Sources of Recent Inflation: Narrative System Priors for DSGEs

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Abstract

This paper introduces narrative system priors for Dynamic Stochastic General Equilibrium (DSGE) models, merging narrative restrictions with system priors to enhance model estimation for policy. Narrative restrictions align structural shocks and parameters to deliver outcomes of a model, significantly refining inference compared to traditional prior restrictions. Meanwhile, system priors provide transparent and economically meaningful constraints on model features, such as the moments of latent variables, impulse response functions, and historical variance decompositions, offering a complementary approach to traditional independent parameter priors-based inference. The problem the econometrician is facing with large-scale DSGE models, however, is that these system priors are highly non-linear functions of structural parameters and in some cases the shocks (for example, latent variables' moments, non-linear functions of steady-state parameters, or historical importance of shocks). As shown, in the latter case, an additional sampling step is required. We combine the two approaches and apply them to identify DSGE models and illustrate the impact of narrative system priors on economic evidence. We demonstrate the usage of this narrative approach by examples of Volker disinflation and the role of supply vs. demand shocks in the recent pandemic episode. Estimation with narrative system priors shows promising result in aligning the evidence from structural, DSGE model and time series models.

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1 Introduction

Dynamic Stochastic General Equilibrium (DSGE) models have become foundational in macroeconomic analysis, adeptly merging theoretical constructs with empirical data to elicit patterns and model properties obscured in the data. A pivotal component of these models is the role of priors in shaping estimation outcomes. The current paradigm elicitates priors for the structural parameters, only recently has the popularity of endogenous, or system priors increased. They not only guide the parameter estimation process but formulate priors over functions of these parameters to enhance the model's capacity to reflect real-world economic dynamics (Andrle and Plašil, 2018).

This paper advances DSGE estimation by integrating of economic narratives into DSGE prior elicitation through narrative system priors. Recent advancements in econometrics underscore that economic narratives act as collective model selection mechanisms, aligning model outcomes with stylized facts or incorporating other sources of information. More importantly in practice, narratives are implicitly applied to model selection through the research's exploitative phase. We propose to integrate beliefs about narratives into the model estimation asserting that narratives are essential for structural identification . (Antolín-Díaz and Rubio-Ramírez, 2018).

Prior formation in DSGE models is crucial for ensuring robust and reliable estimation results. The unknown target density of canonical DSGE models features flat regions resulting in challanges for model identification, as it was shown for the Smets Wouters model (Farkas and Tatar, 2020), therefore priors serve as a foundational ingredient for model identification, particularly when empirical data is scarce or noisy, like that of most macroeconomic time series. Priors constrain the parameter space, leading to more stable estimates and enhance the model's predictive power (Del Negro and Schorfheide, 2008) , while penalizing the likelihood. Prominent practice is that priors are formed over deep parameters of the model, based on partial equilibrium and causal relationships derived from theory and empirical microeconometric where identification is a focus. In other words the current paradigm prescribes structural, bottom-up prior elicitation.

On the other end of the spectrum are system priors. System priors emphasize overarching model characteristics, features of the model after having confronted the data, in order to facilitate a more cohesive integration of economic theory into the modeling framework. System priors allow for the incorporation of economically meaningful constraints, aligning the model more closely with theoretical expectations and empirical observations (Lombardi and Nicoletti, 2012; Andrle and Plašil, 2018).

System priors introduce complex dependencies among structural parameter priors, facilitating the imposition of intuitive and economically meaningful constraints on the model. This approach addresses the limitations of independent parameter priors, which often lead to unintended consequences on the model's

properties. By formulating priors on system properties such as impulse response functions and conditional correlations, historical decompositions, researchers can impose aggregate behavior constraints that resonate well with economic theory and intuition.

However, the system priors are in most cases a non-linear functions of structural parameters and in same cases, that of the shocks. Our work contributes to the formulation of system priors, by generalizing their theory. We show that system priors dependent on the estimated shock processes require an additional sampling step to properly integrate, or in the extreme case, truncate the likelihood and or priors. We make narrative system priors for DSGE feasible in estimation , and show that narrative restrictions combined with system priors a broad range of penalized likelihood and Bayesian estimation methods for DSGEs.

Understanding the dynamic causal effects of structural shocks is a central challenge in macroeconometrics. The traditional reliance on point-identifying restrictions in structural vector autoregressions has been increasingly questioned due to their restrictive nature. In response, the field has seen a shift towards set-identifying sign restrictions, as introduced by Uhlig (2005), which offer a more robust framework by allowing for a range of possible values rather than a single point estimate.

A more recent advancement in this area is the concept of narrative restrictions (NR), which substitute or augment traditional restrictions on structural parameters. NR involve inequalities related to structural shocks during specific historical periods, ensuring that the SVAR's predictions align with narratives about macroeconomic variations (Antolín-Díaz and Rubio-Ramírez, 2018; Ludvigson et al., 2017; Giacomini et al., 2023). These restrictions promise to deliver informative inferences about the effects of structural shocks under weak or uncontroversial assumptions.

Our paper builds on these advancements by exploring the integration of narrative system priors within DSGE models. We propose a novel approach that combines narrative restrictions with system priors to enhance the estimation of economic models. By leveraging historical narratives, our approach aims to improve the representation of real-world economic dynamics and address the challenges faced in structural identification and estimation. It contributes to the growing literature on Narrative Restrictions (henceforth NR), as well as to the DSGE estimation literature.

The integration of narrative system priors and NR into DSGE models represents a significant advancement in macroeconomic modeling. By leveraging historical narratives and system properties, researchers can enhance the estimation process, offering more robust and informative inferences that leads to models that are compatible with intentions. This paper contributes to the literature by providing a comprehensive analysis of identification and inference of DSGEs with NR, proposing a robust Bayesian approach, and highlighting the potential of system priors in macroeconomic analysis.

2 Narrative System Priors

The integration of narrative system priors into macroeconomic models represents a significant advancement in econometrics. This approach merges the strengths of NR with the flexibility and robustness of system priors, aiming to enhance the estimation and inference capabilities of these models. However, despite their promise, NR pose significant econometric challenges. The non-standard nature of these restrictions means that traditional identification results are inapplicable, and there is no known valid frequentist procedure for inference.

NR based on data realizations, like that based on historical variance decopositions (HVD) (Antolín-Díaz and Rubio-Ramírez, 2018) or shocks (Ludvigson et al., 2017) contributions in given times often rely on a Bayesian procedure that truncates the likelihood, as proposed by Antolín-Díaz and Rubio-Ramírez (2018). This approach, being an accept-rejection set restriction, computes likelihood weights that impact posterior maximization by favoring parameter values that minimize the ex ante probability of satisfying the NR. This highlights the dependence between the probability and occurrence of the narrative event and the parameters themselves. Consequently, NR based on likelihood truncation are sensitive to prior choice, complicating the interpretation of empirical results.

To address these challenges, Giacomini et al. (2023) propose an agnostic robust Bayesian approach that eliminates prior sensitivity by truncating the prior over the rotation angle in an SVAR. This method ensures validity from both Bayesian and frequentist perspectives while retains agnosticism of the priors and likelihood shape.

We concur that in essence, both approaches—likelihood truncation and prior truncation—are equivalent, as they ultimately result in the NR penalizing the likelihood and truncating the posterior, as the posterior is the product of the prior and the likelihood. Moreover the purpose of Bayesian estimation is to introduce curvature into the posterior, when the likelihood is flat and hard to traverse for optimizers. However each approach has differing philosophical considerations. Ex ante likelihood truncation restricts the model by carving out sets from the structural errors' distributions incompatible with NR, implying that NR incompatible data is cannot exist. Conversely, robust Bayesian inference, prior truncation, retains the likelihood's shape but carves out incompatible constellations from the prior parameter space given specific data realizations, thus allowing all possible combination of structural shocks to exist, and imposing the NR on the constellation of priors. Both approaches have merits but ultimately result in the same outcome, the posterior needs to be compatible with the NR.

We argue that in DSGE prior elicitation, both approaches should be employed. The curvature introduced by likelihood truncation of NR is a desired property as it contributes to model identification. Prior truncation,

both data-independent and dependent, is commonly practiced by DSGE researchers when forming priors over deep parameters. For example, ensuring the Taylor principle involves truncating the coefficient on the inflation gap in the interest rate rule to be higher than one, or limiting the slope of the Phillips curve to be positive. The rejection of parameters under which the model has no stable unique equilibrium, a fundamental assumption of rational expectations equilibria, can be also seen as a NR.

Since both approaches impact the posterior, by penalizing it, they are equivalent, either can be effectively utilized.

Nevertheless throughout our paper, we advocate for likelihood truncation while leaving priors over structural parameters unaltered. Priors over deep parameters are typically formed by observing partial equilibrium and theoretically motivated relationships. In other words, DSGEs in macroeconomic modeling are derived from a constellation of partial equilibria where parameters governing behaviors are narrowly defined.

In contrast, structural shocks of DSGEs receive far less attention, and are usually treated as residuals and unknowns with highly misspecified processes of the true shocks, with properties like autoregression coefficients and moving average terms flexibly adapted to match data properties. Therefore, we see them as a preferred object to be constrained by NR. The main contribution of robust Bayesian inference by Giacomini et al. (2023) is to assess the sensitivity of the posterior to the choice of the priors on the flat regions of the likelihood. The merit of likelihood truncation a'la Antolín-Díaz and Rubio-Ramírez (2018) is the penal

We argue that conventional DSGE models frequently encounter difficulties in embodying fundamental economic insights due to their rigid structures, the incorporation of narrative-driven priors offers a potential remedy to this challange. However, this approach is not without challenges; the subjectivity introduced by narrative identification can complicate the estimation process. Striking a balance between narrative insights and the rigorous development of priors remains a pivotal challenge in the advancement of DSGE modeling.

3 Motivation

To illustrate the unwanted properties of DSGEs, we estimate the Smets-Wouters model (SW) with US data for the period 1960Q1–2004Q4. The SW model is medium-scale closed economy DSGE model and it has become the standard workhorse model for economic policy analysis and served as a basis for newer generations of DSGE models. We estimate the model using seven key macroeconomic variables: real GDP, real consumption, real investment, the GDP deflator, real wages, employment and the nominal short-term interest rate. [1] The model features a deterministic growth rate driven by labour-augmenting technology

[1]Both real consumption and investments are deflated using the GDP deflator. The hours variable is defined as average weekly hours of all persons in the non-farm business sector times total civilian employment. Originally in Smets and Wouters (2007a) the model was estimated for the sample 1966Q1-2004Q4, however e.g. Cai et al. (2021) also estimated the model starting from 1960Q1. Johannes Pfeiffer's replication package written in Dynare contains data from 1947.

progress and is subject to nominal and real frictions. Nominal rigidities affect the labour and goods markets via Calvo pricing similar to Christiano et al. (2005). Both wages and intermediate product markets are subject to partial indexation to lagged inflation. The real frictions are investment adjustment- and capital utilization costs. Monetary policy follows a Taylor-type rule with interest rate smoothing and a reaction to the inflation gap and the output gap.[2]

The exogenous variation of the model is driven by seven shock processes with estimated conditional variances: standard total factor productivity, monetary policy, investment specific technology, exogenous spending and risk premium and a wage and a price markup shock with an additional MA(1) structure.[3] The latter setup introduces anticipated news shocks for both the regular and the wage Phillips curve. The model is log-linearized around the steady state and net of deterministic growth rate.

3.1 Was the Volker Disinflation Monetary?

By estimating the SW model, we found, surprisingly, that the monetary shock only accounted for about 16 percent of the decline in inflation by the fourth quarter of 1980 during the Volker disinflation. The estimation with priors only on the structural parameters would play a major role in supply shocks (price and wage markup, technology, investment specific technology) in the disinflation process. However, from narrative, historical analysis and the following Antolín-Díaz and Rubio-Ramírez (2018) can suspect that it was a predominantly monetary policy change and, moreover, a tightening of monetary conditions. Below, we will demonstrate that imposing a narrative restriction following our methodology on the historical decomposition of shocks, we can estimate the model such that during this period monetary shocks were the driving force in the evolution of Fed Funds Rate. Then, we will show the implications for the estimated parameters, the impulse responses.

4 Methodology

The method for implementing narrative system priors follows as a natural generalization of Andrle and Plašil (2018) with narrative restrictions. The following discussion first reviews system prior and shows that it is a special case of narrative restrictions, and then derives narrative system priors.

Suppose that $p(y|\theta_k, M_k)$ is the density function of the data $y = (y_1, y_2, ..., y_t)$ under model M_k given model-specific parameters θ_k, where k is either the index of the model, i.e. a discrete variable $(k = 1, 2, ..., K)$, or defines a set of models, i.e. is continuous variable on a measure $\otimes$.

[2]The inflation gap is defined as the deviation from the steady state inflation and the output gap is the difference of output and its flexible price counterpart.

[3]The monetary policy shock is *iid*. To introduce anticipated news shocks we augment the model with auxiliary state variables, similar to Dynare, so the Binder-Pesaran algorithm can be easily applied.

Let the proper prior density of the parameters be given by $p(\theta_k|M_k)$, and let $p(\theta|y, M_k)$ be the posterior density of the parameters given data and model.

Let us define the model using a sufficient statistic $\Psi(\theta_k, y_{\tau,k})$, a function of the deep-parameters and the data until a point in time τ given a model k, that has a proper prior density of $p(\Psi(\theta_k, y_{\tau,k}))$, which is called the system prior Andrle and Plašil (2018). Note the dependence of $p(\Psi(\theta_k, y_{\tau,k}))$ on the data $y_{\tau,k} = (y_{1,k}, y_{2,k}, ...y_{\tau,k})$. Since the DSGE as a filter can invert the data to structural shocks, this forumulation of the system prior is equivalent to the system prior being a function of not only the deep parameters θ but the realized sequence $\epsilon_{1:\tau}$ of structural shocks.

In other words the system prior can be of a property of the model given the data. Although the data is fixed in Bayesian estimation, the prior belief is defined over the structural shocks sequence and parameters, and a priori the structural shocks cannot be treated as given. It is sufficient to realize that the DSGE merely maps the initial states and the structural shocks into observables:

$$p(y_{1:\tau,k}|\theta) = \int \int p(y_{1:\tau,k}|\theta, \epsilon_{1:\tau}, x_0) dx_0 d\epsilon_{1:\tau}$$

Where x_0 is the initial states of the model, that itself is a function of the structural parameters and $\epsilon_{1:\tau}$ is the realization of the structural shocks until period τ.

This representation enables us to rewrite the system prior as a function of the deep parameters and the sequence of structural shocks that generate the data given the parameters $\Psi(\theta_k, y_\tau) = \Psi(\theta_k, \epsilon_{1:\tau}|\theta_k)$. Simplifying the notation we can drop k and the conditioning of the structural shocks on the deep parameters, as they are inputs of the system priors, that is $\Psi(\theta_k, \epsilon_{1:\tau}) = \Psi(\theta, \epsilon_{1:\tau})$. This representation makes it clear that (narrative) system priors are priors about not only the deep parameters but the structural shocks of the data generating process itself. The representation states that the system priors are a function of the structural parameters and the shock realizations. Furthermore, we argue that it is innocouos to assume that the priors over deep parameters of the model are independent of the system priors. The latter assumption implies that $p(\theta|\Psi(\theta_k, \epsilon_{1:\tau})) = p(\theta)$.

Then Bayes' rule can be written as:

$$p(\theta|y, \Psi(\theta, \epsilon_{1:\tau})) = \frac{p(\theta|\Psi(\theta, \epsilon_{1:\tau}))p(y|\theta, \Psi(\theta, \epsilon_{1:\tau}))}{\int p(\theta|\Psi(\theta, \epsilon_{1:\tau}))p(y|\theta, \Psi(\theta, \epsilon_{1:\tau}))d\theta} = \frac{p(\theta)p(y|\theta, \Psi(\theta, \epsilon_{1:\tau}))}{\int p(\theta)p(y|\theta, \Psi(\theta, \epsilon_{1:\tau}))d\theta} \tag{1}$$

The latter simplification holding because the prior distribution, $p(\theta)$, depends only on θ; that is the system prior is not affecting the priors over the deep parameters. As in Antolín-Díaz and Rubio-Ramírez (2018), the system prior characterizing the narrative restrictions depending on the data will not truncate the prior of the

parameters of θ, but the likelihood function.

The a priori likelihood that satisfies the narrative system prior, applying Bayes' rule, can be written as

$$p(y|\theta, \Psi(\theta_k, \epsilon_{1:\tau})) = \frac{p(\Psi(\theta, \epsilon_{1:\tau})|\theta, \epsilon_{1:\tau})p(y|\theta)}{\int p(\Psi(\theta, \epsilon_{1:\tau})|\theta, \epsilon_{1:\tau})p(\epsilon_{1:\tau}|\theta)d\epsilon_{1:\tau}} \tag{2}$$

Combining the truncated likelihood with the narrative system prior and the prior over the deep parameters results in the posterior:

$$p(\theta|y, \Psi(\theta, \epsilon_{1:\tau})) = \frac{p(\theta)p(y|\theta)}{\int p(\theta)p(y|\theta, \Psi(\theta, \epsilon_{1:\tau}))d\theta} \cdot \frac{p(\Psi(\theta, \epsilon_{1:\tau}))}{\int p(\Psi(\theta, \epsilon_{1:\tau})|\theta, \epsilon_{1:\tau})p(\epsilon_{1:\tau})d\epsilon_{1:\tau}} \tag{3}$$

The first term is akin to the posterior of a model without system priors, prior times likelihood divided by a constant. Note the difference in the denominator, i.e. the marginal likelihood, as it is conditional on the system prior.

The second term is the impact of the narrative system prior, where the numerator is the narrative system prior and the denominator is the a priori weight associated with it. It represents a penalty to the posterior, and ensures that only models are admitted that satisfy the narrative system prior. Note the denominator of the second term, it weights the system prior with the probability once structural shock uncertainty is integrated out. It is a correction for the density, such that the posterior under the narrative system priors is a priori proper. This term is numerically challenging to compute and lead in the past to treat it as a constant, and be bundled into the normalizing constant together with the marginal likelihood. The readily available endogenous priors feature in Dynare and advances in computational power allows to overcome such limitations and renders estimation feasible.

4.1 Implementing Narrative System Priors

This section presents the general algorithm to implement narrative system prior estimation. The algorithm uses sequential importance sampling Monte Carol sampling during the numerical optimization routine to render the computation of the weight feasible. We realize that the high autocorrelation of the deep parameters when sampling the posterior lead to high autocorrelation of the components the narrative system prior weight. By initializing the weight at a numerically approximated distribution and using the previous step as proposal densities, one can render estimation of larger models feasible. For step i one can use the previous steps' probability that the ex-ante likelihood satisfies the NSP as the proposal density in a sequential MCMC algorithm, therefore the the weighting representing the ex-ante marginal likelihood integrating out the

uncertainty of the structural shocks ($p(\epsilon_{1:\tau}^{(i)}|\theta^{(i)})$) satisfying the narrative system prior ($p(\Psi(\theta^{(i)}, \epsilon_{1:\tau}^{(i)}))$) :

$$\frac{1}{\int p(\Psi(\theta, \epsilon_{1:\tau})|\theta, \epsilon_{1:\tau})p(\epsilon_{1:\tau})d\epsilon_{1:\tau}} = 1/w^{(i)} \propto \frac{1}{w^{(i-1)}} \tag{4}$$

This enables to cut back the computational time controlled for the information in the conditioning we can fully characterize the predictive distribution[4].We can then use the following algorithm to generate draws from the posterior distribution of a DSGE with NSP:

Algorithm 1: Posterior sampling of a DSGE with Narrative System Priors

1 Initialize a draw, θ^0, from the target density, either at a mode, or preferably in a point of the typical set, and compute the log-posterior: $\ln p(y|\theta^0)$ + $\ln p(\theta^0)$ + $\ln p(\Psi(\theta^0, \epsilon_{1:\tau}))$ - $\ln(w^0)$.

2 This includes the solution of the DSGE model for θ^0 and the evaluation of the log-likelihood:

$$\ln p(y|\theta^0)$$

, log-prior:

$$\ln p(\theta^0)$$

, log-narrative system prior:

$$\ln p(\Psi(\theta^0, \epsilon_{1:\tau}))$$

, where $\epsilon_{1:\tau}$ are the filtration of the structural shocks given θ^0, as well as, the and numerical approximation of the NSP weight,

$$\ln(w^0) = \ln n_{sim} \sum_{k=1}^{n_{sim}} \frac{1}{p(\Psi(\theta^0, \epsilon_{1:\tau}^k)}$$

, based on n_{sim} number of simulations.

3 Compute Σ, the inverse of the Hessian at θ^0.

4 Define the proposal density $q(\theta|\theta^0)$. Without loss of generality, using a Metropolis-Hastings MCMC sampler, it is $q(\theta|\theta^0) = N(\theta^0, c_0^2\Sigma)$.

5 **for** $j \in \{1, 2, ..., N\}$ *draws from the posterior* **do**

a Draw θ' from the proposal distribution.

b Solve the DSGE model for θ' and evaluate $p(Y|\theta')$, $p(\theta')$, $p(\Psi(\theta', \epsilon'_{1:\tau}))$,

c Estimate the NSP weight,w' by simulating the model with filtration for $\epsilon_{1:\tau}$ and θ' as:

$$w' = n_{sim} \sum_{k=1}^{n_{sim}} \frac{1}{p(\Psi(\theta', \epsilon_{1:\tau}^k))}$$

6 **end**

7 Accept θ', i.e. $(\theta^{(n)} = \theta')$, with probability $\min\{1, f(\theta^{(n-1)}, \theta'|Y)\}$ and reject $(\theta^{(n)} = \theta^{(n-1)})$ otherwise, where

$$f(\theta^{(n-1)}, \theta'|Y) = \frac{p(Y|\theta')p(\theta')p(\Psi(\theta', \epsilon'_{1:\tau}))q(\theta'|\theta^{(n-1)})}{p(Y|\theta^{(n-1)})p(\theta^{(n-1)})p(\Psi(\theta^{n-1}, \epsilon_{1:\tau}^{n-1}))q(\theta^{(n-1)}|\theta')}.$$

8 Estimate the posterior expected value of the function $h(\theta)$ by $\frac{1}{N}\sum_{i=1}^{N} h(\theta^{(i)})$.

In the what follows we collect on the first sight, distinct-looking DSGE estimation methods and cast

[4]This rests on the assumption that the parameter posterior $p(\theta)$ remains unchanged, that is we disregard the information content of the external information with respect to the model parameters.

them as narrative system prior to prove that it generalizes DSGE estimation techniques in a comprehensive framework.

4.2 System Priors as a Special Case of Narrative System Priors

Note if narrative system priors are independent of the data, that is if

$$\Psi(\theta, y) = \Psi(\theta) \tag{5}$$

holds, then the denominator in the second term in 3 will integrate to 1. Therefore the posterior will

$$p(\theta|y, \Psi(\theta, y)) \propto p(\theta)p(y|\theta)p(\Psi(\theta)|\theta) \tag{6}$$

With this we showed that system priors in Andrle and Plašil (2018) is a special case of the narrative system priors we propose.

5 Drivers of Post-Pandemic Inflation and Narrative System Priors

To illustrate the impact of narrative restrictions for DSGEs we estimate the SW model with NSP. The SW model is a medium-scale closed economy DSGE model. It has become the standard workhorse model for economic policy analysis and served as a basis for newer generations of DSGE models. We estimated the model with US data for the period 1960Q1–2024Q4 using seven key macroeconomic variables: real GDP, real consumption, real investment, the GDP deflator, real wages, employment and the nominal short-term interest rate.[5] The model features a deterministic growth rate driven by labour-augmenting technology progress and is subject to nominal and real frictions. Nominal rigidities affect the labour and goods markets via Calvo pricing similar to Christiano et al. (2005). Both wages and intermediate product markets are subject to partial indexation to lagged inflation. The real frictions manifest themselves as investment adjustment and capital utilization costs. Monetary policy follows a Taylor-type rule with interest rate smoothing and a reaction to the inflation gap and the output gap.[6]

The exogenous variation of the model is driven by seven mostly AR(1) shock processes with estimated conditional variances: standard total factor productivity, monetary policy, investment specific technology,

[5]Both real consumption and investments are deflated using the GDP deflator. The hours variable is defined as average weekly hours of all persons in the non-farm business sector times total civilian employment. Originally in Smets and Wouters (2007a) the model was estimated for the sample 1966Q1-2004Q4, however e.g. Cai et al. (2021) also estimated the model starting from 1960Q1. Johannes Pfeiffer's replication package written in Dynare contains data from 1947.

[6]The inflation gap is defined as the deviation from the steady state inflation and the output gap is the difference of output and its flexible price counterpart.

exogenous spending and risk premium and a wage and a price markup shock with an additional MA(1) structure.[7] The latter setup introduces anticipated news shocks for both the regular and the wage Phillips curve. The model is log-linearized around the steady state and net of deterministic growth rate.

To account for the effective lower bound and the associated unconventional monetary policy mix, we explicitly model forward guidance using anticipated monetary policy shocsk.

5.1 Forward Guidance and Wage Markup Shocks

We introduced anticipated monetary policy shocks which are identified during periods of the effective lower bound (ELB) binding using the yield curve. Outside of periods of explicit forward guidance, we let the recovered forward guidance shocks to be determined by the fit to the data.

We follow the concept of credible, Odyssean forward guidance from Andrade et al. (2019) and implement them as anticipated monetary policy shocks, i.e. the agents have clairvoyance about the future shocks of monetary policy.

Anticipated news shocks provide a framework to study agents' response to information about fully expected events or shocks. They have been widely used in the DSGE literature and are implemented as lagged structural shocks capturing the information content of future policy actions. Incorporating anticipated news shocks requires expanding the baseline model's Taylor rule to include the moving-average representation of these shocks. This change in the model's structure is necessary to capture the impact of anticipated news shocks and their role in shaping agents' expectations and has implications for the reaction of agents to other shocks as well. In other words, the integration of anticipated news shocks not only changes the information available in the model but also affects how rational agents behave, as it alters the policy function—or decision-making process—of these agents. As the passage indicates, accounting for anticipated news shocks can transform the characteristics of supply shocks, turning them into demand shocks, which has broader implications for economic analysis and policy responses.

Thus incorporating anticipated news shocks in the SW07 model requires modifying the Taylor rule and expanding the model's structure. This extension allows for the analysis of forward-looking adaptive beliefs in response to a credibly committed forward guidance.

$$r_t = \rho r_{t-1} + (1-\rho)(\theta_\pi \pi_t + \theta_x x_t) + \epsilon_t^R + \sum_{l=1}^{L} \epsilon_{t-l}^{R,FG,l} \tag{7}$$

Anticipated news shocks in this representation are announcements by the central bank in period $t-l$ that the interest rate will change l periods later, i.e. in period t. They can be implemented in a DSGE with the

[7] The monetary policy shock is *iid*.

help of new auxiliary variables $f_{k,t}$, that capture the cumulative impact of the forward guidance for periods beyond k and have a recursive definition, as proposed by Laséen and Svensson (2011):

$$f_{k,t} = f_{k+1,t-1} + \epsilon_t^{R,FG,k}. \tag{8}$$

If the central bank communicates guidance on the interest rate for L periods ahead, there would be $1, 2, 3...L$ forward guidance shocks that affect the monetary policy rule in period t, and thus the Taylor Rule can be written recursively as follows:

$$r_t = \rho r_{t-1} + (1-\rho)(\theta_\pi \pi_t + \theta_x x_t) + \epsilon_t^R + f_t, \tag{9}$$

$$f_t = f_{1,t-1}, \tag{10}$$

$$f_{1,t} = f_{2,t-1} + \epsilon_t^{R,FG,1}, \tag{11}$$

$$f_{2,t} = f_{3,t-1} + \epsilon_t^{R,FG,2}, \tag{12}$$

$$f_{3,t} = f_{4,t-1} + \epsilon_t^{R,FG,3}, \tag{13}$$

$$\vdots \tag{14}$$

$$f_{L,t} = \epsilon_t^{R,FG,L}, \tag{15}$$

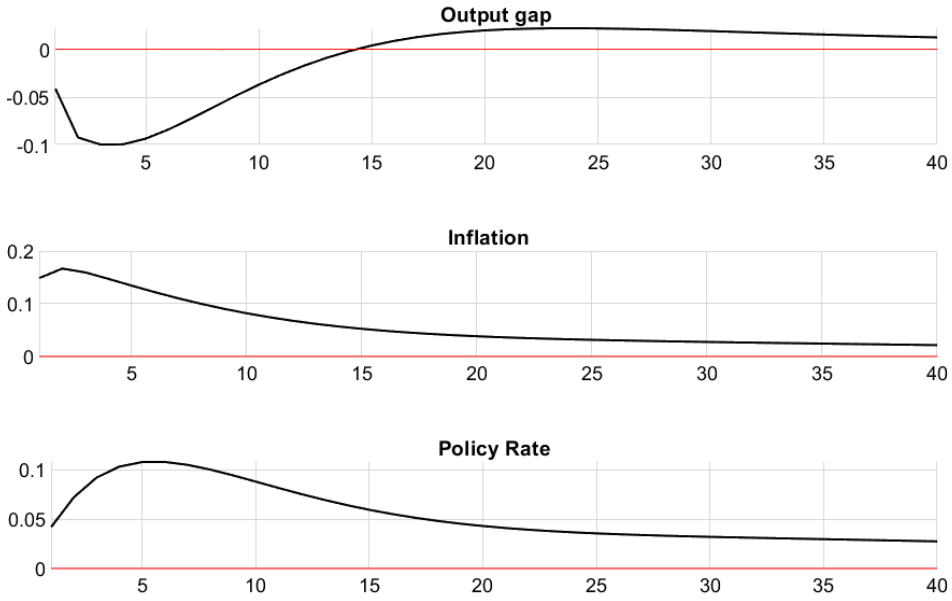
Note the missing index for the auxiliary variable f_t as it is the cumulative forward guidance shock in period t entering the Taylor rule, f_t is the sum of all news shocks revealed in period t: $f_t = \sum_{l=1}^{L} \epsilon_{t-l}^{R,FG,l}$

When analyzing the dynamics of wage markup shocks in an economy where monetary policy remains unchanged, it is crucial to understand the implications on inflation, employment, and overall economic stability. Wage markup shocks refer to sudden and unexpected changes in wages that are not aligned with productivity gains, often resulting from bargaining power shifts between employers and employees, or external factors like regulatory changes and social movements advocating for higher wages. In cases when monetary policy has promised not to change the interest rates, a sudden increase in wages can lead to both increased prices and output on impact. The main channel is through inflation, although wage increases boost consumer demand , as households have more disposable income,the inflationary pressures are muted. Wage gains are not offset by reductions in investments and by resulting expected increases in marginal costs, thus inflation does not increase the same degree. The muted response of initial inflation leads to a lower policy rate that in turn does not curb demand.

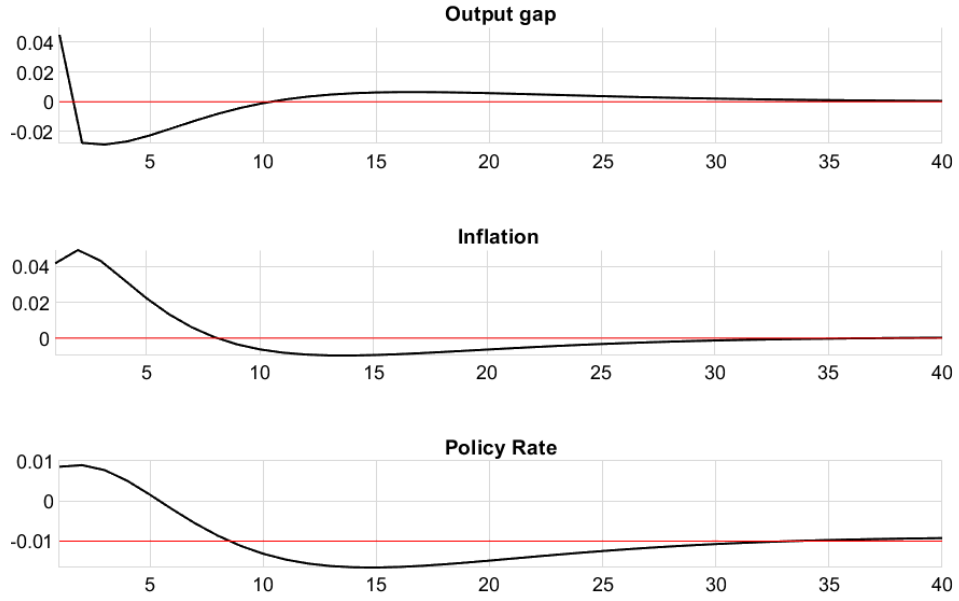
In other words, in the presence of forward guidance, wage markups that appear to be on impact as demand shocks.

Figure 1: Transmission of Wage Markup Shocks

(a) Original Smets-Wouters Model



(b) Smets-Wouters Model with Forward Guidance



Notes:The wage markup impulse responses are obtained with the estimated model parameters of the SW model on the updated dataset 1960Q1-2023Q4.
The top panel (a) shows the transmission of the wage markup shocks in the SW model; (b) the lower panel shows the transmission of the wage markup shocks in the SW model with forward guidance shocks up-to 6 quarters ahead.
Source: authors' calculations.

We show this shifting nature wage markup shocks in the following Figure: The top panel, Figure 1a, shows the usual transmission of wage markup shocks in the SW model where wage markups drive up inflation, and demand drops as monetary policy contemporaneously responds.

The lower panel, Figure 1b, shows the transmission of wage markup shocks in the SW model with forward guidance shocks. As anticipated monetary policy shocks are set zero, the on impact reaction of monetary policy is muted leading to, on impact, increased inflation and output. In summary, the absence of monetary policy interventions in response to wage markup shocks changes the classification of the shock in a simple sign-restriction setting.

5.2 Volker Disinflation

Using our method, we impose a narrative prior that monetary policy shock is the overwhelming driver of the unexpected movement in the federal funds rate. In other words, the absolute value of the contribution of monetary policy shocks to the unexpected movement in the federal funds rate is larger than the sum of the absolute value of the contributions of all other structural shocks. By using this narrative, our estimated parameters are significantly changed for the interest rate smoothing parameter (higher in the case of narrative priors), and trend growth of output (0.5 vs. 0.43). Looking at the resulting impulse responses, we found that the introduction of our narrative prior makes monetary policy less potent on inflation. In addition, the long run variance decompositions also change systematically. The role of financial premium rises in explaining output growth and the role of monetary policy shock rises in explaining inflation variation. The narrative restriction, increased the role of monetary policy shock on inflation during the disinflation to around 24 percent from 16 percent. More notably, the monetary shock accounted for around two thirds in the change in headline inflation. So, disinflation became merely a monetary phenomenon.

5.3 Drivers of Post-Pandemic Inflation - The Narrative

The post-pandemic inflation has emerged as a complex interplay of various economic factors, as highlighted in recent literature. Key elements driving this phenomenon include supply-side disruptions, demand-side rebounds, and shifts in policy stances. We focus on the first two and argue that properly modeling monetary policy stance contributes to a better understanding of the drivers. Understanding these dynamics is crucial for grasping the broader economic implications of pandemic.

The trigger of the pandemic-inflation was the significant supply chain disruptions and labor market constraints that emerged as a direct consequence of the COVID-19 pandemic. Numerous studies indicate that the pandemic resulted in unprecedented bottlenecks within supply chains, leading to shortages of essential

inputs and creating friction in the labor market. These disruptions not only hindered production but also led to increased production costs, thereby exerting upward pressure on prices across various sectors.

As economies began to reopen, a surge in consumer spending was observed, fueled by pent-up demand and expansive fiscal policies. This sudden increase in demand, together with constrained supply, became a pivotal factor contributing to the inflationary pressures evident in the post-pandemic period. The combination of consumers eager to spend and limited availability of goods created a scenario ripe for inflationary trends to take hold.

Additionally, the role of monetary policy cannot be understated. The FED adopted highly accommodative measures during the pandemic, announcing forward guidance to keep interest rates low and quantitative easing policies. While these strategies were instrumental in fostering financial stability and achieving favorable financing conditions, they also inadvertently reinforced inflation expectations among consumers and businesses alike. This shift in expectations has further complicated the inflation landscape, leading to adjustments in wage-setting and pricing decisions.

Additionally, the persistence of inflation has been amplified by second-round effects of wage pressures. As firms face rising costs due to increased demand and supply constraints, they often pass these costs onto consumers through higher prices. Wage increases to attract and retain talent in a tight labor market further contributed to inflation, and in absence of monetary policy tightening further contributed to the inflationary pressures.

Giannone and Primiceri (2024) have studied the source of inflationary dynamics through the lens of VARs identified through sign-restrictions. Their research indicates that the post-pandemic inflation can be attributed to equal share supply and demand shocks. They suggest that while some components, like supply constraints, were temporary, accommodative policy response fueled demand had a similar size effects on inflation. They point out that expansive fiscal policies implemented during the pandemic, such as direct stimulus payments and unemployment benefits, substantially boosted consumer spending, pushing the aggregate demand curve upwards. This surge in demand, coupled with the reopening of the economy, led to increased pressure on prices as businesses struggled to meet the swift uptick in consumer activity. The paper notes that U.S. inflation was influenced by global supply chain disruptions, although these played a less significant role compared to demand factors. The bottlenecks in production and logistics did contribute to higher costs for certain goods, but the predominant inflationary pressure came from domestic demand-side dynamics. As consumers returned to pre-pandemic spending levels, the mismatch between demand and supply capacities further exacerbated inflation. With regards to monetary policy, it argues that the Federal Reserve's initial hesitation to tighten monetary policy allowed inflation to persist longer than anticipated.

To illustrate their point we borrow Figure 2 from their paper. Panel (c) shows that the joint role of

monetary and non-monetary demand far exceeded supply.

In contrast, Bernanke and Blanchard (2023) argue that the the inflation surge beginning in 2021 was predominantly driven by price shocks—particularly from commodities—rather than an overheating labor market. Using a dynamic model, the authors illustrate the complex interactions between prices, wages, and inflation expectations, emphasizing that initial inflation was influenced by fiscal and monetary policies alongside global economic conditions. Bernanke and Blanchard (2023) conclude that while labor market conditions did evolve to impact inflation significantly, the primary factors were external price shocks and sector-specific disruptions, suggesting a nuanced understanding of inflation's drivers is essential for effective policy formulation.

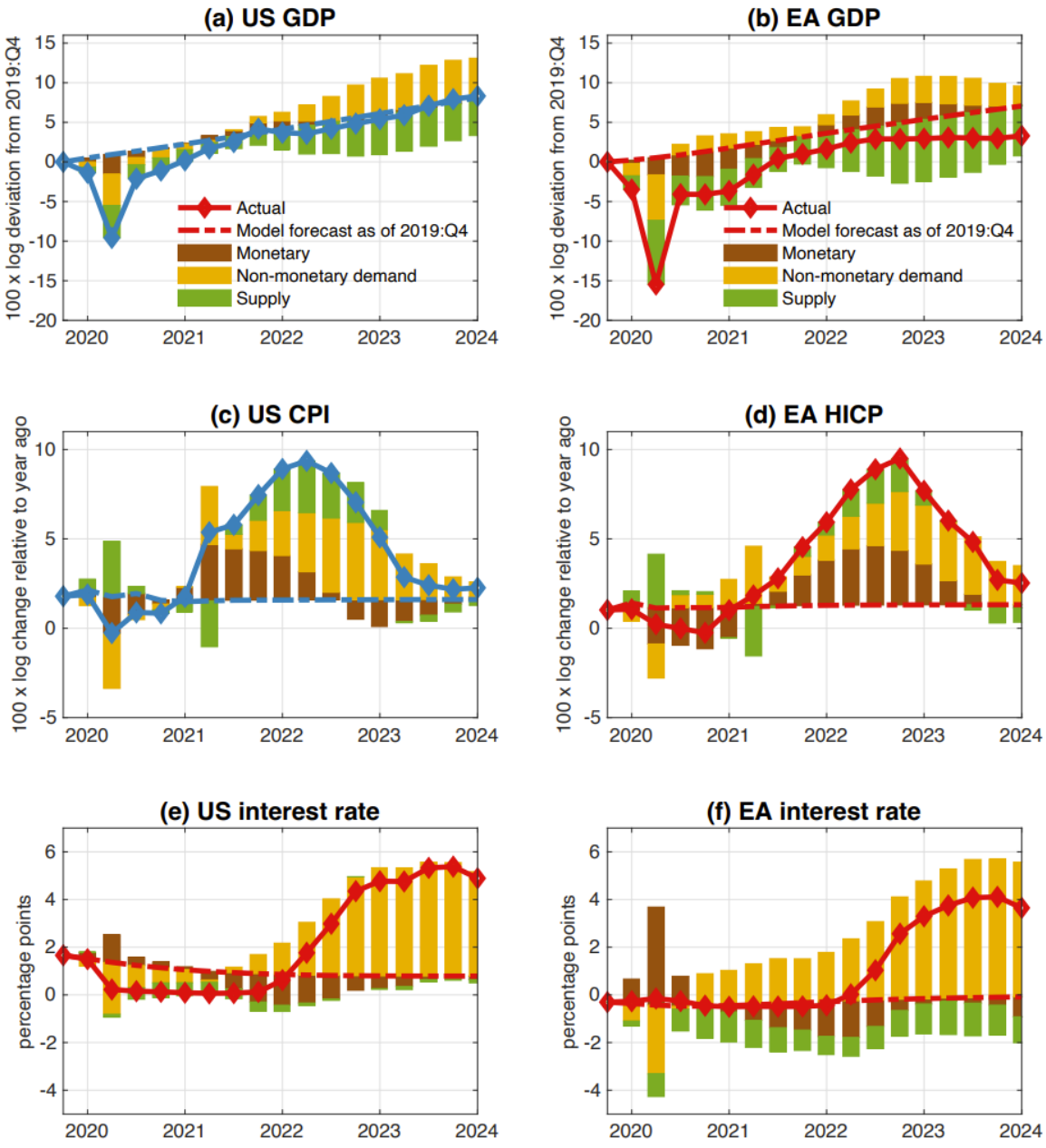
5.4 Drivers of Post-Pandemic Inflation in the Smets-Wouters Model

The Smets-Wouters model is as a structural model serves as the basis of most policy models used in central banks. Therefore it is interesting to understand to which shocks it attributes the surge in inflation. Through the historical variance decomposition of inflation during this period we can understand the relative role of demand and supply factors. To categorize the shocks in the baseline specification of the model we follow Smets and Wouters (2007b) original definition: Demand shocks include the risk premium, investment-specific technology, and exogenous spending shocks; while technology, markup shocks are supply shocks. We leave monetary policy in its own category.

By re-estimating the baseline SW model we can quantify the relative importance of demand, supply, monetary shocks in shaping post-pandemic inflation trends. Figure 3b and 4b shows the historical decomposition of US inflation into its drivers over the period of 2018-2024. Focusing on the onset of the COVID-19 pandemic, the model attributes the drop in inflation to a combination of tight monetary policy, and negative demand shocks, and deflationary price markup shocks. In 2020Q1 the model finds that supply shocks were net inflationary, mainly driven by a positive wage markup shock. A potential misspecification of the markup shocks could be attributed to their ARMA nature, as a key portion of the Pandemic response was a collapse of confidence, that the model has limited scope to account for. As price markups turn inflationary the contribution of supply shocks to inflation increase, leading to accounting for almost all of the rise in inflation following its through. The baseline SW model sees the net effect of monetary policy to be neutral over this episode. Most strikingly, the sum of contribution of demand shocks to inflation remains negative over the rise in inflation, 2019Q4-2022Q1.

In addition, Smets, 2024, and Hodge et al, 2025 also argue that large portion, around half of the surge in inflation was caused by fiscal policy measures, which are also mostly demand shocks in nature. To bring the

Figure 2: Giannone and Primiceri (2024)'s Drivers of the Post-Pandemic Inflation in the US and in the Euro Area



Source:Giannone and Primiceri (2024)

Notes: The model is identified through sign restrictions: "In this three-variable SVAR, we identify three types of disturbances: (i) demand shocks, which are assumed to move GDP, prices and nominal interest rates in the same direction; (ii) supply shocks, which are assumed to move GDP and prices in opposite directions; and (iii) monetary policy shocks, which are assumed to move nominal interest rates in the opposite direction of GDP and prices. The restriction on the sign of the interest rate to identify monetary policy shocks is imposed for four consecutive periods, because we wish to identify meaningful, not just occasional, deviations from the past conduct of monetary policy" (Giannone and Primiceri, 2024, p.19)

narrative evidence that the post-pandemic inflation was most likely a combination of demand and supply factors to an equal degree we use narrative system priors. In estimation we impose the narrative system prior that demand factors accounted for around half of the increase in inflation over 2019Q4-2022Q1. To represent our confidence in the narrative, we assume that the 95% of the narrative prior needs to be in the positive domain resulting it the following NSP:

$$p(\Phi(\theta, \epsilon^{D}_{2019Q4:2022Q1})) \sim \mathcal{N}(0.5 * \Delta\pi, 0.25 * \Delta\pi) \tag{16}$$

where $\epsilon^{D}_{2019Q4:2022Q1})$ denotes the collection of demand shocks, that is shocks that move inflation and output on impact the same direction; $\Delta\pi$ is the change of GDP deflator inflation over 2019Q4-2022Q1, that is our NSP is:

Narrative Restriction: For the periods of 2019Q4-2022Q1, demand shocks' contribution is positive and accounts for around half of the increase in inflation. In other words, the sign of the contribution of shocks moving output and inflation in the same direction is positive, and the sum of the contributions amounts to 50% of the changes in inflation.

To account for unconventional monetary policy and forward guidance we introduced anticipated monetary shocks and re-estimated the SW model with NSP.

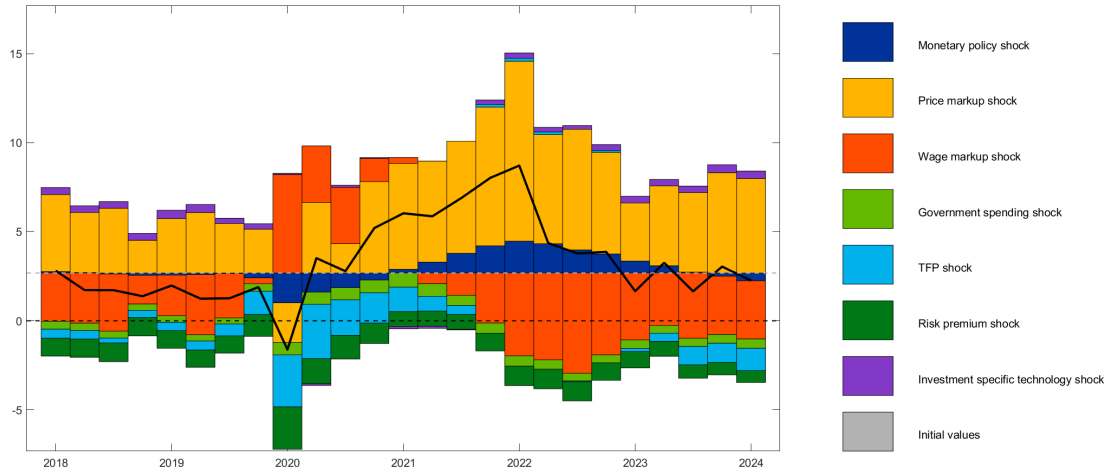
Table 1 compares the posterior estimates of parameters of N Figure 3b and 4b shows the changes in inflation through the lens of the SW model with forward guidance and narrative priors. As discussed before, introducing additional anticipated monetary policy shocks changes wage markups to be demand shocks on impact. One can observe, that with narrative system priors, demand shocks became dominant in the first phase of inflation surge and the supply disruption and commodity price related supply shocks gained importance only afterwards. Later on, demand shocks' role faded away and even turned negative, mostly as a result of negative wage markup shocks. Narrative system priors partially overcame the deflationary role of demand shocks, but did not fully eliminate the disconnect between the DSGE and the VAR based estimates.

Despite NSP, the contribution of demand shocks to post pandemic inflation remains limited in DSGEs that possibly originates from the property of DSGEs that demand factors play a limited role in determining inflation. Or results highlight the potential fallacy of classifying structural shocks as demand and supply without studying their transmission.

Overall, estimation with narrative system priors helps in connecting the DSGE model to the VAR evidence and

Figure 3: Drivers of the Post-Pandemic Inflation

(a) Smets-Wouters Model



Notes:Chart shows the historical variance decomposition of inflation in the original SW model.
Source: authors' calculations.

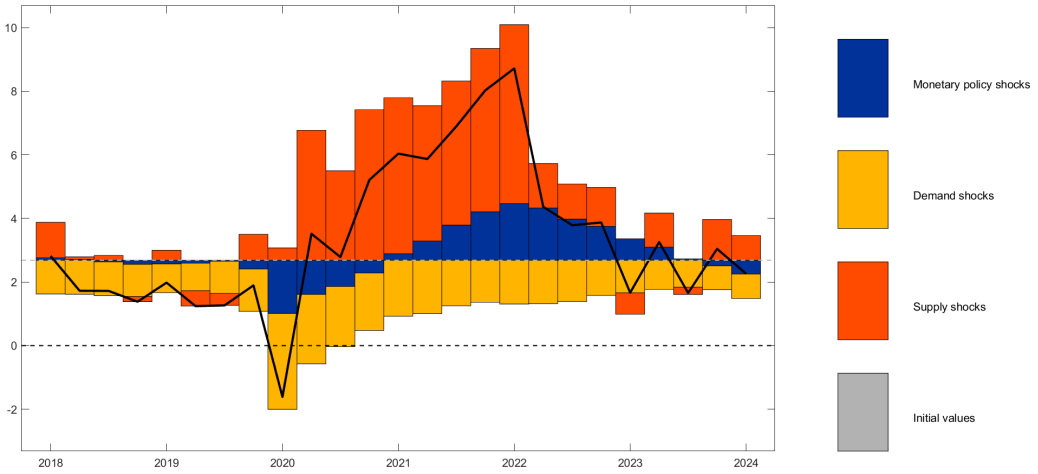
(b) Smets-Wouters Model with Narrative System Priors



Notes:Chart shows the historical variance decomposition of inflation in the SW model with system priors where the system prior is that the contribution of demand shocks explains half of the inflation increase over 2019Q4-2022Q1. The prior has a shape of normal distribution with 50% mean and 25% standard deviation.
Source: authors' calculations.

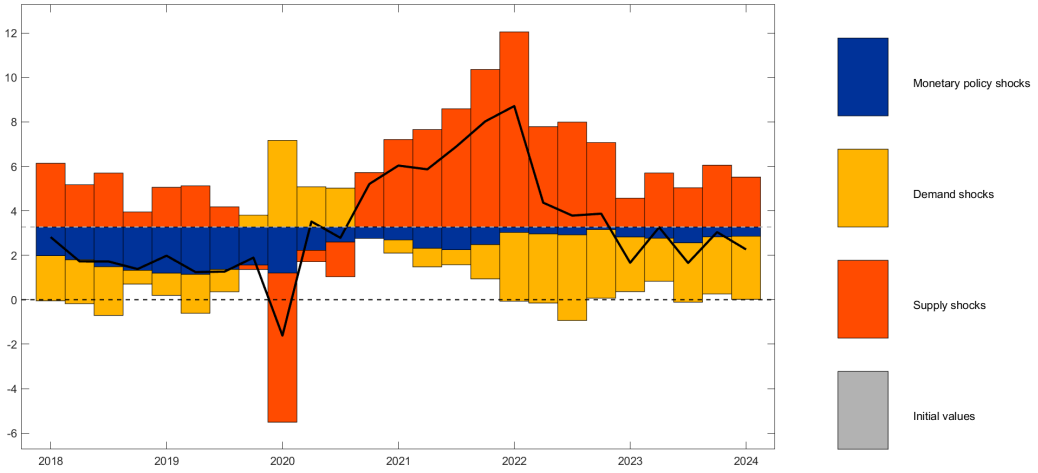
Figure 4: Drivers of the Post-Pandemic Inflation

(a) Smets-Wouters Model



Notes:Chart shows the historical variance decomposition of inflation in the original SW model.
Source: authors' calculations.

(b) Smets-Wouters Model with Narrative System Priors



Notes:Chart shows the historical variance decomposition of inflation in the SW model with system priors where the system prior is that the contribution of demand shocks explains half of the inflation increase over 2019Q4-2022Q1. The prior has a shape of normal distribution with 50% mean and 25% standard deviation.
Source: authors' calculations.

Table 1: Posterior Estimates of the Smets-Wouters Model

	SW Baseline		SW with NSP		SW Baseline		SW with NSP
	Posterior Mean and CI		Mode		Posterior Mean and CI		Mode
φ	5.93	[4.38,7.68]	5.4882	α	0.21	[0.18,0.23]	0.1927
σ_c	1.41	[1.20,1.66]	1.3953	σ_a	0.48	[0.43,0.52]	0.4513
h	0.73	[0.65,0.80]	0.7122	σ_b	0.24	[0.19,0.28]	0.2425
ξ_w	0.75	[0.67,0.84]	0.7375	σ_g	0.52	[0.47,0.57]	0.52
σ_l	2.10	[1.21,3.02]	1.9198	σ_I	0.46	[0.38,0.54]	0.4498
ξ_p	0.65	[0.56,0.73]	0.6563	σ_r	0.23	[0.21,0.25]	0.2399
ι_w	0.56	[0.35,0.77]	0.5919	σ_p	0.13	[0.10,0.16]	0.1410
ι_p	0.24	[0.11,0.38]	0.2285	σ_w	0.25	[0.21,0.28]	0.2443
ψ	0.46	[0.30,0.65]	0.5471	ρ_a	0.98	[0.97,0.99]	0.9588
Φ	1.65	[1.53,1.79]	1.615	ρ_b	0.27	[0.12,0.48]	0.01824
r_π	2.04	[1.77,2.33]	2.0295	ρ_g	0.97	[0.96,0.99]	0.9760
ρ	0.82	[0.77,0.85]	0.8153	ρ_I	0.69	[0.59,0.78]	0.7094
r_y	0.10	[0.07,0.14]	0.0847	ρ_r	0.17	[0.07,0.28]	0.1270
r_{dy}	0.21	[0.17,0.25]	0.2232	ρ_p	0.96	[0.92,0.99]	0.9039
$\bar{\pi}$	0.67	[0.50,0.86]	0.8180	ρ_w	0.97	[0.94,0.99]	0.9717
$\overline{\beta}$	0.13	[0.07,0.22]	0.1605	μ_p	0.80	[0.66,0.90]	0.7448
$\bar{l}$	0.88	[-0.68,2.45]	0.1031	μ_w	0.89	[0.82,0.94]	0.8881
$\bar{\gamma}$	0.47	[0.43,0.49]	0.4322	ρ_{ga}	0.57	[0.44,0.70]	0.5261

Notes: The table shows the posterior mode the baseline SW model and the SW model with NSP estimation, respectively.

6 Conclusion

In this paper we introduced narrative system priors for DSGE models, merging narrative restrictions with system priors to enhance model estimation for policy. We have shown that narrative system priors by penalizing the posterior, aligns structural shocks and parameters,i.e. the outcomes of a model with economic narrative. By bringing economic narrative to the Bayesian framework it refines inference compared to traditional prior restrictions.

Narrative priors are of outmost importance in providing meaningful constraints on model especially when the priors are non-linear functions of model parameters, e.g. moments of latent variables, impulse response functions, and historical variance decompositions. This might offer a complementary role to traditional independent parameter priors-based inference.

We have shown, how to overcome the problem of normalizing constant with the help of an additional Monte-Carlo to approximate the priori probability of the system prior.

Estimation of the canonical DSGE model of Smets-Wouters with narrative system priors shows promising results in aligning the evidence from structural, DSGE model and time series models. Analysing the post-pandemic inflation surge, we found that supply shocks gradually gained importance and demand shocks contributed to the initial rise in inflation in contrast to the baseline estimate. We also highlight the importance of shock classification of economic narratives, by illustrating that wage markup shocks behave as demand

shocks on impact in presence of constrained monetary policy. The historical variance decomposition of the Smets-Wouters model with narrative system priors imposed is more aligned with VAR-based empirical evidence but shows limitations inherent to structural models.

Integrating economic narratives into structural may open up new avenues to revisit existing frameworks and potentially transforms macroeconomic analysis.

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