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Abstract

We propose an unobserved components model with stochastic volatility and structural shocks to explore the relevant factors that influence trend inflation in the USA. Using structural shocks that incorporate a broad set of information for the US economy, we find that four structural shocks have significant effects on trend inflation: productivity, price mark-up, government policy, and finance. During and in the aftermath of the Great Recession, trend inflation became more volatile after incorporating the structural shocks, implying that long-run inflation expectations tended to be less well-anchored in these periods.

Keywords: trend inflation, structural shocks, dynamics of inflation expectations, unobserved components, stochastic volatility.

JEL Classification: C11, C32, E31, E37.

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1 Introduction

According to central bankers, policymakers and economic theory, well-anchored inflation expectations are of utmost importance for the formulation and implementation of macroeconomic policies. In the same vein, the trend inflation rate—a latent variable that can be regarded as an estimate of long-run inflation expectations—has become an important tool for tracking down the behavior of long-run inflation expectations and for gauging whether the latter are well-anchored or not. The seminal work of Stock and Watson (2007) introduced the unobserved components model with stochastic volatility (UCSV model), which has become one of the most prominent tools for estimating trend inflation. Ever since then, various modeling approaches aimed at improving the trend inflation estimates derived from the original univariate UCSV model have been developed—see, for example, Chan et al. (2016), Mertens (2016), Stock and Watson (2016), Chan et al. (2018), Hwu and Kim (2019), Mertens and Nason (2020) and Nason and Smith (2021), among others. However, the statistical procedures implemented by this strand of literature typically assume that the trend in inflation follows a random walk, thus treating the underlying dynamics of long-run inflation expectations as a black box.

Recently, some papers have tried to investigate the relevant factors that drive the trend in inflation. The estimation results presented by Cecchetti et al. (2017) show that labor market slack has a statistically significant—although quantitatively small—effect on trend inflation in the USA, but that inflation expectations have no effect at all. Correa-López et al. (2019) found a significant but quantitatively small role of short-term inflation expectations, economic slack, and openness variables in twelve Euro Area countries. Kamber and Wong (2020) focused on how global factors (namely, foreign shocks) affect both trend inflation and the inflation gap, finding that these have only a marginal role in driving the former but an important influence on the latter. In summary, although some factors have been found to effect trend inflation, the respective parameter estimates are quantitatively small.[1]

When conducting a regression analysis of trend inflation on aggregate variables, it can be challenging to eliminate the possible endogeneity issues, which can result in positive or negative biases associated with the potentially relevant variables. Barnichon and Mesters (2020) have recently proposed utilizing well-chosen independently identified shocks derived from structural models to deal with such endogeneity issues in macroeconomic equations—for example, when estimating the Phillips curve. In order to investigate the underlying drivers of trend inflation in the spirit of Barnichon and Mesters (2020), we propose an unobserved components model with stochastic volatility and structural shocks (UCSV-X model), which we estimate using a Bayesian estimation procedure. The proposed framework aims at exploring the relevant structural shocks that influence trend inflation in the USA by incorporating the eight shocks that can be regarded as the main structural determinants of the US economy according to the DSGE-dynamic factor model of Gelfer (2019): monetary policy, government policy, productivity, price mark-up, wage mark-up, preference, investment, and a finance shock.[2]

[1] For example, in the papers by Cecchetti et al. (2017) and Correa-López et al. (2019), the coefficients on the significant factors that may affect trend inflation are always smaller than 0.1.

[2] Fu and Li (2022) have also used these eight structural shocks to mitigate the possible endogeneity problems when estimating the uncovered interest parity condition with time-varying parameters.

The main findings can be summarized as follows. First, we find that only four structural shocks have significant effects on trend inflation: the productivity shock, the price mark-up shock, the government policy shock, and the finance shock. Specifically, the significant effects of the shocks to productivity, price mark-up, and government policy are quantitatively important. Second, although the estimated trend inflation obtained from the UCSV-X model is similar to the one obtained from the UCSV model up until the Great Recession of 2007-9, the trend inflation estimates obtained from the UCSV-X model are more volatile during and in the aftermath of the Great Recession. Following Bernanke (2007), well-anchored long-run inflation expectations should be relatively insensitive to incoming data, which implies that trend inflation estimates should not respond to transitory shocks. However, the empirical findings derived from the UCSV-X model imply that long-run expectations of inflation have tended to be less well-anchored because of the effects derived from the four structural shocks during and after the Great Recession of 2007-9. Finally, we implement a Bayesian model comparison exercise to justify our UCSV-X model. The results show strong evidence in favor of the UCSV-X model over the UCSV model.

The rest of the paper is organized as follows. Section 2 presents the UCSV-X model and describes the relevant aspects of the Bayesian estimation approach and the Bayesian model comparison strategy. Section 3 summarizes and discusses the main empirical results. Finally, section 4 concludes the paper.

2 Model and estimation

This section is composed of three parts. First, we introduce the UCSV-X model, which we use to study the effects of structural shocks on the trend component of inflation. Second, we describe the implementation of the Bayesian estimation procedure. Third, we summarize the Bayesian model comparison strategy for comparing the UCSV-X and UCSV models.

2.1 The unobserved components model with stochastic volatility and structural shocks

Following the unobserved components model with stochastic volatility of inflation developed by Stock and Watson (2007), the proposed UCSV-X model aims at studying the effects of a set of relevant structural shocks for trend inflation. Assuming that π_t denotes the inflation rate, we construct the following model:

$$\pi_t = \tau_t + \epsilon_t^{\pi}, \qquad \epsilon_t^{\pi} \sim \mathcal{N}(0, e^{h_t}), \tag{1}$$

$$\tau_t = \tau_{t-1} + x_{t-1}'\beta_\tau + \epsilon_t^{\tau}, \qquad \epsilon_t^{\lambda} \sim \mathcal{N}(0, e^{g_t}), \tag{2}$$

$$h_t = h_{t-1} + \epsilon_t^{h}, \qquad \epsilon_t^{h} \sim \mathcal{N}(0, \omega_h^2), \tag{3}$$

$$g_t = g_{t-1} + \epsilon_t^{g}, \qquad \epsilon_t^{g} \sim \mathcal{N}(0, \omega_g^2), \tag{4}$$

where τ_t is the trend inflation; ϵ_t^{π} is the inflation gap; h_t and g_t are the stochastic volatilities associated with the inflation rate and trend inflation, respectively; ϵ_t^{τ}, ϵ_t^{h}, and ϵ_t^{g} are mutually and serially uncorrelated error terms; and x_t is a vector that contains the eight structural shocks identified by the DSGE model of Gelfer (2019). Hence, the proposed UCSV-X model decomposes π_t into τ_t and ϵ_t^{π}, where both unobserved components have time-varying volatility evolving according to a random walk process, and quantifies the response of τ_t to x_t via the estimated vector of parameters β_τ. Importantly, as shown in equation (2), the effect of each of the eight structural shocks on τ_t is measured by incorporating the lagged structural shocks, that is, x_{t-1}. Therefore, we interpret these estimation results to be informative in the Granger causality sense.

The structural shocks contained in x_t correspond to the ones identified by Gelfer (2019), who extended the Federal Reserve Bank of New York (FRBNY) DSGE model with financial frictions of Del Negro and Schorfheide (2013) by considering a data-rich environment.[3] In brief, he constructed a DSGE-dynamic factor model (DSGE-DFM) to identify the main shocks that drive the structural determinants of the US economy. The FRBNY DSGE-DFM has two main advantages: (i) the series that are not directly incorporated inside the DSGE model are allowed to load on economic variables and structural processes that are inside the DSGE model; and (ii) it produces better forecasts of variables that are directly modeled inside the DSGE model (including GDP, consumption, investment growth, inflation, and interest rates). Thus, Gelfer (2019)'s model provides more robust identified structural shocks than the original FRBNY DSGE model.

The eight relevant structural shocks derived from Gelfer (2019)'s FRBNY DSGE-DFM are the following: a monetary policy shock, which corresponds to an unexpected shock to the risk-free interest rate driven by the monetary authority; a government policy shock, which corresponds to a spending shock to the government portion of GDP driven by the fiscal authority; a total factor productivity shock faced by intermediate firms that affect firms' production; a price mark-up shock—a shock to the mark-up above marginal costs that monopolistically competitive intermediate firms charge final good producing firms; a wage mark-up shock—a shock to the monopolistic power households have over their specialized labor; a preference shock—a shock to the discount rate that alters households' consumer and savings decisions; an investment shock—a shock that affects the marginal efficiency of investment of capital producers; and, finally, a finance shock driven by entrepreneurs and banks, which corresponds to a risk shock that affects the spread between the bank deposit rate and the bank lending rate. The posterior medians of the eight structural shocks used to estimate the UCSV-X model are plotted in figure 1 below.

The UCSV-X model presented in equations (1) through (4) considers that, consistent with the Beveridge–Nelson decomposition, the trend in inflation, τ_t, corresponds to the infinite-horizon forecast of the inflation rate, π_t, conditional on an information set available in period t, Ω_t:

$$\tau_t = \lim_{j\to\infty} E\left[\pi_{t+j}|\Omega_t\right]. \tag{5}$$

As discussed by Mertens (2016), defining τ_t as an expectation has important consequences

[3] The FRBNY DSGE model by Del Negro and Schorfheide (2013) represents an extension of the Smets and Wouters (2003, 2007) New Keynesian DSGE model that incorporates credit market frictions, which follow the financial accelerator model developed by Bernanke et al. (1999). Following also the work of Boivin and Giannoni (2006) and Kryshko (2011), Gelfer (2019) considered the model of Del Negro and Schorfheide (2013) and proceeded to incorporate a large set of economic and financial series (ninety-seven quarterly data series) in the estimation of the state parameters and the structural DSGE parameters using an adaptive Metropolis-within-Gibbs sampling algorithm.

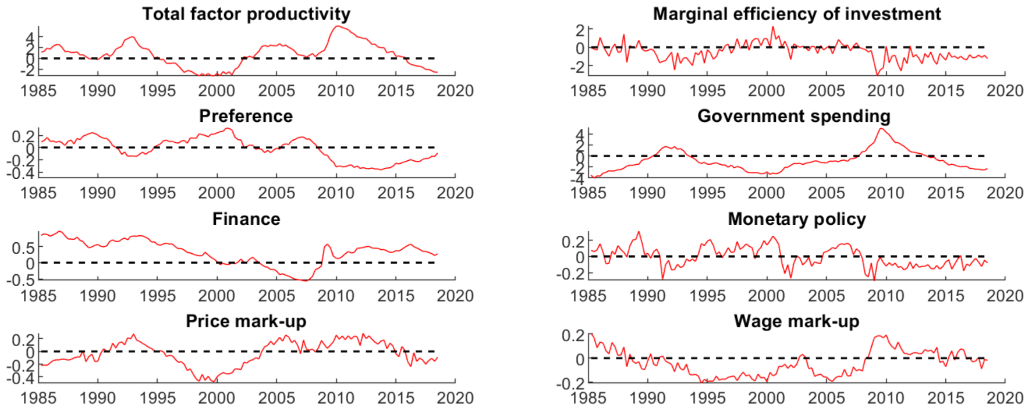

Figure 1: Posterior medians of the eight structural shocks estimated from the FRBNY DSGE-DFM model of Gelfer (2019) for the USA, 1985Q1-2018Q3

for the dynamics of π_t since differencing equation (5) yields a unit root process for τ_t:

$$\tau_t = \tau_{t-1} + \lim_{j\to\infty} E\left[\pi_{t+j}|\Omega_t\right] - \lim_{j\to\infty} E\left[\pi_{t+j}|\Omega_{t-1}\right] = \tau_{t-1} + \overline{e}_t, \tag{6}$$

where $\overline{e}_t$ denotes the trend shocks, which form a martingale-difference sequence. Therefore, from equations (2) and (6) it is possible to observe that:

$$\overline{e}_t = x'_{t-1}\beta_\tau + \epsilon_t^\tau, \tag{7}$$

which implies that τ_t follows a random walk given the trend shocks $\overline{e}_t$ that can also influence its trajectory.

To summarize, by including the eight shocks that drive the structural determinants of the US economy, the UCSV-X model proposed in this section quantifies the relative importance of each structural shock for trend inflation. In this sense, this model specification is related to the recent work by Carvalho et al. (2023), who developed a theory for the inflation trend where the latter is driven by long-run inflation expectations such that these are affected by short-run inflation surprises. The proposed UCSV-X model considers a broader set of information that can influence long-run inflation expectations by explicitly incorporating the set of structural shocks into the estimation of trend inflation.

2.2 Bayesian estimation

We assume the following prior distributions: $\tau_0 \sim \mathcal{N}(\mu_{\tau_0}, V_{\tau_0})$, $h_0 \sim \mathcal{N}(\mu_{h_0}, V_{h_0})$, and $g_0 \sim \mathcal{N}(\mu_{g_0}, V_{g_0})$, where $\mu_{\tau_0} = \mu_{h_0} = \mu_{g_0} = 0$ and $V_{\tau_0} = V_{h_0} = V_{g_0} = 10$. We choose a non-informative prior for β_τ, thus assuming that $\beta_\tau \sim \mathcal{N}(\beta_0^\tau, V_{\beta_\tau})$, where $\beta_0^\tau = 0_{n\times 1}$, and $V_{\beta_\tau} = 10I_n$. We also assume that ω_h^2 and ω_g^2 follow a inverse gamma distribution as follows: $\omega_h^2 \sim \mathcal{IG}(\nu_h, S_h)$ and $\omega_g^2 \sim \mathcal{IG}(\nu_g, S_g)$, such that $\nu_h = 3$, $S_h = 1 * (\nu_h - 1)$, $\nu_g = 3$, and $S_g = 1 * (\nu_g - 1)$.

We estimate the UCSV-X model depicted in equations (1) through (4) using Markov chain Monte Carlo (MCMC) methods. Specifically, our sampling scheme comprises the following steps:

1. Draw τ from $p(\tau|y, x, h, g, \tau_0, \beta_\tau)$.
2. Draw β_τ from $p(\beta_\tau|\tau, x, g, \beta_0^\tau, V_{\beta_\tau})$.
3. Draw h from $p(h|y, \tau, h_0, \omega_h^2)$.
4. Draw g from $p(g|\tau, x, \tau_0, \beta_\tau, \omega_g^2)$.
5. Draw τ_0 from $p(\tau_0|\tau, x, g, \beta_\tau, \mu_{\tau_0}, V_{\tau_0})$.
6. Draw g_0 from $p(g_0|g, \omega_g^2, \mu_{g_0}, V_{g_0})$.
7. Draw h_0 from $p(h_0|h, x, g, \mu_{h_0}, V_{h_0})$.
8. Draw ω_h^2 from $p(\omega_h^2|h, h_0, \nu_{\omega_h^2}, S_{\omega_h^2})$.
9. Draw ω_g^2 from $p(\omega_g^2|g, g_0, \nu_{\omega_g^2}, S_{\omega_g^2})$.

Since the main purpose of our paper consists in exploring how the structural shocks in x_{t-1} affect the trend inflation τ_t, in this section we only describe steps 1 and 2 of the sampling algorithm. This is so because the implementation of steps 3 through 9 is standard, so a summary of these steps is presented in appendix A.

To sum up, we use the precision sampler developed by Chan and Jeliazkov (2009) to sample τ. We first stack equation (1) over t to obtain $\pi = \tau + z$. Next, we stack equation (2) over t and obtain $H\tau = \alpha_\tau + X\beta_\tau + \epsilon^\tau$. Left-multiplying the latter by H we have that $\tau = H^{-1}\alpha_\tau + H^{-1}X\beta + H^{-1}\epsilon^\tau$, where

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ -1 & 1 & 0 & 0 & \dots & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \ddots \\ 0 & 0 & 0 & 0 & -1 & 1 \end{bmatrix}, \quad \text{and} \quad \alpha_\tau = \begin{pmatrix} \tau_0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}.$$

Let us denote $\Sigma_h = \text{diag}(e^{h_1}, e^{h_2}, \dots, e^{h_T})$ and $\Sigma_g = \text{diag}(e^{g_1}, e^{g_2}, \dots, e^{g_T})$. The conditional likelihood given the states τ corresponds to:

$$(2\pi)^{-\frac{T}{2}}|\Sigma_h|^{-\frac{1}{2}}e^{-\frac{1}{2}(y-\tau)'\Sigma_h^{-1}(y-\tau)}. \tag{8}$$

The prior density of τ implied by equation (2) is given by:

$$(2\pi)^{-\frac{T}{2}}|(H'\Sigma_g^{-1}H)^{-1}|^{-\frac{1}{2}}e^{-\frac{1}{2}(\tau-H^{-1}\alpha_\tau-H^{-1}X\beta_\tau)'H'\Sigma_g^{-1}H(\tau-H^{-1}\alpha_\tau-H^{-1}X\beta_\tau)}. \tag{9}$$

Therefore, combining equations (8) and (9) we have that:

$$(\tau|y, x, h, g, \tau_0\beta_\tau) \sim \mathcal{N}(\hat{\tau}, K_\tau^{-1}),$$

where $K_\tau = \Sigma_h^{-1} + H'\Sigma_g^{-1}H$ and $\hat{\tau} = K_\tau^{-1}(\Sigma_h^{-1}y + H'\Sigma_g^{-1}(\alpha_\tau + X\beta_\tau))$.

Finally, the prior density of β_τ is given by:

$$(2\pi)^{-\frac{n}{2}}|V_{\beta_\tau}|^{-\frac{1}{2}}e^{-\frac{1}{2}(\beta_\tau-\beta_0^\tau)'V_{\beta_\tau}^{-1}(\beta_\tau-\beta_0^\tau)}, \tag{10}$$

so that combining equations (8) and (10) we have:

$$(\beta_\tau|\tau, x, g, \beta_0^\tau, V_{\beta_\tau}) \sim \mathcal{N}(\hat{\beta}_\tau, K_{\beta_\tau}^{-1}),$$

such that $K_{\beta_\tau} = V_{\beta_\tau}^{-1} + X'\Sigma_g^{-1}X$ and $\hat{\beta}_\tau = K_{\beta_\tau}^{-1}(V_{\beta_\tau}^{-1}\beta_0^\tau + X'\Sigma_g^{-1}(\tau - H^{-1}\alpha_\tau))$.

2.3 Model comparison

We follow a standard Bayesian strategy to carry out the model comparison between the UCSV-X and UCSV models for the US inflation rate. Assuming that y is the actual observed data, the posterior odds ratio, *i.e.*, the ratio of the two posterior model probabilities, can be specified as:

$$\frac{p(\text{UCSV-X}|y)}{p(\text{UCSV}|y)} = \frac{p(y|\text{UCSV-X})}{p(y|\text{UCSV})} \times \frac{p(\text{UCSV-X})}{p(\text{UCSV})},$$

where $p(\text{UCSV-X}|y)$ and $p(\text{UCSV}|y)$ are the posterior probabilities for the UCSV-X and UCSV models, respectively; $p(y|\text{UCSV-X})$ and $p(y|\text{UCSV})$ are the marginal likelihoods under the UCSV-X and UCSV models, respectively; and $p(\text{UCSV-X})$ and $p(\text{UCSV})$ are the prior probabilities for the UCSV-X and UCSV models, respectively. Therefore, $p(\text{UCSV-X}|y)/p(\text{UCSV}|y)$ is the posterior odds ratio; $p(y|\text{UCSV-X})/p(y|\text{UCSV})$ is the Bayes factor; and $p(\text{UCSV-X})/p(\text{UCSV})$ is the prior odds ratio.

Assuming that the two models are equally probable *a priori*, the prior odds ratio is equal to one, so the posterior odds ratio is equal to the Bayes factor. Since the UCSV model is nested in the UCSV-X model, we use the Savage-Dickey density ratio to compute the Bayes factor (Verdinelli and Wasserman , 1995):

$$\text{BF} = \frac{p(\beta_\tau = 0)}{p(\beta_\tau = 0|y)}. \tag{11}$$

The Bayes factor BF in favor of the unrestricted UCSV-X model shown in equation (11) computes the Bayes factor as the density ratio $p(\beta_\tau = 0)/p(\beta_\tau = 0|y)$. If $\beta_\tau = 0$ is more likely under the prior relative to the posterior—that is, the numerator is larger than the denominator in equation (11), then there is evidence in favor of the unrestricted UCSV-X model.

3 Empirical results

We computed the inflation rate π_t as the annualized log percentage change of the core personal consumption expenditures (PCE) index, *i.e.*, $\pi_t = 400 \ln(P_t/P_{t-1})$, where P_t is the quarterly core PCE index extracted from the Federal Reserve Bank of St. Louis Economic Database (FRED). We considered the PCE inflation rate because, as mentioned by Chan et al. (2018), its historical data has been revised to reflect methodology changes and the Federal Reserve's long-run inflation objective is stated in terms of PCE inflation. The estimation period was 1985Q1-2018Q3 since the structural shocks identified by the FRBNY DSGE-DFM of Gelfer (2019) are only available for this period. Figure 2 shows the π_t series.

Table 1 presents the main results obtained from the UCSV-X model, showing the effects of a one standard deviation increase in each structural shock contained in x_{t-1} on the trend inflation τ_t, measured by the parameters β_τ in equation (2).

The main results can be summarized as follows. First, we find that only four structural shocks affect the trend component of the inflation rate: the productivity shock, the price mark-up shock, the government policy shock, and the finance shock. The estimated credible

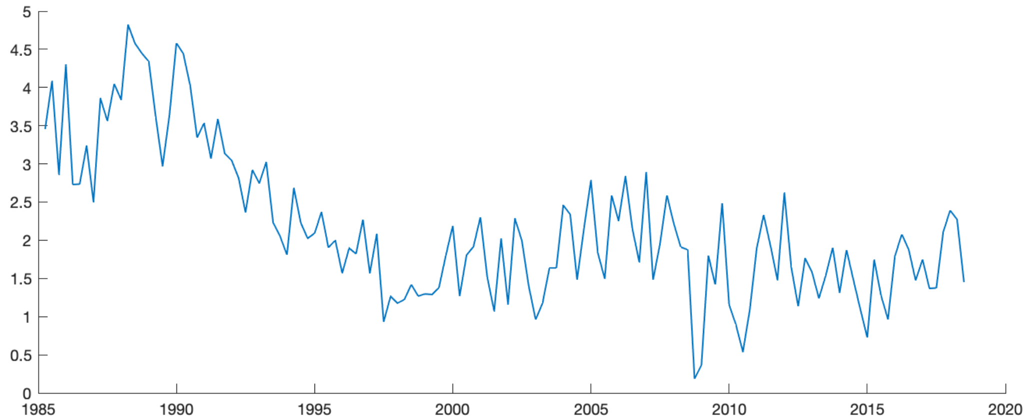

Figure 2: Core PCE inflation rate in the USA, 1985Q1-2018Q3

Table 1: Estimated effects of structural shocks on US trend inflation, 1985Q1-2018Q3[a]

Structural shocks	Posterior means of β_τ parameters
Productivity shock	**0.213*** **
Investment shock	-0.113
Preference shock	-0.023
Government policy shock	**-0.112** **
Finance shock	**-0.064** **
Monetary policy shock	0.054
Price mark-up shock	**-0.191** **
Wage mark-up shock	0.003

Notes: [a]The inflation rate corresponds to the core PCE inflation rate.

***Indicates that the 95% credible interval excludes zero.

**Indicates that the 90% credible interval excludes zero.

intervals for the posterior means of the parameters on these four lagged structural shocks exclude zero, which suggests that such structural shocks can influence the trend inflation in the USA.

Second, the productivity shock is the only one that has a positive effect on the inflation trend; while the price mark-up shock, the government policy shock, and the finance shock affect negatively the trend component of the inflation rate. Long-run inflation expectations tend to increase when the economy experiences a productivity shock, possibly reflecting the higher expected long-run inflation due to a total factor productivity shock faced by intermediate firms which would allow them to increase prices for final goods producing firms. Long-run expectations of inflation tend to decrease when the economy experiences a price shock—that is, a shock to the mark-up above marginal costs that intermediate firms charge final good-producing firms, possibly capturing the increased search pressure by firms that implies more competition in the economy and that pushes down long-run expected inflation.

This theoretical mechanism is also emphasized by Bénabou (1992) and Hwu and Kim (2019), who found that trend inflation is negatively correlated with the price mark-up shock and that there is a negative correlation coefficient between innovations to trend inflation and the inflation gap, respectively.

Third, we find that the relevant policy shock that influences long-run inflation expectations is the government policy shock and not the monetary policy shock. If the economy experiences a shock to the government portion of GDP driven by the fiscal authority, long-run expected inflation tends to decline. Thus, our results corroborate the findings by Dupor and Li (2015), who also found that increases in government spending led to a decline in survey measures of expected inflation (although the effect is not statistically different from zero in their benchmark specification). Finally, we also find a smaller negative effect of a finance shock—a risk shock that increases the spread between the bank deposit and lending rates—on trend inflation, showing that a higher interest rate spread tends to decrease expectations of inflation as entrepreneurs and banks expect a reduction in economic activity.

Figure 3 below shows the trend inflation obtained from the estimated UCSV-X model compared with the one obtained from the standard UCSV model in order to show how the incorporation of the structural shocks affects the estimates of trend inflation. It is possible to observe that the two series follow closely each other; however, the two estimates of trend inflation can differ substantially mainly during and in the aftermath of the Great Recession of 2007-9. This result indicates that long-run expectations of inflation have tended to be less well-anchored during and in the aftermath of the Great Recession because of the effects associated with the four relevant structural shocks identified above—namely, productivity, price mark-up, government policy, and finance.

In addition, in figure 4 we compare the stochastic volatility of the trend inflation rate obtained from the UCSV-X and UCSV models. We find that the two time-varying volatilities obtained from both models are virtually identical since the Great Recession of 2007-9. This suggests that the less anchored expectations of inflation—captured by the more volatile trend inflation in the UCSV-X model—are more likely associated with the relevant structural shocks rather than due to higher stochastic volatility estimates derived from the model specification.

Finally, to justify our model specification, we carried out the Bayesian model comparison exercise between the UCSV-X and UCSV models described in section 2.3. We obtained that the 2log(BF) is 57.66. Since the 2log(BF) is greater than 10, following Kass and Raftery (1995) we interpret this result as strong evidence in favor of the UCSV-X model over the UCSV model. This result implies that incorporating the structural shocks provides useful information for estimating the trend inflation in the USA.

4 Concluding remarks

This paper aims at identifying the relevant structural shocks that can influence the trend in inflation in the USA. To do so, we provide an extension of the seminal UCSV model which consists in incorporating the eight structural shocks that can be regarded as the main structural determinants of the US economy into the estimation of trend inflation. We call this

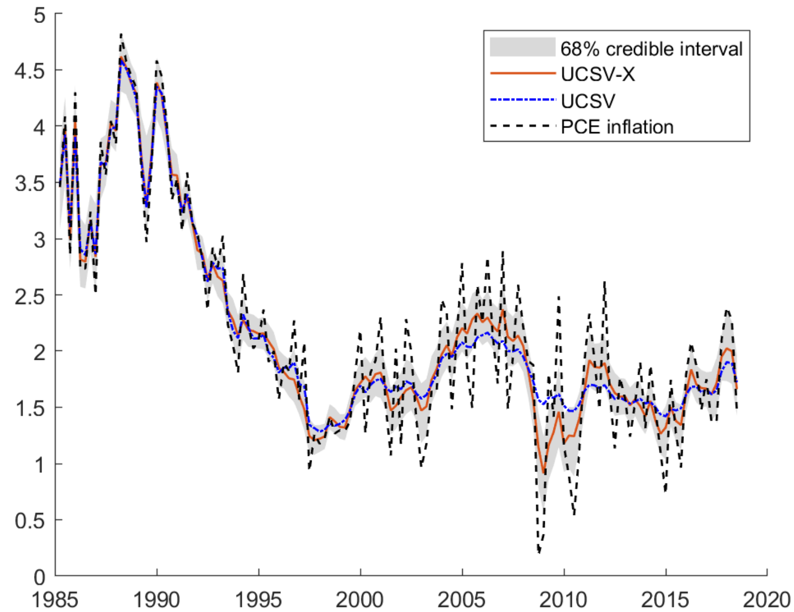

Figure 3: Trend inflation estimates for the US economy obtained from the UCSV-X and UCSV models. The inflation rate corresponds to the core PCE inflation rate for the period 1985Q1-2018Q3. Shaded areas represent the 68% credible interval of the estimates obtained from the UCSV-X model

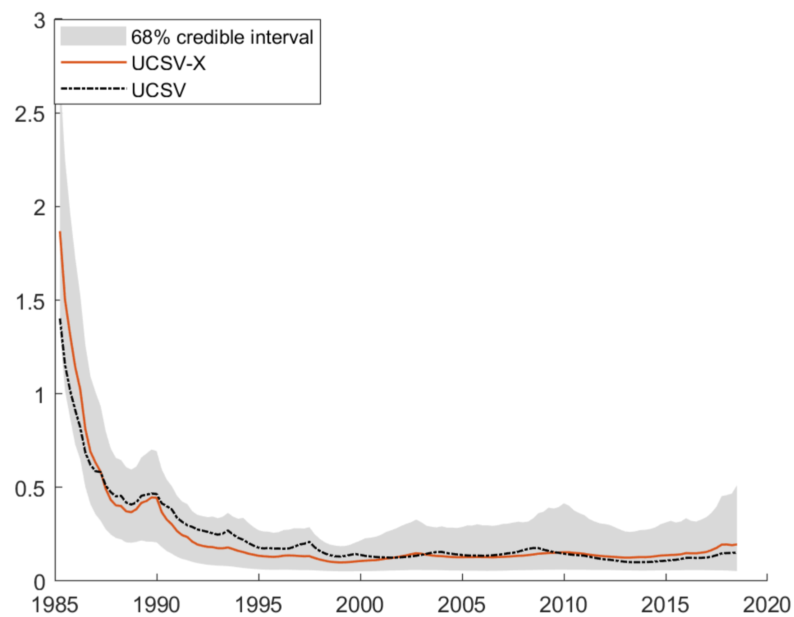

Figure 4: Posterior estimates of the time-varying standard deviation of the trend component of the inflation rate in the USA, $e^{g_t/2}$, obtained from the UCSV-X and UCSV models. The inflation rate corresponds to the core PCE inflation rate for the period 1985Q1-2018Q3. Shaded areas represent the 68% credible interval of the estimates obtained from the UCSV-X model

proposed extension the UCSV-X model, which is estimated for the period 1985Q1-2018Q3 using a Bayesian sampling algorithm.

The main results can be summarized as follows. First, we identify that only four structural shocks have significant effects on the trend component of the inflation rate: the productivity shock, the price mark-up shock, the government policy shock, and the finance shock. Second, since the Great Recession of 2007-9, the trend inflation estimates obtained from the UCSV-X model are more volatile than the ones obtained from the UCSV model. These findings imply that long-run expectations of inflation have been less well-anchored because of the effects derived from the four relevant structural shocks that effect trend inflation during and in the aftermath of the Great Recession. Finally, the results obtained from a Bayesian model comparison exercise show strong evidence in favor of the UCSV-X model over the UCSV model, which means that the structural shocks contain relevant additional information in informing the estimates of trend inflation.

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A Further details on the Bayesian sampling estimation procedure

This appendix provides the relevant details regarding steps 3 through 9 outlined in section 2.2. First, in steps 3 and 4, we draw h and g from $p(h|y, \tau, h_0, \omega_h^2, \beta_z, \rho)$ and $p(g|\tau, x, \tau_0, \beta_\tau, \omega_g^2)$, respectively, following the auxiliary mixture sampler of Kim et al. (1998).

Second, with respect to steps 5 through 7, we have that:

$$
\begin{aligned}
(\tau_0|\tau, x, g, \beta, \mu_{\tau_0}, V_{\tau_0}) &\sim \mathcal{N}(\hat{\tau}_0, K_{\tau_0}^{-1}),\\
(g_0|g, \omega_g^2, \mu_{g_0}, V_{g_0}) &\sim \mathcal{N}(\hat{g}_0, K_{g_0}^{-1}),\\
(h_0|h, x, g, \mu_{h_0}, V_{h_0}) &\sim \mathcal{N}(\hat{h}_0, K_{h_0}^{-1}),
\end{aligned}
$$

where $K_{\tau_0} = \frac{1}{V_{\tau_0}} + \frac{1}{e^{g_1}}$ and $\hat{\tau}_0 = K_{\tau_0}^{-1}(\frac{\mu_{\tau_0}}{V_{\tau_0}} + \frac{\tau_1 - x_1\beta_\tau}{e^{g_1}})$; $K_{g_0} = \frac{1}{V_{g_0}} + \frac{1}{\omega_g^2}$ and $\hat{g}_0 = K_{g_0}^{-1}(\frac{\mu_{g_0}}{V_{g_0}} + \frac{g_1}{\omega_g^2})$; $K_{h_0} = \frac{1}{V_{h_0}} + \frac{1}{\omega_h^2}$ and $\hat{h}_0 = K_{h_0}^{-1}(\frac{\mu_{h_0}}{V_{h_0}} + \frac{h_1}{\omega_h^2})$.

Finally, to implement steps 8 and 9, we point out that the conditional densities of ω_h^2 and ω_g^2 are:

$$
\begin{aligned}
(\omega_h^2|h, h_0) &\sim \mathcal{IG}(\nu_{\omega_h^2} + \frac{T}{2}, (S_h + (h - h_0)'H'H(h - h_0))/2),\\
(\omega_g^2|g, g_0) &\sim \mathcal{IG}(\nu_{\omega_g^2} + \frac{T}{2}, (S_g + (g - g_0)'H'H(g - g_0))/2).
\end{aligned}
$$