecting the economy at these frequencies, aligning well with the theoretical shock discussed in equation (1). (ii) It induces changes in the federal fund interest rate, a necessary condition for estimating equation (7). Shocks that do not move the interest rate would yield statistically insignificant estimates of the level effect, $\beta_{1,j}$,

[18] Appendix A provides a detailed description of the data.

and would not explain variation in interest rates. (iii) It causes both the output gap and inflation to rise, implying that the interest rate should also increase in response. This predictable response ensures consistency with the Taylor rule results in Section 3.1.

Furthermore, estimating local projections offers two key advantages. First, with a well-identified shock, as in this case, endogeneity is not a concern, allowing OLS to be used without bias in the interaction term coefficient. Second, this specification involves estimating only one interaction term, which reduces the number of parameters and simplifies the interpretation of uncertainty's effect on monetary policy.

Using data from the first quarter of 1983 to the last quarter of 2018, the top panel of Figure 1 reports the estimates of $\hat{\beta}_{1,j}\overline{Shock} + \hat{\beta}_{2,j}(\widetilde{JLN} \times \overline{Shock})$ from equation (7) for values of ranging j from 0 to 11. In this expression, $\hat{\beta}_{i,j}$ (for $i = 1, 2$) are the estimated coefficients, $\overline{Shock}$ denotes one standard deviation of the shock and $\widetilde{JLN}$ corresponds to either the 25th or the 75th percentile of the distribution of the JLN measure. The blue line shows the predicted responses under low uncertainty, (25th percentile), while the red line represents responses under high uncertainty (75th percentile). Figure 1 shows that the impulse response function (IRF) under low uncertainty (blue line) consistently lies above the IRF under high uncertainty (red line). This indicates that, for a given shock, the Federal Reserve raises interest rates by less when uncertainty is elevated, consistent with a more cautious policy response. The bottom panel of Figure 1 reports the 95% confidence intervals for $\hat{\beta}_{2,j}$. These intervals exclude zero, providing statistical evidence that the two plotted IRFs are different from each other. For nearly all values of j, the interaction term $\hat{\beta}_{2,j}$ is statistically significant. Figure 1 reinforces the findings of Table 1: as uncertainty rises, the Federal Reserve adopts a more cautious stance, adjusting the interest rate less in response to a shock that generates a boom in the economy.

4 Propagation effect

In Section 3, I showed that higher uncertainty leads the Federal Reserve to respond more cautiously to economic conditions. In this section, I examine the broader implications of elevated uncertainty for key macroeconomic variables. Specifically, I estimate equation (7) using inflation (π_t) or unemployment (u_t)

as the dependent variable:

$$\Delta y_{t+j,t-1} = \alpha + \beta^y_{1,j} Shock_t + \beta^y_{2,j}(JLN_{t-1} \times Shock_t) + \beta^y_{3,j} JLN_{t-1} + \delta^y_j X_{t-1} + \tilde{u}_t \tag{8}$$

where $\Delta y_{t+j,t-1}$ denotes the change in inflation or unemployment from $t-1$ to $t+j$.[19] All other variables are defined as before, with one exception: the control set X_{t-1} now includes the lagged interest rate and excludes the lag of the dependent variable. For example, when inflation is the dependent variable, lagged inflation is excluded to avoid it appearing on both sides of the equation. I estimate equation (8) using OLS over the sample period from the first quarter of 1983 through the last quarter of 2018. The business cycle shock is again normalized to represent a boom—i.e., an increase in inflation and a decrease in unemployment. Accordingly, I expect $\beta^\pi_{1,j} > 0$ for inflation and $\beta^u_{1,j} < 0$ for unemployment. I focus on these two variables because stabilizing inflation and unemployment is central to the Federal Reserve's mandate, and both play key roles in macroeconomic models. Moreover, I focus on unemployment rather than output, as the business cycle shock, by construction, induces larger fluctuations in unemployment than in output. The primary focus in equation (8) is the coefficient $\beta^y_{2,j}$, which captures the effect of uncertainty on inflation or unemployment. The theoretical model presented in Section 2 suggests that shocks propagate more strongly through the economy when uncertainty is higher because (i) the Federal Reserve responds less aggressively—raising interest rates by a smaller amount—and (ii) uncertainty has no direct effect on economic variables. This mechanism implies that $\beta^\pi_{2,j} > 0$ for inflation and $\beta^u_{2,j} < 0$ for unemployment: higher uncertainty amplifies the response of inflation and unemployment to shocks through more muted monetary policy—a purely indirect channel. However, uncertainty may also have direct effects on inflation and unemployment, which cannot be ruled out a priori. For instance, firms might perceive shocks as smaller during periods of elevated uncertainty, similar to the monetary authority, and adjust prices less. This would lead to lower inflation and imply $\beta^\pi_{2,j} < 0$. Other direct channels could yield different predictions, complicating the interpretation of the interaction term. This discussion underscores the importance of estimating equation (8), as the sign of $\beta^y_{2,j}$ is not immediately clear ex ante. While my empirical strategy does not disentangle the specific mechanisms at play, the objective of this analysis is to assess how uncertainty influences the overall propagation of shocks, rather than to identify the underlying channels.

[19] Inflation is measured using the GDP deflator, consistent with Angeletos, Collard, and Dellas (2020).

Figure 2 presents the estimates of equation (8) with unemployment as the dependent variable. This figure is constructed analogously to Figure 1. The top panel reports estimates of $\hat{\beta}^u_{1,j}\overline{Shock} + \hat{\beta}^u_{2,j}(\widetilde{JLN} \times \overline{Shock})$ for j ranging from 0 to 11, where $\hat{\beta}^u_{i,j}$ $(i = 1, 2)$ are the estimated coefficients, $\overline{Shock}$ denotes one standard deviation of the shock, and $\widetilde{JLN}$ corresponds to either the 25th or the 75th percentile of the distribution of the JLN measure. The blue line shows predicted unemployment responses under low uncertainty (25th percentile), while the red line represents responses under high uncertainty (75th percentile). The top panel reveals that the impulse response function (IRF) under low uncertainty (blue line) is always above the IRF under high uncertainty (red line). This indicates that, for a given shock, unemployment declines more when uncertainty is elevated. As expected during an economic boom, unemployment decreases overall. The bottom panel of Figure 2 reports the 95% confidence intervals for $\hat{\beta}^u_{2,j}$ for j ranging from 0 to 11. These intervals do not include zero, indicating that the difference between the two IRFs is statistically significant. Indeed, for nearly all horizons, the interaction term coefficients $\hat{\beta}2, j^u$ are statistically significant.

Similarly, Figure 3 presents the estimates of equation (8) with inflation as the dependent variable. The top panel reports the predicted values of $\hat{\beta}^\pi_{1,j}\overline{Shock} + \hat{\beta}^\pi_{2,j}(\widetilde{JLN} \times \overline{Shock})$ for j ranging from 0 to 11, where $\hat{\beta}^\pi_{i,j}$ $(i = 1, 2)$ are the estimated coefficients from equation (8), $\overline{Shock}$ denotes one standard deviation of the shock, and $\widetilde{JLN}$ corresponds to the 25th or 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values under low uncertainty (25th percentile), and the red line under high uncertainty (75th percentile). The top panel shows that the IRF under low uncertainty (blue line) is always below the IRF under high uncertainty (red line). This indicates that, for a given shock, inflation rise more when uncertainty is elevated. Notably, inflation does not vary substantially over the sample period,[20] which may explain why, under low uncertainty, the IRF for inflation is occasionally negative despite the positive shock. The bottom panel of Figure 3 reports the 95% confidence intervals of $\hat{\beta}^\pi_{2,j}$ for j ranging from 0 to 11. These intervals do not include zero, indicating that the difference between the two IRFs is statistically significant. Indeed, for nearly all horizons, the interaction term coefficients $\hat{\beta}^\pi_{2,j}$ are statistically significant.

To summarize, this section provides evidence that the "boom shock" identified by (Angeletos, Collard, and Dellas, 2020) propagates more strongly through the economy when uncertainty is higher:

[20] However, inflation interacted with the JLN measure of uncertainty does vary, enabling the estimation of the interaction term $\hat{\beta}^\pi_{2,j}$ in equation (8).

unemployment declines more, and inflation rises more. This outcome is consistent with a more cautious interest rate response by the Federal Reserve during periods of heightened uncertainty.

5 Robustness checks

This section presents a series of robustness checks to support the validity of the empirical findings. Section 5.1 describes the robustness of the Taylor Rule considering the effect of uncertainty (Section 3.1). Section 5.2 assesses the robustness of the local projections for the interest rate response (Section 3.2). Finally, Section 5.3 evaluates the robustness of the results related to unemployment and inflation dynamics (Section 4).

5.1 Robustness checks of the Taylor rule considering uncertainty

This section discusses the robustness checks for the Taylor rule considering the effect of uncertainty. All tables discussed below follow the structure of Table 1. Specifically, columns (1), (3), and (5) report estimates of the "benchmark" Taylor Rule (equation (5)), while columns (2), (4), and (6) show estimates of the Taylor Rule considering uncertainty (equation (6)). Columns (1) and (2) are estimated using OLS, columns (3) and (4) use GMM estimation, and columns (5) and (6) are based on Greenbooks data.

5.1.1 Alternative measure of uncertainty

The benchmark measure of uncertainty used in this paper is the JLN uncertainty based on 3-month-ahead forecasts. To test the robustness of the findings, I also consider alternative forecast horizons: 1-month-ahead and 12-month-ahead forecasts. The results for these alternative measures are reported in Table B.1 and Table B.2, respectively. The findings remain consistent: the interaction terms are negative, and the interaction term with inflation is statistically significant.

The VIX index can also serve as a measure of uncertainty. However, it is not the benchmark measure in this study, as it primarily reflects stock market volatility rather than broader economic uncertainty. Indeed, the VIX is often used to identify uncertainty shocks.[21] Moreover, the mapping between the VIX and the signal-to-noise ratio discussed in Section 2 is not straightforward. Nevertheless, the VIX remains useful for assessing whether a broader notion of uncertainty influences the Federal Reserve's

[21] See, for example, Bloom (2009).

Taylor rule. Table B.3 reports results using the VIX in place of the JLN measure. The sample period is shorter, beginning in the first quarter of 1990 due to data availability. The findings remain robust: the interaction terms are negative, and the interaction term with inflation is statistically significant.

5.1.2 Different Measures of Inflation: PCE and GDP Deflator

Different studies have used various measures of inflation. For example, Clarida, Gali, and Gertler (2000) employed the GDP deflator, while Carvalho, Nechio, and Tristao (2021) used personal consumption expenditure (PCE) or the consumer price index (CPI). To account for these differences, Table B.4 and Table B.5 report results using GDP deflator inflation and PCE inflation, respectively. In both cases, the interaction terms remain negative, reinforcing the robustness of the findings. I adopt CPI inflation as the benchmark measure because the "benchmark" Taylor rule (equation (5)) estimated with CPI inflation yields more robust results: the response to inflation is more positive and statistically significant.

5.1.3 Federal Funds Rate

In the benchmark specification, as discussed in Appendix A, the federal funds rate is replaced by the shadow rate proposed by Wu and Xia (2016) for the period from the first quarter of 2009 to the last quarter of 2015. This substitution is standard in the literature, as the federal funds rate was constrained by the zero lower bound during this period. In contrast, the Wu and Xia (2016) shadow rate accounts for the effects of unconventional monetary policy, such as quantitative easing, thereby providing a more accurate measure of the stance of monetary policy. Table B.6 presents results using the federal funds rate over the entire sample period. The interaction term coefficients remain negative, confirming the robustness of the findings. As expected, all coefficients are smaller in magnitude, since the federal funds rate exhibits less variation than the Wu and Xia (2016) shadow rate.

5.2 Robustness checks of local projections of the interest rate

This section presents two robustness checks for Figure 1. The first check replaces the JLN measure of uncertainty with VIX index. The second substitutes the business cycle shock with the risk bond premium shock from Gilchrist and Zakrajšek (2012). All figures in this section are constructed analogously to Figure 1. The top panel reports estimates from equation (7) of $\hat{\beta}_{1,j}\overline{Shock}+\hat{\beta}_{2,j}(\widetilde{Uncertainty}\times\overline{Shock})$ for

j values from 0 to 11, where $\hat{\beta}_{i,j}$ for $i = 1, 2$ are the estimated coefficients, $\overline{Shock}$ denotes one standard deviation of the shock, and $\widetilde{Uncertainty}$ corresponds to the 25th or 75th percentile of the distribution of VIX or the JLN measure. The blue line shows predicted values under low uncertainty (25th percentile), and the red line under high uncertainty (75th percentile). The bottom panel reports the 95% confidence intervals for $\hat{\beta}_{2,j}$.

5.2.1 Alternative measure of uncertainty

Figure B.1 presents the estimates of equation (7) using the VIX in place of the JLN measure of uncertainty. The results again show that when uncertainty is higher, the Federal Reserve raises the interest rate by less—indicating a more cautious monetary policy stance. This finding closely mirrors the benchmark results in Figure 1, with both figures exhibiting very similar patterns.

5.2.2 Excess bond premium shock

As an alternative to the business cycle shock from Angeletos, Collard, and Dellas (2020), I use the excess bond premium shock from Gilchrist and Zakrajšek (2012), which reflects a decline in the excess bond premium. This shock leads to an increase in the federal funds rate and output, but has little effect on inflation—motivating the choice of business cycle shock as the baseline measure. Figure B.2 presents the estimates of equation (7) using the excess bond premium shock. The results are consistent with those obtained using the business cycle shock: when uncertainty is higher, the Federal Reserve raises interest rates less aggressively. Moreover, the interaction terms $\hat{\beta}_{2,j}$ are statistically significant for most horizons.

5.3 Robustness checks of the propagation effect

This section presents robustness checks for the propagation effects shown in Figure 2 and Figure 3. In the first check, the JLN measure of uncertainty is replaced with the VIX index. In the second, I use an alternative shock—the excess bond premium shock from Gilchrist and Zakrajšek (2012). All figures in this section are constructed using the same methodology as in the benchmark analysis.

5.3.1 Different measure of uncertainty

Figure B.3 and Figure B.4 present estimates of equation (8) for unemployment and inflation, respectively, using the VIX in place of the JLN measure of uncertainty. Figure B.3 shows that the impulse response function of unemployment remains more negative under high uncertainty, with results nearly identical to those obtained using JLN. A similar pattern holds for inflation in Figure B.4, where inflation rises more when uncertainty is elevated. Both figures support the conclusion that, when uncertainty is higher, the business cycle shock has a stronger impact on the economy.

5.3.2 Excess bond premium shock

As with the local projections for the interest rate, I replace the business cycle shock with the excess bond premium shock from Gilchrist and Zakrajšek (2012), which represents a decline in the excess bond premium. Figure B.5 displays the impulse response function of unemployment using this alternative shock. The results closely mirror those obtained with the business cycle shock: unemployment declines more when uncertainty is higher, indicating stronger shock propagation. Similarly, Figure B.6 reports the impulse response function of inflation, showing that inflation tends to rise more under higher uncertainty. Although the overall impact of the shock on inflation is modest—making heterogeneous effects harder to detect—the results remain robust. Specifically, when uncertainty is elevated, the excess bond premium shock propagates more strongly through the economy, with unemployment falling further and inflation increasing slightly more.

6 A simple New Keynesian model

In this section, I develop a simple linearized New Keynesian model to account for the empirical findings. The model builds on the framework introduced in Section 2, in which the monetary authority observes only a noisy signal of the underlying shock. I use the model to estimate impulse response functions to both demand and cost-push shocks under two levels of signal precision, where a less precise signal corresponds to higher uncertainty.

6.1 Model Environment

Following the textbook New Keynesian framework,[22] the monetary authority minimizes a quadratic loss function subject to the New Keynesian Phillips Curve and the Euler equation for output. The optimization problem is:

$$\min_{\{r_t\}_{t=0}^{\infty}} \mathbb{E}\left[\sum_{t=0}^{\infty} \delta^t(\pi_t^2 + \lambda_y y_t^2)|\mathcal{I}_0\right]$$

s.t.

$$\pi_t = ky_t + \delta\mathbb{E}\left(\pi_{t+1}|\mathcal{I}_t\right) \tag{9}$$

$$y_t = \mathbb{E}\left(y_{t+1}|\mathcal{I}_t\right) - \sigma\left[r_t - \mathbb{E}\left(\pi_{t+1}|\mathcal{I}_t\right)\right] + d_t \tag{10}$$

$$d_t = \rho d_{t-1} + u_t^d \tag{11}$$

where π_t denotes inflation, y_t the output gap, r_t the interest rate, and d_t a demand shock, with all variables expressed as deviations from steady state. The parameter λ_y captures the relative weight the monetary authority places on output gap stabilization. Equation (9) is the New Keynesian Phillips curve, where k denotes its slope. Equation (10) is the Euler equation, modified to include a demand shock, with σ representing the intertemporal elasticity of substitution. I model the shock as demand-driven rather than a cost-push shock because the business cycle shock analyzed in Section 3.2 and Section 4 displays characteristics consistent with a demand-driven expansion. In Section 6.4, I solve the same model with a cost-push shock and show that it yields predictions inconsistent with the empirical evidence—specifically, unemployment increases rather than decreases. This distinction supports interpreting the business cycle shock in Angeletos, Collard, and Dellas (2020) as a demand shock. Equation (11) describes the law of motion of the demand shock. The expectation operator $\mathbb{E}(\cdot, |, \mathcal{I}_t)$ denotes rational expectations conditional on the information set $\mathcal{I}_t$. I further assume that both the monetary authority and the private sector have the same information set.[23] Following Section 2, I assume that the information set includes only a noisy signal of the demand shock. Specifically, the signal is given by $s_t = d_t + \nu_t$, where

[22]For example, see Galí (2015).

[23]For example, Svensson and Woodford (2003a,b); Lippi and Neri (2007) assume symmetric information in New Keynesian models similar to the one used in this paper.

$u_t^d \sim N(0, \sigma^2_{u^d})$ and $\nu_t \sim N(0, \sigma^2_\nu)$. Under this assumption, inflation and the output gap are not part of the information set. In Section 6.5, I relax this restriction and allow the information set to include two additional independent noisy signals, one for inflation, π_t, and one for the output gap, y_t.

The model presented thus far is not microfounded. At first glance, it may seem inconsistent that private agents do not observe their own demand shock in equation (10), even though the true underlying demand shock, d_t, enters directly into the equation. However, the model can be interpreted through the lens of bounded rationality as in Gabaix (2014). In this interpretation, agents may perfectly observe their individual shocks but choose not to use this information when forming forecasts, as incorporating it is costly. For example, in an economy with many agents, each agent might find it less costly to base forecasts on publicly available aggregate information rather than processing and incorporating their own private signals into these forecasts.

It is also worth noting that the main results discussed in Section 6.2, Section 6.3, and Section 6.4 remain unchanged whether the information set in equation (9) and equation (10) corresponds to full information or to the monetary authority's information set, which contains only a noisy signal of the underlying shock. This invariance arises because, in this setup, the monetary authority does not observe aggregate variables such as inflation and the output gap, and thus cannot learn about private sector information through observed outcomes.[24]

In this model, as shown by Pearlman, Currie, and Levine (1986) and Svensson and Woodford (2003a,b), certainty equivalence and the separation principle hold. Certainty equivalence implies that optimal policy under noisy information mirrors the policy under full information, except that the monetary authority responds to an efficient estimate of the state variables rather than their true values. The separation principle allows the optimization and the signal extraction problems to be solved independently. The signal extraction problem can be solved using the Kalman filter, as all variables are normally distributed. I assume the monetary authority has a normal prior on $d_0 \sim N(0, \sigma^2_{d_0})$, where $\sigma^2_{d_0}$ is the steady-state variance obtained from the Kalman filter. This setup allows the signal extraction problem to be addressed using the steady-state Kalman filter. Under this assumption, $\sigma^2_{d_0}$ is determined by the variances of the demand shock innovations, $\sigma^2_{u^d}$, and of the noise, σ^2_ν; it is not a free parameter.

[24] Under asymmetric information, as discussed in Svensson and Woodford (2004), certainty equivalence typically holds, but the separation principle may fail. Intuitively, when the monetary authority observes aggregate outcomes with noise, it can potentially extract more information than from a simple signal extraction problem, since equilibrium outcomes depend on its own actions and the private sector's responses, and private agents may hold superior information.

I further assume that the variances of u_t and ν_t are time-invariant, implying that the signal-to-noise ratio, defined as $\lambda = \frac{\sigma^2_{d_0}}{\sigma^2_{\nu}}$, remains constant over time. A lower signal-to-noise ratio corresponds to higher uncertainty, which can result either from a decrease in the variance of the demand shock innovations or an increase in the variance of the measurement error.

Thus, the variance of the demand shock affects only the signal extraction problem and has no direct impact on the equilibrium allocation. Consequently, in the model, a change in the level of uncertainty—absent any other fundamental shock—does not alter equilibrium outcomes. This feature is valuable because it allows the analysis to focus on how shocks propagate under different levels of uncertainty without confounding these effects with direct impacts of uncertainty itself. In other words, uncertainty shocks—interpreted here as variations in the variance of the demand shock or the measurement error—do not influence the equilibrium directly.

This modeling choice aligns with the empirical focus of the paper, which is not on the effects of uncertainty shocks per se, but on how uncertainty conditions the response of the economy to other variables (as in the Taylor rule estimation in Section 3.1) and to shocks (as in the local projection analysis in Section 3.2 and Section 4). Specifically, the analysis centers on the estimated interaction terms in the empirical specifications equation (6), equation (7), and equation (8). Allowing uncertainty to directly affect equilibrium outcomes would complicate the interpretation of these results, as it would make harder the distinction between the direct effects of uncertainty and its interaction with other shocks—making it harder to isolate the mechanism the paper aims to study.

For these reasons, the model provides a clear, simple and tractable framework for examining how the impulse response functions (IRFs) of endogenous variables to exogenous shocks vary with different levels of uncertainty. Specifically, Figure 1, Figure 2, and Figure 3 present the empirical counterparts of this exercise by showing the IRFs of the interest rate, unemployment, and inflation, respectively, to demand shocks for both low and high levels of uncertainty.

The model is solved under discretion. This framework closely resembles that of Woodford (1999), but with two key differences. First, Woodford (1999) assumes full information for both the monetary authority and the private sector, whereas my model features partial information: the monetary authority observes only a noisy signal of the demand shock. Second, Woodford (1999) includes an interest rate smoothing motive in the loss function, specified as $\mathbb{E}\left[\sum_{t=0}^{\infty}\delta^t(\pi_t^2+\lambda_y y_t^2+\lambda_r r_t^2)|\mathcal{I}_0\right]$, where λ_r is the interest rate smoothing parameter. This term is essential in the full-information case; without it, divine coincidence holds, allowing the monetary authority to fully offset demand shocks and keep both inflation and the output gap at their steady-state levels. In contrast, divine coincidence does not hold in my model due to partial information. The monetary authority cannot fully neutralize the shock, as the noisy signal prevents perfect identification of its magnitude. Given the similarity between my model and that of Woodford (1999), I adopt his parameter values without recalibrating the model. This is justified by the model's stylized nature: it is intended to qualitatively rationalize the empirical findings rather than provide a quantitative analysis. Its purpose is to offer a qualitative insight into how uncertainty affects monetary policy and macroeconomic dynamics.

6.2 Impulse response function to a demand shock

Figure 4 illustrates the impulse response functions to a one percent increase in the demand shock under low and high uncertainty, corresponding to a more and less precise signal-to-noise ratio, respectively. The blue line represents low uncertainty (high signal-to-noise ratio), and the red line represents high uncertainty (low signal-to-noise ratio). The top left panel shows the IRF of the interest rate: the monetary authority raises the rate by less when uncertainty is higher, as the red line lies below the blue line throughout. The top right panel presents the IRF of inflation, with inflation consistently higher under elevated uncertainty (red line above blue line). The bottom left panel displays the IRF of the output gap, which is also larger under high uncertainty. Together, these panels demonstrate that the monetary authority reacts more cautiously to demand shocks when uncertainty is greater, resulting in greater propagation of the shock throughout the economy. Consequently, both inflation and the output gap exhibit stronger responses.

This model's IRFs qualitatively aligns with the empirical findings shown in Figure 1, Figure 2, and Figure 3. While the empirical analysis focuses on unemployment rather than the output gap—since the business cycle shock of Angeletos, Collard, and Dellas (2020) is specifically constructed to explain variations in unemployment—the model establishes a clear connection between the two. In particular, a larger output gap implies lower unemployment. Thus, the model's qualitative predictions are consistent with the empirical results: under higher uncertainty, unemployment responds more strongly to demand shocks.

Finally, the bottom right panel of Figure 4 illustrates the perceived demand shock—that is, the monetary authority's estimate of the actual shock affecting the economy. This plot highlights a key insight: under higher uncertainty, the monetary authority perceives the shock to be smaller, which explains its more cautious policy response. However, in equilibrium, the realized demand shock is the same regardless of the uncertainty level. To clear the market, a lower interest rate under high uncertainty requires a larger increase in inflation and the output gap.

The proposed model, though highly stylized, effectively rationalizes the empirical findings. It is notable that such a simple framework can capture key patterns observed in the data. Beyond matching the empirical results, the model provides valuable intuition for how demand shocks propagate under different levels of uncertainty. As uncertainty increases, the monetary authority perceives the shock to be smaller and therefore raises interest rates less aggressively. This more cautious policy response leads to higher inflation and a larger output gap, as market-clearing conditions require these adjustments.

While the model is solved under discretion, it is important to note that, in this particular setup, identical results would arise under commitment. Specifically, the impulse response functions are the same across the two policy regimes because neither the Euler equation nor the New Keynesian Phillips Curve imposes binding constraints on the monetary authority's interest rate decisions. As a result, under commitment, the Lagrange multipliers associated with these constraints are identically zero in equilibrium and do not influence the model's dynamics. This outcome reflects the fact that a demand shock generates a positive co-movement between inflation and the output gap, allowing the policymaker to stabilize both simultaneously through interest rate adjustments. However, this equivalence does not hold for all types of shocks. For example, a cost-push shock creates a trade-off between inflation and the output gap, in which case the Lagrange multipliers are nonzero and, thus, the solutions under discretion and commitment are different.

So far, I have analyzed the case in which the monetary authority and the private sector share the same information set. However, in this particular setup, the impulse responses reported in Figure 4 would be identical even if the private sector had full information—meaning that it perfectly observes the demand shock, rather than a noisy signal. As shown by Svensson and Woodford (2004), when the private sector has more information than the monetary authority, certainty equivalence still holds. Intuitively, this is because the monetary authority cannot influence the private sector's expectations through its actions since the private sector already possesses more information. As a result, policy decisions under asymmetric information have no additional effect beyond those under full information, and the same optimal rule applies. However, in general, the separation principle does not hold under asymmetric information. When the private sector has access to more information than the monetary authority, the latter does not rely on a simple signal extraction problem. Instead, it also accounts for the fact that endogenous variables embed the decisions of the better-informed private sector. This makes the estimation problem more complex than standard filtering, thereby violating the separation principle. In my setup, however, the monetary authority does not observe endogenous variables but only a noisy signal of the fundamental demand shock—a signal that is independent of the private sector's actions. This restriction ensures that the separation principle still holds in this particular environment.

6.3 Impulse response function to a noise-demand shock

To further understand the cautious reaction of the monetary authority described in Section 6.2, it is useful to examine the IRFs to a one percent increase in the noise component of the signal about the demand shock. Specifically, I analyze the case where the noise in the signal, ν_t, increases only in the first period while the fundamental demand shock remains zero, $d_t = 0$, in all periods. I refer to this as a "noise-demand shock" since it represents an increase in the noise component of the signal related to a demand shock. Importantly, under full information, this shock would have no effect on the economy, as it does not affect any fundamentals in the economy. Indeed, the variable ν_t appears only in the signal observed by the monetary authority and private agents.

Figure 5 reports the IRFs to a one percent noise-demand shock under low and high uncertainty, corresponding to a high and low signal-to-noise ratio, respectively. The blue line represents low uncertainty, while the red line represents high uncertainty. The top left panel shows the IRF of the interest rate: the monetary authority raises the interest rate by less when uncertainty is higher, as indicated by the red line lying below the blue line. The top right panel presents the IRF of inflation, showing that inflation declines less under higher uncertainty. The bottom left panel displays the IRF of the output gap, which similarly contracts less when uncertainty is higher. The bottom right panel reports the perceived demand shock as estimated by the monetary authority.

Although no fundamental demand shock has occurred, the monetary authority interprets part of the noisy signal as evidence of a genuine demand shock, leading it to tighten policy unnecessarily. In reality, no such shock is present, and the monetary authority's response to the noise-demand shock induces a recession that would not have occurred if the interest rate had remained unchanged. However, because the noise shock is i.i.d., the monetary authority quickly learns that no fundamental demand shock has affected the economy, and the effects are short-lived.

This experiment illustrates why the monetary authority is cautious in reacting to signals about fundamental shocks: it aims to avoid inducing unnecessary recessions by overreacting to signals that may reflect noise rather than true economic disturbances. This mechanism provides further intuition for the cautious policy stance observed under higher uncertainty. In such situations, a larger portion of the signal is attributed to the noise component, making the monetary authority more concerned that increasing interest rates could inadvertently trigger a recession.

6.4 Impulse response function to a cost-push shock

In Section 6.1 and Section 6.2, I modeled the business cycle shock of Angeletos, Collard, and Dellas (2020) as a demand shock and showed that the model could qualitatively replicate the empirical findings. To further support this interpretation, I now solve the same model using a cost-push shock instead of a demand shock. The model structure remains unchanged, except that the demand shock is removed from the Euler equation, equation (10), and a cost-push shock, μ_t, is introduced into the New Keynesian Phillips Curve. Specifically, equation (9) becomes:

$$\pi_t = ky_t + \delta\mathbb{E}\left(\pi_{t+1}|\mathcal{I}_t\right) + \mu_t$$

where μ_t follows an AR(1) process. As in the previous case, the monetary authority observes only a noisy signal of the shock, and cannot directly observe neither inflation or the output gap. All parameter values remain the same as in the previous specification.

Figure 6 reports the impulse response functions to a one percent increase in the cost-push shock under both low and high uncertainty, corresponding to more and less precise signal-to-noise ratios, respectively. The blue line represents low uncertainty (high signal-to-noise ratio), while the red line represents high uncertainty (low signal-to-noise ratio). The top left panel displays the impulse response of the interest rate. The monetary authority responds more cautiously under higher uncertainty, as the cost-push shock is perceived to be smaller. This is reflected in the red line (high uncertainty) consistently lying below the blue line (low uncertainty). The bottom left panel presents the IRF of the output gap, which is negative. Under higher uncertainty, the output gap is closer to zero, implying that unemployment increases—and increases more when uncertainty is lower. This result follows from the fact that, in the model, the output gap is directly pinned down by the path of interest rates through the Euler equation. The top right panel displays the impulse response of inflation. Unlike the interest rate and the output gap, inflation is only mildly affected by uncertainty—the red and blue lines lie close together. This pattern arises from two opposing forces operating through the New Keynesian Phillips Curve. First, when uncertainty is higher, the smaller contraction in output reduces downward pressure on inflation. Second, higher uncertainty leads agents to expect lower future inflation, as they perceive the cost-push shock to be smaller. Through the expectations channel, this dampens current inflation. These two effects offset each other, resulting in only modest differences in inflation across uncertainty levels.

These results contrast with the empirical findings in Section 4. As shown in Figure 2, unemployment is negative and becomes more negative when uncertainty is higher. Moreover, Figure 3 demonstrates that the IRFs of inflation under low and high uncertainty are statistically different. These discrepancies motivate the interpretation of the business cycle shock as a demand shock. In fact, a cost-push shock can only account for the empirical result that interest rates are lower under higher uncertainty, but it cannot explain the observed behavior of inflation and unemployment.

Finally, the bottom right panel of Figure 6 shows the perceived cost-push shock—that is, the monetary authority's estimate of the actual shock. Under higher uncertainty, the shock is perceived to be smaller, which explains the more cautious interest rate response.

In Figure 6, the model is solved under discretion. By contrast, Figure B.7 reports the same experiment solved under commitment. Unlike the case of the demand shock discussed in Section 6.2, the impulse response functions differ between discretion and commitment because cost-push shocks generate a trade-off between stabilizing inflation and the output gap. As a result, the New Keynesian Phillips Curve becomes a binding constraint under commitment, and its associated Lagrange multiplier—which influences interest rate decisions only in the commitment case—is different from zero. Nonetheless, the qualitative results remain largely unchanged. Under commitment, the monetary authority still responds less aggressively to the cost-push shock as uncertainty increases; the output gap remains negative but becomes less negative under higher uncertainty; and inflation rises, though its magnitude remains relatively unaffected by the level of uncertainty. These results confirm the interpretation of the business cycle shock as a demand shock.

6.5 Robustness check of the information set

In Section 6.1, I assumed that the monetary authority observes only a noisy signal of the fundamental demand shock and cannot directly observe inflation or the output gap. While this assumption may appear unrealistic, it serves a practical purpose: it simplifies the model by restricting observables to a single variable—the signal of the demand shock. Consequently, the signal-to-noise ratio is determined directly by the ratio of the variances of the demand shock and the noise component. This setup enables a straightforward comparison of high and low signal-to-noise environments by varying the variance of either the shock or the noise while holding the other constant.

In this section, I relax the previous assumption and allow the monetary authority to additionally observe both inflation and the output gap, albeit with noise. Specifically, it observes $\tilde{\pi}_t = \pi_t + \nu_{\pi,t}$ and $\tilde{y}_t = y_t + \nu_{y,t}$, where $\nu_{\pi,t} \sim N(0, \sigma_\nu^2)$ and $\nu_{y,t} \sim N(0, \sigma_\nu^2)$. If the monetary authority could perfectly observe either inflation or the output gap, it could directly infer the demand shock, rendering the signal of the shock redundant and eliminating uncertainty in the model.

Under these assumptions, the signal-to-noise ratio depends on the variances of u_t, ν_t, $\nu_{\pi,t}$, and $\nu_{y,t}$. As a result, four variances now determine the level of uncertainty, making the comparison between high and low uncertainty more complex. To simplify, I assume that all measurement errors—ν_t, $\nu_{\pi,t}$, and $\nu_{y,t}$—share the same variance, σ_ν^2.

Figure B.8 reports the impulse response functions to a one percent increase in the demand shock under both low and high uncertainty, corresponding to more and less precise signal-to-noise ratios, respectively. The figure is constructed analogously to Figure 4. The blue line represents low uncertainty (high signal-to-noise ratio), while the red line represents high uncertainty (low signal-to-noise ratio). The top left panel displays the IRF of the interest rate, the top right shows the IRF of inflation, the bottom left presents the IRF of the output gap, and the bottom right reports the perceived demand shock.

This robustness check replicates the same patterns observed in Figure 4: under higher uncertainty, the monetary authority reacts less aggressively to the demand shock, resulting in greater shock propagation, with both inflation and the output gap increasing. The main difference between Figure 4 and Figure B.8 lies in the magnitude of the IRFs. In the robustness exercise, for the same level of uncertainty, the IRF of the interest rate is slightly larger, while the IRFs of inflation and the output gap are smaller.

This occurs because the perceived demand shock is marginally larger in Figure B.8, prompting the monetary authority to raise the interest rate more, which in turn dampens inflation and the output gap. Notably, the same parameterization is used in both figures. However, in the robustness case, the monetary authority receives three signals, leading to a more precise estimate of the realized demand shock. This improved precision explains the difference in IRF magnitudes between Figure 4 and Figure B.8.

7 Different possible interpretations of uncertainty

Throughout the paper, I have interpreted uncertainty as the precision of the signal regarding the fundamental shock. This interpretation has served to motivate the empirical analysis and provide a structural explanation for the findings. However, the empirical measures of uncertainty employed—specifically JLN and VIX—are broad in nature and may admit alternative interpretations. For example, they could reflect changes in the variances of underlying shocks or represent uncertainty about model parameters, as in Brainard (1967). Given these possibilities, it is worthwhile to consider whether alternative modeling approaches could also rationalize the empirical results.

Section 7.1 demonstrates that the seminal framework of Brainard (1967) is consistent with my empirical results and further shows that his model and mine are closely related in structure and implications. In addition, Section 7.2 explores how a risk-averse monetary authority would, similarly, adopt a more cautious approach to raising interest rates as uncertainty increases.

7.1 Parameter-uncertainty, Brainard (1967)

Let me propose a simple model in the spirit of Brainard (1967). The model is static, and the monetary authority's objective is to minimize expected losses, given by:

$$\min_r \mathbb{E}\left[\lambda_y y^2 + \pi^2 | \mathcal{I}\right]$$

subject to the following constraints:

$$\pi = ky$$

$$y = -\gamma_r r + d$$

The first constraint is a static Phillips Curve, while the second represents a static Euler equation. All variables are defined as before, with the only new element being γ_r, which denotes the strength of monetary policy—that is, the sensitivity of output to the interest rate. Importantly, γ_r is not known with certainty by the monetary authority. This setup introduces parameter uncertainty, a situation in which agents—in this case, the monetary authority—do not have perfect knowledge of a model parameter. I further assume that the monetary authority believes that both the demand shock, d, and the strength of monetary policy, γ_r, follow a joint normal distribution:

$$\begin{pmatrix} \gamma_r \\ d \end{pmatrix} \sim N\left(\begin{bmatrix} \bar{\gamma}_r \\ \bar{d} \end{bmatrix}, \begin{bmatrix} \sigma^2_{\gamma_r}, \sigma_{\gamma_r,d} \\ \sigma_{\gamma_r,d}, \sigma^2_d \end{bmatrix} \right)$$

Under these assumptions, the optimal interest rate is given by:

$$r^* = \frac{\mathbb{E}(\gamma_r d|\mathcal{I})}{\sigma^2_{\gamma_r} + \bar{\gamma}_r{}^2} \tag{12}$$

This equation shows that as parameter uncertainty—captured by the variance of γ_r—increases, the monetary authority becomes more cautious in its response to a positive demand shock ($d > 0$), raising the interest rate by less. Furthermore, from the Euler equation and the Phillips Curve, it follows that a smaller interest rate leads to a larger output gap and higher inflation.

Thus, this theoretical result can rationalize the empirical findings in Section 3 and Section 4, provided that the JLN measure of uncertainty is positively correlated with parameter uncertainty. Appendix E shows that these two variables are positively correlated. Therefore, the empirical results presented in this paper can also be interpreted structurally through the lens of Brainard (1967)'s framework.

However, interpreting the empirical results through the lens of parameter uncertainty requires caution. Firstly, while Brainard (1967) presents a static model, dynamic models with uncertainty about multiple parameters can yield the opposite prediction: the monetary authority should respond more aggressively as uncertainty increases.[25] This highlights the importance of specifying parameter uncertainty in a particular way to rationalize my empirical findings. However, it is not straightforward to determine empirically which parameters are unknown to the monetary authority. Secondly, parameter uncertainty introduces non-linearities into the model's solution, complicating both its analytical tractability and in-

[25] See, for example, Craine (1979) and Kimura and Kurozumi (2007).

terpretation. In contrast, the model proposed in Section 6, which focuses on uncertainty about shocks, remains linear and offers a clear, intuitive explanation of the empirical results. Thirdly, uncertainty about shocks provides a novel rationale for the monetary authority's cautious behavior. Nonetheless, uncertainty about shocks and parameter uncertainty share a common theoretical foundation: the distinction between a shock and a parameter is ultimately a modeling choice. From a theoretical standpoint, both forms of uncertainty reflect imperfect information about an underlying variable in the model.

7.2 Risk Aversion

The models discussed thus far assume a quadratic objective function, under which the variance of the shock, σ_d^2, does not directly affect the monetary authority's optimal policy. In the model presented in Section 6, the variance of the shock influences only the signal extraction problem; it has no direct role in the policy decision. In Brainard's model, the variance of the shock does not appear in the solution at all. In this sense, the monetary authority in both models behaves as if it is risk-neutral.

However, it is also reasonable to consider a risk-averse monetary authority.[26] Under this assumption, it is straightforward to see why greater uncertainty—interpreted here as an increase in the variance of the fundamental shock—would lead to a more cautious policy response to a given demand shock. A risk-averse monetary authority seeks to minimize not only expected losses but also the potential variability of outcomes, which naturally results in more conservative interest rate adjustments as uncertainty rises for a given demand shock. Note again that my work focuses on studying how demand shocks propagate through the economy under different levels of uncertainty, not on analyzing uncertainty shocks per se.

This interpretation of uncertainty aligns closely with the empirical measures of JLN and VIX. When economic activity becomes more difficult to forecast—as reflected by a higher JLN measure—it is plausible that the variance of underlying shocks has increased. Similarly, the VIX, which captures market-based expectations of volatility, is also expected to rise with greater shock variance. Thus, interpreting uncertainty as the variance of shocks provides a natural connection between the empirical measures and a risk-averse monetary authority's cautious response.

Thus, my empirical findings admit an alternative structural interpretation: the monetary authority

[26] In the New Keynesian model, the monetary authority minimizes the representative household's lifetime utility, which reflects risk aversion. However, once the model is log-linearized—as in my analysis—risk aversion no longer influences the policy trade-offs. The resulting objective function is quadratic, and the model behaves as if the policymaker were risk-neutral.

responds more cautiously as uncertainty increases because it is risk-averse.

The model proposed in Section 6, as previously discussed, does not incorporate higher-order terms, implying that the variance of shocks influences the monetary authority's decisions only through the filtering problem. While this is a limitation, it also allows for a clear and direct examination of how uncertainty shapes the monetary authority's cautiousness as uncertainty rises. The value of the model lies in its simplicity: it provides a transparent framework that isolates the mechanism through which uncertainty affects monetary policy. Extending the analysis to include higher-order approximations could offer a richer perspective on how shocks propagate under different levels of uncertainty. However, such extensions reduce clarity of interpretation and tractability, as higher-order effects complicate the equilibrium characterization. Given that the primary purpose of the model in this paper is to provide a clear structural interpretation of the empirical findings, its stylized nature is intentional. It is striking that such a simple framework can successfully rationalize the empirical patterns documented in Section 3 and Section 4.

8 Conclusions

I provide evidence that the Federal Reserve adopts a more cautious stance when economic activity becomes harder to forecast—a condition interpreted as heightened uncertainty. To support this finding, I employ two distinct and complementary empirical approaches.

The first approach estimates a Taylor rule in which the coefficients on inflation and the output gap are interacted with the Jurado, Ludvigson, and Ng (2015) measure of uncertainty. This specification reveals how the Federal Reserve's responsiveness to economic indicators varies with the level of uncertainty.

The second approach uses local projections of the interest rate, regressing it on an exogenous demand shock interacted with the uncertainty measure. This method offers additional insight into how uncertainty alters the monetary authority's reaction to economic shocks.

Furthermore, I provide evidence that, under higher uncertainty, demand shocks generate larger fluctuations in unemployment and inflation. To reach this conclusion, I estimate local projections of these variables in response to a well-identified demand shock, allowing for an interaction term with my measure of uncertainty.

My empirical results are rationalized through a simple New Keynesian model in which the monetary authority cannot directly observe the underlying demand shock, but only a noisy signal of it. Although stylized, the model provides clear intuition: in response to a positive demand shock, a noisier signal causes the monetary authority to perceive the shock as smaller, leading to a smaller interest rate response. However, market-clearing conditions require inflation and the output gap to rise in order to absorb the shock. As a result, the weaker policy response amplifies the shock's impact on the economy.

Finally, a series of robustness checks confirm the consistency and validity of the empirical findings, reinforcing the conclusion that heightened uncertainty prompts a more cautious monetary policy response, which in turn leads to greater propagation of shocks throughout the economy.

The model proposed in this paper is not the only framework capable of rationalizing the empirical findings. Parameter uncertainty or a risk-averse monetary authority would yield similar predictions regarding a more cautious policy response under heightened uncertainty. Determining which channel primarily drives this behavior is beyond the scope of this paper. However, an avenue for future research is to estimate the signal-to-noise ratio of fundamental shocks using alternative methodologies or to quantify uncertainty about specific model parameters. Such analyses would allow for a clearer assessment of whether partial information about shocks, parameter uncertainty, or risk aversion plays the dominant role in shaping the monetary authority's cautiousness.

Another direction for future research is to measure uncertainty more directly from the Federal Reserve's information set. For instance, since 2009, the Federal Reserve has published inflation and GDP forecasts of individual members of the FOMC. Although the available time series is currently too short for robust empirical analysis, it holds significant potential for future study. Developing and applying alternative measures of uncertainty—particularly those derived from policymakers' own information set—would further enhance our understanding of how uncertainty influences monetary policy decisions.

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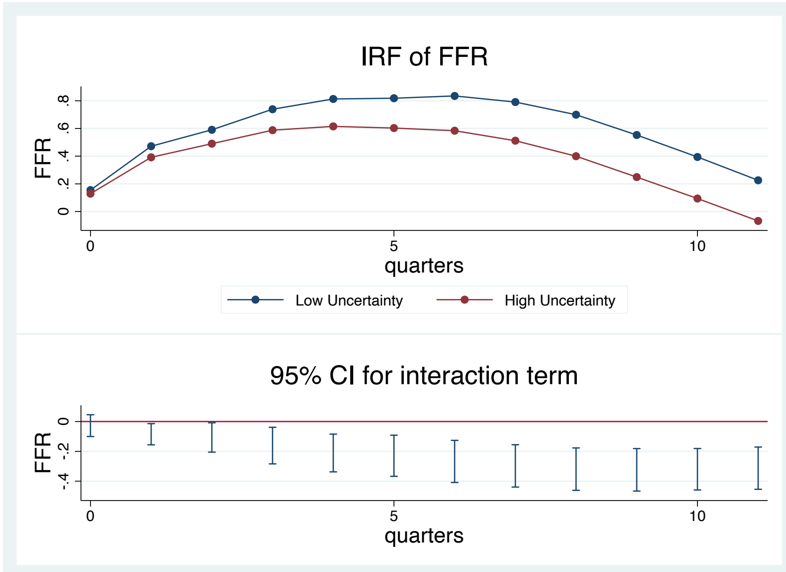
Table 1: Estimated Taylor Rule

	(1) OLS	(2) OLS	(3) GMM	(4) GMM	(5) Greenbooks	(6) Greenbooks
π^{cpi}	1.46***	1.73***	1.85***	2.12***	1.88***	1.73***
	(0.42)	(0.34)	(0.41)	(0.25)	(0.43)	(0.40)
$\pi^{cpi}\times$ JLN		-1.13**		-1.16**		-1.55*
		(0.46)		(0.48)		(0.90)
y^*	1.34***	1.33***	1.10***	1.07***	0.76***	0.84***
	(0.20)	(0.18)	(0.23)	(0.15)	(0.19)	(0.19)
$y^*\times$ JLN		-0.31**		-0.09		-0.05
		(0.14)		(0.17)		(0.20)
JLN		0.13		0.29		0.29
		(0.16)		(0.25)		(0.28)
ρ	0.87***	0.85***	0.88***	0.82***	0.89***	0.89***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.02)	(0.02)
N	139	139	139	139	122	122
R^2	0.961	0.965	0.951	0.959	0.981	0.983

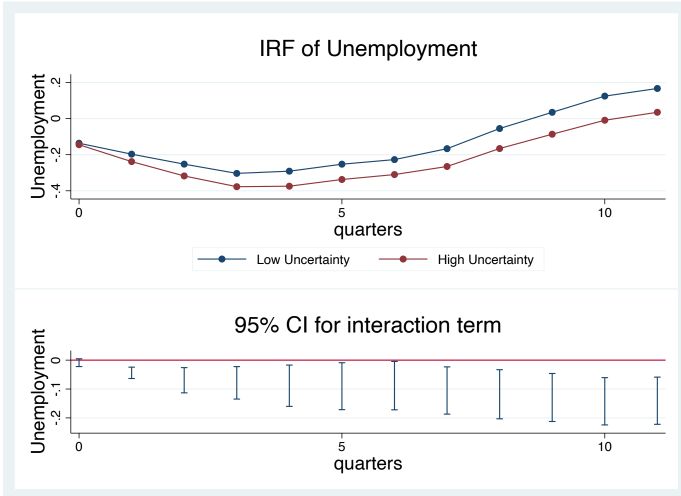
Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and the output gap, the Federal Reserve tends to react more cautiously when uncertainty is higher: the interaction term coefficients are both negative.

Figure 1: Local projections of the interest rate



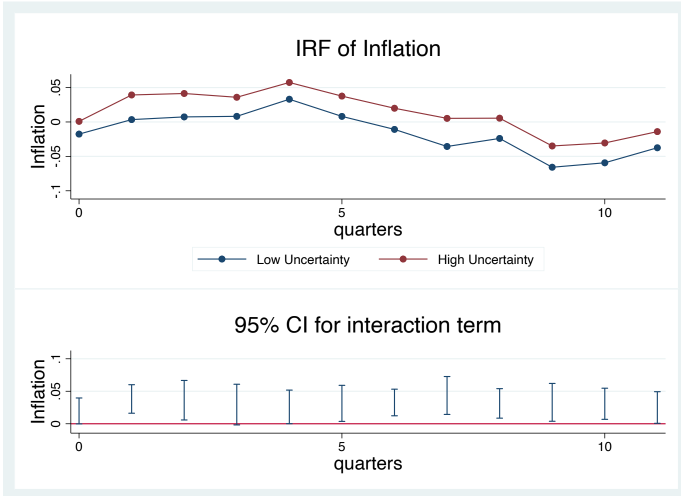
The top panel reports equation (7) estimates of $\hat{\beta}_{1,j}\overline{Shock} + \hat{\beta}_{2,j}(\widetilde{JLN} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}_{i,j}$ for $i = 1, 2$ are the estimated coefficients, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty, (75th percentile). The top panel shows that the impulse response function (IRF) of the interest rate under low uncertainty (blue line) is always above the IRF under high uncertainty (red line), indicating that the Federal Reserve tends to react more cautiously when uncertainty is higher. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}_{2,j}$. These intervals do not contain a value equal to zero, demonstrating that the two plotted IRFs are statistically different from each other. Indeed, for more or less all horizons, the coefficients $\hat{\beta}_{2,j}$ are statistically significant.

Figure 2: The propagation effect on unemployment



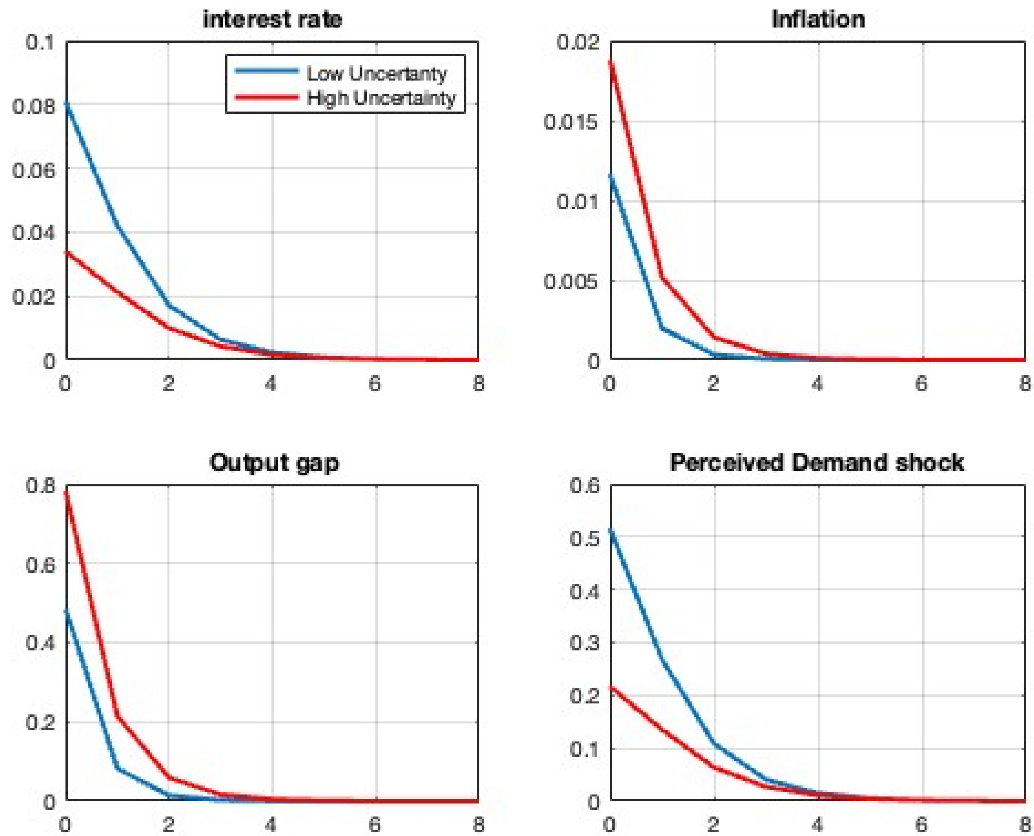
The top panel reports estimates of $\hat{\beta}^u_{1,j}\overline{Shock} + \hat{\beta}^u_{2,j}(\widetilde{JLN} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^u_{i,j}$ for $i = 1, 2$ are the estimated coefficients of equation (8) using unemployment as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty, (75th percentile). The top panel shows that the impulse response function (IRF) of unemployment under low uncertainty (blue line) is always above the IRF under high uncertainty (red line), indicating that unemployment tends to reduce by more when uncertainty is high. Notice that unemployment is over all decreasing, as it is expected when the economy is in a boom. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}^u_{2,j}$. These intervals do not contain a value equal to zero, showing that the two IRFs are statistically different from each other. Indeed, for more or less all horizons, the coefficients $\hat{\beta}^u_{2,j}$ are statistically significant.

Figure 3: The propagation effect on inflation



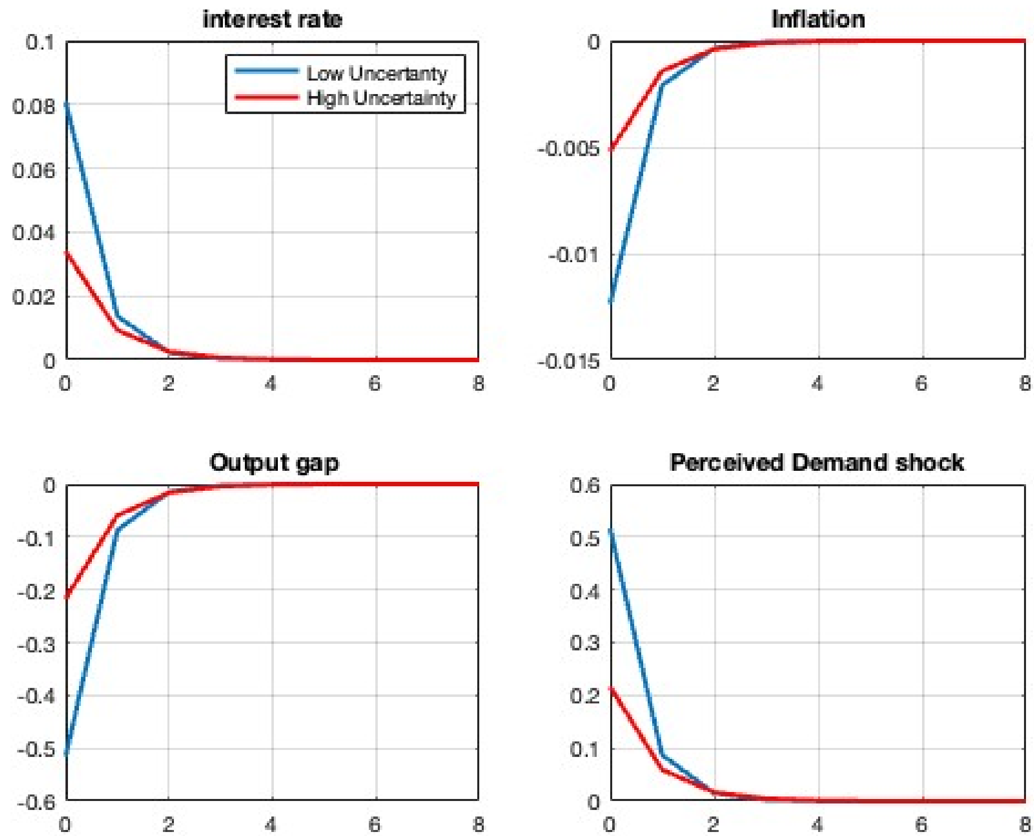
The top panel reports estimates of $\hat{\beta}^{\pi}_{1,j}\overline{Shock} + \hat{\beta}^{\pi}_{2,j}(\widetilde{JLN} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^{\pi}_{i,j}$ for $i = 1, 2$ are the estimated coefficients of equation (8) using inflation as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function (IRF) of inflation under low uncertainty (blue line) is always below the IRF under high uncertainty (red line), indicating that inflation tends to increase by more when uncertainty is high. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}^{\pi}_{2,j}$. These intervals do not contain a value equal to zero, showing that the two IRFs are statistically significantly different from each other. Indeed, for more or less horizons, the coefficients $\hat{\beta}^{\pi}_{2,j}$ are statistically significant.

Figure 4: Model-implied impulse response function to a positive demand shock



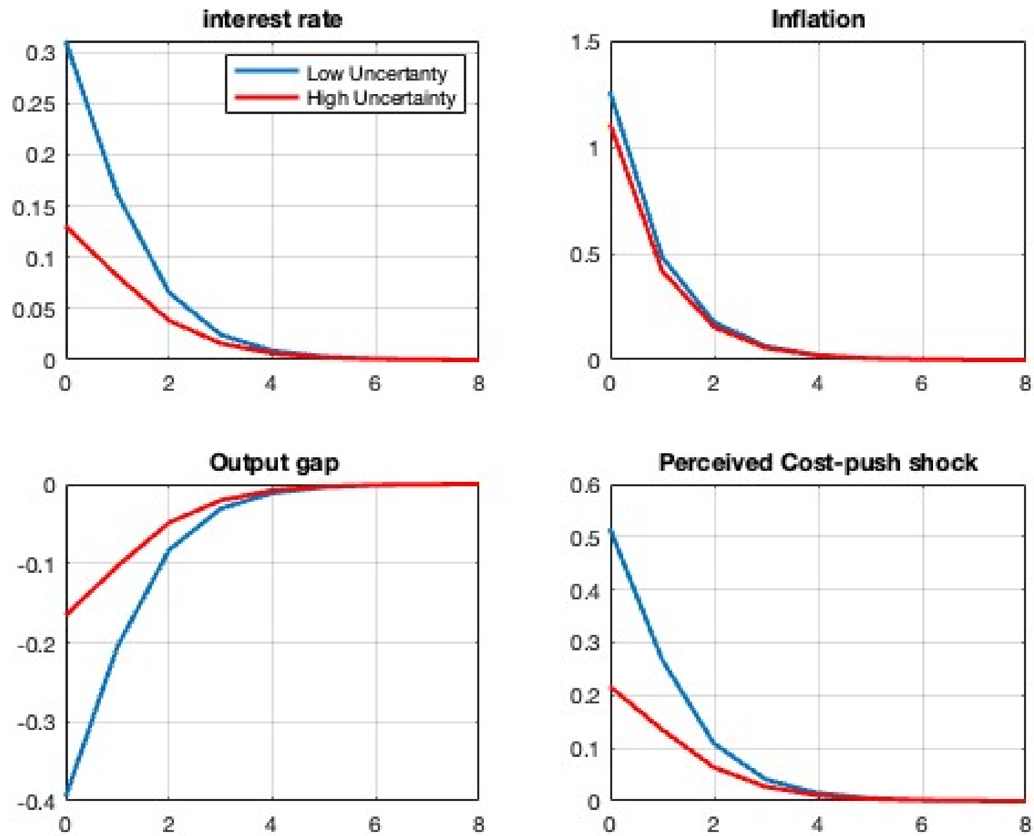
The left top panel reports the IRF of the interest rate to a 1% increase of the demand shock. The top right reports the IRF of inflation. The bottom left reports the IRF of the output gap. The bottom right panel reports the perceived demand shock by the monetary authority. Blue (red) lines show the IRFs under low (high) uncertainty. The figure shows that under high uncertainty, the monetary authority reacts less aggressively to the demand shock. This turns out to generate a larger propagation of the shock into the economy: inflation and the output gap are more positive.

Figure 5: Model-implied impulse response function to a positive noise-demand shock



The top left panel shows the impulse response of the interest rate to a 1% increase in the noise-demand shock. The top right panel reports the impulse response of inflation, while the bottom left panel displays the impulse response of the output gap. The bottom right panel shows the perceived demand shock as estimated by the monetary authority. Blue lines correspond to the low-uncertainty case, while red lines represent the high-uncertainty case. The figure illustrates that under higher uncertainty, the monetary authority responds less aggressively to the noise-demand shock, resulting in a milder recession: both inflation and the output gap decline by less. Under full information, the monetary authority would not adjust the interest rate in response to a noise shock, as it does not affect fundamentals.

Figure 6: Model-implied impulse response function to a positive cost-push shock



The left top panel reports the IRF of the interest rate to a 1% increase of the cost-push shock. The top right reports the IRF of inflation. The bottom left reports the IRF of the output gap. The bottom right panel reports the perceived cost-push shock by the monetary authority. Blue (red) lines show the IRFs under low (high) uncertainty. The figure shows that under high uncertainty, the monetary authority reacts less aggressively to the cost-push shock. This turns out to generate a smaller reduction in the output gap and not a significant difference in inflation.

ONLINE APPENDIX

Cautious Monetary Policy

Andrea Ferrara

A Data

This section describes the data used in detail. Appendix A.1 describes the data used in the Taylor rule considering uncertainty, Section 3.1 and Section 5.1. Appendix A.2 describes the data used in the "reduced form" Taylor rule, Section 3.2 and Section 4, and used to study the propagation mechanism, Section 5.2.

A.1 Taylor rule considering uncertainty

In this section, I provide a detailed explanation of the data used in Section 3.1 and Section 5.1. The data downloaded from the historical archive of FRED labeled as real time data are the following:

1. The interest rate is the federal funds rate observed in the last day of each quarter. For the lower bound period, 2009q1 - 2015q4, the federal funds rate is replaced by the shadow rate of Wu and Xia (2016).

2. CPI inflation is constructed as the annualized growth of the CPI index for each quarter.

3. PCE inflation is constructed as the annualized growth of the PCE index for each quarter.

4. GDP inflation is constructed as the annualized growth of the GDP deflator index for each quarter.

I complement this dataset with the following variables:

1. JLN measure is the uncertainty measure of Jurado, Ludvigson, and Ng (2015): it is the last monthly observation in each quarter.

2. The set of instruments for the GMM are taken directly from Carvalho, Nechio, and Tristao (2021).

3. Expected inflation and expected output are from the Greenbook data.

4. VIX is the CBOE volatility index and it is constructed as the average of the last month in each quarter.

A.2 "Reduced form" Taylor rule

In this section, I provide a detailed explanation of the data used in Section 3.2, Section 4 and Section 5.2. The data used are the following:

1. The federal funds rate, the JLN measure and VIX are constructed as in Appendix A.1.

2. I extended the sample period of Angeletos, Collard, and Dellas (2020) for constructing the business cycle shock. See their online appendix and the replication package for a detailed explanation of the data used. These same data are also used as controls. Furthermore, unemployment and inflation constructed this way are used as dependent variables in Section 4.

3. The excess bond premium shock is directly taken by Gilchrist and Zakrajšek (2012).

B Robustness checks

This section reports the results of the robustness checks discussed in Section 5.

Table B.1: Taylor rule using the 1-month JLN measure

	(1) OLS	(2) OLS	(3) GMM	(4) GMM	(5) Greenbooks	(6) Greenbooks
π^{cpi}	1.46***	1.70***	1.85***	2.10***	1.88***	1.68***
	(0.42)	(0.34)	(0.41)	(0.25)	(0.43)	(0.41)
$\pi^{cpi}\times$ jnl_1_e		-1.12**		-1.16**		-1.65*
		(0.46)		(0.47)		(0.94)
y^*	1.34***	1.32***	1.10***	1.06***	0.76***	0.84***
	(0.20)	(0.18)	(0.23)	(0.15)	(0.19)	(0.19)
$y^*\times$ jnl_1_e		-0.31**		-0.10		-0.03
		(0.14)		(0.18)		(0.20)
jnl_1_e		0.12		0.27		0.32
		(0.16)		(0.24)		(0.29)
ρ	0.87***	0.85***	0.88***	0.82***	0.89***	0.88***
	(0.04)	(0.05)	(0.04)	(0.06)	(0.02)	(0.02)
N	139	139	139	139	122	122
R^2	0.961	0.965	0.951	0.959	0.981	0.983

Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react less aggressively when uncertainty is high: the interaction term coefficients are both negative.

Table B.2: Taylor rule using the 12-month JLN measure

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	GMM	GMM	Greenbooks	Greenbooks
π^{cpi}	1.46***	1.93***	1.85***	2.27***	1.88***	1.98***
	(0.42)	(0.39)	(0.41)	(0.29)	(0.43)	(0.39)
$\pi^{cpi}\times$ jnl_12		-1.11**		-1.31**		-1.27
		(0.56)		(0.58)		(0.81)
y^*	1.34***	1.37***	1.10***	1.06***	0.76***	0.80***
	(0.20)	(0.20)	(0.23)	(0.15)	(0.19)	(0.18)
$y^*\times$ jnl_12		-0.35**		-0.01		-0.08
		(0.16)		(0.19)		(0.19)
jnl_12		0.10		0.39		0.22
		(0.17)		(0.28)		(0.25)
ρ	0.87***	0.87***	0.88***	0.83***	0.89***	0.89***
	(0.04)	(0.04)	(0.04)	(0.06)	(0.02)	(0.02)
N	139	139	139	139	122	122
R^2	0.961	0.965	0.951	0.957	0.981	0.983

Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react more cautiously when uncertainty is high: the interaction term coefficients are both negative.

Table B.3: Taylor rule using VIX as measure of uncertainty

	(1) OLS	(2) OLS	(3) GMM	(4) GMM	(5) Greenbooks	(6) Greenbooks
π^{cpi}	0.45	0.63	1.25***	1.78***	1.58***	1.09*
	(0.59)	(0.43)	(0.41)	(0.28)	(0.57)	(0.65)
$\pi^{cpi}\times$ VIX		-1.26**		-1.20***		-1.97**
		(0.50)		(0.38)		(0.77)
y^*	1.28***	1.49***	1.24***	1.24***	0.81***	1.12***
	(0.26)	(0.21)	(0.18)	(0.13)	(0.22)	(0.29)
$y^*\times$ VIX		-0.53***		-0.44***		-0.26
		(0.20)		(0.14)		(0.23)
VIX		0.06		0.28		0.20
		(0.11)		(0.29)		(0.14)
ρ	0.91***	0.89***	0.88***	0.73***	0.90***	0.91***
	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)
N	115	115	115	115	111	111
R^2	0.976	0.981	0.975	0.966	0.978	0.981

Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on VIX, are divided by $1-\rho$. The variable VIX is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react more cautiously when uncertainty is high: the interaction term coefficients are both negative.

Table B.4: Taylor rule using GDP deflator as measure of inflation

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	GMM	GMM	Greenbooks	Greenbooks
π^{gdpd}	1.43**	2.03***	1.11	2.68***	2.14***	2.23***
	(0.66)	(0.70)	(0.97)	(0.63)	(0.48)	(0.40)
$\pi^{gdpd}\times$ jnl_3_e		-0.35		-1.25		-1.51
		(0.62)		(0.91)		(1.23)
y^*	1.48***	1.45***	1.52***	1.37***	0.79***	0.84***
	(0.30)	(0.31)	(0.39)	(0.22)	(0.18)	(0.18)
$y^*\times$ jnl_3_e		-0.82**		-0.60		-0.12
		(0.41)		(0.61)		(0.24)
jnl_3_e		-0.27		-0.29		0.19
		(0.18)		(0.37)		(0.33)
ρ	0.91***	0.90***	0.94***	0.84***	0.89***	0.89***
	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)
N	139.00	139.00	139.00	139.00	122.00	122.00
R^2	0.96	0.96	0.95	0.96	0.98	0.98

Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react less aggressively when uncertainty is high: the interaction term coefficients are both negative.

Table B.5: Taylor rule using PCE inflation

	(1) OLS	(2) OLS	(3) GMM	(4) GMM	(5) Greenbooks	(6) Greenbooks
π^{pce}	2.15***	2.36***	2.11***	2.27***	0.55	1.81
	(0.39)	(0.32)	(0.31)	(0.30)	(1.72)	(1.91)
$\pi^{pce}\times$ jnl_3_e		-0.34		-0.91*		-1.08
		(0.28)		(0.47)		(3.41)
y^*	1.27***	1.31***	1.43***	1.30***	0.89**	1.07**
	(0.16)	(0.14)	(0.14)	(0.14)	(0.36)	(0.43)
$y^*\times$ jnl_3_e		-0.52***		-0.29		-0.35
		(0.13)		(0.18)		(0.57)
jnl_3_e		-0.21*		-0.08		0.00
		(0.12)		(0.18)		(0.57)
ρ	0.84***	0.82***	0.83***	0.81***	0.91***	0.92***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
N	139.00	139.00	139.00	139.00	72.00	72.00
R^2	0.97	0.97	0.96	0.97	0.97	0.97

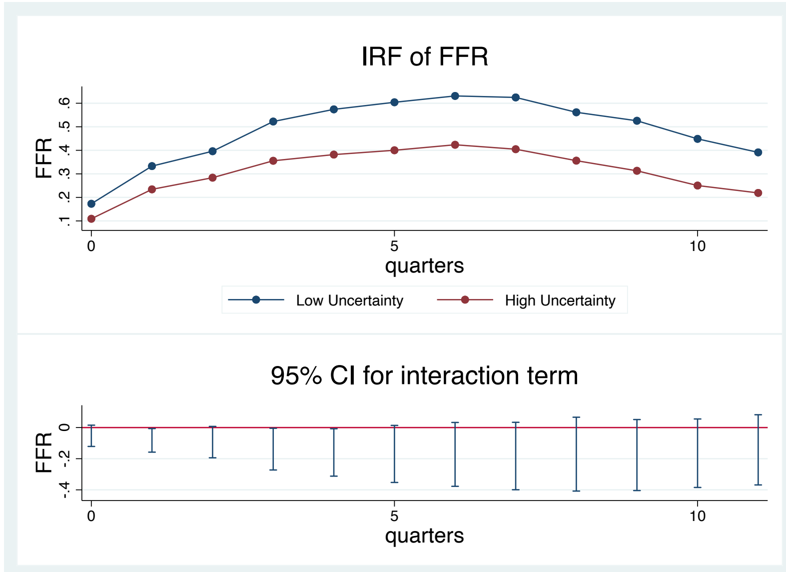
Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react more cautiously when uncertainty is high: the interaction term coefficients are both negative.

Table B.6: Taylor rule without using the shadow rate

	(1) OLS	(2) OLS	(3) GMM	(4) GMM	(5) Greenbooks	(6) Greenbooks
π^{cpi}	1.38***	1.54***	1.38**	1.68***	1.69***	1.59***
	(0.38)	(0.33)	(0.57)	(0.34)	(0.40)	(0.44)
$\pi^{cpi}\times$ jnl_3_e		-0.78*		-1.12*		-0.71
		(0.46)		(0.63)		(0.84)
y^*	1.06***	1.05***	0.87***	0.87***	0.54***	0.58***
	(0.16)	(0.16)	(0.24)	(0.19)	(0.16)	(0.18)
$y^*\times$ jnl_3_e		-0.34*		-0.15		-0.18
		(0.18)		(0.31)		(0.17)
jnl_3_e		-0.03		0.17		0.02
		(0.17)		(0.28)		(0.25)
ρ	0.85***	0.85***	0.92***	0.87***	0.88***	0.89***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.03)	(0.03)
N	139	139	139	139	122	122
R^2	0.954	0.958	0.937	0.948	0.979	0.981

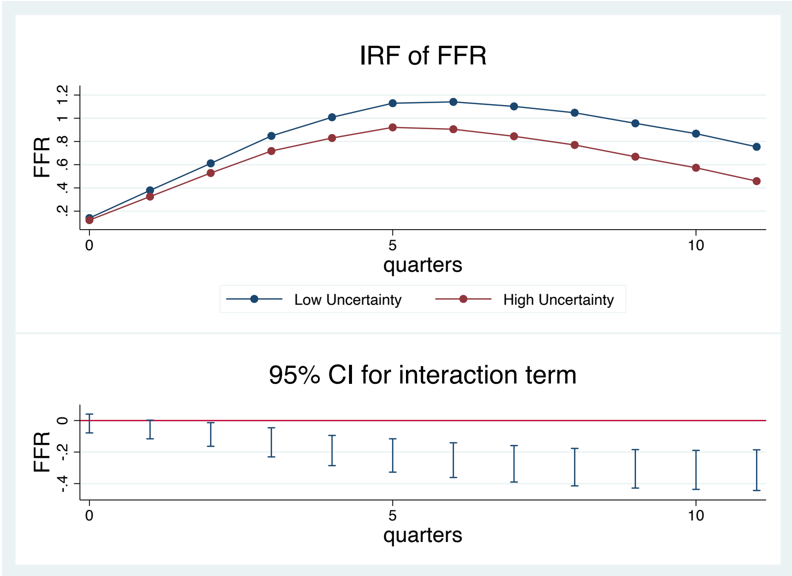
Columns (1), (3), and (5) report the estimates of equation (5), the "benchmark" Taylor rule, and columns (2), (4), and (6) report the estimates of equation (6), the Taylor rule considering uncertainty. Columns (1) and (2) report the estimates using OLS; columns (3) and (4) report the estimates using GMM; columns (5) and (6) report the estimates using Greenbooks data. All the coefficients in the table, except the coefficient on JLN, are divided by $1-\rho$. The variable JLN is standardized. The table shows that, keeping constant inflation and output gap, the Federal Reserve tends to react more cautiously when uncertainty is high: the interaction term coefficients are both negative.

Figure B.1: Local projections of the interest rate using VIX as measure of uncertainty



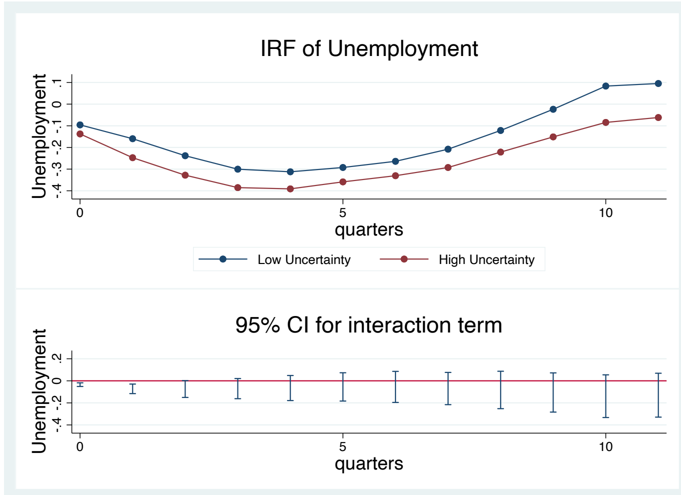
The top panel reports equation (7) estimates of $\hat{\beta}_{1,j}\overline{Shock} + \hat{\beta}_{2,j} * (\widetilde{VIX} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}_{i,j}$ for $i = 1, 2$ are the estimated coefficients, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{VIX}$ is the 25th or the 75th percentile of the distribution of the VIX measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function (IRF) of interest rates under low uncertainty (blue line) is always above IRF when uncertainty is high (red line), indicating that the Federal Reserve tends to react more cautiously when uncertainty is higher. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}_{2,j}$. These intervals do not contain a value equal to zero, showing that the two plotted "reduced form" Taylor rules are statistically significantly different from each other. Indeed, for more or less horizons, the coefficients $\hat{\beta}_{2,j}$ are statistically significant.

Figure B.2: Local projections of the interest rate using the excess boom premium shock



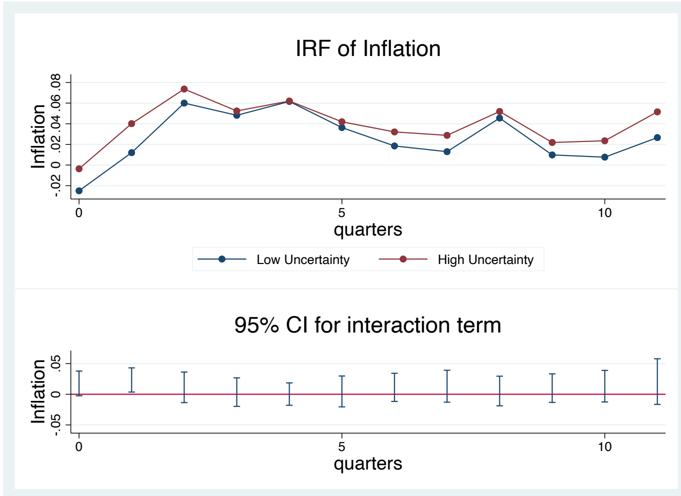
The top panel reports equation (7) estimates of $\hat{\beta}_{1,j}\overline{Shock} + \hat{\beta}_{2,j} * (\widetilde{JLN} * \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}_{i,j}$ for $i = 1, 2$ are the estimated coefficients, $\overline{Shock}$ is equal to one standard deviation of the excess boom premium shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty(75th percentile). The top panel shows that the impulse response function (IRF) of interest rates under low uncertainty (blue line) is always above IRF under high uncertainty (red line), indicating that the Federal Reserve tends to react less aggressively when uncertainty is higher. The bottom panel reports the 95% confidence intervals of the coefficient $\hat{\beta}_{2,j}$. These intervals do not contain a value equal to zero, showing that the two IRFs are statistically different from each other. Indeed, for more or less all horizons, the coefficients $\hat{\beta}_{2,j}$ are statistically significant.

Figure B.3: The propagation effect on unemployment using VIX as measure of uncertainty



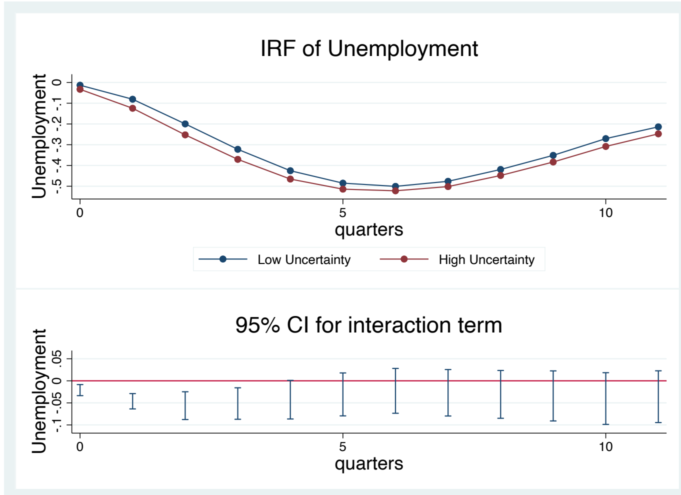
The top panel reports estimates of $\hat{\beta}^u_{1,j}\overline{Shock} + \hat{\beta}^u_{2,j}(\widetilde{VIX} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^u_{i,j}$ for $i = 1, 2$ are the estimated coefficients of equation (8) using unemployment as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{VIX}$ is the 25th or the 75th percentile of the distribution of the VIX measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function (IRF) of unemployment under low uncertainty (blue line) is always above the IRF under high uncertainty (red line), indicating that unemployment tends to reduce by more when uncertainty is higher. Notice that unemployment is over all decreasing, as it is expected when the economy is in a boom. The bottom panel reports the 95% confidence intervals of the coefficient $\hat{\beta}^u_{2,j}$. The first three intervals do not contain a value equal to zero, showing that the IRFs are statistically different from each other.

Figure B.4: The propagation effect on inflation using VIX as measure of uncertainty



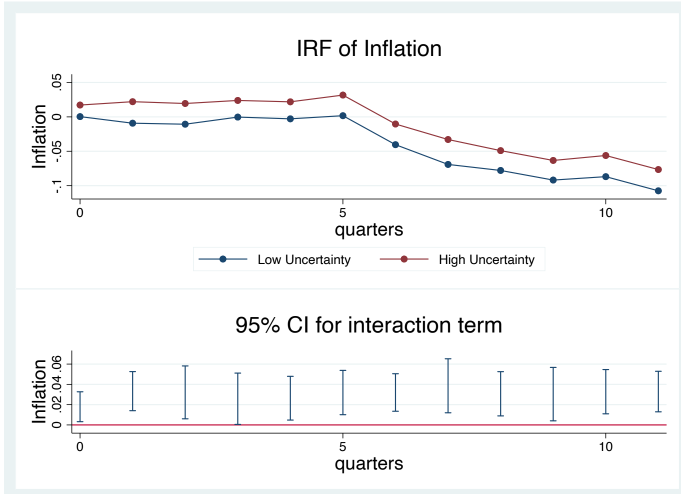
The top panel reports estimates of $\hat{\beta}^{\pi}_{1,j}\overline{Shock} + \hat{\beta}^{\pi}_{2,j}(\widetilde{VIX} \times \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^{\pi}_{i,j}$ for $i = 1, 2$ are the estimated coefficients of equation (8) using inflation as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the business cycle unemployment shock and $\widetilde{VIX}$ is the 25th or the 75th percentile of the distribution of the VIX measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function of inflation under low uncertainty (blue line) is always below the IRF under high uncertainty (red line), indicating that inflation tends to increase by more when uncertainty is higher. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}^{\pi}_{2,j}$. For the first two periods, these intervals do no contain the value equal to zero, showing that the tIRFs are statistically different from each other.

Figure B.5: The propagation effect on unemployment using the excess boom premium shock



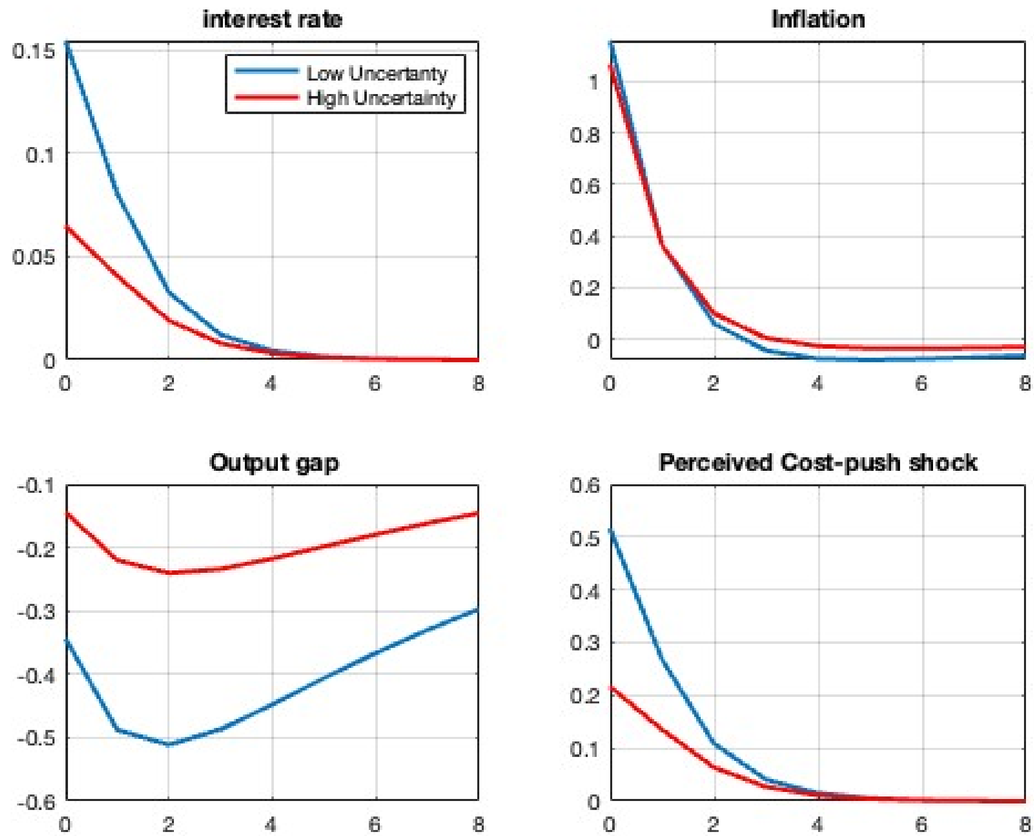
The top panel reports estimates of $\hat{\beta}^u_{1,j}\overline{Shock}+\hat{\beta}^u_{2,j}(\widetilde{JLN}*\overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^u_{i,j}$ for $i=1,2$ are the estimated coefficients of equation (8) using unemployment as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the excess boom premium shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function of unemployment under low uncertainty (blue line) is always above the IRF under high uncertainty (red line), indicating that unemployment tends to reduce by more when uncertainty is higher. Notice that unemployment is over all decreasing, as it is expected when the economy is in a boom. The bottom panel reports the 95% confidence intervals of the coefficients $\hat{\beta}_{2,j}$. These intervals do not contain a value equal to zero, showing that the two IRFs are statistically significantly different from each other. Indeed, for more or less all values horizons, the coefficients $\hat{\beta}_{2,j}$ are statistically significant.

Figure B.6: The propagation effect on inflation using the excess boom premium shock



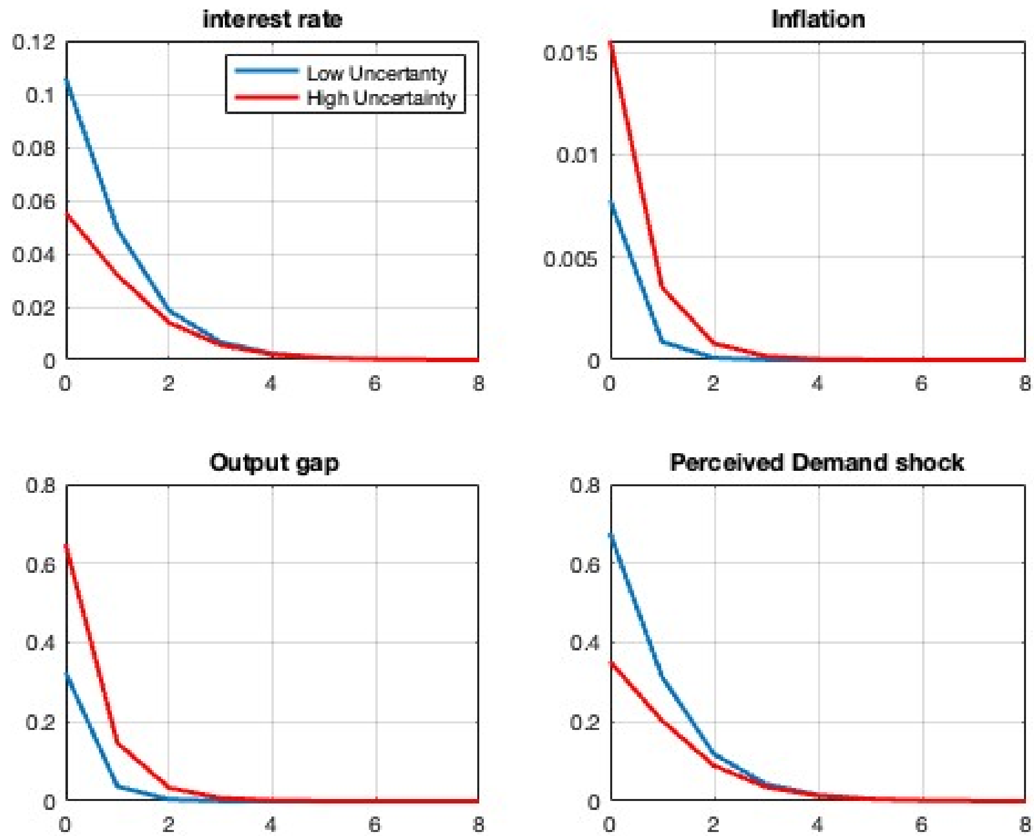
The top panel reports estimates of $\hat{\beta}^{\pi}_{1,j}\overline{Shock} + \hat{\beta}^{\pi}_{2,j}(\widetilde{JLN} * \overline{Shock})$ for values of j from 0 to 11, where $\hat{\beta}^{\pi}_{i,j}$ for $i = 1, 2$ are the estimated coefficients of equation (8) using inflation as the dependent variable, $\overline{Shock}$ is equal to one standard deviation of the excess boom premium shock and $\widetilde{JLN}$ is the 25th or the 75th percentile of the distribution of the JLN measure. The blue line represents the predicted values for low uncertainty (25th percentile), and the red line represents the predicted values for high uncertainty (75th percentile). The top panel shows that the impulse response function under low uncertainty (blue line) is always below the IRF under high uncertainty (red line), indicating that inflation tends to increase by more when uncertainty is higher. The bottom panel reports the 95% confidence intervals of the coefficient $\hat{\beta}^{\pi}_{2,j}$. These intervals do not contain a value equal to zero, showing that the two IRFs are statistically different from each other. Indeed, for more or less all horizons, the coefficients $\hat{\beta}^{\pi}_{2,j}$ are statistically significant.

Figure B.7: Model-implied impulse response function to a positive cost-push shock under commitment



The left top panel reports the IRF of the interest rate to a 1% increase of the cost-push shock. The top right reports the IRF of inflation. The bottom left reports the IRF of the output gap. The bottom right panel reports the perceived cost-push shock by the monetary authority. Blue (red) lines show the IRFs under low (high) uncertainty. The figure shows that under high uncertainty, the monetary authority reacts less aggressively to the cost-push shock. This turns out to generate a smaller reduction in the output gap and not a significant difference in inflation.

Figure B.8: Model-implied impulse response function to a positive demand shock - robustness



The left top panel reports the IRF of the interest rate to a 1% increase of the demand shock. The top right reports the IRF of inflation. The bottom left reports the IRF of the output gap. The bottom right panel reports the perceived demand shock by the monetary authority. Blue (red) lines show the IRFs under low (high) uncertainty. The figure shows that when uncertainty is higher, the monetary authority reacts more cautiously to the demand shock. This turns out to generate a larger propagation of the shock into the economy: inflation and output gap are more positive.

C A general framework to motivate equation (2)

This section presents a general framework to describe the class of models that have equation (2) as a solution. Building on Svensson and Woodford (2003a), the model is in discrete time and considers a monetary authority that minimizes a quadratic loss function subject to linear constraints.

The monetary authority loss function is:

$$\sum_{t=0}^{\infty} \mathbb{E}\left[\delta^t Y_t' W Y_t | \mathcal{I}_0\right] \tag{13}$$

where Y_t is the vector of target variables, as, for example, inflation and the output gap, $\mathbb{E}$ is the expectation operator given the monetary authority information set at time zero, $\mathcal{I}_0$, W is a positive-semidefinite weight matrix and δ is the discount factor. The constraints faced by the monetary authority are

$$\Omega \mathbb{E}\left(x_{t+1} | \mathcal{I}_t\right) = A_X X_t + A_x x_t + B r_t \tag{14}$$

$$X_{t+1} = \mathrm{P} X_t + u_{t+1} \tag{15}$$

where X_t is a vector of exogenous (state) variables, x_t is a vector of endogenous variables, r_t is a vector containing the monetary authority instruments, and u_t is a vector of innovations. Ω, A_X, A_x, B and P are matrices with given coefficients. $\mathbb{E}\left(x_{t+1} | \mathcal{I}_t\right)$ is the rational expectation of the endogenous variables at time $t+1$, x_{t+1}, given the monetary authority information set at time t, $\mathcal{I}_t$[27]. Equation (14) represents the law of motion of the endogenous variables; for example, it can contain the Euler equation and the Philips curve. On the other hand, equation (15) represents the law of motion of the exogenous variables, such as demand or supply shocks. Furthermore, the monetary authority information set contains the structure of the economy, i.e., the monetary authority knows equations (14) and (15) and the matrices W, Ω, A_X, A_x, B and P. Finally, the monetary authority objective is to minimize the loss function, equation (13), subject to her constraints, equations (14) and (15), given her information set $\mathcal{I}_0$.

The model can be solved under two different assumptions: commitment or discretion. Under commitment the monetary authority commits to a state-contingent plan and deviations from it are impossible.

[27] I am assuming that the private agents in the economy and the monetary authority have the same information set. This assumption is maintained throughout all the paper. See Svensson and Woodford (2004) for a discussion about asymmetric information sets.

In contrast, under discretion, the monetary authority makes decisions period by period without being bound by past promises, allowing her to adjust policy based on current conditions.

C.1 Solution under commitment

Under commitment, the solution for the monetary authority's instruments takes the following form:

$$r_t^* = F\mathbb{E}\left(X_t|\mathcal{I}_t\right) + \Phi\Gamma_{t-1} \tag{16}$$

where Γ_{t-1} is the vector of Lagrange multipliers associated with the constraints in equation (14), known at time t. The Lagrange multipliers represent the promises made by the monetary authority in the past. F and Φ matrices of appropriate dimensions. This equation is the same as equation (2). In this model, as shown by Svensson and Woodford (2003b), the separation principle and certainty equivalence apply, implying the functional form of equation (16). The separation principle states that the optimization problem and the signal extraction problem can be solved separately, implying that equation (16) holds independently of what the information set of the monetary authority is and that the information structures only affect the monetary authority expectations about the fundamental shocks. Certainty equivalence states that the matrices F and Φ are independent of the problem's information structure. They can be derived by solving the model under the assumption of full information, meaning that $\mathbb{E}\left(X_t|\mathcal{I}_t\right) = X_t$. This assumption means that the monetary authority perfectly knows the state variables of the economy. The main assumption for equation (16) to hold are: (i) quadratic loss function and linear constraints, and (ii) the monetary authority and private sector have the same information set[28]. Thus, a solution of the form as equation (16) is very general because it nests many linearized models with different information structures.

C.2 Solution under discretion

Under discretion, the solution for monetary authority's instruments takes the following form:

$$r_t^* = \tilde{F}\mathbb{E}\left(X_t|\mathcal{I}_t\right)$$

[28]This assumption can be relaxed and it is sufficient to assume that the monetary authority has less information than the private sector.

$\tilde{F}$ is a matrix of appropriate dimensions that can be different from the matrix in equation (16). Also, in this case, the separation principle and certainty equivalence apply. The main difference with respect to the commitment solution is the absence of the Lagrange multipliers. Indeed, under discretion, the monetary authority does not make any promises, and she can adjust the interest rate as she wants. For the purpose of this paper, it is possible to think about the discretion case as a particular case of the solution under commitment: the Lagrange multipliers are always equal to zero. Indeeed, the paper does not aim to estimate exactly the matrices F or $\tilde{F}$, which depend on the assumption of discretion or commitment.

D Mapping between the JLN measure of uncertainty and the signal-to-noise ratio, λ_t

The goal of this section is to show how the signal-to-noise ratio discussed in equation (4) is directly related to the JLN measure of uncertainty. I start describing how this measure of uncertainty is constructed, and afterwards, I will show how to map it into the signal-to-noise ratio.

The JLN measure of uncertainty is constructed in two different steps. In the first step, for many macroeconomics time series, z_j, as for example, inflation and the output gap, Jurado, Ludvigson, and Ng (2015) construct a measure of the h-period ahead conditional volatility, defined by:

$$\mathcal{U}_{jt}^{z}(h) \equiv \sqrt{\mathbb{E}\left[\left(z_{jt+h} - \mathbb{E}\left[z_{jt+h} \mid \mathcal{I}_t\right]\right)^2 \mid \mathcal{I}_t\right]}$$

In the second step, this measure for each time series z_j is aggregated using a weighted average:

$$JLN_t(h) \equiv \mathcal{U}_t^z(h) = \text{plim}_{N_z \to \infty} \sum_{j=1}^{N_z} w_j \mathcal{U}_{jt}^z(h)$$

The interesting part is how $JLN_t(h)$ carries information about the signal-to-noise ratio, λ_t. For simplicity and without loss of generality, assume that only one macroeconomic time series, z_t, is considered and it follows an AR(1) process, i.e., $z_t = \rho z_{t-1} + \eta_t$, where $\eta_t \sim N(0, \sigma_{\eta t}^2)$. Assume, further, that the information set contains a noise signal, $\tilde{z}_t$ about z_t, i.e., $\tilde{z}_t = z_t + \tilde{\nu}_t$, where $\tilde{\nu}_t \sim N(0, \sigma_{\tilde{\nu}_t}^2)$ and a prior about z_t that is normally distributed, i.e. $z_t \sim N(\mu_z, \sigma_{z_t}^2)$. In this case, it is possible to interpret z_t as the fundamental shock (or the only state variable) in the economy. Assume further that η_t and $\tilde{\nu}_t$ are orthogonal. Under these assumptions and for $h = 1$, it is possible to show that:

$$JLN_t(1) = \sqrt{\sigma^2_{\eta_{t+1}} + \rho^2 \sigma^2_{z_t} \left(\frac{1}{1+\lambda_t} \right)} \tag{17}$$

where λ_t is the signal-to-noise ratio, in this case defined by $\lambda_t = \frac{\sigma^2_{z_t}}{\sigma^2_{\tilde{\nu}_t}}$. Appendix F.2 derives this equation and generalizes it for different values of h and for a generic ARMA(1,i) process[29] for z_t. Under the assumptions discussed above, equation (17) shows that the measure of Jurado, Ludvigson, and Ng (2015) can be decomposed in three different forces: a measure of volatility of the innovation, $\sigma^2_{\eta_{t+1}}$, a measure of the volatility of the prior, $\sigma^2_{z_t}$, and the signal-to-noise ratio, λ_t. Finally, notice that the volatility of the innovation is orthogonal to the signal-to-noise ratio, implying that the correlation between $\sigma^2_{\eta_{t+1}}$ and λ_t should be close to zero in the data.

The JLN measure is estimated using a large dataset of macroeconomic times and not only one time series containing information about the fundamental shock in the economy. However, the JLN measure still contains information about the signal-to-noise ratio of the fundamental shock, λ_t. Indeed, in a linearized model, as the one discussed in Section 2 and with one fundamental shock, it must be that in equilibrium, all the endogenous variables, x_t, can be written as a linear function of the fundamental shock, z_t, and other state variables, s^z_t. So, it is possible to write each endogenous variable, $x_{i,t}$ as a linear function of z_t and other state variables s^z_t, i.e. $x_{i,t} = l_{i,1} z_t + l_{i,2} s^z_t$. In this case, equation (17) can be written as $JLN_t(1) = l_{i,1}\sqrt{\sigma^2_{\eta_{t+1}} + \rho^2 \sigma^2_{z_t} \left(\frac{1}{1+\lambda_t} \right)} + other\_terms$, where $other\_terms$ are terms that are orthogonal to the signal-to-noise ratio, λ_t.

Thus, the measure of Jurado, Ludvigson, and Ng (2015) contains information about the object of interest: the signal-to-noise ratio of the fundamental shock in the economy, λ_t. Furthermore, these two variables are negatively correlated: a more precise signal, a higher λ_t, implies a lower value of the JLN measure and, thus, lower uncertainty in the economy. This negative correlation could only be violated in one scenario: if the variance of the prior, $\sigma^2_{z_t}$, moves systematically more and in the same direction of the signal-to-noise ratio, λ_t. This would for example generate an overall increase in the JLN measure when

[29]The choice of the ARMA(1,i) process is dictated by that the fact that the AR component of the process must have only one lag because otherwise more signals are needed. This would make the signal extraction problem having more than one signal-to-noise ratio. However, this assumption is not very restrictive because solution objects, such as consumption or inflation, in many standard macro models follow an ARMA(1,i): the AR(1) is the backward looking component and the MA(i) depends on the number of lags of the shocks.

both the signal-to-noise ratio and the variance of the prior increase. This situation seems economically unrealistic because it means that, when the economy is in a recession, a period of high variance, a high $\sigma^2_{z_t}$, the signal should be more precise. Furthermore, notice that the term $\sigma^2_{\eta_{t+1}}$ in equation (17) is orthogonal to λ_t by construction, meaning that future innovation of the fundamental should not be correlated with the precision of today's signal. Thus, the JLN measure contains information about the signal-to-noise ratio, and these two variables are negatively correlated.

E Parameter-uncertainty and JLN

Following Section D, I can again assume that only one macroeconomic time series, z_t, is considered, and it follows an AR(1) process, i.e., $z_t = \rho z_{t-1} + \eta_t$, where $\eta_t \sim N(0, \sigma^2_{\eta t})$. Assume, further, that the parameter ρ is unknown and that it follows a normal distribution, $\rho \sim N(\bar{\rho}, \sigma^2_{\rho t})$. This assumption is, in spirit, an assumption about parameter uncertainty as in Brainard (1967). Indeed, this assumption is like assuming that the monetary authority does not exactly know the parameter value γ_r in the model of Section 7.1. In contrast to what is assumed in Section D, suppose that z_t is perfectly observable and, thus, there is no measurement error. In this case, it is immediate to show that the measure of JLN becomes:

$$JLN_t(1) = \sqrt{\sigma^2_{\eta t} + z_t^2 \sigma^2_{\rho t}}$$

This equation shows that as parameter uncertainty, $\sigma^2_{\rho_t}$, increases, the JLN measure increases.

F Algebra details

F.1 Deriving equation (4)

Consider $\frac{\lambda_t}{1+\lambda_t}$ and take a Taylor approximation of the first order around $\bar{\lambda}$. Doing so, I get:

$$\frac{\lambda_t}{1+\lambda_t} \approx \frac{\bar{\lambda}}{1+\bar{\lambda}} + \frac{1}{(1+\bar{\lambda})^2}(\lambda_t - \bar{\lambda})$$

Inserting this equation into equation (3), I get

$$\mathbb{E}\left(X_t|\epsilon_t\right) \approx \frac{\bar{\lambda}}{1+\bar{\lambda}}\epsilon_t + \frac{1}{(1+\bar{\lambda})^2}(\lambda_t - \bar{\lambda})\epsilon_t$$

Plugging this expression in equation (2) and collecting terms, I get immediately equation (4) where $\bar{\beta} = F\frac{\bar{\lambda}^2}{(1+\bar{\lambda})^2}$ and $\bar{\gamma} = F\frac{1}{(1+\bar{\lambda})^2}$.

F.2 Jurado, Ludvigson and Ng

F.2.1 Deriving equation (17)

The object of interest is:

$$JLN_t(1) = \sqrt{\mathbb{E}\left[\left(z_{t+1} - \mathbb{E}\left[z_{t+1} \mid \tilde{z}_t\right]\right)^2 \mid \tilde{z}_t\right]}$$

Under the assumption made, it is possible to show that:

$$\begin{pmatrix} z_{t+1} \\ \tilde{z}_t \end{pmatrix} \sim N\left[\begin{pmatrix} \rho\mu_z \\ \mu_z \end{pmatrix}, \begin{pmatrix} \sigma^2_{\eta_{t+1}} + \rho^2\sigma^2_{z_t}, & \rho\sigma^2_{z_t} \\ \rho\sigma^2_{z_t}, & \sigma^2_{z_t} + \sigma^2_{\tilde{\nu}_t} \end{pmatrix}\right]$$

I immediately get that:

$$\mathbb{E}\left[z_{t+1} \mid \tilde{z}_t\right] = \rho\mu_z + \rho\frac{\lambda_t}{1+\lambda_t}\left(\tilde{z}_t - \mu_z\right)$$

where $\lambda_t = \frac{\sigma^2_{z_t}}{\sigma^2_{\tilde{\ni}_t}}$. Thus,

$$\begin{aligned}
&\mathbb{E}\left[\left(z_{t+1} - \mathbb{E}\left[z_{t+1} \mid \tilde{z}_t\right]\right)^2 \mid \tilde{z}_t\right] && (18)\\
&= \mathbb{E}\left[\left(\rho z_t + \eta_{t+1} - \rho\mu_z - \rho\frac{\lambda_t}{1+\lambda_t}\left(\tilde{z}_t - \mu_z\right)\right)^2 \mid \tilde{z}_t\right] \\
&= \sigma^2_{\eta_{t+1}} + \mathbb{E}\left[\left(\rho z_t - \rho\mu_z - \rho\frac{\lambda_t}{1+\lambda_t}\left(\tilde{z}_t - \mu_z\right)\right)^2 \mid \tilde{z}_t\right] \\
&= \sigma^2_{\eta_{t+1}} + \rho^2\mathbb{E}\left[\left(z_t - \mu_z - \frac{\lambda_t}{1+\lambda_t}\left(\tilde{z}_t - \mu_z\right)\right)^2 \mid \tilde{z}_t\right] \\
&= \sigma^2_{\eta_{t+1}} + \rho^2\mathbb{E}\left[\left(z_t - \mathbb{E}\left(z_t \mid \tilde{z}_t\right)\right)^2 \mid \tilde{z}_t\right] \\
&= \sigma^2_{\eta_{t+1}} + \rho^2\sigma^2_{z_t}\left(\frac{1}{1+\lambda_t}\right)
\end{aligned}$$

where the first equality comes from the definition of z_{t+1} and of $\mathbb{E}[z_{t+1} \mid \tilde{z}_t]$. The second equality comes from the orthogonality of η_{t+1}. The third equality is given by some algebra. The fourth equality is from the definition of $\mathbb{E}[z_t \mid \tilde{z}_t]$. The last equality derives from the properties of the variance for conditional normal distributions. Taking the square root of this last equation, the desired result is obtained. Notice that equation (18) could have been obtained immediately applying the definition of the conditional variance for normal distributions.

F.2.2 Generalizing equation (17) for different values of h

The object of interest is now:

$$JLN_t(h) = \sqrt{\mathbb{E}\left[\left(z_{t+h} - \mathbb{E}[z_{t+h} \mid \tilde{z}_t]\right)^2 \mid \tilde{z}_t\right]}$$

Using the properties of an AR(1) process, I immediately get that

$$z_{t+h} = \rho^h z_t + \sum_{j=0}^{h-1} \eta_{t+h-j}$$

Thus, using the assumption that innovation are independent across time, I get:

$$\begin{pmatrix} z_{t+h} \\ \tilde{z}_t \end{pmatrix} \sim N\left[\begin{pmatrix} \rho^h \mu_z \\ \mu_z \end{pmatrix}, \begin{pmatrix} \sum_{j=0}^{h-1} \rho^{2j} \sigma^2_{\eta_{t+h-j}} + \rho^{2h}\sigma^2_{z_t}, & \rho^h \sigma^2_{z_t} \\ \rho^h \sigma^2_{z_t}, & \sigma^2_{z_t} + \sigma^2_{\tilde{\nu}_t} \end{pmatrix}\right]$$

Using the same steps as in equation (18), it is immediately to show that

$$JLN_t(h) = \sqrt{\sum_{j=0}^{h-1} \rho^{2j} \sigma^2_{\eta_{t+h-j}} + \rho^{2h} \sigma^2_{z_t} \left(\frac{1}{1+\lambda_t}\right)}$$

Thus, it is still true that the JLN measure is informative of the signal-to-noise ratio. This equation also shows that for longer time horizons, a larger value of h, the JLN measure is less informative of the signal-to-noise ratio.

F.2.3 Generalizing equation (17) for a generic ARMA(1,i) process

Consider the ARMA(1,i) process:

$$z_t = \rho z_{t-1} + \eta_t + \sum_{k=1}^{i} \theta_k \eta_{t-k}$$

It is immediately to show that:

$$z_{t+h} = \rho^h z_t + \sum_{k=0}^{h-1} \rho^k \eta_{t+h-k} + \sum_{k=1}^{i} \theta_k \left(\sum_{j=0}^{h-1} \rho^j \eta_{t+h-j-k} \right)$$

Thus, I have that:

$$\begin{pmatrix} z_{t+h} \\ \tilde{z}_t \end{pmatrix} \sim N \left[\begin{pmatrix} \rho^h \mu_z \\ \mu_z \end{pmatrix}, \begin{pmatrix} \rho^{2h} \sigma^2_{z_t} + \sum_{k=0}^{h-1} \rho^{2k} \sigma^2_{\eta_{t+h-k}} + \sum_{k=1}^{i} \theta_k^2 \sum_{j=0}^{h-1} \rho^{2j} \sigma^2_{\eta_{t+h-j-k}}, & \rho^h \sigma^2_{z_t} \\ \rho^h \sigma^2_{z_t}, & \sigma^2_{z_t} + \sigma^2_{\tilde{\nu}_t} \end{pmatrix} \right]$$

Using the same steps as in equation (18), it is possible to show that

$$JLN_t(h) = \sqrt{\sum_{k=0}^{h-1} \rho^{2k} \sigma^2_{\eta_{t+h-k}} + \sum_{k=1}^{i} \theta_k^2 \sum_{j=0}^{h-1} \rho^{2j} \sigma^2_{\eta_{t+h-j-k}} + \rho^{2h} \sigma^2_{z_t} \left(\frac{1}{1+\lambda_t} \right)}$$

Thus, it is still true that the JLN measure is informative of the signal-to-noise ratio. This equation also shows that for longer time horizons, a larger value of h, the JLN measure is less informative of the signal-to-noise ratio.