Robust monetary policy under shock uncertainty

Mario Carceller[*]
Jan Willem van den End[†]

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Abstract

We analyze the effects of shock uncertainty for the Federal Reserve during the turbulent 2022 inflation episode and its impact on optimal monetary policy. Theoretically we model shock uncertainty as the inability to estimate the true sources of observed inflation disturbances, which impedes to distinguish whether supply or demand forces are at play. Assuming that the output gap and the true shock distribution are unobserved, we develop a new method that allows to make an informed guess about the relative importance of supply and demand shocks. We argue that this restricted information set represents the knowledge that policymakers had at the time. We find that the hiking cycle was too aggressive and could have push the output gap deep into the negative territory, making the optimal policy response in this scenario a dovish one. Thus, we align with the voices that at the time were flagging the extensive risks of a strong hiking cycle.

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[*]University of Lausannne: mario.carcellerdelarco@unil.ch.

[†]De Nederlandsche Bank, Vrije Universiteit: w.a.van.den.end@dnb.nl

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1 Introduction

The year 2022 was a particularly turbulent one for central banking. The economic effects of Covid-19 were still felt into the economy, while geopolitical risk materialized in the form of the Russia-Ukraine conflict. As a result, advanced economies experienced a surge in inflation whose causes were extremely difficult to understand in real time. The initial consensus was that inflation was a global phenomenon that emanated from the the Russia-Ukraine conflict itself, which put central bankers in a difficult position given the risk of an economic slowdown as exemplified by Panetta (2022). Other policymakers also pointed out the need to fight inflation while balancing a serious risks (Powell, 2022; Macklem, 2022). Furthermore, it was rather unclear what the optimal policy was at the time. Romer and Romer (2023) pointed out that a sharp hiking cycle was expected to have substantial negative impact on GDP growth, while Gómez Jiménez et al. (Frth) argues that U sharp increases in the policy rate (i.e. a strong hike after low rates for a prolonged period of time) are associated with banking crises. From a policy point of view, Ajello et al. (2022) factored in a 60 % recession probability if monetary policy became overly restrictive.

Wether starting a strong hiking cycle was a good idea or not depends on the combination of shocks that led the economy up to that point. There is a recent debate in which some authors agreed with the initial policy perspective of supply sources being the main source of disturbances in the US and the euro area, for instance Bańbura et al. (2024), Bai et al. (2024), De Santis (2024), Ascari et al. (2024) or Liu and Nguyen (2023). Nonetheless others like Giannone and Primiceri (2024), Ascari et al. (2023), Gonçalves and Koester (2022) or Garcia-Revelo et al. (2025) instead highlight that demand forces were key. Bergholt et al. (Frth) finds that demand shocks are actually the main driver of inflation in the US, the euro area, as well as a number of other economies. This distinction is of extreme importance. As highlighted by the newkeynesian economics, monetary policy should respond aggressively to demand shocks given that they generate co-movement between inflation and the output gap, while the optimal response to supply shocks is more attenuated. In the later case taming down inflation leads to a worsening of the output gap, thus creating a trade off that results in a moderate optimal response, a known central bank's dilemma resolved by weighting its two stabilization objectives.

This debate exemplifies the complexities of central banking in the post pandemic world, characterized by understanding the stance of the economic outlook and finding the right balance between fighting inflation while taking risks of inducing a contraction in output. In the Federal Reserve Board, Powell (2023) speaks about the need for a risk management approach while Waller (2023) emphasizes that central bankers will deal with a high degree of uncertainty regularly. In the ECB sentiment was similar with Lagarde and de Guindos (2022) announcing a move towards a data driven meeting-to-meeting approach to policy decisions, and Schnabel (2023) speaking about how parameter uncertainty and modeling assumptions creep into in their estimates. Confusing supply and demand shocks can be costly as pointed out by Fatás and Singh (2024). The authors highlight that the risks of confusing supply and demand shocks are large and may become entrenched, having permanent effects on output growth.

Against this background, in this paper we ask ourselves if the initial concerns about the adverse effects associated with a strong policy hike were justified under the information set that policymakers had at the time, or if on the contrary the effects of monetary tightening were correctly weighted. To do so, we develop a new methodology that applies to linear DSGE models that infers a distribution over shock realizations consistent with the central bank's information set, in a similar fashion to Orphanides and Williams (2007) and Giannoni (2007). Our methodological contribution is that we consider a different set of information frictions, which we regard as more aligned with the actual information set of policymakers at the time: (i) inflation is observable contemporaneously, (ii) the output gap or other state variables that would help infer it are only observable with a lag, (iii) the true shock distribution is unknown, and (iv) the true parameters of the economy are known with certainty.[1]

Assumptions (ii) and (iii) lie at the core of our reading of the uncertain landscape policymaking was facing at the time. We consider the output gap to be an unobserved variable given the lack of availability in real time of consistent and robust estimates. The seminal papers of Orphanides (2001) and Orphanides and van Norden (2002) noted that output gap estimates may be problematic because real-time policy recommendations differ considerably from those obtained with ex-post revised data. These results were corroborated by Marcellino and Musso (2011), Ince and Papell (2013), Kangur et al. (2019), Aiyar and Voigts (2025). The seminal paper Orphanides (2003) shows that real-time output-gap estimates during the Great Inflation help explain how accommodative pre-Volcker monetary policy was: in 1974, real-time estimates were about 11 percentage points lower than the corresponding estimates based on revisions

[1] In our setting we don't allow the central bank to have a guess of the shock distribution that would allow to implement Bayesian techniques. Instead, we focus on how the central bank can exploit its information about the structure of the economy and the observation about inflation to gauge the likelihood of being under the influence of supply and demand shocks when setting policy.

using data available through 2002. More recently Quast and Wolters (2023) points out that output gap revisions can be as large as the output gap itself, with particularly large revisions after recessions. Revisions are so volatile that they may even change the economic interpretation of certain events, which we take as solid evidence that the central banks in the 2022 inflationary episode could not know whether the economy was underperforming or overheated, and thus could not neither conclude supply or demand shocks were dominant. Furthermore, Van Cleve et al. (2019) mentions that output gap estimates are highly relevant during the interest rate decision process at the Federal Reserve. Reliable work that aims to understand decision making under the uncertainty faced during this particular period should not rely on output gap estimates.[2]

Given all of the above, we argue that the policy environment at the time can be adequately modeled as *Knightian uncertainty*. According to Knight (1921), epistemic uncertainty relates to events with unknown or objectively unmeasurable probabilities. This contrasts to measurable uncertainty or risk, which can be quantified based on known probability distributions of events. In case of fundamental uncertainty however, the data distribution is unknown, either intrinsically or because of practical limitations. This goes with an unknown event space and indeterminate outcomes. Our preferred way of introducing such uncertainty in the model is via assumption (iii).

Within the realm of linear DSGE models, our methodological contribution is then based on exploiting (i) and (iv). We ask ourselves how informative they are as to guide the central banker to optimally commit to a Taylor Rule coefficient against inflation. Knowledge of the parameters of the economy allows the central banker to pin down the *Shock Marginal Rate of Substitution (SMRS)*, which we define as the increase in the magnitude of one shock such that, when combined with a marginally smaller other shock, it can still jointly deliver the observed inflation. In the methodological section we show that the SMRS is a straight forward function of the parameters of the economy once converted into Sims (2002). We find that when the SMRS is equilibrated (i.e.≈ 1), then the magnitude necessary for each shock to explain inflation is roughly the same, and we cannot conclude that neither supply or demand forces were likely driving inflation. In this case it is not possible to guess if the output gap is negative or not. This is not the case when the SMRS approaches either zero or infinity, then the required size of either the supply or demand shock required to explain inflation would be extremely high.[3] Under the assumption that both shocks have zero mean, differentiable and monotonically decreasing pdfs, then the SMRS would allow us to guess that the likely source of inflation is one of the two. This has great implications for optimal policy. We find that the steeper the SMRS is, the stronger is the optimal Taylor rule response to inflation in terms of welfare. This result arises because when it is flat, supply shocks must be considerably smaller in size in order to explain inflation than demand shocks, and that provides evidence that the output gap is likely negative. In this case the optimal Taylor rule coefficient is rather small, contrarily of what happens when the SMRS is steep, in which case demand shocks are more likely and a strong interest rate hike is optimal.

After the theoretical results, we apply our methodology to an estimated version of the model Smets and Wouters (2007), in a scenario built to match the state of the US economy during the inflation peak in 2022Q2. We find that supply shocks where almost surely the main driver of inflation at the time. This result arises from both the specific calibrated scenario we use to do our exercise, discussed in the text, but also because our parameter estimations with data up to the prepandemic period suggest that the SMRS was extremely flat, with a value of 0.055. As a result the central bank would find optimal to react to inflation as mildly as possible, since it estimates the output gap to be in the interval $[-7\%, -10.5\%]$, when inflation peaked close to 9%. We take this as evidence that the initial concerns about the potential risks arising from the strong 2022 hiking cycle were properly funded, regardless of what ex post we find to be the true source of the disturbances. Particularly, we find that our optimal Taylor rule response to inflation is equal to one, considerably lower than the initially estimated value of 1.78. Our conclusion closely aligns with Bainard's attenuation principle (Brainard, 1967), which implies that under uncertainty the central bank should respond to shocks more cautiously and in smaller steps than in conditions without uncertainty due to a fundamental lack of information.

Our attenuation result sharply contrasts previous findings in the uncertainty literature. Orphanides and Williams (2007) and Giannoni (2007) both find that the central bank should optimally react strongly to inflation, and with a great

[2]When estimating DSGE models the output gap is not generally included as an observable, but rather it is inferred by the model assumptions after taking GDP (or its growth rate) as the relevant observable variable, which implies taking a strong stance of the model-implied sign and magnitude of the output gap itself when making policy recommendations. We do not focus on estimation, but rather we maintain our work on the theoretical side to understand the optimal central bank response to account for this uncertainty.

[3]In all practical applications of our theory we will read the SMRS as "the change in size of a supply shock needed to compensate a demand shock to still maintain inflation at the observed rate". As explained in Figure 1 a *flat* SMRS implies that large magnitude changes in demand shocks are compensated by small supply shocks and viceversa.

deal of persistence in order to prevent expectations to deanchor and to alleviate informational frictions. Similar results have been found using robust control (Hansen et al., 2006; Hansen and Sargent, 2008), and under signal extraction (Aoki, 2003; Nimark, 2008). Dennis et al. (2009) applies robust control to a New Keynesian model concluding as well that the policymaker should react decisively to shocks. The info-gap literature defines that a robust risk management strategy aims at achieving small losses, but and in any case less than a given critical value (Ben-Haim et al., 2018; Ben-Haim and Van den End, 2022). They find that a policy rule that reacts strongly to inflation and the output gap is more robust to natural-rate uncertainty than an estimated Taylor-rule–type response.

Optimal monetary policy is found to be strong in the papers mentioned above generally because the approaches mentioned focus on the commitment problem of a policymaker that minimizes unconditional welfare losses. Adam and Woodford (2012) models robust monetary policy using robust control in an optimal commitment Ramsey problem to also find that monetary policy should focus particularly on inflation disturbances. In their setting the authors emphasize that this commitment is implemented in the form of a particular articular stance of the trade off between stabilizing inflation and output. The reason why our results are so different with respect to the literature is because we are focusing on solving a conditional expectation based on the state of the economy during the worse part of the inflation surge in the US. Considering the estimated deeply negative output gap during the peak of inflation discussed above, our results align with the optimal trade off argument, in which reducing inflation via pushing even further the output gap comes at the cost of worsening an already considerably negative output gap.

Our findings are consistent with Beaudry et al. (2023), that finds optimal to initially look through inflation before introducing a hawkish stance in the presence of supply shocks. We argue that this approach is appropriate in this setting considering the earlier mentioned work, furthermore Bobeica and Hartwig (2023) suggests that the Covid-19 shock created a considerable break in the economy, which justifies a reassessment of the policy stance that relies strongly in available information (Lagarde and de Guindos, 2022). Prudence and proper risk management in light of uncertainty was also a building block of the *Bernanke review* Bernanke (2024)

Lastly, similarly to us work by Dück and Verona (2023) finds that acknowledging uncertainty about the correct model implies that a cautious monetary policy response. A similar argument is made by Ferrara (2025). On the contrary Dupraz et al. (2023) argues that following the Brainard principle can lead into cautiousness bias. Haberis et al. (2025) develop a framework for conducting monetary policy under different uncertainty types to systematic incorporation of risk-management considerations, showing the effort from the Bank of England to enhance their policy decisions. Dizioli (2025) and Tetlow (2018) considers optimal interest rate policy with uncertain inflation persistence, while Dizioli (2025) also expands the analysis to other modeling frictions.

To measure the robustness of our results we consider the criticism that Fratto and Uhlig (2020) does to standard New Keynesian DSGE models given that, when estimated, they imply a particularly flat NKPC that point to supply factors as the main driver of inflation movements. Similar arguments and the particular relevance of non linearities, both in the wage and price Phillips, curve have been put forward by Harding et al. (2022) and Harding et al. (2023). Given that the slope of our estimated NKPC is considerably small at a value of 0.014, we then investigate what would the optimal response to inflation be in an identical setting as our original medium scale exercise, albeit with an artificially steeper NKPC than the originally estimated one. We find that our main quantitative result is still intact: in order to conclude that the estimated Taylor rule coefficient is optimal, the NKPC should have been ten times steeper than its originally estimated value. We take this as evidence that unless the economy was in a considerably more likely influence of demand shocks that we find with our estimation, the optimal robust response to inflation is strictly smaller than the Federal Reserve's prepandemic stance.

In what follows, section 2 dives into our newly proposed methodology, section 3 discussed the theoretical results in a small scale model, while 4 discusses the quantitative results and robustness. Section 5 concludes.

2 Methodology

Our approach rests on the assumption that the central bank cannot statistically pin down the true shock combination that determines the state of the economy at time t due to a lack of observability. Under this uncertainty the central bank must assess the potential welfare losses and the optimal policy response to the observables. In this section we explain how the central bank can use its knowledge about the structure of the economy to estimate the unobserved state and apply a robust policy response. We define robust monetary policy to shock uncertainty as the policy levers that mitigate the risk of extreme welfare losses.

Our methodology roots in the linear-DSGE class of models, which can be represented as in Sims (2002) from,

$$X_t = \Gamma X_{t-1} + \Psi \eta_t$$

Where X_t is a vector containing all state variables of the economy and η_t is a vector of i.i.d. shocks with the joint cumulative probability distribution $F^{\eta}(z)$. Γ and Ψ are known non-linear combination of parameters that defines the dynamics of the economy with agents having rational expectations. We focus on policymaker uncertainty by considering optimal policy in a setting in which it is not able to observe all the state variables of the economy neither the distribution of the shocks.[4] If the policymaker cannot observe all state variables, then is unable to pin down the shock realizations that generate them. Furthermore, without knowing the shock distribution it is not possible to determine via maximum likelihood the conditional shock distribution given the observables.

This setting resembles that of the ambiguity literature in that we assume a lack of prior knowledge about the distribution of shocks, and since we don't allow the decision maker to have an informed prior, we focus on the case in which Bayesian estimation techniques cannot be used. We assume that the central bank makes an informed guess conditional on the true Γ and Ψ, observed X_{t-1}, and a subset of X_t. We then define the information set of the policymaker at time t as $\Omega_t = \{X_{t-1}, \Gamma, \Psi, \bar{X}_t\}$, where $\bar{X}_t \in X_t$ is the subset of observed state variables in real time. Note that $F^{\eta}(\cdot)$ is not included. For the rest of the paper we will use the bar upper script to define observed values.

This information set can be tough of deviations from well established fields in the uncertainty literature. In the signal extraction literature, $\Omega_t^{signal} = \{X_{t-1}, \Gamma, \Psi, \tilde{X}_t, F^{\eta}(z)\}$ where the observed variables include a noisy signal $\tilde{X}_t = X_t + \epsilon_t$. As a matter of comparison, Ω_t can then be thought of as a special case of Ω_t^{signal} in which the variance of some of the components in ϵ_t is zero, while infinite in others. In this case the signal received from some of the variables would be the true observation (no noise), or uninformative (infinite variance). One just has to assume that the policymaker cannot observe $F^{\eta}(z)$, the true shock distribution, to collapse to the type of uncertainty we tackle in this paper.

Another way to think about our information set is as a generalization of the shock decomposition exercise. Here $\Omega_t^{decomp} = \{X_{t-1}, \Gamma, \Psi, X_t, F^{\eta}(z)\}$ with all state variables observed. Knowing the state of the economy in the previous and current periods allows to pin point exactly the entire shock vector η_t. If there are more shocks than observables, one can exploit $F^{\eta}(z)$ with maximum likelihood techniques in a state space model to pin down the conditional shock distribution. Both the signal extraction and shock decomposition exercises depend on knowing (or relying on an estimation) the shock distribution, which is the key information friction we analyze in this paper.

In this paper the goal of the policymaker is to estimate $\hat{F}_t^{\eta}(z)|\Omega_t$. To illustrate the basic mechanism of the estimation technique we propose, let's assume that $\bar{X}_t = \{\bar{x}_t\} \in X_t$ and assuming there are only two shocks in this economy $\eta_t = [\eta_t^1, \eta_t^2]'$ we can write the Sims (2002) specification for this variable as:[5]

$$\bar{x}_t = \Gamma^x X_{t-1} + \Psi^{x,1}\eta_t^1 + \Psi^{x,2}\eta_t^2 \qquad \Rightarrow \qquad \eta_t^1 = \frac{1}{\Psi^{x,1}}\left(\bar{x}_t - \Gamma^x X_{t-1}\right) - \frac{\Psi^{x,2}}{\Psi^{x,1}}\eta_t^2$$

We denote $\frac{\Psi^{x,2}}{\Psi^{x,1}}$ as the *Shock Marginal Rate of Substitution (SMRS)*. Note that if the *SMRS* is close to 0, the relative size of η_t^2 necessary to explain $\bar{x}_t$ is significantly larger than η_t^1, and vice versa if the *SMRS* approaches infinity. Under the assumption that shocks have zero mean and they have smooth, monotonic, convex pdfs the SMRS is then telling us which shock has to be smaller in size to explain $\bar{X}_t$, meaning which shock combination is most likely according to the model structure. Understanding the SMRS implies knowing the relative size of each shock necessary to explain the observed variables, minimizing (1) via a gradient descent algorithm yields the model implied most parsimonious shock combination. Notice that if the entire vector of state variables is observed, then the result of (1) would be the true shock combination, in a similar fashion to a standard shock decomposition.

$$MIN_{\eta_t} \quad J(\eta_t) = \frac{1}{2}(\bar{x}_t - x_t(\eta_t))^2 \tag{1}$$

Where $\bar{x}_t$ is the observed value on a given period and $x_t(\eta_t)$ is the implied observation determined by the shock vector η_t. The key contribution of our paper is to derive the shock distribution conditional on the information set of the policymaker Ω_t. The end result is to find the distribution $\hat{F}^{\eta}(z)|\Omega_t$, that explains $\bar{X}_t$ from the theoretical model:

$$\hat{F}^{\eta}(z) \mid \Omega_t = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}_{\{\eta_i \leq z\}}$$

[4]Policymaker uncertainty means that agents know the structure of the economy and the shock process, which implies traditional rational expectations and thus allows to derive expectations accordingly.

[5]In terms of notation: $X_t = \begin{pmatrix} x_t \\ \vdots \end{pmatrix}$, $\Gamma = \begin{pmatrix} \Gamma^x \\ \vdots \end{pmatrix}$, $\Psi = \begin{pmatrix} \Psi^x \\ \vdots \end{pmatrix}$

Where $\mathbf{1}_{\{\eta_i \leq z\}}$ is the indicator function, and the set of $\Theta := \{\eta_i\}_{i=1}^n$ is determined solving (1) using gradient descent under the altered gradient $\Delta\tilde{J}^i(\eta_t)$:

$$\Delta\tilde{J}^i_{\bar{X}_t}(\eta_t) = \Delta J_{\bar{X}_t}(\eta_t)U^i \qquad \Delta J_{\bar{X}_t}(\eta_t) = \Psi^{\bar{X}}(\bar{X}_t - X(\eta_t)) \tag{2}$$

Where $\Delta J_{\bar{X}_t}(\eta_t)$ is the gradient of the problem considering only $\bar{X}_t$. $U^i \sim Dir(1, \cdots, 1)$ follows a Dirichlet distribution. We introduce U^i to acknowledge the uncertainty around (1) and avoiding over-relying on observed information.[6] Intuitively, the gradient descent algorithm that uses the true gradient $\Delta J(\eta_t)$ would yield the true shock combination if all state variables were observed (i.e. $\bar{X}_t = X_t$ using $\Delta F(\eta_t) = \Psi^X(X_t - X(\eta_t))$). In the simple case of two state variables and two shocks with $X_t = [x_t^1, x_t^2]'$ and $\bar{X}_t = x_t^1$, the gradient using $\bar{X}_t$ is by construction biased:

$$\begin{pmatrix} \Delta\eta_t^1 \\ \Delta\eta_t^2 \end{pmatrix} = \begin{pmatrix} \Psi^{x^1,1}(\bar{x}_t^1 - x_t^1(\eta)) \\ \Psi^{x^1,2}(\bar{x}_t^1 - x_t^1(\eta)) \end{pmatrix} + \underbrace{\begin{pmatrix} \Psi^{x^2,1}(\bar{x}_t^2 - x_t^2(\eta)) \\ \Psi^{x^2,2}(\bar{x}_t^2 - x_t^2(\eta)) \end{pmatrix}}_{\text{unobserved}} \tag{3}$$

To reach the true shock combination we would need to know $(\bar{x}_t^2 - x_t^2(\eta))$. Since this is outside of the information set of the policymaker, and both the sign and magnitudes are then unobserved, it is only possible to rely on $(\bar{x}_t^1 - x_t^1(\eta))$. U^i then determines the robustness of the solution found by (1): if $\Psi^{\bar{X}}$ strongly identifies a candidate shock combination due to the SMRS, then the perturbation won't cause significant dispersion and the variance of Θ would be relatively small. On the contrary, U^i would generate a large variance in Θ if the relative size of the elements of $\Psi^{\bar{X}}$ are rather similar, (i.e. if the SMRS is close to 1). In section 3 we explain using a three equation NK model how these differences matter.

Due to the nature of (2), the support of $\hat{F}^\eta|\Omega_t$ is truncated by the direction of $\bar{x}_t^1 - x_t^1(\eta))$, meaning that it restricts to shocks that point exclusively to the direction of the observables.[7] We then correct $\hat{F}^\eta(z)$ by matching its observed variance to that of a zero mean normal distribution with the same truncated variance. Appendix C shows the intuition of the benefits of normalization.

3 Theoretical framework

In this section we analyze the theoretical properties of shock uncertainty. First we explain the basic model we consider and how it fits our approach. Then we run our methodology against a positive observation of inflation, first in a setting in which both shocks have the same strength to then conclude to the different optimality results implies by SMRS tilted towards one of the two shocks.

3.1 A basic NK model

Before arriving into the quantitative results of the paper, in this section we theoretically analyze the effects of shock uncertainty in a small scale New Keynesian model, and show how the SMRS is informative. We consider two AR(1) shocks in this economy, a mark-up shock μ_t and a preference shock φ_t.[8] The relevant case we consider is when the central bank is able to perfectly observe the inflation rate, but remains in the dark on the output gap, meaning $\bar{X}_t = \bar{\pi}_t$. Our model equations are:

$$\pi_t = \beta\mathbb{E}_t(\pi_{t+1}) + \kappa(Y_t + \gamma_\mu\mu_t)$$
$$Y_t = \mathbb{E}_t(Y_{t+1}) - \sigma(i_t - \mathbb{E}_t(\pi_{t+1})) + \gamma_\varphi(\varphi_t - \mathbb{E}(\varphi_{t+1}))$$
$$i_t = \phi_\pi\pi_t$$

Where Y_t, π_t and i_t represent output, the inflation rate and the nominal policy rate as deviations from their respective steady state values. γ_μ and γ_φ represents the "strength" of mark-up and preference shocks, while $\mathbb{E}(\cdot)$ is

[6] Notice that a Dirichlet distribution parametrized with ones is a generalization of the uniform distribution in which all numbers add up to one. We use this distribution to represent the lack of knowledge of the true realized shock, as is common in the uncertainty literature (Harenberg et al., 2019).

[7] Intuitively if the observed variable is inflation, and for exposition it is above target, the model would point towards shock combination in which all shocks are inflationary, and this eliminates the possibility of having a demand shock that would generate extremely high inflation, that is compensated by a slightly dissinflationary supply shock.

[8] We consider these two shocks for easy comparison with the Smets and Wouters (2007) model used in section 4, but also for the clean interpretation of the theoretical results.

then the rational expectations operator, which implies that agents understand the structure of the economy and know the composition of shocks.[9] Shock innovations thus follow an *i.i.d.* zero-mean distribution, known to the agents but not to the policymaker. Furthermore, σ and ϕ represent the intertemporal elasticity of substitution and the Frisch elasticity of labor supply. The central bank reacts with full and credible commitment following a standard Taylor Rule that is known by the agents.[10]

Our paper then represents the problem of a policymaker that under Ω_t tries to commit to a given ϕ_π similar to Giannoni (2007) and Orphanides and Williams (2007). Rational agents that understand the economy and know that under the stability condition $\phi_\pi \geq 1$ the economy is stationary. Then inflation expectations can only de-anchor in the short and medium run. We focus on this case to isolate shock uncertainty in the policymaking process from assumptions about expectation formation, which in itself would add an additional layer of uncertainty. This distinguishes our approach from Orphanides and Williams (2007), who assume that the central bank is uncertain about the formation of expectations by economic agents.

Equation (4) represents the model in Sims (2002) form. A feature of the New Keynesian model is that it is purely forward looking, which implies that Γ would be a null matrix.

$$X_t = \Psi \eta_t \tag{4}$$

The SMRS of the model then simplifies to:

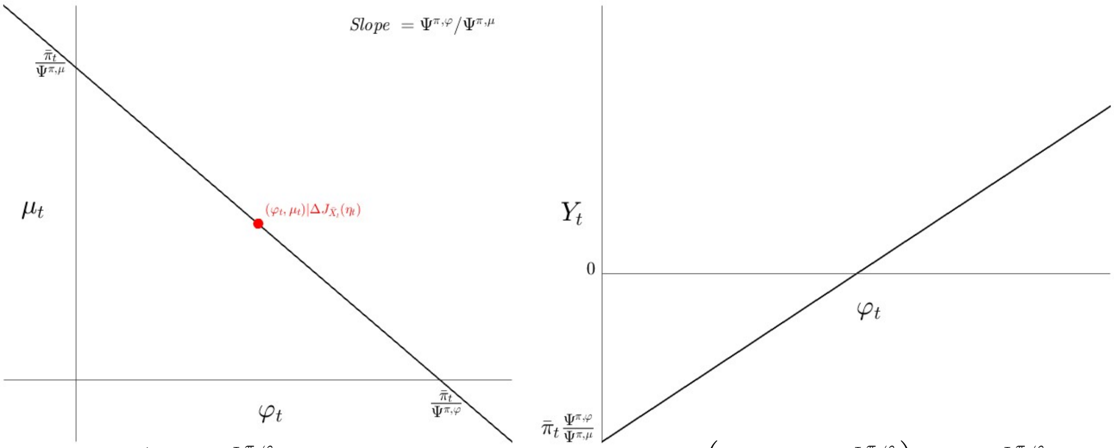
$$\mu_t = \frac{1}{\Psi^{\pi,\mu}}\bar{\pi}_t - \frac{\Psi^{\pi,\varphi}}{\Psi^{\pi,\mu}}\varphi_t \qquad \text{with:} \quad SMRS = \frac{\Psi^{\pi,\varphi}}{\Psi^{\pi,\mu}} = \frac{\gamma_\varphi(1-\rho_\varphi)}{\gamma_\mu(1-\rho_\mu)} \tag{5}$$

The left panel of figure 1, sketches equation (5) would look like for an observed inflationary shock. The term $\frac{1}{\Psi^{\pi,\mu}}$ determines the magnitude of the supply shock needed to explain inflation in isolation, under the assumption that both shocks have the same persistence, $\frac{\gamma_\varphi}{\gamma_\mu}$ pins down the SMRS: the change in size of a supply shock needed to compensate a demand shock to still maintain inflation at the observed rate is a function of the relative strength of these two shocks. A large SMRS implies that demand shocks move output quite aggressively, which implies that demand shocks are more likely to drive inflation. Intuitively, a large SMRS (i.e. a proportionately small $\Psi^{\pi,\mu}$) implies that the supply shock necessary to explain inflation in isolation is equal to $\frac{\bar{\pi}}{\Psi^{\pi,\mu}}$, which is strictly larger than $\frac{\bar{\pi}}{\Psi^{\pi,\varphi}}$, the required demand shock. The logic is the same for a SMRS close to zero.

[9] We loosely refer to γ_μ and γ_φ as strength parameters. Another interpretation is that, given that we consider the true pdfs of the distribution of shocks innovations to be differentiable, symmetric and monotonically decreasing, these two parameters can be understood as the variance coefficient of these distributions if the disturbances are normalized to have a variance of 1. This interpretation allows us our results to be consistent with the widely known fact that shock distributions are heterogeneous in both variance and persistence.

[10] In this section we keep the calibration to standard values in the literature: $\beta = 0.99, \sigma = 1, \kappa = 0.05, \gamma_\varphi = 1,$ and $\rho_\varphi = \rho_\mu = 0.9$. γ_μ is set equal to 1 initially, but in section **??** we will consider different values to calibrate different scenarios of the SMRS.

Figure 1: Support of the conditional shock distribution



$\mu_t = \frac{1}{\Psi^{\pi,\mu}}\bar{\pi}_t - \frac{\Psi^{\pi,\varphi}}{\Psi^{\pi,\mu}}\varphi_t$ $\qquad$ $Y_t = \left(\Psi^{y,\varphi} - \Psi^{y,\mu}\frac{\Psi^{\pi,\varphi}}{\Psi^{\pi,\mu}}\right)\varphi_t + \bar{\pi}_t\frac{\Psi^{\pi,\varphi}}{\Psi^{\pi,\mu}}$

The left hand panel is a representation of equation (5), while the right hand panel represents the output gap that would prevail under the same shock combination on the left hand panel. The red dot shows the point represents the centrality measure of Θ as the shock combination found with an unaltered $\Delta J_{\bar{X}_t}(\eta_t)$.

The right panel of Figure 1 represents Y_t as a function of φ_t conditional on (5), which is by construction upward sloping. Y_t is by assumption unknown, however, if the central bank can determine $\hat{F}^{\eta}(z) \mid \Omega_t$ from (5) then it can guess the likely distribution of the output gap at time t. The output gap will be negative if the observed level of inflation $\bar{\pi}_t$ is solely explained by a mark-up shock, and vice versa if inflation is driven by a preference shock. The higher the contribution of the demand shock that drives inflation, the higher the output gap, becoming positive eventually. Hence, assessing the source of inflation is crucial for the central bank.

The central bank cares about Y_t given that as in Giannoni (2007), we assume that it chooses the optimal interest response to inflation to commit to ex ante. We define optimal policy as the one that minimizes expected welfare losses at time t in the context of uncertainty, we specify the following canonical loss function. Where λ_y is the relative weight of the output gap in the loss function.

$$\mathbb{E}_t(\mathcal{L}) = \sum_{j=0}^{\infty} \mathbb{E}_t(\pi_{t+j}^2 + \lambda_y Y_{t+j}^2 | \Omega_t) \tag{6}$$

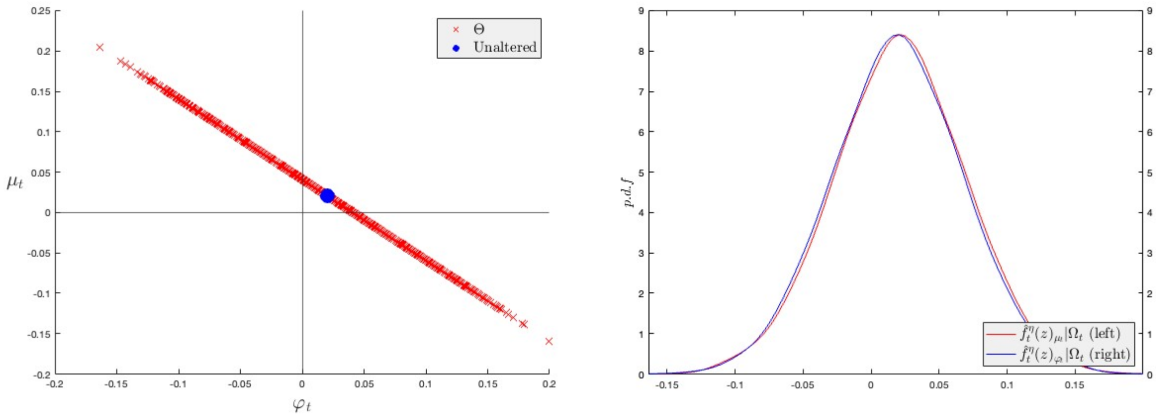
Notice that expectations are formed conditional on the information set of the central bank, which implies that it uses $\hat{F}^{\eta}(z)|\Omega_t$ to compute expectations.

3.2 Optimal policy under $SMRS = 1$

In this section we describe what $\hat{F}_t^{\eta}|\Omega_t$ looks like in a setting with a SMRS strictly equal to 1 and show that optimal monetary policy in this setting has an interior solution.[11] The support of $\hat{F}_t^{\eta}(z)|\Omega_t$ is (5), which is clearly seen in the left panel of figure 2 together with Θ. The central point of our perturbation, which is the realization of η_i under no distortion in $\Delta J_{\bar{\pi}_t}(\eta_t)$ shows both shocks being equally large and a fairly large dispersion in $\hat{F}_t^{\eta}|\Omega$ represented by the distribution of red dots. In the right hand panel of Figure 2 we show the marginal pdfs of $\hat{F}_t^{\eta}|\Omega$ with respect to both shocks, and we can see that these are equal, meaning that indeed with an SMRS equal to one the information set of the central bank is not informative regarding the source of inflation.

[11] Given (5), we achieve so by setting $\gamma_\mu = \gamma_\varphi$ and $\rho_\mu = \rho_\varphi$.

Figure 2: $\hat{F}^{\eta}_t(z)|\Omega_t$ for a three equation NK with $SMRS = 1$



Red crosses in the left hand panel includes the shock set Θ simulated over $n = 10.000$ realizations of the random vector U^i for the small scale New Keynesian model calibrated sich that the SMRS$= 1$. The blue dot is the point within Θ for which the gradient is not altered (as red dot in Figure 1), the centrality point of our estimation procedure. The red (blue) line on the right panel of the figure corresponds to the marginal pdf of the conditional shock distribution with respect to supply (demand) shock, its notation $\hat{f}^{\eta}_t(z)_{\mu_t}|\Omega_t$ ($\hat{f}^{\eta}_t(z)_{\varphi_t}|\Omega_t$).

Under the uncertainty that we study in this paper the central bank needs to set a monetary policy that, defined as the adequate response to inflation, best reduces the likelihood of delivering large welfare losses. Uncertainty yields a tradeoff, reported in Figure 3. To understand the intuition behind our results it is useful to consider the standard New Keynesian logic behind supply and demand shocks: if it was known that the shock is demand driven, the central bank would ex ante choose to react strongly against inflation. Under this shock inflation and the output gap co-move, taming inflation also implies eliminating excessive production in the economy. However if the central bank knows the shock is supply driven, then it would prefer to "look through inflation", and then respond in a moderate way. A strong hike would push an already depressed output further down, which would tame inflation at the expense of a long and painful recession. Our optimality results can be understood as how the informativeness of the SMRS is able to help us understand the likelihood of each of these two opposing forces.

The left three panels of figure 3 speak to this trade off, highlighting the risk of making a wrong assessment by looking at the loss distribution of supply and demand driven states of the world according to three different ϕ_π coefficients.[12] If the central bank chooses to ex ante commit to react mildly to inflation deviations from target, the loss distribution of supply driven states of the world determined by (6) under the $\hat{F}^{\eta}_t(z)|\Omega_t$ implied by Figure 2 would be contained, however if the true shock combination turns out to be steaming from the demand side of the economy, there are potential tail losses that are considerably large. The opposite occurs if ϕ_π is set too high: in demand driven states of the world losses are contained but under supply ones the interest rate hike would push the output gap down from an already weak position, generating a deeper and longer recession. The optimal point then is reflected in the right panel: there is an optimal ϕ_π that minimizes expected losses to a minimum. This point is what we refer to as robust monetary policy to shock uncertainty. These results lie at the core of the Brainard attenuation principle.

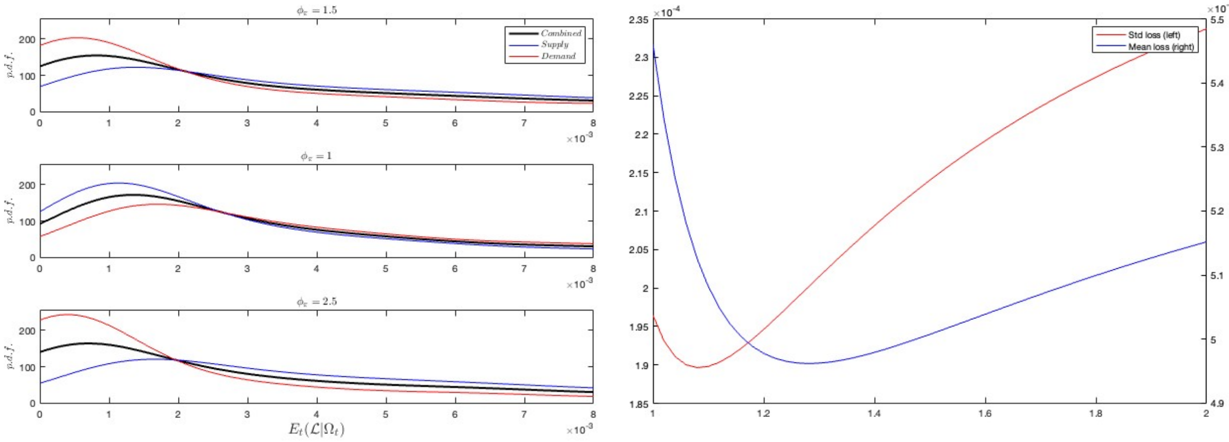
In the right hand panel of 3 we show that the optimal Taylor Rule response is interior, highlighting that the two trade offs mentioned above conflict each other and both must be weighted accordingly. As shown in section 4, it might also be the case that there is a corner solution in the support of ϕ_π if the SMRS is very close to zero.

3.3 The informativeness of the SMRS

It is key to consider that the value of the SMRS greatly affects $\hat{F}^{\eta}_t(z)|\Omega_t$. Figure 4 shows that when the SMRS is close to 1, as in the previous section, there is a lot of dispersion in the range of potential explanations of observed inflation. Given that both shocks need to be the same size to explain inflation distortions, we cannot conclude that one shock is more likely than the other. Note that this the SMRS is *steep* (i.e. larger than 1) then the required supply shocks needed to explain inflation would be rather large, this is why in the bottom panel we observe that with almost all certainty in this case the demand shock is positive, whereas the supply one could take a wide range of values. If the

[12] Supply (demand) driven state of the world are defined as a shock combination in Θ in which $\mu_t \Psi^{\pi,\mu} > (<) 0.5\bar{\pi}_t$.

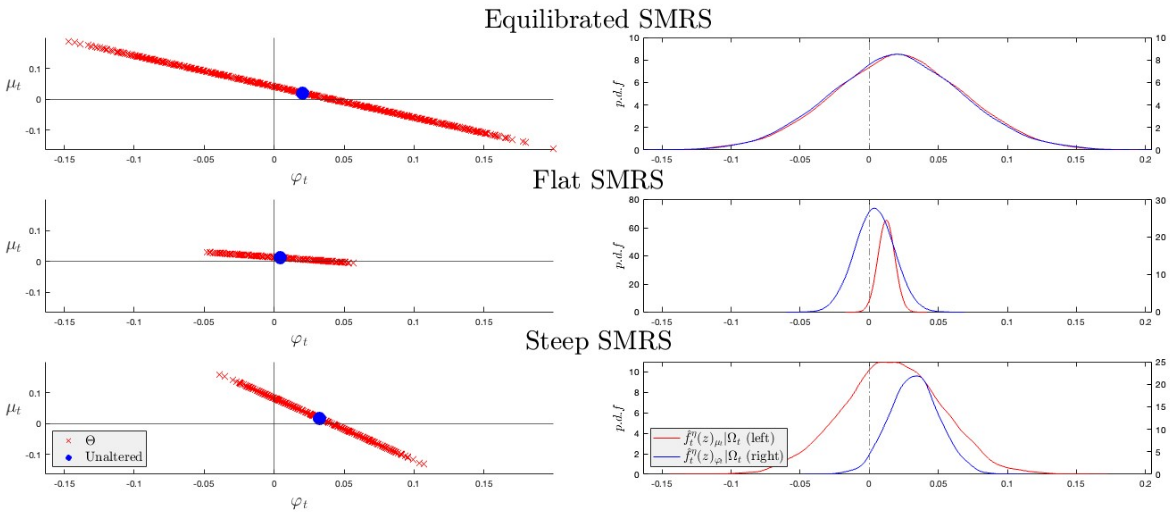
Figure 3: Optimal policy response under $SMRS = 1$



The three panels on the left represent the expected loss distribution derived from (6) under the estimated $\hat{F}_t^{\eta}(z)|\Omega_t$ for three calibrations of the of ϕ_π. The black line represents the unconditional distribution, while the blue (red) lines show the shock distribution conditional on inflation being predominantly driven by supply (demand) forces. Supply (demand) driven states of the world are defined as a shock combination in Θ in which $\mu_t \Psi^{\pi,\mu} > (<) \bar{\pi}_t/2$. The right panel shows the expected value and standard deviation of the loss distribution as a function of ϕ_π.

SMRS is *steep*, then the contrary occurs and demand shocks are the ones that in size musth be larger. This result is derived from $\Delta J_{\bar{X}_t}$ and the impact that U^i has. When the original gradient collapses to a particular region of the support of the distribution in (2), perturbations do not impact its value as much as when the gradient doesn't clearly point towards one shock type or another.

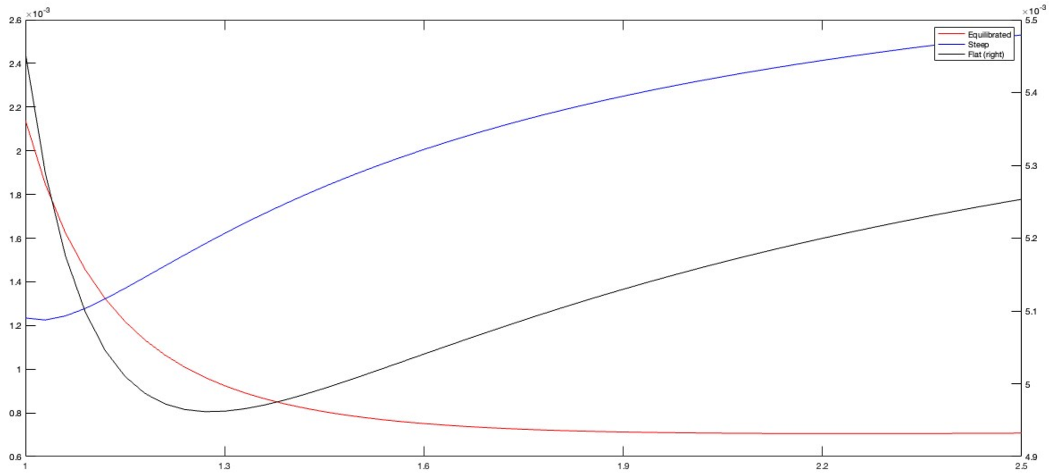
Figure 4: $\hat{F}^{\eta}(z)|\Omega_t$ under different SMRS slopes



Similar to Figure 2, the three panels on the left show the set Θ ($n = 10.000$) for three different slopes of the SMRS. The red (blue) lines on the right panels of the figure corresponds to the marginal pdf of the conditional shock distribution with respect to supply (demand) shock. To calibrate these scenarios we changed γ_μ from the original calibration to 3 for the flat SMRS, and 0.5 for the steep case, with a trivial effect on the SMRS given equation (5).

The implication of different slopes is straight forward. If the information set of the central bank points toward likely demand driven inflation, then one can conclude that the output gap might be positive. As the red line in figure 5 shows, the optimal response to inflation si the largest of the three scenarios considered. On the contrary if we consider supply shocks to be dominant and the output gap negative, then the stabilization trade off appears and the optimal response is much milder. This result is very strong. Considering the information set we endow the decision maker with, it is clear that the parametrization of the economy plus the observation of inflation are enough to understand the risk of the decided policy stance.

Figure 5: Optimal Taylor Rule response as a function of the SMRS



As the right hand side panel of figure 3, this figure shows the expected value of the loss distribution as a function of ϕ_π for the three SMRS calibrations discussed in the exercise.

4 Application to the US economy

In this section we now consider our algorithm to disentangle the potential drivers of shocks in the case of the inflationary episode of 2022. Since 2020, the US and other advanced economies have faced a series of unprecedented inflationary shocks, which led to an increase in inflation substantially above target. The GDP deflator in the US peaked at 8.8% in 2022Q2 (see 6). Given the already mentioned discussion regarding the origins of this inflation, in this section we tackle the main question of our paper: given the information set available at the time, what were the likely causes on post pandemic inflation? What is the policy recommendation that arises from analyzing shock uncertainty vie the SMRS? Was the quick rise on the hiking cycle justified or was it risky? We find that the SMRS, in an estimated version of Smets and Wouters (2007) with data up until 2019, was extremely flat, which implies that the initial concern of inflation mainly driven by supply forces was well justified. Given the potential consequences, when then find that recession risk was so large that monetary policy should have taken a considerably more dovish approach. Our welfare results show that indeed the optimal response to inflation was as low as one.

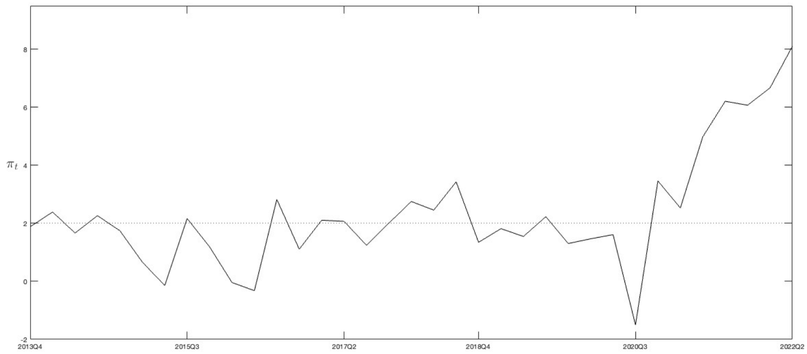
Exercise environment Our analysis is based on Smets and Wouters (2007), with includes a widely recognized benchmark medium-scale log-linearized DSGE model for policy analysis. The model equations pin down the dynamics of capital formation, consumption, investment, the rental rate of capital, labor, wages, inflation, and the value of the capital stock. The model dynamics are driven by supply shocks (technology, wage and price mark-up), demand shocks (risk premium, government spending), and a monetary policy shock. The mark-up and preference shocks affect the dynamics of the model through the New Keynesian Phillips curve (NKPC) and the IS curve, equations (7) and (8) respectively:

$$\pi_t = \pi_1 \pi_{t-1} + \pi_2 \mathbb{E}(\pi_{t+1}) - \pi_3 (mpl_t - w_t) + \mu_t \tag{7}$$

$$c_t = c_1 c_{t-1} + (1 - c_1)\mathbb{E}(c_{t+1}) + c_2(l_t - l_{t+1}) - c_3(i_t - \pi_{t+1}) + c_3(\varphi_t - \mathbb{E}(\varphi_{t+1})) \tag{8}$$

In (7) inflation depends on past and expected future inflation and on mark-up shock μ_t. The effect of mark-up shocks on the economy is determined by the Calvo price adjustment parameter which has a rather strong influence on π_3. In (8), consumption c_t depends on past and expected future consumption, expected growth in hours worked (l_t, l_{t+1}), the real interest rate gap, and a preference shock φ_t. A positive preference shock (demand shock) increases

Figure 6: Annualized percentage change in US GDP deflator



Q-o-Q annualized inflation as measured by the GDP deflator from 2013Q4 until the peak of the inflation surge in 2022Q2.

consumption and exerts upward pressure on real factor prices, and thus on inflation. We focus our analysis on the likelihood of supply and demand driven inflation on the preference and mark up shocks. In order to get a better understanding of the driving forces of behind our results we assume that the mark-up and preference shocks follow an AR(1) process, instead of an ARMA(1,1) process as in SW.

To assess whether the response of the US Federal Reserve was robust in an environment of shock uncertainty, we estimate the model parameters in the sample period 1954Q4-2019Q4 to avoid estimation issues due to the pandemic.[13] We run our methodology from section 2 considering the end point T to be the peak of inflation in the recent surge, 2022Q2. From the components of Ω_T, we still restrict $\bar{X}_T = \pi_T$, Γ and Ψ are derived from the model estimation, while we keep $\eta = [\varphi_t, \mu_t]'$ as in section 3. We do so to keep our results tractable and two dimensional, nonetheless our methodology can easily handle more than two dimensions, which we keep for future research. Furthermore, the state of the economy in the 2022Q1 (i.e. X_{T-1}) is based on the result of a Kalman filter computed on the estimated model posteriors starting the recursion in 1991Q2.[14] In this setting we find an estimate of the output gap $Y_{2022Q1} = -2.66\%$, which will be known to the central banker together with all the state variables in that period when optimizing

4.1 Results and robust monetary policy

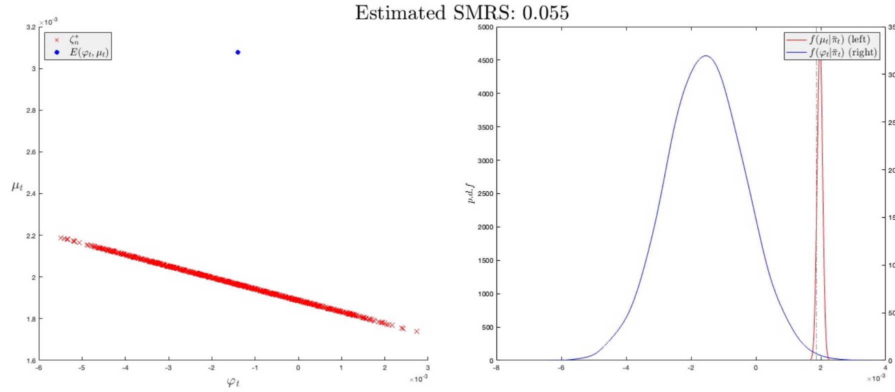
Figure 8 shows the results of our methodology. The expected shock combination in 2022Q2 shows an economy that is severely hit by a supply shock, and a negative demand one. The endogenous persistence of the model would have led to a shock combination that would have triggered an inflation rate considerably above the observed one, which materialized in μ_T being considerably lower than $E_{T-1}(\mu_T)$. Because of the slope fo the low SMRS, the estimate of the demand shock has barely moved and remains negative. Interestingly, the supply shock is quite tightly identified around 0.002, while the demand shock has a considerably wide range of possible values, all of which are negative but have different implications on the output gap as discussed below. As we explained in Section 3, the algorithm under Smets and Wouters (2007) has an extremely low estimated $SMRS = 0.055$ which implies that demand shocks do not greatly move the inflation rate in the economy, and thus inflation is more likely a product of supply forces.

[13]The estimation results can be found in table B.1 in the appendix, figures B.1 and B.2 show the median estimated IRFs to a mark up and preference shock that will influence the SMRS in this exercise.

[14]Both for estimation and the Kalman filter on the initial conditions we use the same observables as in the original Smets and Wouters (2007), except the policy rate, for which we use Wu and Xia (2016) shadow rate instead to account for unconventional monetary easing during the ZLB period. Contrary to the original paper, in the estimation we considered all shocks to me AR(1) processes, while for the Kalman Filter we considered as AR(1) only φ_t and μ_t while the others are kept as MA(1). We took this last decision to make sure that all the persistence of the model during our simulations occurs due to either the endogenous persistence of the state variables (via Γ) or due to the estimated persistence of the two shocks of interest.

Figure 7: Simulated shock combinations explaining the inflation rate in 2022Q2, based on SW

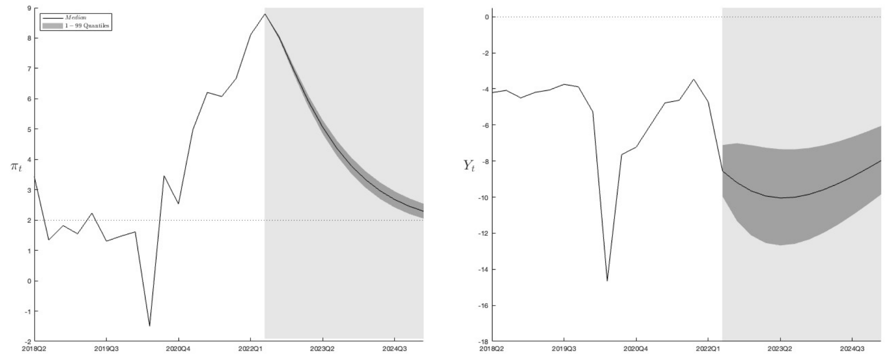
Estimated SMRS: 0.055



Red crosses in the left hand panel includes the shock set Θ simulated over $n = 10.000$ realizations of the random vector U^i for the estimated Smets and Wouters (2007) and the calibrated scenario to match the 2022Q2 economy. The blue dot is the point within Θ for which the gradient is not altered (as red dot in Figure 1), the centrality point of our estimation procedure. The red (blue) line on the right panel of the figure corresponds to the marginal pdf of the conditional shock distribution with respect to supply (demand) shock.

We can then use our estimate $\hat{F}^{\eta}|\Omega_T$ to determine the path of the two variables that enter the loss function. In the shaded area of panels in Figure 8 the black line represents the median scenario under the estimated parameter combination, which shows that inflation was expected to fall gradually and slowly settle around its 2% target, while the output gap is expected to fall to -9% on impact, and worsen slightly before recovering. Uncertainty around the evolution of the output gap however is substantial: the 1-99 quintiles of the distribution on impact show that the output gap could be between -7% all the way to -10.5%. Note the large contrast with the evolution of inflation, which remains within a 0.75% range for the entire simulated period. The output gap evolution over the horizon shows a key source of concern: up to 2023Q2 the top of the quantile distribution barely moves, which contrast with the considerable worsening of the worst case scenario, with an output gap deeply negative at -13%. This highlights how shock uncertainty matters by showing that the central bank cannot predict this key state variable in real time. Uncertainty then implies, in terms of welfare, quite adverse consequences, considering that there is a possibility of incurring extremely high losses. We can then conclude that in this setting, precisely due to the high variance of demand shocks, uncertainty materializes because, not because the main source of shocks is unclear, but rather because the flatness of the SMRS implies a wide range of potential values of demand shocks that directly affect the output gap.

Figure 8: Simulated shock combinations explaining the inflation rate in 2022Q2, based on SW



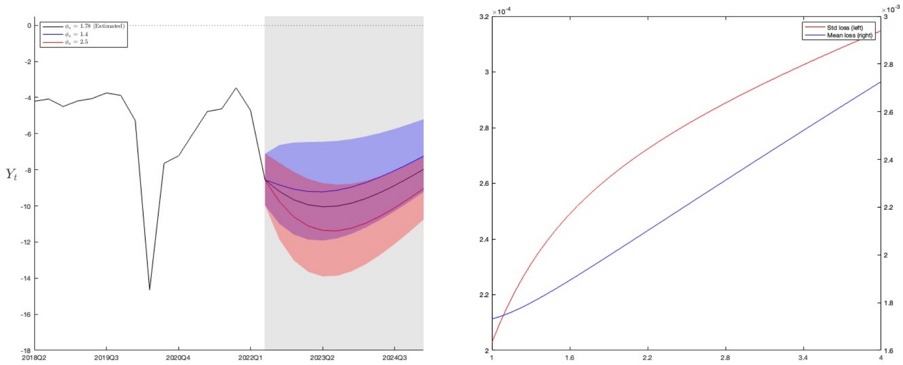
Simulated path for inflation and the output gap under the estimated $\hat{F}^{\eta}|\Omega_T$. The light gray area represents the simulated periods starting in 2022Q2, with the solid black line being the median of the distribution, and the dark gray area the [1,99] quantiles of it. Before 2022Q2 the inflation black line represents observed inflation as the annualized Q-o-Q GDP deflator, while the output gap is the calibrated result of the Kalman filter as discussed in the introduction of section 4.

In terms of welfare, this uncertainty can be costly. The red shaded region of figure 9 shows the inter quantile range when the central bank, in order to minimize welfare distortions, decides to react considerably stronger than the estimated Taylor Rule response to inflation. In this case the results may be detrimental. Figure 9 shows that the trajectory of the output gap changes considerably, pushing down the lower bound of the inter quantile range to -14%, and ensuring a worsening of it in the best case scenario up to 2025Q1. In this case reducing the Taylor rule coefficient does improve welfare losses associated to the output gap than in a hawkish scenario: there is a solid change of starting the economic recovery faster and the worse case output losses are eliminated. The inflation outlook does not change significantly from one Taylor rule response to another, the projected paths can be seen in figure xxx in the appendix.

When considering expected welfare losses in the right panel, we find solid evidence that the central bank should optimally use a dovish approach. This is at the core of the Brainard principle: in order to eliminate the possibility of incurring extremely large welfare losses, it is optimal to be prudent and avoid overreaction to avoid a bad realization under a detrimental state of the world. In this regard, we clearly show that the initial concerns that a hiking cycle could have been considerably detrimental where properly sustained also under the consideration of shock uncertainty.

The low SMRS in this exercise appears as a result of a flat estimated Phillips Curve ($\pi_3 = 0.014$ in eq (7)), in the next section we discuss this contextualize this result with previous work and focus on the implications on the SMRS and optimal policy.

Figure 9: Simulated shock combinations explaining the inflation rate in 2022Q2, based on SW



On the left hand side we can find the simulated path the output gap under the estimated $\hat{F}^\eta|\Omega_T$ under two different $\phi_\pi = 1.4$ (blue), and $\phi_\pi = 2.5$ (red). The light areas represents the simulated periods starting in 2022Q2, with the solid lines being the median of the distribution, with the shaded blue and red areas being the [1,99] quantiles of it. Before 2022Q2 the output gap is the calibrated result of the Kalman filter as discussed in the introduction of section 4. The right panel shows the expected value and standard deviation of the loss distribution as a function of ϕ_π.

4.2 Phillips Curve steepness as key driver

In the previous section we show that the response of the Taylor rule is optimally equal to one. In this section we highlight that this result arises not only from the state of the economy in 2022Q2, but also from the estimated coefficients via the flatness of the NKPC. Fratto and Uhlig (2020) showed that estimated DSGE models, with an emphasis in Smets and Wouters (2007), when estimated imply a particularly flat NKPC that lead to the conclusion that inflation is considered to be driven essentially by supply factors. We acknowledge this posture and in this section we consider the effects of shock uncertainty when the NKPC is artificially higher. By doing so, we highlight the importance of our results, given that when the information set of the central bank is as limited as Ω_t, the central bank is still able to leverage its understanding of the structure of the economy to set optimal policy. We conclude that with a higher NKPC, which directly increases the SMRS, the central bank factors in a higher estimated variance of mark up shocks and thus a bigger role in demand forces to drive up inflation, consistent with the results of figure 4. Figure xxx in the appendix shows how the shock conditional distribution changes with changes in the NKPC slope. We find that for the estimated Taylor Rule coefficient against inflation to be optimal the NKPC must have been roughly ten times steeper than the estimated value. We take such a big difference in optimality as evidence that precaution was still optimal, with the Brainard principle still laying a relevant role in understanding shock uncertainty.[15]

Figure 10 shows this result. On the two panels on the left we can observe how the expected evolution of inflation and the output gap change with steeper NKPCs.[16] The influence of a steeper NKPC is stark. Inflation is expected to reach the 2% target considerably sooner than under the estimated calibration, while the output gap will narrow much faster. The steeper the NKPC is, the faster the recovery would be, in which case the central bank can optimally hike the interest rate but strongly with respect to inflation achieving the optimal path under this uncertainty.

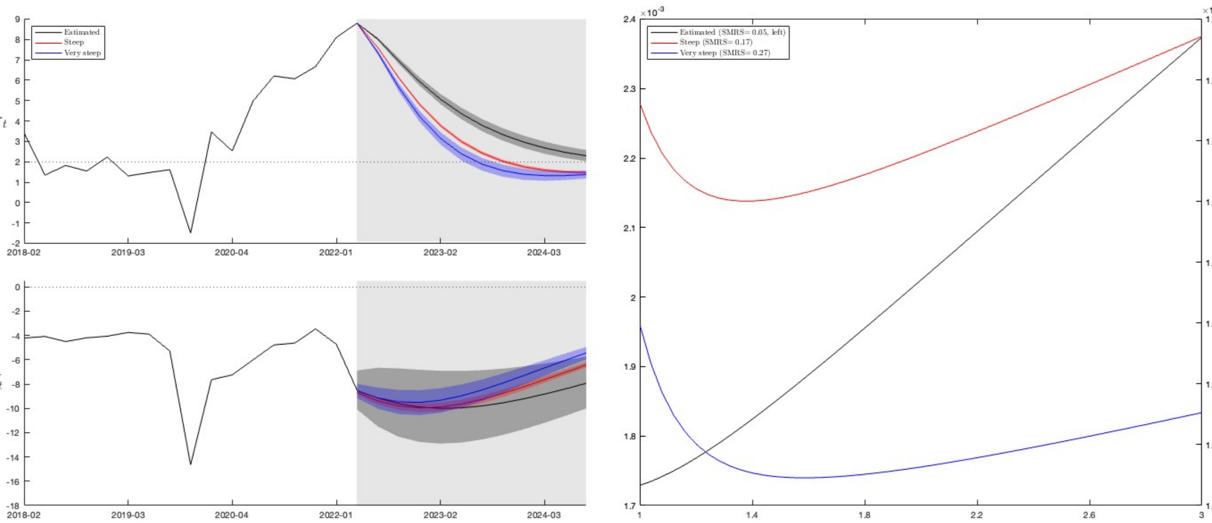
We can then conclude that the optimality result found in the previous section did not happen due to the extreme situation the economy was in 2022Q2, but rather that the structure of the economy pointed, conditional on only observing the inflation rate, to supply shocks being dominant in explaining inflation fluctuations. The right panel of Figure 10 shows the loss function (6) as a function of ϕ_π under the three different NKPCs, showing that the optimal response to inflation shifts to the right the steeper the NKPC becomes. The red line shows the optimal response if the NKPC was five times steeper, in which case the optimal response would be around 1.1 in order to balance the stabilization trade off. Reaching for the minimal response is no longer optimal since the concerns of a long deep

[15] The conditional shock distributions can be found in the figure D.1 in the appendix.

[16] From a technical perspective, we choose to augment the steepness of the NKPC by artificially multiplying π_3 in equation (7). We took this approach in order to isolate the effect of the steepness of the curve without altering any parameter that would result in a change in the steady state values of the model. By taking this ad-hoc approach, we are approximating the effects only in the log-linearized version of the model, making our results comparable.

recession are not present, and there is more room for a hiking cycle that helps bring down inflation faster now that is more strongly influenced by demand.

Figure 10: Shock distribution considering different NKPC slopes



On the two left hand side panels we can find the simulated path inflation and the output gap under the estimated $\hat{F}^{\eta}|\Omega_T$ *with the estimated parameter values (black), as well as counterfactual cases in which the NKPC is five times steeper (red), or ten times steeper (blue). The shaded areas represents the simulated periods, with the solid lines being the median of the distribution, and the shaded area the [1,99] quantiles of it. Before 2022Q2 the output gap is the calibrated result of the Kalman filter as discussed in the introduction of section 4 while the series for inflation are the Q-o-Q GDP deflator growth rates. The right panel shows the expected value of the loss distribution as a function of* ϕ_π *for the three scenarios.*

Notice that in the counterfactual case in which the NKPC is ten times steeper than initially estimated, represented by the blue lines, the policy trade off becomes even more favorable to the central bank, and thus its optimal reaction is in the neighborhood of 1.78, the estimated value in the 1954Q4-2019Q4 estimation sample. The conclusion of this exercise is then clear. Considering how far are the estimated NKPC slope with respect to the one that would make optimal the estimated coefficient, we argue that the policy stance of the Federal Reserve was too aggressive, and the reason is because the economy was in a fragile state and hiking was simply too dangerous. Given this result, we conclude that the strength of the hiking cycle that took place was simply too contractionary through the eyes of a policymaker that was surrounded by deep uncertainty about the true state pf the economy. Given our results, we then conclude that Brainard's attenuation principle applies in the sense that under deep uncertainty the risk of making the wrong decision may be very costly, and thus a strong reaction is suboptimal.

5 Conclusion

This paper studies how shock uncertainty shaped optimal monetary policy during the 2022 inflation surge. We define shock uncertainty as the policymaker's inability, in real time, to disentangle whether observed inflation originates primarily from supply or demand forces. This matters because optimal policy differs sharply across these shocks: demand driven inflation calls for aggressive tightening, whereas supply driven inflation raises a stronger trade off between inflation and output stabilization.

Our methodological contribution is to formalize this identification problem in the family of linear DSGE models under an information set meant to reflect what we argue is an accurate representation of the policymaker's information set during at the time: inflation is observed contemporaneously, while the output gap and the true shock distribution are unobserved. We infer a distribution over potential shock realizations consistent with observed inflation using the Shock Marginal Rate of Substitution (SMRS), which is derived from the structural parameters of the economy, and we define as the increase in the magnitude of the supply shock such that, when combined with a marginally smaller demand shock, together can still jointly deliver observed inflation. The SMRS summarizes how informative inflation is about the underlying shock mix and therefore about the likely sign of the output gap. Theoretically we show that a steeper SMRS makes demand driven states of the world more plausible and raises the optimal inflation coefficient in a Taylor rule, whereas a flatter SMRS tilts probability mass toward supply driven states, which implies attenuation.

Quantitatively, we apply the method to an up to date estimation of (Smets and Wouters, 2007), in a calibrated scenario matching the U.S. economy around the inflation peak in 2022Q2. We find an extremely flat estimated SMRS (0.055), implying that it was safe to assume at the time that inflation was driven by supply forces, generating a deeply negative output gap. In that state, further disinflation via aggressive tightening is welfare costly because it worsens an already severe output contraction. The welfare maximizing Taylor rule coefficient on inflation is then one, well below the estimated value of 1.78. Hence, under the restricted information set we model, the 2022 hiking cycle appears excessively aggressive, and optimal policy would have been comparatively more dovish, consistent with the concerns about recession risks that other authors had risen.

Our attenuation result contrasts with much of the uncertainty literature that often finds that policy should respond strongly to inflation. The key difference is that previous work typically aims to determine ex-ante unconditional loss minimization under commitment, whereas our exercise is explicitly about optimality conditional on the economy's state during the inflation peak. When the output gap is likely already far below potential, the marginal cost of tightening dominates, restoring the classic trade-off logic behind attenuation.

We also probe robustness to concerns that estimated New Keynesian models imply an overly flat Phillips curve. Even imposing a substantially steeper NKPC, our main conclusion remains: rationalizing an aggressive inflation coefficient as optimal in the 2022Q2 scenario requires an NKPC slope roughly an order of magnitude larger than the estimate. The results underscore a policy lesson for post-pandemic central banking: when inflation rises in an environment where the shock mix is hard to identify and slack is poorly measured in real time, the risk of over-tightening is high, and a disciplined risk-management approach may warrant a more cautious stance.

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A Data sources

In order to estimate the Smets and Wouters (2007) model we use the same observable variables as the original paper, with the exception of the policy rate, for which we use Wu and Xia (2016) instead.

Definition of data variables

- consumption = LN((PCEC / GDPDEF) / LNSindex) * 100
- investment = LN((FPI / GDPDEF) / LNSindex) * 100
- output = LN(GDPC1 / LNSindex) * 100
- hours = LN((PRS85006023 * CE16OV / 100) / LNSindex) * 100
- inflation = LN(GDPDEF / GDPDEF(-1)) * 100
- real wage = LN(COMPNFB / GDPDEF) * 100
- interest rate = XuXia16

Source of the original data

- `GDPC1`: Real Gross Domestic Product - Billions of Chained 2017 dollars; seasonally adjusted annual rate).
  Source: U.S. Department of Commerce, Bureau of Economic Analysis.
- `GDPDEF`: Gross Domestic Product: Implicit Price Deflator (2017=100, Seasonally Adjusted).
  Source: U.S. Department of Commerce, Bureau of Economic Analysis.
- `PCEC`: Personal Consumption Expenditures - Billions of Dollars, Seasonally Adjusted Annual Rate.
  Source: U.S. Department of Commerce, Bureau of Economic Analysis.
- `FPI`: Fixed Private Investment - Billions of Dollars, Seasonally Adjusted Annual Rate.
  Source: U.S. Department of Commerce, Bureau of Economic Analysis.
- `CE16OV`: Civilian Employment: 16 Years & Over - Thousands of Persons, Seasonally Adjusted.
  Source: U.S. Department of Labor, Bureau of Labor Statistics.
- `CE16OV_index`: index version of `CE16OV`.
  Construction: `CE16OV` with unit base (1992:Q3=1).
- `XuXia16`: Wu & Xia (2016) shadow rate series, quarterly aggregates.
  Source: author's web page Downloaded September 26th 2024.
- `CNP16OV`: Civilian Noninstitutional Population: 16 Years & Over - Thousands of Persons, Seasonally Adjusted.
  Source: U.S. Department of Labor, Bureau of Labor Statistics.
- `CNP16OV_index`: index version of `CNP16OV`.
  Construction: `CNP16OV` with unit base (1992:Q3=1).
- `PRS85006023`: Nonfarm Business, All Persons, Average Weekly Hours Duration - index (1991Q1=100), seasonally adjusted.
  Source: U.S. Department of Labor, Bureau of Labor Statistics.
- `COMPNFB`: Nonfarm Business Sector: Hourly Compensation for All Workers - index (1992Q1), seasonally adjusted.
  Source: U.S. Department of Labor, Bureau of Labor Statistics. Base 01-01-1992=100.

B Smets and Wouters (2007) estimation results

Table B.1: Prior and posterior distributions os structural parameters

		Prior			Posterior	
	Parameter	Dist.	Mean	Stdev	Mode	Stdev
ρ_a	TFP shock persistence	beta	0.500	0.2000	0.9733	0.0122
ρ_b	Risk-premium shock persistence	beta	0.500	0.2000	0.8787	0.0292
ρ_g	Government spending shock persistence	beta	0.500	0.2000	0.9697	0.0112
ρ_I	Inv. specific technology shock persistence	beta	0.500	0.2000	0.8061	0.0710
ρ_r	Monetary policy shock persistence	beta	0.500	0.2000	0.1311	0.0612
ρ_p	Price mark-up shock persistence	beta	0.500	0.2000	0.8399	0.0698
ρ_w	Wage mark-up shock persistence	beta	0.500	0.2000	0.9814	0.0090
μ_p	Price mark-up shock MA parameter	beta	0.500	0.2000	0.7223	0.1166
μ_w	Wage mark-up shock MA parameter	beta	0.500	0.2000	0.9682	0.0097
φ	Investment adjustment cost parameter	norm	4.000	1.5000	4.1359	1.1280
σ_c	Risk aversion	norm	1.500	0.3750	1.1768	0.1719
h	Habit formation parameter	beta	0.700	0.1000	0.5495	0.0646
ξ_w	Calvo wage stickiness	beta	0.500	0.1000	0.8103	0.0424
σ_l	Inverse Frisch elasticity	norm	2.000	0.7500	1.5128	0.5699
ξ_p	Calvo price stickiness	beta	0.500	0.1000	0.8488	0.0385
ι_w	Wage indexation	beta	0.500	0.1500	0.5751	0.1390
ι_p	Price indexation	beta	0.500	0.1500	0.3114	0.1007
ψ	Capital utilization adjustment cost	beta	0.500	0.1500	0.8789	0.0541
ϕ_p	Fixed-cost	norm	1.250	0.1250	1.5340	0.0771
ϕ_π	Taylor-rule response to inflation	norm	1.500	0.2500	1.7792	0.1760
ρ_R	Taylor-rule smoothing	beta	0.750	0.1000	0.8713	0.0175
ϕ_y	Taylor-rule response to the output gap	norm	0.125	0.0500	0.0917	0.0224
$\phi_{\Delta y}$	Taylor-rule response to output-gap growth	norm	0.125	0.0500	0.2064	0.0229
π^*	Steady-state inflation	gamm	0.625	0.1000	0.7853	0.0821
$100(\beta^{-1}-1)$	Discount-rate parameter	gamm	0.250	0.1000	0.2100	0.0917
$\bar{\ell}$	Steady-state hours worked	norm	0.000	2.0000	-0.1425	1.0475
$\bar{\gamma}$	Trend growth rate	norm	0.400	0.1000	0.3914	0.0235
ρ_{ga}	Loading of TFP shock in government spending process	norm	0.500	0.2500	0.5358	0.0811
α	Capital share in production	norm	0.300	0.0500	0.2027	0.0357
σ_a	Std. dev. of TFP shock innovation	invg	0.100	2.0000	0.4066	0.0242
σ_b	Std. dev. of risk-premium shock innovation	invg	0.100	2.0000	0.0878	0.0098
σ_g	Std. dev. of government spending shock innovation	invg	0.100	2.0000	0.4607	0.0241
σ_I	Std. dev. of investment-specific technology shock innovation	invg	0.100	2.0000	0.3214	0.0309
σ_r	Std. dev. of monetary policy shock innovation	invg	0.100	2.0000	0.1879	0.0112
σ_p	Std. dev. of price mark-up shock innovation	invg	0.100	2.0000	0.1185	0.0124
σ_w	Std. dev. of wage mark-up shock innovation	invg	0.100	2.0000	0.3767	0.0222

Replication of the estimation in Smets and Wouters (2007) using the estimation sample is 1954Q4-2019Q4. The *Dist.* column indicates the prior distribution family: *beta* = Beta prior, *gamm* = Gamma prior, *invg* = Inverse-Gamma. The posterior distribution is obtained using the Metropolis-Hastings algorithm

Figure B.1: IRFs to mark up shock

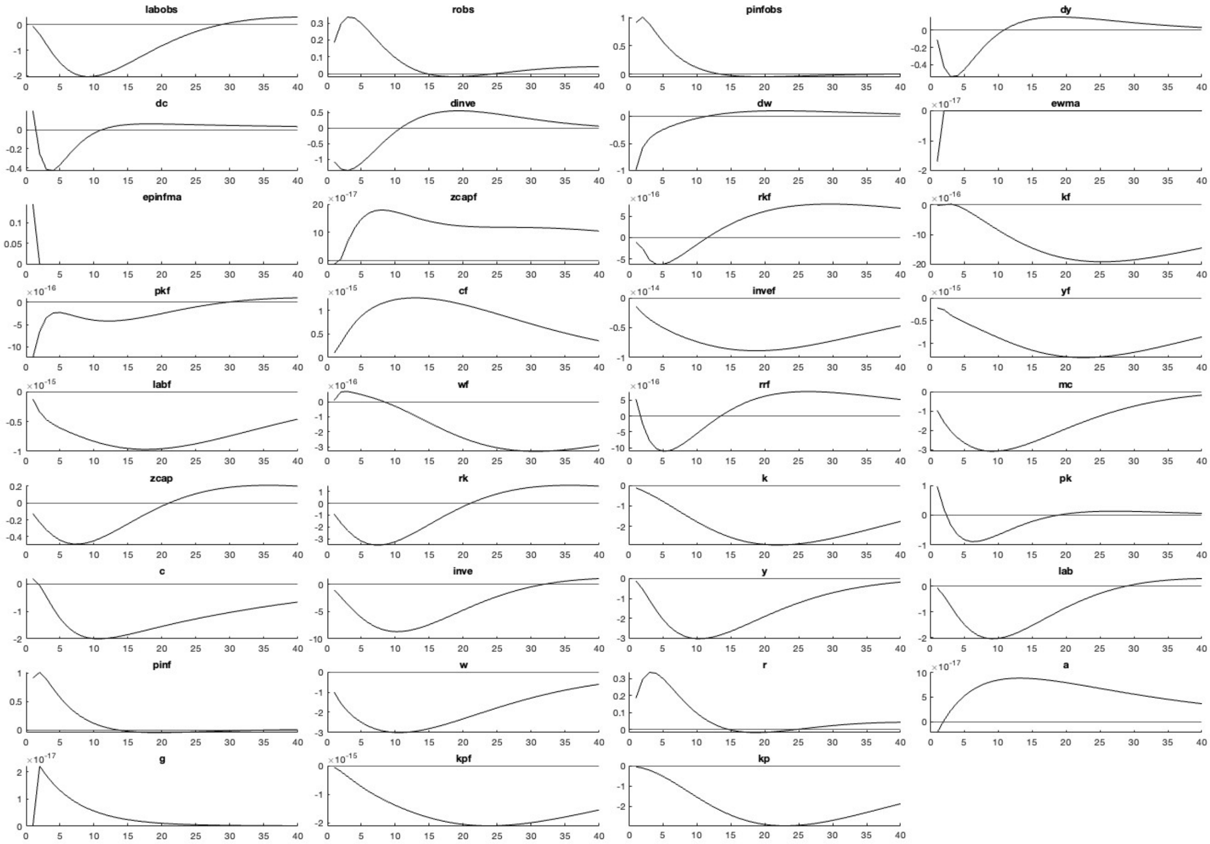
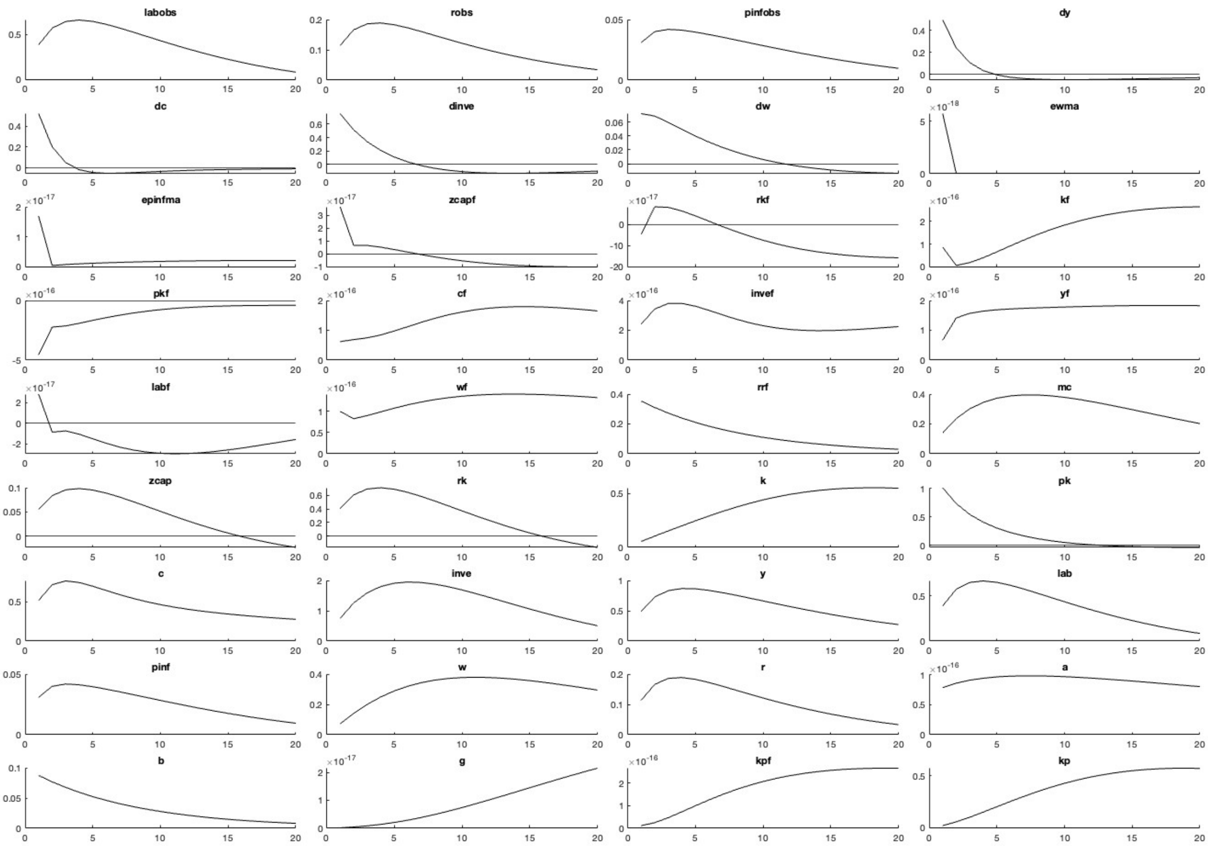


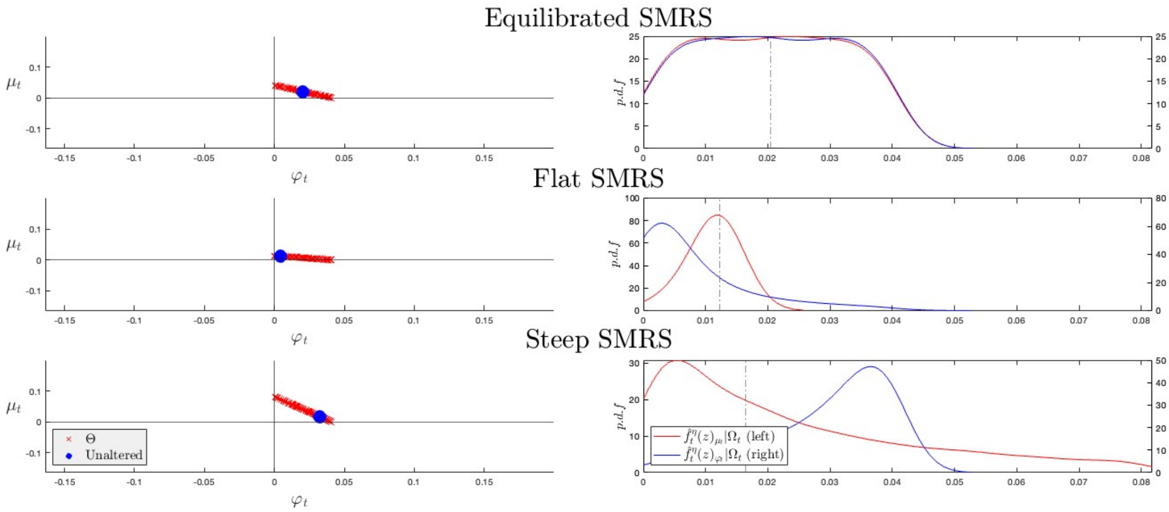
Figure B.2: IRFs to preference shock



C Distribution normalization

We normalize the distribution of shocks because the unobserved component of equation (3) implies that there results of simply altering the gradient of the problem as shown in (2) implies that we are discriminating towards shocks in the direction of the observed state variables. For exposition of the need for normalization figure C.1 shows the same result as figure 4 without our normalization procedure. in the left hand side we can see that in case of an inflationary shock the shock combinations found would consist of inflationary supply and demand shocks only. We render these result as too restrictive since we intuitively cannot reject the hypothesis that inflation is driven by one large inflationary shock, while being compensated by a mildly deflationary observation of the others. these combinations would appear outside the first quadrant of the figures on the left panels.

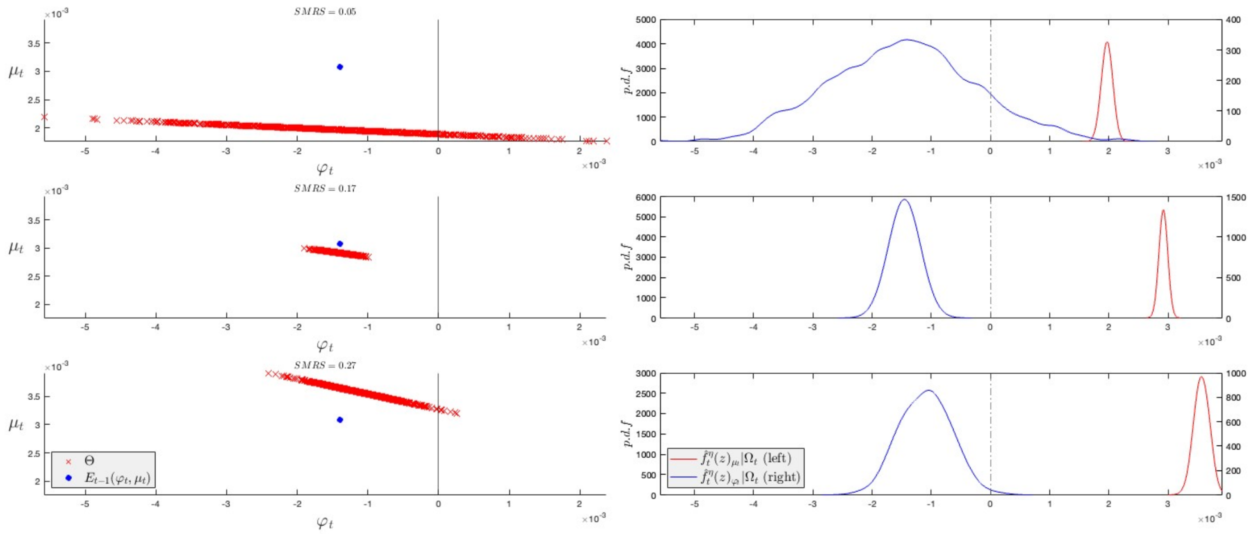
Figure C.1: $\hat{F}_t^{\eta}(z)|\Omega_t$ without normalization



D Supplementary figures section 4

In the figure below we can observe that, consistent with the intuition provided in the text, the steeper the SMRS is, the less identified the supply shock is. This feature, as well as the different model dynamics that are at play after a change of a structural parameter, explain the main results found.

Figure D.1: SMRS with different NKPC slopes for estimated Smets and Wouters (2007)



The three panels on the left show the set Θ ($n = 10.000$) for three different slopes of the NKPC. The red (blue) lines on the right panels of the figure corresponds to the marginal pdf of the conditional shock distribution with respect to supply (demand) shock. To calibrate these scenarios we artificially changed the estimated parameter π_3 by multiplying it by 5 for the Steep case, and by 10 for the Very steep one.