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**Working Paper**

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Cardiff Economics Working Papers, No. E2018/1

**Provided in Cooperation with:**

Cardiff Business School, Cardiff University

*Suggested Citation:* Mumtaz, Haroon; Theodoridis, Konstantinos (2018) : The federal reserve's implicit inflation target and macroeconomic dynamics: A SVAR analysis, Cardiff Economics Working Papers, No. E2018/1, Cardiff University, Cardiff Business School, Cardiff

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January 2018

ISSN 1749-6010

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# The Federal Reserve’s implicit inflation target and Macroeconomic dynamics. A SVAR analysis.\*

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January 2018

## Abstract

This paper identifies shocks to the Federal Reserve’s inflation target as VAR innovations that make the largest contribution to future movements in long-horizon inflation expectations. The effectiveness of this scheme is documented via Monte-Carlo experiments. The estimated impulse responses indicate that a positive shock to the target is associated with a large increase in inflation and long-term interest rates in the US and the industrialised world. Target shocks are estimated to be a vital factor behind the increase in inflation during the pre-1980 period and are an important driver of the decline in long-term interest rates over the last two decades.

Key words: SVAR, DSGE model, inflation target. International transmission.

JEL codes: C5, E1, E5, E6

## 1 Introduction

In the aftermath of the Great Recession, nominal interest rates in the US have remained persistently close to the zero lower bound (ZLB). This unique situation has highlighted the potential limitations of conventional monetary policy. While many central banks have pursued unconventional monetary policies such as quantitative easing, their effectiveness in stimulating the real economy is not undisputed (see Gambacorta *et al.* (2014)). In this scenario, the role of the Federal Reserve’s (Fed) implicit inflation target has returned to the forefront. Some commentators have argued that a target higher than 2 percent should be considered in order to mitigate the negative effects of the ZLB on the effectiveness of monetary policy (see Ball (2014)). Potential changes in the Fed’s implicit target are also of interest from a historical perspective. In a seminal paper, Ireland (2007) shows that this target level varied substantially and was one of the main factor behind the ‘great inflation’ of the 1970s. Gürkaynak *et al.* (2005) show that adding a time-varying inflation target is crucial in trying to understand the response of forward interest rates to macroeconomic developments.

In this paper, we propose a structural vector autoregression (SVAR) that can be used to identify shocks to the inflation target. The identification scheme exploits the idea that innovations to the

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inflation target are the main driver of long-horizon inflation expectations in the medium to the long-run. In other words, we apply the identification of Uhlig (2004a) to estimate the inflation target shock as the VAR innovation that makes the largest contribution to the forecast error variance (FEV) of a measure of long-horizon inflation expectations.

We use an extensive Monte-Carlo experiment to evaluate this identification scheme. Using an estimated DSGE model that features a central bank with a time-varying inflation target as the data generating process (DGP), we show that this simple strategy can successfully recover the inflation target shock and its impact on macroeconomic and financial variables. This identification scheme continues to perform well even if the DGP is characterised by regime switches in policy activism or if agents in the model have imperfect information regarding the target.

Estimates of this SVAR using US data indicate that an inflation target shock that raises long-horizon inflation expectations by 1 percent has a large impact on the US economy. In our benchmark model, this shock is associated with an impact on CPI inflation of about 1.2 percent, one year ahead, and a peak increase in short and long-term interest rates of about 3 percent. Real GDP growth is estimated to increase by about 0.8 percent in response to this shock after one year, albeit, with the estimated response displaying less persistence than the interest rate and inflation responses. The contribution of this shock to the FEV of GDP growth and inflation is 30 percent and 55 percent, respectively, at the 5 year horizon. The shock is especially important for long-term interest rates with a contribution to FEV of over 70 percent at this horizon. A historical decomposition indicates that in the absence of inflation target shocks, the 1970s would have seen low interest rates and inflation and the persistent decline of long term interest rates witnessed since the 1990s would have been substantially smaller.

Our empirical results also indicate that the US inflation target shock has important international implications. When we use a factor augmented VAR (FAVAR) to estimate the spillover effect of the target shock on macroeconomic and financial variables for 21 industrialised economies, we find evidence that this shock contributed to the strong co-movement in international inflation rates and global disinflation highlighted in Mumtaz and Surico (2012) and Ciccarelli and Mojon (2010). Similarly, on average across this panel of countries, the level of the yield curve would have been lower during the 1980s in the absence of US target shocks and the decline in yields seen after the mid-1990s would have been less pronounced. Our results also provide some support for the arguments presented in Rey (2016) and Miranda-Agrippino and Rey (2015) regarding the importance of US monetary policy: The US inflation target shock has an important impact on short-term interest rates for all countries in the panel.

The role of the Fed's inflation target has been considered in a number of recent studies. Kozicki and Tinsley (2005) present a generalised VAR model that includes a law of motion for the inflation target set by the monetary authority and the target perceived by the private sector, both of which are assumed to be unobserved by the econometrician. The estimates of these quantities suggest substantial time-variation with the target declining in the post-1980 period. Similar results are reported by papers such as Ireland (2007) and De Graeve *et al.* (2009). This strand of the literature pursues a more structural approach and incorporates time-varying inflation targets into DSGE and Macro-finance DSGE models, respectively.

Relative to this literature, the approach developed in the current paper is more data-driven. This offers two potential advantages. The first is simplicity and applicability – our SVAR model can be readily applied to economies that have a range of features. In contrast, approaches based on DSGE model and state-space models require additional assumptions that need to be tailored to the economy in question. Second, our VAR based approach is likely to provide a better fit to the data when compared to models that impose a larger degree of cross-equation restrictions and thus provides an empirical benchmark.

Given our data driven approach, we are able to generalise the results presented in a prominent macro-finance literature (see De Graeve *et al.* (2009), Rudebusch and Swanson (2012), and Ireland (2015) amongst others) that links US inflation target shocks to US long-term interest rates. Our analysis not only supports these findings but also suggests that US target shocks drive long-term rates *internationally*. The evidence that we present also indicates that US target shocks may be an important factor behind the cross-country correlation in long-term rates highlighted in studies such as Jotikasthira *et al.* (2015) and Chin *et al.* (2015).

The analysis in the paper has important policy implications. The results, again, highlight the important part played by the Fed’s target in shaping the temporal evolution of inflation and long-term interest rates. From a historical perspective, these results are consistent with the explanation of the great inflation of the 1970s that relies on the Fed’s policy rather than adverse non-policy shocks. Looking forward, the estimates suggest that this aspect of the Fed’s policy can be an effective tool in stimulating the economy and raising the level of inflation. This also sheds some light on the effectiveness of the FED’s forward guidance policy which can be considered as an implicit (anticipated) inflation target shock.

Our analysis also suggests that US monetary policy is an important driver of fluctuations in international short-term rates, long-term rates and inflation. This is consistent with the ideas in Rey (2016) who argues that with free cross-border capital flows, monetary policy in many economies is not fully independent of a centre country such as the US. For monetary authorities in these countries, this not only underscores the importance of the US economy, but also suggests that any attempts at normalisation of inflation and interest rates may require a coordinated effort.

The paper is organised as follows: Section 2 describes the SVAR used in this study and provides a description of the Monte-Carlo experiment used to test the method’s performance. Empirical results are presented in section 3 while section 4 concludes.

## 2 Identifying shocks to the inflation target

Our empirical strategy is based on the following simple idea. From a theoretical point of view, long-horizon inflation expectations  $\pi^{LH}$  are driven by shocks to the central bank’s inflation target ( $\varepsilon_t^{\pi^*}$ ) and range of additional disturbances ( $\tilde{\varepsilon}_t$ ) which include technology shocks and policy and non-policy aggregate demand shocks:

$$\pi^{LH} = f\left(\varepsilon_t^{\pi^*}, \tilde{\varepsilon}_t\right) \quad (1)$$

However, over the medium to long-run horizons the role of  $\varepsilon_t^{\pi^*}$  dominates in relative terms. While  $\tilde{\varepsilon}_t$  can affect long-horizon inflation expectations, fluctuations in  $\pi^{LH}$  in the medium to long-run are largely driven by shocks to the inflation target. In other words, if on average across the sample, the monetary authority reacts systematically to changes in inflation and is, at least, perceived to be credible in the long-run, then long-horizon inflation expectations would coincide with the inflation target. As a consequence, any further changes in long-horizon inflation expectations reflect shocks to the inflation target.

We use a VAR model to approximate these economic disturbances. In particular, we estimate:

$$Y_t = \alpha + \sum_{j=1}^P \beta_{t-j} Y_{t-j} + A_0 \varepsilon_t \quad (2)$$

where the endogenous variables  $Y_t$  include a measure of long-horizon inflation expectations  $\hat{\pi}^{LH}$

and a set of macroeconomic and financial variables  $X_t$ , and we order  $\hat{\pi}^{LH}$  first for simplicity. The orthogonal shocks are denoted by  $\varepsilon_t$  and  $A_0$  represents the contemporaneous impact matrix such that  $A_0 A_0' = \Sigma$ . It is well known that  $A_0$  is not unique but the space spanned by these matrices can be written as  $\tilde{A}_0 Q$  where  $Q$  is an orthonormal rotation matrix such that  $Q'Q = I$

The shock to the inflation target is then identified by imposing the restriction that this shock makes the largest contribution the forecast error variance (FEV) of  $\hat{\pi}^{LH}$ . Consider the VAR in structural moving average form:

$$Y_t = B(L) A_0 \varepsilon_t$$

The  $k$  period ahead forecast error of the  $it$ th variable is given by:

$$Y_{it+k} - \hat{Y}_{it+k} = e_1 \left[ \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q \varepsilon_{t+k-j} \right]$$

where  $e_1$  is a selection vector that picks out  $\hat{\pi}^{LH}$  in the set of variables. Following Uhlig (2004a), the proposed identification scheme thus amounts to finding the column of  $Q$  that solves the following maximisation problem:

$$\arg \max_{Q_1} e_1' \left[ \sum_{k=0}^K \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q_1 Q_1' \tilde{A}_0' B_j' \right] e_1$$

such that  $Q_1' Q_1 = 1$ . Here  $Q_1$  is the column of  $Q$  that corresponds to the shock that explains the largest proportion of the FEV of the first variable in the VAR,  $\hat{\pi}^{LH}$ . As shown by Uhlig (2004b), the maximisation can be re-written as eigenvalue eigenvector problem and a solution can be readily obtained.

The proposed identification differs from the method used in Michelis and Iacoviello (2016) to identify target shocks. These authors impose exact long-run restrictions on the behaviour of inflation and interest rates. In contrast, our approach is more agnostic and focuses on the medium run dynamics of variables rather than their behaviour in the infinite future which may be hard to pin down with a limited sample (see Erceg *et al.* (2005)). In a recent contribution, Arias *et al.* (2016) uses a mix of sign and zero restrictions to identify the systematic component of monetary policy as embodied in the contemporaneous coefficients in a policy rule. In related work, Uribe (2017) uses a mix of long-run and sign restrictions to distinguish between permanent and transitory monetary policy shocks and provides evidence in favour of the Neo Fisher effect. In contrast, our approach focuses on the implicit inflation target and imposes no explicit restrictions on the interest rate equation in the SVAR model.

In order to evaluate the effectiveness of this identification scheme we consider an extensive Monte-Carlo experiment. As described in detail below, we use a DSGE model that allows for a time-varying inflation target as our data generating process (DGP). The aim is to check if the proposed identification scheme is able to recover the inflation target shock and provide a reliable estimate of its transmission.

## 2.1 DSGE Model

We use a DSGE model based on De Graeve and Theodoridis (2016). The technical appendix contains a detailed description of the model equations. Here we describe the key features of the model economy. In this economy, households consume, supply labour and accumulate capital – subject to an investment adjustment cost. Households have monopoly power over their wages. A fraction of them receive a random signal to set their wage optimally, with the remaining agents

set wages based on a backward looking indexation rule. Households decide optimally about the degree of the capital utilisation, which is again subject to a cost, that determines the level of capital services. Intermediate good producers hire labour and capital services from households in order to produce. They have a monopoly over the price they charge, with price-setting subject to the same friction as wages. All the model features discussed so far are common with those in the literature (Smets and Wouters (2007), Christiano *et al.* (2005), Justiniano *et al.* (2010)).

In addition, in our model, agents have access to both short ( $b_t^S$ ) and long-term government debt ( $\bar{b}_t^L$ ). Following Woodford (2001) the latter asset is modelled as perpetuities that cost  $p_{L,t}$  at time  $t$  and pay an exponentially decaying coupon  $\kappa^s$  at time  $t + s + 1$  where  $0 < \kappa \leq 1$ . As explained in Woodford (2001) and Chen *et al.* (2012), the advantage of this formulation is that the price in period  $t$  of a bond issued  $s$  periods ago  $p_{L-s,t}$  is a function of the current price  $p_{L,t}$

$$p_{L-s,t} = \kappa^s p_{L,t} \quad (3)$$

This relation allows us to express the balance sheet equation and government budget constraint in a simple form (see the discussion in Chen *et al.* (2012)). Furthermore, in order to keep the analysis simple and tractable, we rule out the possibility of a secondary market for long-term bonds, implying that agents who buy long-term debt must hold it until maturity. In addition, long-term debt is a modelled as a less liquid asset than short-term debt. This is achieved by making the profit function of the  $j$  financial intermediary to be subject to an adjustment cost:

$$\xi_{j,t} = \underbrace{b_{j,t}^h + \frac{r_{t-1}^S}{\pi_t} b_{j,t-1}^S + \frac{p_{L,t} r_t^L}{\pi_t} b_{j,t-1}^L}_{\text{revenues}} - \underbrace{\frac{b_{j,t}^S}{\varepsilon_t^S} - \frac{p_{L,t} b_{j,t}^L}{\varepsilon_t^{\bar{b}^L}} - \frac{r_{t-1}^h}{\pi_t} b_{j,t-1}^h - \frac{x}{2} (\delta_{j,t-1}^B - \vartheta \delta_{t-2}^B - (1 - \vartheta) \delta^B)^2 \frac{\Gamma_{t-1}}{\pi_t}}_{\text{expenditures}}$$

where  $\delta_{j,t}^B = \frac{b_{j,t}^S}{\bar{b}_{j,t}^L}$ ,  $r_t^S$  is the policy rate,  $r_t^L$  denotes the long-term interest rate,  $\varepsilon_t^S$  and  $\varepsilon_t^{\bar{b}^L}$  are Smets and Wouters (2007) ‘haircut’ asset-specific shocks that affect the balance sheet of the financial intermediary:

$$b_{\kappa,t}^h = \frac{b_{\kappa,t}^S}{\varepsilon_t^S} + \frac{\bar{b}_{\kappa,t}^L}{\varepsilon_t^{\bar{b}^L}} \quad (4)$$

$\frac{x}{2} (\delta_{j,t-1}^B - \vartheta \delta_{t-2}^B - (1 - \vartheta) \delta^B)^2$  is the liquidity friction and its size is captured by the parameter  $x$ . Finally, the parameter  $\vartheta$  indicates the degree of liquidity smoothing. Our set-up gives rise to an endogenous term-premium and this drives a wedge between expectations about the policy rate and the long-term interest rate.

The Government’s budget constraint is given by

$$b_t^S + \bar{b}_t^L + T_t = \frac{r_{t-1}^S}{\pi_t} b_{t-1}^S + \frac{r_t^L}{\pi_t} \frac{p_{L,t}}{p_{L,t-1}} \bar{b}_{t-1}^L + g_t y_t$$

where the left hand side is the total (short plus long-term) debt issued by the government at time  $t$  plus lump-sum taxes ( $T_t$ ) used to pay interest. Taxes are adjusted according to the following rule:

$$T_t = \Phi \left( \frac{b_{t-1}^S + \bar{b}_{t-1}^L}{b^S + \bar{b}^L} \right)^\theta \quad (5)$$

As in De Graeve *et al.* (2009) monetary authorities set policy based on the following rule

$$\frac{\bar{\pi}r_t}{r\bar{\pi}_t} = \left(\frac{\bar{\pi}r_{t-1}}{r\bar{\pi}_{t-1}}\right)^{\phi_R} \left(\frac{\pi_t}{\bar{\pi}_t}\right)^{(1-\phi_R)\phi_\pi} \left(\frac{y_t}{y}\right)^{(1-\phi_R)\phi_y} e^{\sigma_R\omega_{R,t}} \quad (6)$$

The inflation target shock evolves according to

$$\bar{\pi}_t - 0.999\bar{\pi}_{t-1} = \rho_{\bar{\pi}} (\bar{\pi}_{t-1} - 0.999\bar{\pi}_{t-2}) + \sigma_{\bar{\pi}}\omega_{\bar{\pi},t} \quad (7)$$

### 2.1.1 Perceived versus Actual Inflation Target Shocks

Agents in the model discussed above observe both the inflation target and monetary policy shocks. Following Erceg and Levin (2003), Gürkaynak *et al.* (2005) and Del Negro and Eusepi (2011) we also consider a version of the model where this assumption is relaxed. In this version, agents do not observe the source of departure of the (log linearly approximated) policy rate from its rule, namely

$$\hat{r}_t = \phi_R \hat{r}_{t-1} + (1 - \phi_R) (\phi_\pi \hat{\pi}_t + \phi_y \hat{y}_t) + \hat{o}_t \quad (8)$$

where

$$\hat{o}_t = [1 - (1 - \phi_R)\phi_\pi] \hat{\pi}_t - \phi_R \hat{\pi}_{t-1} + \hat{m}_t \quad (9)$$

In other words agents in the economy observe  $\hat{o}_t$  but not its individual components, however, they can obtain an estimate about the inflation target ( $\hat{\pi}_t^{KF}$ ) and monetary policy shock ( $\hat{m}_t^{KF}$ ) shocks by solving a Kalman Filter extraction problem. In this economy it is the Kalman Filter estimate of the inflation target shock ( $\hat{\pi}_t^{KF}$ ) that enters in the price and wage Phillips curve equations and not the actual inflation target process which is assumed to be unobserved.

### 2.1.2 Active versus Passive Monetary Policy

The benchmark model does not incorporate the possibility that over some periods, monetary policy may have been passive with  $\phi_\pi < 1$ . Under these circumstances, inflation expectations are de-anchored and respond persistently to structural shocks. In order to take this into account, we consider a Markov switching version of the benchmark model that allows for regime switches in the policy rule between an active/hawkish ( $\phi_\pi > 1$ ) and passive/dovish ( $\phi_\pi < 1$ ) state:

$$\hat{r}_t - \hat{\pi}_t = \phi_R(s_t^c) (\hat{r}_{t-1} - \hat{\pi}_{t-1}) + (1 - \phi_R(s_t^c)) (\phi_\pi(s_t^c) (\hat{\pi}_t - \hat{\pi}_t) + \phi_y(s_t^c) \hat{y}_t) + \hat{m}_t \quad (10)$$

where  $s_t^c$  follows a first order Markov chain with transition probabilities  $P^c = \begin{bmatrix} p_{11}^c & 1 - p_{22}^c \\ 1 - p_{11}^c & p_{22}^c \end{bmatrix}$ .

As there is by now a large body of empirical evidence showing that uncertainty also evolves across time, we allow the standard deviation of all structural shocks to follow a Markov first order process  $s_t^\sigma$  with a transition matrix  $P^\sigma = \begin{bmatrix} p_{11}^\sigma & 1 - p_{22}^\sigma \\ 1 - p_{11}^\sigma & p_{22}^\sigma \end{bmatrix}$ .

## 2.2 Monte Carlo Simulations

We first consider the benchmark DSGE model. Note that the versions of the model that do not feature regime switching are estimated using standard Bayesian techniques (see An and Schorfheide (2007)). We use the data set of Smets and Wouters (2007) with the sample truncated at 2007Q4 to avoid issues with the zero lower bound. Information about the prior and the posterior distribution of the structural parameter vector can be found in the technical Appendix. Briefly, the prior



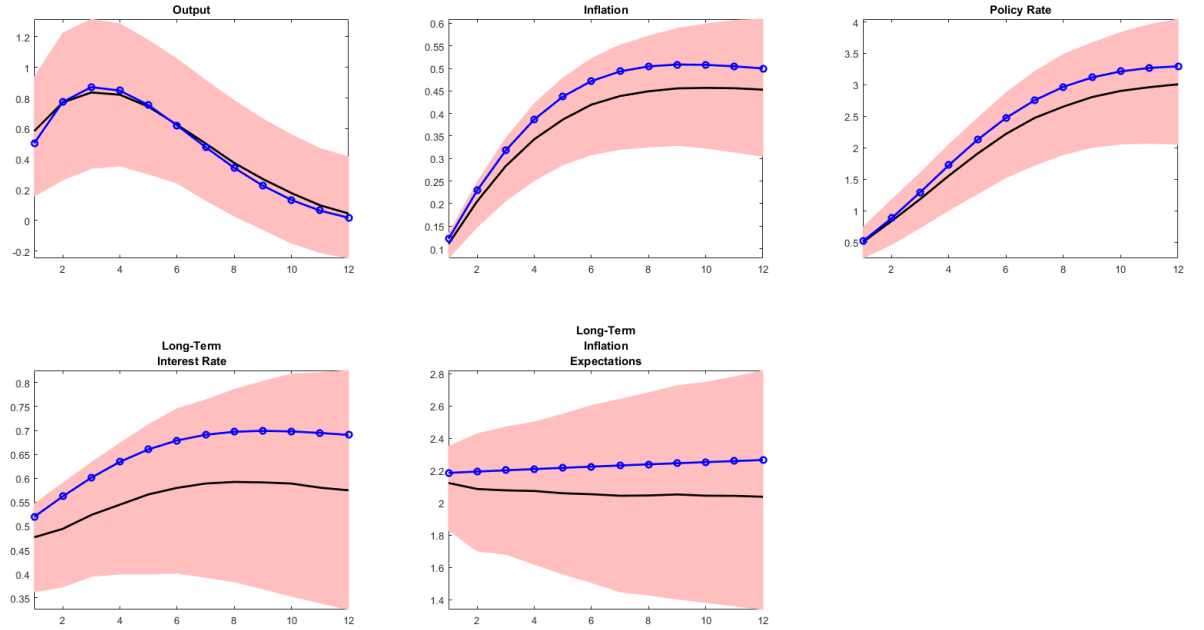


Figure 1: Using posterior mode estimates. The black line and the shadow pink area correspond to the pointwise 50, 5 and 95 percentiles of the simulated distribution. The blue circle line represents the DSGE true response to an inflation target shock.

moments of the structural parameters coincide with those in Smets and Wouters (2007) study, while the posterior ones are very similar to those in the existing literature.

The Monte-Carlo experiment is based on 1000 simulated data sets of 200 observations.<sup>1</sup> At each replication we simulate series for output, inflation, the short-term and the long-term interest rate and 10 year ahead inflation expectations. This set of endogenous variables is used to estimate a  $VAR(P)$  model where the lag length is determined via the Schwarz criterion. The identification scheme discussed above is applied to identify the target shock and the resulting impulse responses are stored.

Figure 1 shows the results from the experiment when the structural parameter vector for the benchmark DGP is set equal to the estimated posterior mode. The black line and the shaded area correspond to the point wise 50, 5 and 95 percentiles of the simulated distribution using the proposed identification scheme. The blue circle line represents the underlying response to the inflation target shock in the DSGE model. A shock that increases the target causes the real interest rate to fall stimulating real activity and inflation. The figure suggests that the VAR estimates of the response to this shock provide a close approximation of true responses in the DGP.<sup>2</sup>

Next, we check if the performance of the identification scheme is robust to different DSGE parameter values. To this end, we draw 1000 parameter vectors from the estimated DSGE posterior

<sup>1</sup> Actually 10200 observations are simulated each time and the first 10000 pseudo data points are dropped to eliminate the effects caused by the initial conditions.

<sup>2</sup> In the technical appendix, we show that, in this experiment, when the shock is identified using long run restrictions (as in Michelis and Iacoviello (2016)), the performance of SVAR deteriorates substantially. In particular, the estimated response of output is biased downwards and error bands for all variables are extremely wide.

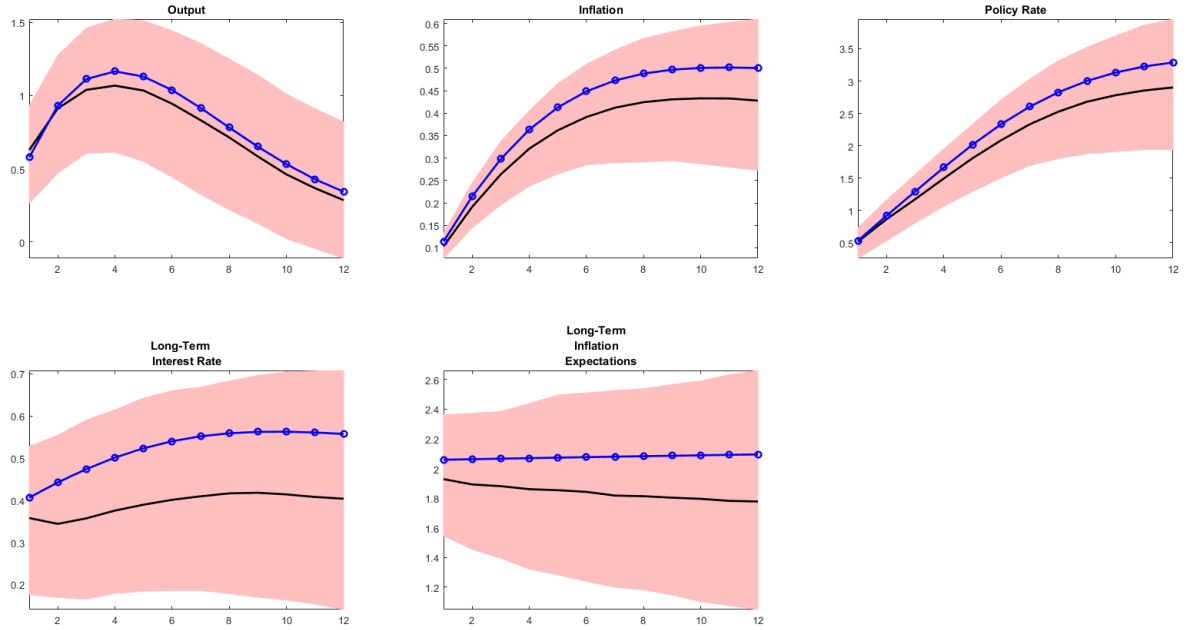


Figure 2: Using draws from the estimated DSGE posterior. See notes to figure 1.

distribution and use them to simulate the 1000 data sets for the experiment. Figure 2 illustrates again that the success of the VAR identification scheme does not depend on a particular DSGE parameter vector.

Next, we investigate whether the econometrician can identify the inflation target shock successfully when the agents in the economy cannot observe the target directly. We repeat the simulation steps mentioned in the first experiment but we use the posterior mode estimates of the model where the inflation target and monetary policy shocks are unobserved. Figure 3 suggests that even in this case the identification scheme performs remarkably well. This is because agents learn about the true shock and the inference error does not survive long enough to have an effect on the *long-horizon* inflation expectations.<sup>3</sup>

Our next exercise examines the ability of the scheme to recover the true shocks when monetary authorities' preferences towards inflation switch stochastically between dovish and hawkish regimes and shock variances are subject to heteroscedasticity. This version of the model is solved and estimated using the RISE toolbox (see (Maih, 2015)). As documented in (Maih, 2015), RISE employs a perturbation solution for the switching DSGE model, with estimation carried out via MCMC methods. As shown in the technical appendix, the posterior estimates indicate large changes in the policy-rule coefficients across the two regimes. In particular, the posterior mode estimate of  $\phi_\pi$  is 0.9 in the dovish regime and 1.8 in the hawkish state. The smoothed regime probabilities suggest that the hawkish regime prevailed after the mid-1980s – a result documented in most studies that consider regime switching DSGE models (see for e.g. Bianchi (2013)). As before, we simulate data from this version of the model using the posterior mode of the structural parameters and estimate the SVAR and the response to target shocks.

<sup>3</sup>In the technical appendix we present a further experiment that shows that the identification scheme continues to perform well when measurement error is added to the generated inflation expectations series.

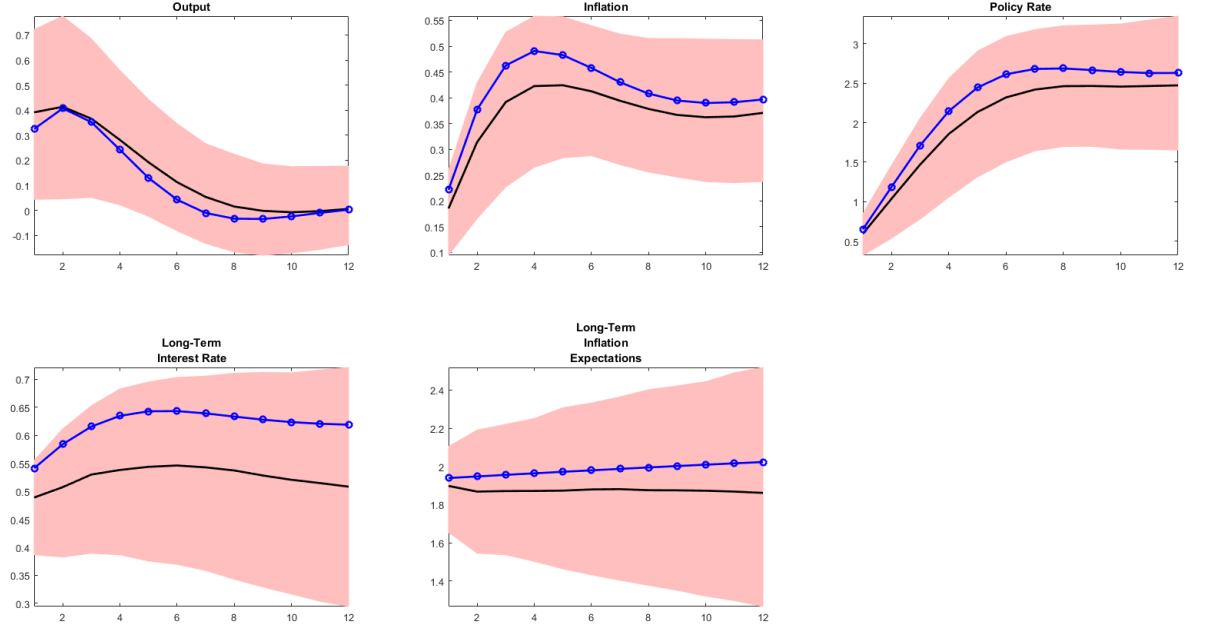


Figure 3: Using the version of the model with unobserved target and policy shock. See notes to figure 1.

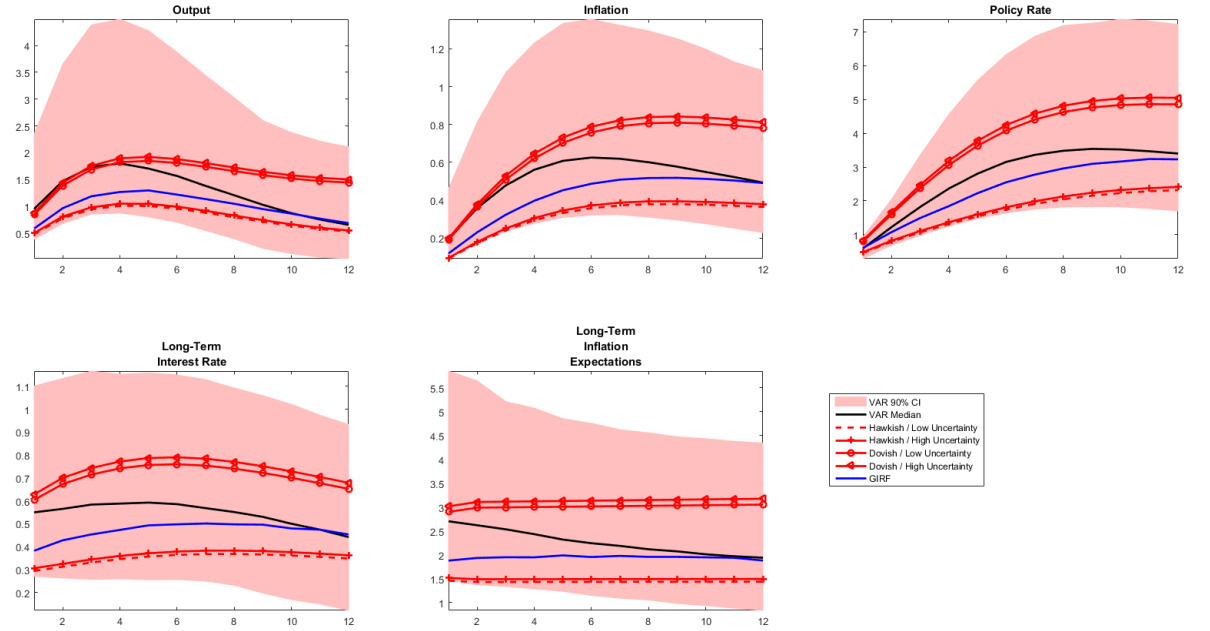


Figure 4: Using the Markov switching DSGE model as the DGP.

Figure 4 presents the results from this simulation. The figure presents the regime specific DSGE responses to the target shock and the generalised response (GIRF) which averages across the regimes. The median estimates from the SVAR estimation suggests that the identification scheme continues to perform remarkably well even in this environment. The median VAR responses are fairly close to the GIRF from the model. The Monte-Carlo distribution of the SVAR impulse response is somewhat wider in this experiment. However this is not entirely unexpected as the linear VAR ignores any non-linear dynamics in the DGP. Note that the VAR identification scheme continues to perform well, because when the sample is considered as a whole, the impact of dovish regimes is mitigated by the presence of regimes during which the monetary authority responds actively to inflation. As a consequence, inflation target shocks continue to exert a major influence on *long-horizon* inflation expectations in this economy.

### 3 Empirical Analysis

We apply the structural VAR introduced above to US data in our benchmark model that focusses on a core set of macroeconomic variables. We then consider the possible transmission of the US target shock to a set of industrialised economies.

#### 3.1 Results for the United States

##### 3.1.1 Data and model specification

Implementation of the SVAR model described above requires a series for long-horizon inflation expectations. The existing literature typically uses either survey based measures or those derived from financial market prices. For our purpose, an important concern relates to the span of the data available. In other words, it may be the case that shocks to the inflation target are not observed regularly and therefore the proposed identification strategy is more effective in a reasonably long sample. With this in mind, our benchmark proxy for  $\pi^{LH}$  is a spliced survey based measure of long horizon PCE inflation expectations used in the Federal Reserve board model. This measure (with mnemonic PTR) is available on a quarterly basis from 1968Q1 to 2016Q3. In the earlier part of the sample PTR uses estimates of inflation expectations from Kozicki and Tinsley (2001). Data for the 1980s is obtained from the discontinued Decision Makers poll (DMP). Published by Richard Hoey, this survey aimed to capture the 5 to 10 year ahead expectations of participants in the financial markets. From 1991Q4 onwards, the series is based on 1 to 10 year ahead inflation expectations taken from the Survey of Professional Forecasters.

We check the robustness of the results by using an alternative measure based on blue chip economic indicators and the Livingstone survey. 10 year ahead expectations regarding CPI inflation are available from the latter survey since 1991 and are published in June and December of each year. This survey represents the views of academic and non-academic economists. Prior to 1991, this series is based on long horizon forecasts of CPI inflation included in blue chip economic indicators. These forecasts are published in March and October and are available from October 1979.<sup>4</sup> As this data is bi-annual, we use a mixed frequency version of the VAR model (see Schorfheide and Song (2015)) described below. As this series is available at a lower frequency and for a smaller period, PTR remains our preferred proxy for  $\pi^{LH}$ .

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<sup>4</sup>From 1979 to 1983, the blue chip forecasts are for the GNP deflator. A combined series is made available by the Federal Reserve Bank of Philadelphia.

The benchmark VAR model is given by:

$$Y_t = \alpha + \sum_{j=1}^P \beta_{t-j} Y_{t-j} + v_t \quad (11)$$

where  $\alpha$  is a vector of intercepts,  $Y_t$  includes  $\hat{\pi}^{LH}$ , real GDP growth ( $y_t$ ), CPI inflation ( $\pi_t$ ), the 10 year government bond yield ( $I_t$ ) and the three month treasury bill rate ( $R_t$ ). The data for the 10 year yield is obtained from Global Financial data. All remaining variables are taken from the Federal Reserve bank of St. Louis FRED database. Appendix A describes the data sources in detail. When the blue chip and Livingstone series is used for  $\hat{\pi}^{LH}$ , the model is augmented by an observation equation that implements the assumption that the observed expectations data is an average of missing observations in the previous and current quarter. These missing observations are treated as latent variables with the transition equation given by 11 in companion form.

The lag length  $P$  for the benchmark model is set to 2.<sup>5</sup> We adopt a Bayesian approach to model estimation and use a Gibbs sampling algorithm to approximate the posterior distribution of the parameters. As described in the technical appendix, we use a natural conjugate prior with tightness set to values commonly used in the literature for US data. As discussed below, the results are not sensitive to the tightness of the prior. The appendix provides details of the conditional posterior distributions and the steps of the Gibbs sampler. We also provide a description of the extended algorithm used to estimate the mixed frequency VAR model when the inflation expectations based on the blue chip and Livingstone surveys is employed in the estimation.

As discussed above, the shock to the implicit inflation target is identified via the restriction that this shock makes the largest contribution to the FEV of  $\hat{\pi}^{LH}$  at horizon  $K$ . The benchmark model uses  $K = 40$ , but the results are robust to using a longer horizon.

### 3.1.2 Empirical Results

Figure 5 presents the inflation target implied by the historical decomposition from the benchmark SVAR model that uses PTR as the measure of long-horizon inflation expectations. This is calculated as the portion of (annual) inflation driven by the identified inflation target shocks, with the remaining innovations set to zero. The estimates of the target level show a number of similarities to estimates of this object presented in Kozicki and Tinsley (2005), Coibion and Gorodnichenko (2011) and Ireland (2007). In particular, the mid and the late 1970s saw the target rise substantially with peaks of 8 to 10 percent. The rise in the estimated target in these periods lagged the increase in actual inflation suggesting that the Fed was accommodating the impact of inflationary shocks (see Kozicki and Tinsley (2005)). After the appointment of Paul Volcker to the chairmanship of the Fed in 1979Q4, both target and actual inflation declined. After the mid-1980s, the target level has hovered close to the 2 percent mark.

### Impulse responses

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<sup>5</sup>Both the Schwarz criterion and a marginal likelihood comparison suggests a lag length of 1. We employ an extra lag to capture any remaining dynamics. The results are robust to using  $P = 1$  or  $P = 4$ .

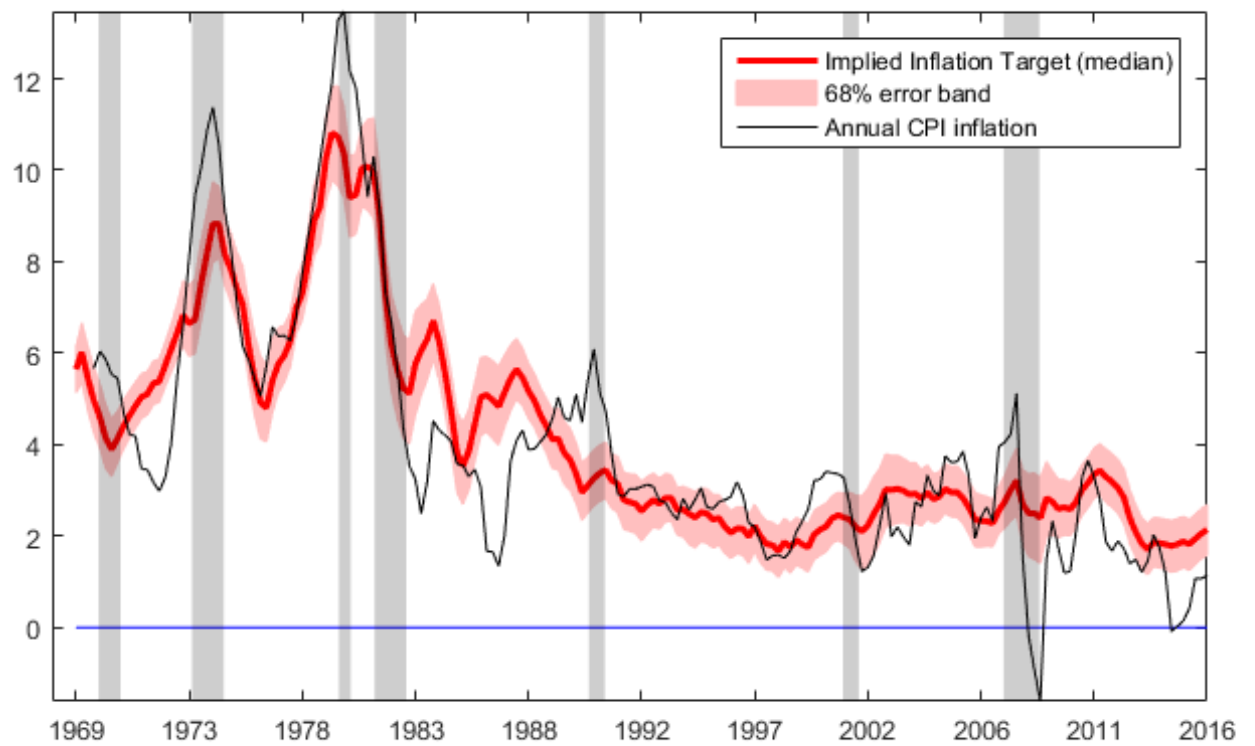


Figure 5: The Federal Reserve's inflation target and actual inflation.

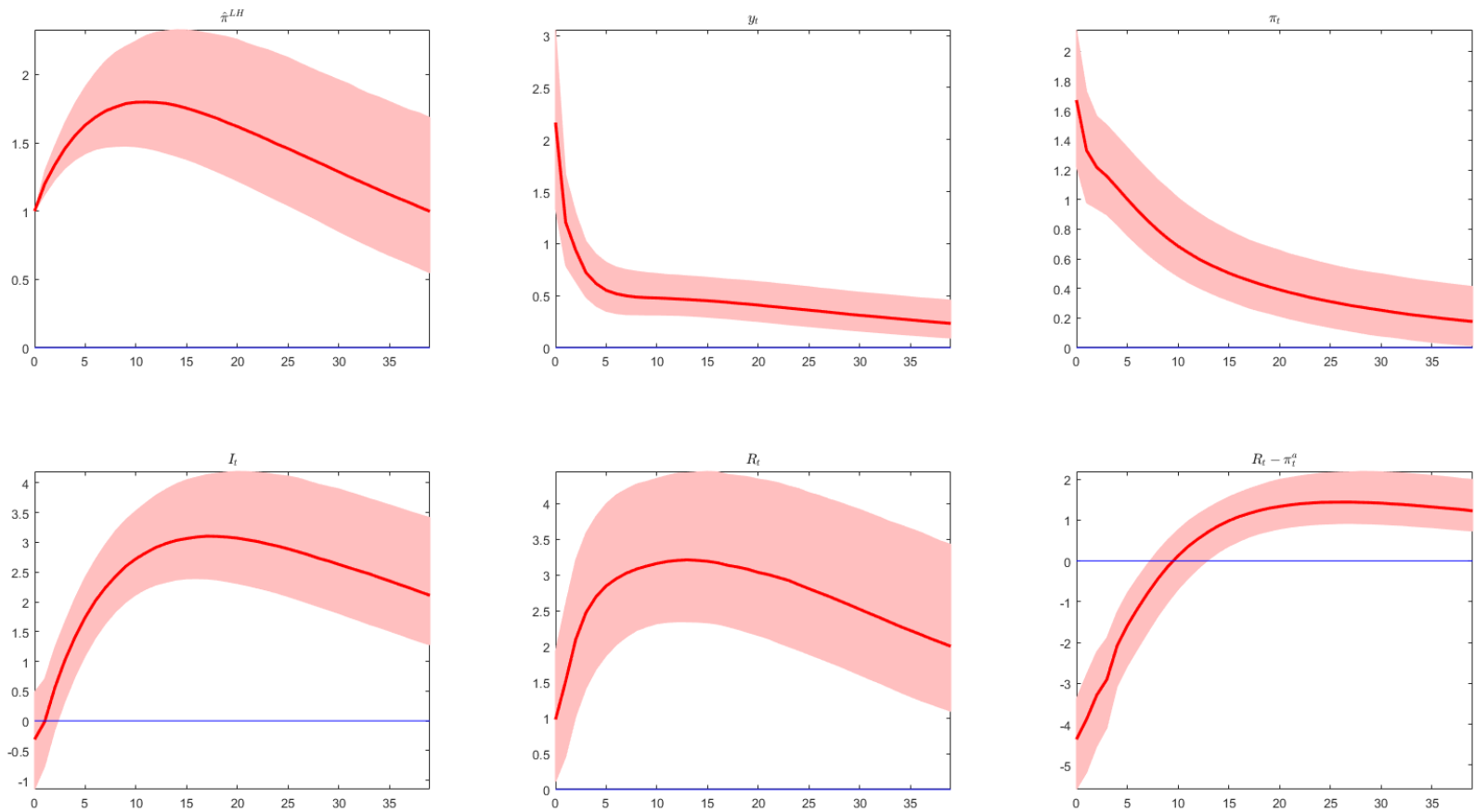


Figure 6: Impulse response to an inflation target shock. The responses are shown for PTR ( $\hat{\pi}^{LH}$ ), real GDP growth ( $y_t$ ), CPI inflation ( $\pi_t$ ), the 10 year government bond yield ( $I_t$ ), the three month treasury bill rate ( $R_t$ ) and the real interest rate where  $\pi_t^a = \sum_{i=0}^3 \pi_{t-i}$ . The solid lines are posterior medians while the shaded area is the 68% error band.

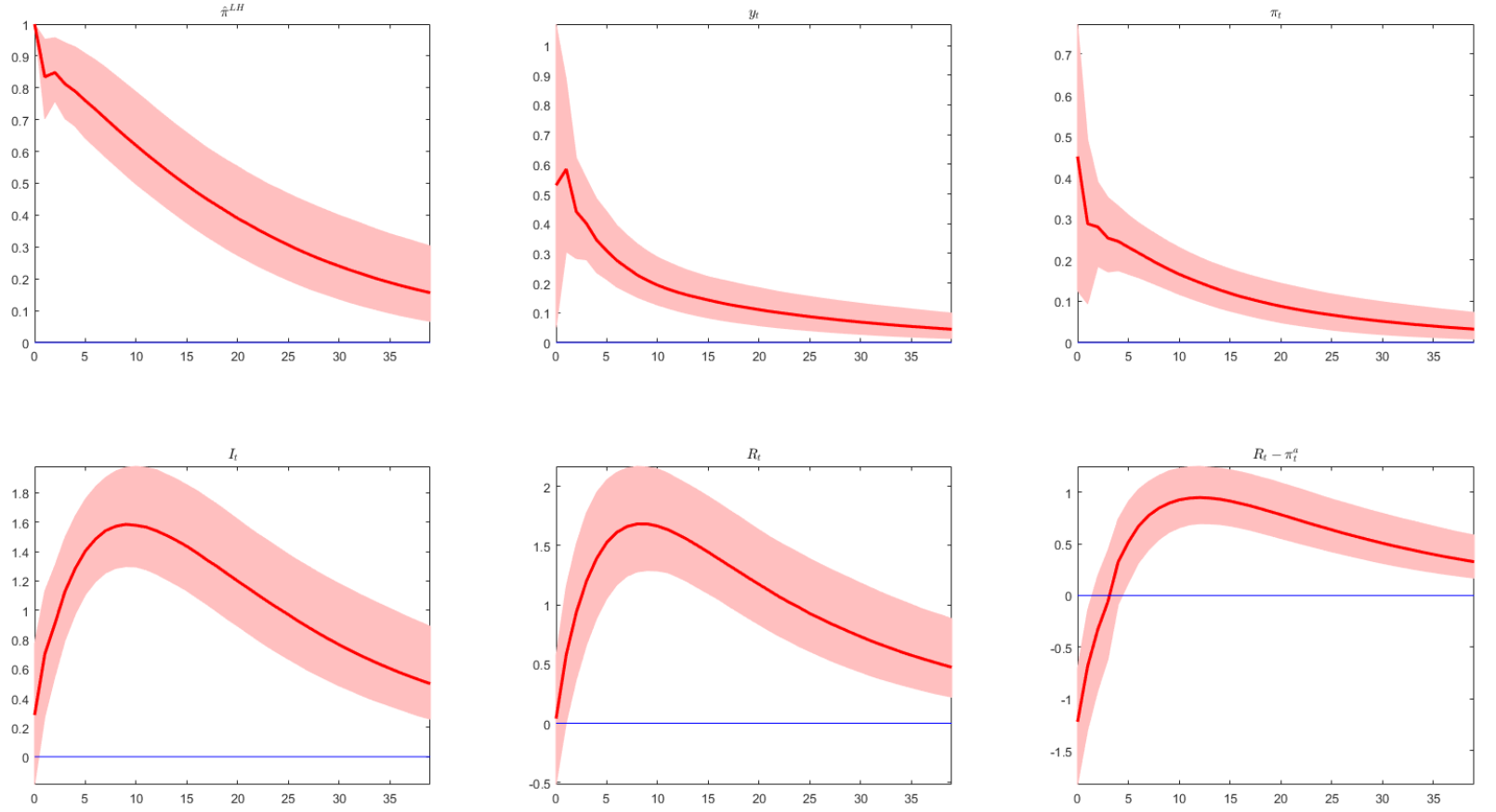


Figure 7: Impulse response to an inflation target shock. The responses are shown for Blue Chip/Livingstone survey ( $\hat{\pi}^{LH}$ ), real GDP growth ( $y_t$ ), CPI inflation ( $\pi_t$ ), the 10 year government bond yield ( $I_t$ ), the three month treasury bill rate ( $R_t$ ) and the real interest rate where  $\pi_t^a = \sum_{i=0}^3 \pi_{t-i}$ . The solid lines are posterior medians while the shaded area is the 68% error band.



Figure 6 presents the impulse responses to inflation target shocks. The figure presents the response to a shock that raises  $\hat{\pi}^{LH}$  by 1 percent on impact. The impact effect on GDP growth and inflation is estimated to be large but dissipates quickly. At the one year horizon the response of GDP growth is 0.8 percent, while inflation rises by 1.2 percent, with the response estimated to be persistent. The last panel in the figure shows that the implied increase in annual inflation  $\pi_t^a$  is larger compared to the rise in the short-rate over the first three years of the horizon. As a consequence, the ex-post real interest rate declines substantially, before increasing by about 1.5 percent over the second half of the horizon. While the response of the long rate  $I_t$  is more sluggish than that of the short-rate, the magnitude of the two responses is very similar at long horizons.

In order to check the robustness of these results to the measure of long-horizon inflation expectations, we re-estimate the VAR model using the series based on the blue chip forecasts and the Livingstone survey. As discussed above, this VAR model entails the estimation of missing inflation expectations data, as well as the VAR parameters. Note also that the estimation sample excludes the 1970s due to data unavailability. The impulse responses from this alternative model are shown in figure 7. The response of GDP growth and inflation to this shock is highly persistent and the null hypothesis of a zero response can be rejected over most of the sample period. The magnitude of the two responses, however, is estimated to be smaller than the benchmark model. As in the benchmark model, the real rate declines, with the response reversing after one year. Both the short and the long-term interest rate responses are large and persistent, albeit the peak response is estimated to be smaller than the benchmark case. In summary, the estimated responses from this model are qualitatively similar to the benchmark case. The estimated magnitude is smaller than benchmark. This may reflect the fact that the mixed frequency VAR treats some of the observations on  $\hat{\pi}^{LH}$  as unobserved and thus contains less information than the benchmark model for the task of identifying the inflation target shock. An alternative explanation can be based on the fact that the post-1980 sample is dominated by the Great Moderation and a decline in the impact of structural shocks over this period is well documented in the literature (see for example Galí and Gambetti (2009)). The latter explanation would suggest that these estimates may represent the lower end of the range of the impact of this shock. Nevertheless, the effects of the inflation target shock are still estimated to be sizeable and are clearly different from zero from a statistical perspective.

The results of the benchmark model are robust to other changes in model specification. Details of these additional robustness checks are given in the on-line technical appendix. First, we expand the benchmark VAR model by adding the first three principal components extracted from a large panel of macroeconomic and financial data for the US (FRED-QD database provided by the St. Louis Fed). This allows us to incorporate a large amount of information into the model and to account for potential information insufficiency (see Forni and Gambetti (2014)). The impulse responses from this model are shown in Figure 2 of the technical appendix. The results are very close to the benchmark estimates indicating robustness with respect to this issue. Similarly, when the benchmark model is estimated on pre-2007 data, the results are largely unaffected (see Figure 3 in the technical appendix). As mentioned above, using a lag length of 1 or 4 does not alter the key conclusions (See Figures 4 and Figure 5 in the technical appendix). Figure 6 in the technical appendix shows that if the FEV restrictions are imposed using a horizon of 80 quarters, the key results survive. Finally, Figure 7 shows that the use of a flat prior leads to conclusions that are similar to the benchmark case.

While the Monte-Carlo experiment in section 2.1 provides strong evidence on the effectiveness of the proposed identification scheme, it is interesting to further scrutinise the properties of the identified shock. For this purpose, we follow Ben Zeev and Pappa (2017) and consider the cross-correlation between the estimated target shock and shocks identified in the literature to be important for business cycle fluctuations. As shown in Figure 8, we consider monetary policy

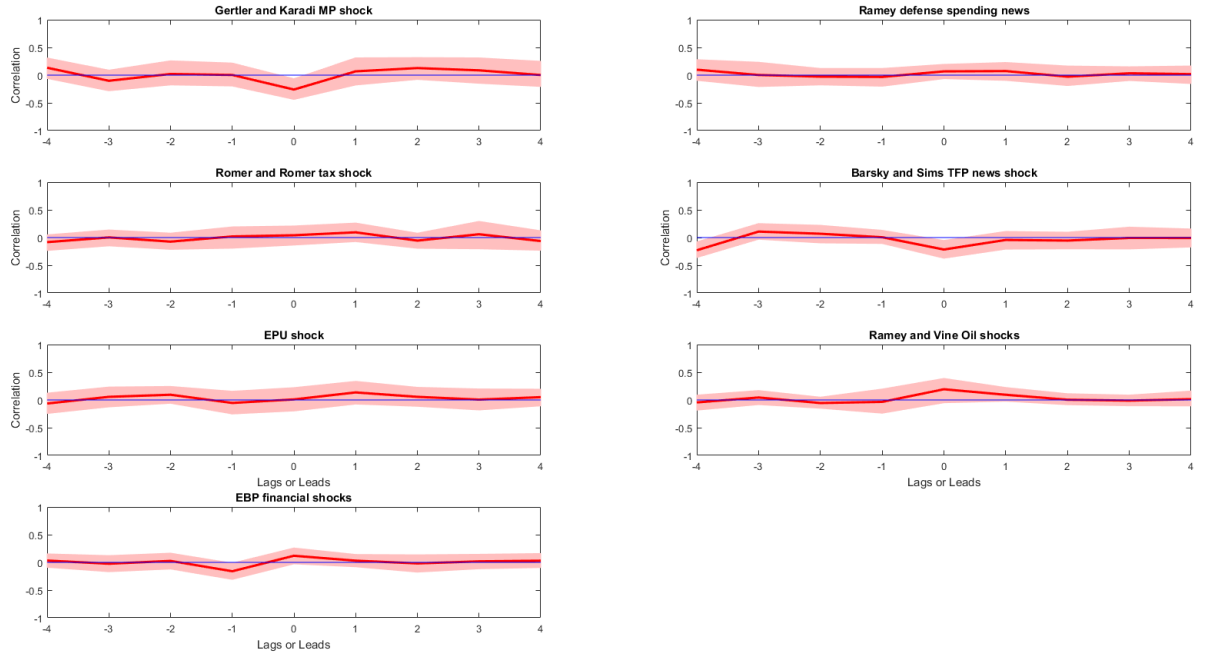


Figure 8: Correlation between the target shock and other structural shocks. The sold line is the median correlation, while the error band represents the 95 percent confidence interval obtained via bootstrap.

shocks identified by Gertler and Karadi (2015) and fiscal shocks taken from Ramey (2011) and Romer and Romer (2010). Policy uncertainty (EPU) shocks are proxied as residuals to an AR(4) model using the economic policy uncertainty index of Baker *et al.* (2017). TFP news shocks are taken from Barsky and Sims (2011) while we use the measure of oil shocks constructed by Ramey and Vine (2011). Finally we consider the innovations to the excess bond premium (see Gilchrist and Zakrajsek (2012)) obtained via a recursive VAR (using GDP, CPI, a short term interest rate and the excess bond premium) as a measure of financial shocks. Figure 8 shows that the estimated correlations are insignificant at most lags or leads. Moreover, the magnitude of the estimated correlations is small in all cases. This provides evidence that the shock identified in our SVAR model is distinct from other policy and non-policy disturbances.

In summary, the benchmark results and the sensitivity analysis suggests the following conclusion: a unit inflation target shock is estimated to have an impact on US GDP growth, CPI inflation, the short and long term interest rate that is sizeable from an economic and statistical perspective. We now turn to evaluating the contribution of inflation target shocks.

## **Variance and historical decomposition**

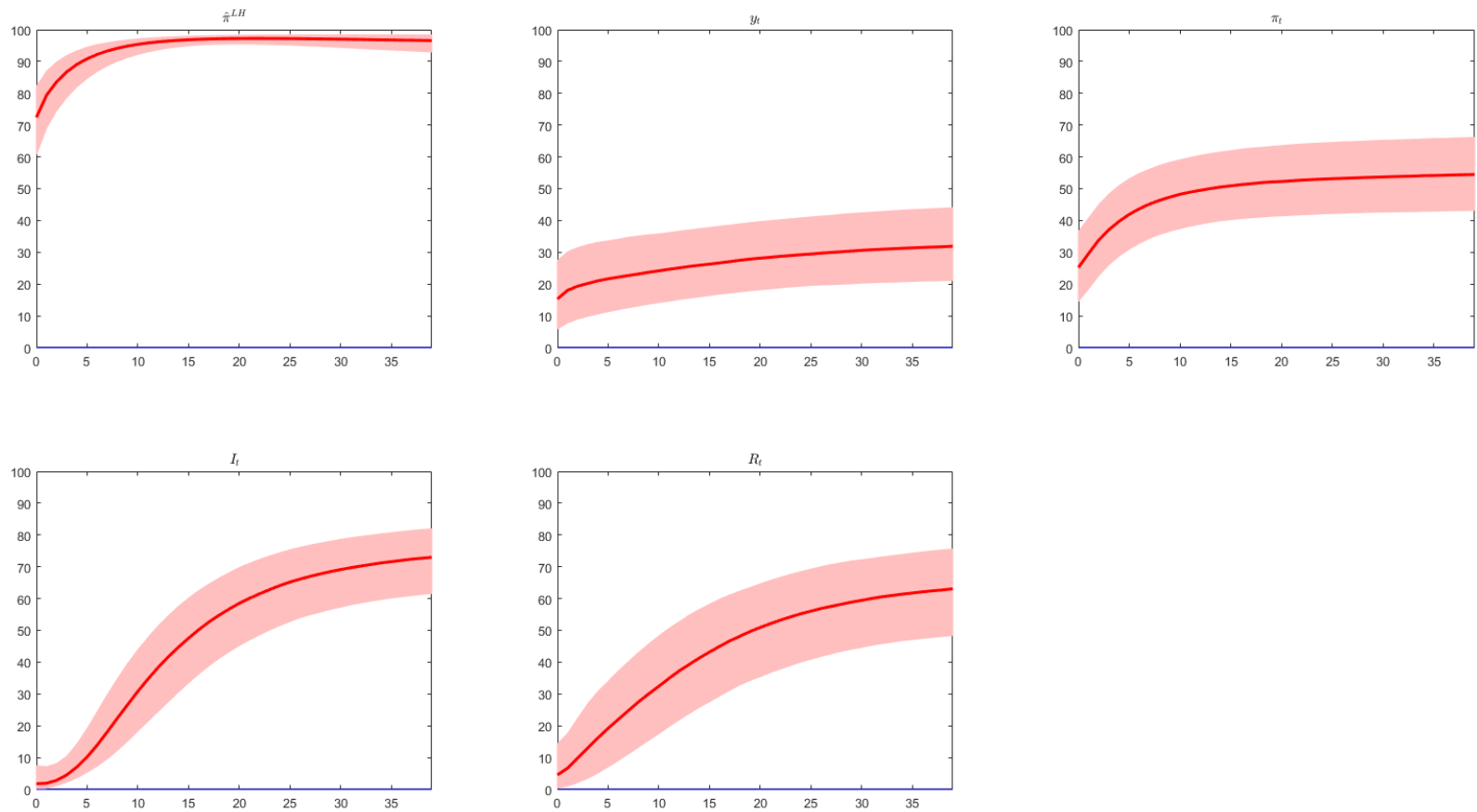


Figure 9: Contribution of the inflation target shock to the FEV. The contributions are shown for PTR ( $\hat{\pi}^{LH}$ ), real GDP growth ( $y_t$ ), CPI inflation ( $\pi_t$ ), the 10 year government bond yield ( $I_t$ ), the three month treasury bill rate ( $R_t$ ). The solid lines are posterior medians while the shaded area is the 68% error band.

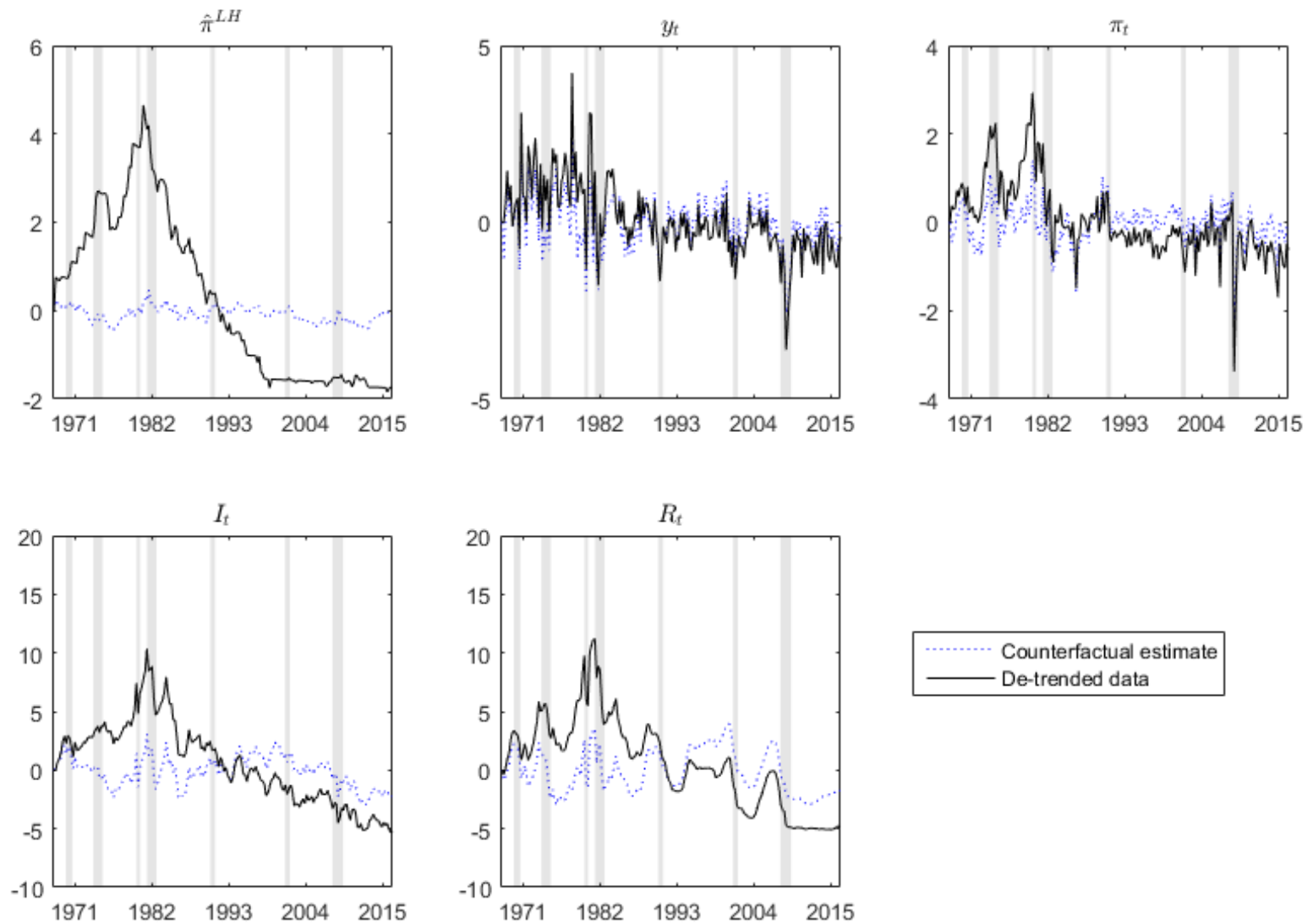


Figure 10: Contribution of shocks other than inflation target shocks to the de-trended data. The contributions are shown for PTR ( $\hat{\pi}^{LH}$ ), real GDP growth ( $y_t$ ), CPI inflation ( $\pi_t$ ), the 10 year government bond yield ( $I_t$ ), the three month treasury bill rate ( $R_t$ ). The shaded vertical bands show NBER recession dates.

Figure 9 shows the contribution of the inflation target shock to the forecast error variance (FEV) estimated using the benchmark model. By construction, the shock explains the bulk of the FEV of  $\hat{\pi}^{LH}$ . At the two year horizon, the shock contributes about 23% to the FEV of GDP growth. The contribution to FEV of CPI inflation at this horizon is estimated to be about 48%. It is interesting to note that these contributions are larger than those typically reported for the monetary policy shock (see for example Bernanke *et al.* (2005a)). The bottom panels of the figure show that this shock makes the most important contribution to the FEV of  $I_t$  and  $R_t$  explaining the bulk of the FEV at long horizons.

A similar conclusion is reached when examining the contribution of this shock to the historical fluctuations in these interest rates. Figure 10 plots (de-trended) data for the endogenous variables along with the counter-factual estimates from the VAR assuming that the inflation target shock equals zero at each point in time. The second row of the figure shows that after the early 1990s the counter-factual estimate of the interest rates is above the observed data, implying that fluctuations in the implicit target of the Fed helped to keep these rates at depressed levels over the last two decades. The inflation target shock made a strong positive contribution to inflation during the mid and late-1970s. The great inflation is largely absent in the counter-factual scenario and the impact of inflationary shocks in the early and the late 1970s is muted. The counter-factual estimate of inflation largely remains above the actual data after the mid-1980s providing some support for the hypothesis that systematic policy contributed to low inflation seen over the Great Moderation. It is interesting to note that in the absence of these shocks, GDP growth is estimated to have been higher over the last two decades.

Decomposition results based on the VAR that uses the blue chip\Livingstone inflation expectation series suggests similar conclusions. The inflation target shock is estimated to explain about 50 percent of the FEV of the short and long term interest rate. As in the benchmark case, the shock makes a modest contribution to GDP growth. We estimate that the contribution to the inflation FEV is about 20 percent at the two year horizon. While still sizeable, this estimate is smaller than the benchmark case. As discussed above, this may reflect the decline in the impact of shocks over the Great Moderation period or the fact that the blue chip\Livingstone data is available at a lower frequency and for a smaller time span.<sup>6</sup>

### 3.2 International transmission

The results presented above constitute fairly strong evidence that inflation target shocks can have a sizeable impact on US interest rates and inflation. There is a sizeable empirical literature that shows that shocks that affect the US policy rate can have important consequences for the rest of the world. For example, Kim (2001) and Canova (2005) provide evidence that US monetary policy shocks transmit to foreign economies. It is therefore interesting to consider if a similar result holds for inflation target shocks. Given that these shocks are estimated to affect the level of the US yield curve, their potential effect is likely to be different from monetary policy shocks.

In our analysis, we consider the transmission of US target shocks to a panel of macroeconomic and financial data for 21 industrialised economies from North America, Europe and East Asia. For this purpose, we augment the benchmark VAR model (see equation 11) in the following manner:

$$\tilde{Y}_t = \tilde{\alpha} + \sum_{j=1}^P \tilde{\beta}_j \tilde{Y}_{t-j} + \tilde{v}_t \quad (12)$$

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<sup>6</sup>These additional results are presented in the technical appendix.

where  $\tilde{Y}_t = \begin{pmatrix} Y_t \\ F_t \end{pmatrix}$  with  $Y_t$  denoting the set of endogenous variables used in the benchmark VAR and  $F_t$  representing a set of  $k$  unobserved factors estimated using the panel of international data. In particular, the model incorporates the following observation equation:

$$\begin{pmatrix} Y_t \\ X_{it} \end{pmatrix} = \begin{pmatrix} I_N & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Y_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ e_{it} \end{pmatrix} \quad (13)$$

Here,  $X_{it}$  denotes the panel of  $i = 1, 2, \dots, M$  international series,  $\Lambda$  is a  $M \times k$  matrix of factor loadings and  $e_{it}$  denotes the idiosyncratic shocks with variances  $r_i$ . The US inflation target shock is again identified via the restriction that this shock makes the largest contribution to the FEV of  $\hat{\pi}^{LH}$  at horizon  $K = 40$ . Given the response of  $\tilde{Y}_t$  to this shock, equation 13 allows us to estimate the response of the variables of interest for the US and foreign economies.

Details of the series included in  $X_{it}$  are presented in Appendix A. For each country, the panel includes data on real activity, inflation, the yield curve, broad money and credit and asset prices such as stock returns and the real exchange rate with respect to the US.<sup>7</sup> The span of the data is restricted to 1975 Q1 to 2015 Q4 in order to obtain a balanced panel and to exclude the Bretton Woods period.

As described in the technical appendix, we adopt a Bayesian approach to estimation and use a Gibbs sampler to approximate the posterior distribution of the parameters of this factor augmented VAR model (see Bernanke *et al.* (2005b)). The number of factors  $k$  represents an important specification choice for this model. Our selection procedure is based on comparing the marginal likelihood for  $k = 2, 3, \dots, 8$ . This exercise indicates that the fit of the model is maximised for  $k = 7$ , with the same number of factors suggested by the Bai and Ng (2002) statistics.

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<sup>7</sup>In addition, we include a set of global commodity prices (such as oil and gas prices) to further account for common shocks not captured by  $F_t$ .

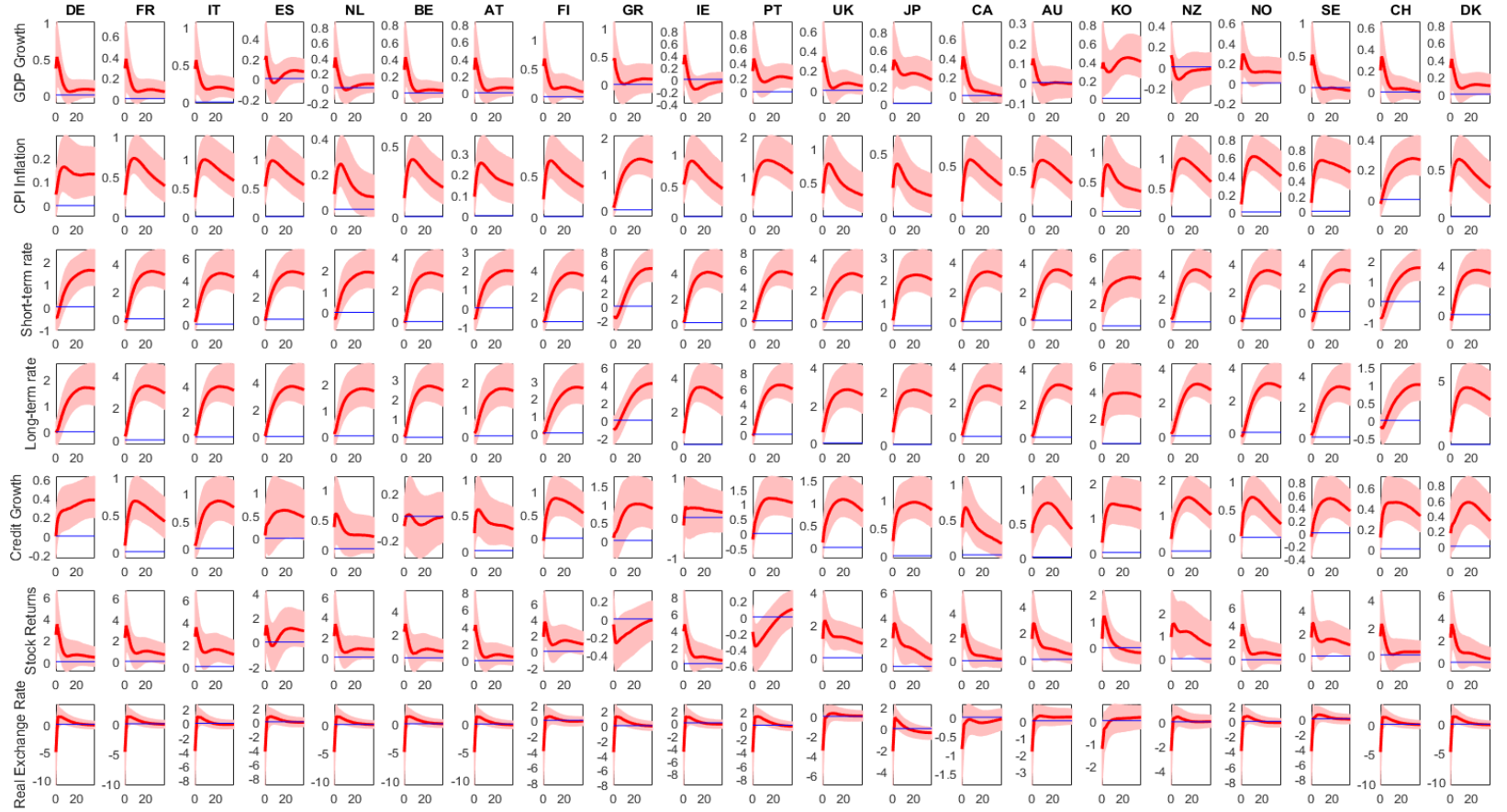


Figure 11: Response to a US inflation target shock. The shock is normalised to increase  $\hat{\pi}^{LH}$  by 1 percent on impact. Short-term rate denotes a three month treasury bill rate while the long term rate is the ten year government bond yield. The figure shows the posterior median (solid line) and the 68 percent error band (shaded area).



### 3.2.1 Impulse responses

The responses of US variables to a one unit expansionary inflation target shock in this model are shown in the technical appendix and are very similar to those obtained from the benchmark model – i.e. there is an increase in output, inflation, short and long-term rates and the real interest rate declines. Instead, in figure 11, we focus on the response of key foreign variables. It is clear from the third and the fourth row of the figure that the level of the yield curve in all countries is affected strongly by this shock with both long and short-term rates displaying large and persistent increases. While the short-term rate increases, the accompanying rise in annualised inflation is large enough to offset this over the first 1 to 2 years of the horizon and ex-post real interest rate declines in all countries. The top row of the figure shows that the shock has a positive impact on GDP growth in all 19 countries. There is some heterogeneity in the magnitude of the response – the impact is relatively large in Euro area countries such as Germany, France and Italy and economies such as Canada, Japan and South Korea while GDP growth in Australia and New Zealand displays a much smaller increase. In response to the shock, CPI inflation displays an increase across countries that is uniformly more persistent than the rise in GDP growth. The fifth row of the figure shows that the target shock has an impact on credit growth in most countries with this variable estimated to rise, on average, by about 0.5 percent at the one year horizon. However, for most countries, this increase in credit growth largely reflects the impact of the shock on inflation – in real terms, credit growth declines on average across countries for about three years after the shock. The response of stock returns to the target shock is larger on impact than that of credit growth. With the exception of Greece and Portugal, the expansionary US shock is associated with an increase in stock returns, with an average impact of about 2 percent at the one year horizon. Note that the large increase in stock prices relative to inflation suggests that these results hold in real terms as well. This provides some support for the arguments in Miranda-Agrippino and Rey (2015) regarding the role of US monetary policy in driving a global financial cycle. Finally, the real exchange rate (expressed as foreign (i.e US) CPI in domestic currency relative to domestic CPI) appreciates for all countries with the growth rate showing a sharp decline on impact. This reflects the nominal depreciation of the dollar after the expansionary target shock. Note, however, that the effect unwinds quickly and there is no evidence that changes in the real exchange rate affects trade flows. When we construct the response of the trade balance (displayed in the technical appendix), the estimates are almost universally indistinguishable from zero from a statistical perspective. This taken together with the response of stock returns and real interest rates points to a transmission mechanism that is driven by world asset markets that are increasingly integrated. A decline in US real interest rates in response to this shock may encourage monetary authorities elsewhere to pursue an expansionary policy in order to prevent or offset any effects on domestic inflation and output via capital outflows from the US and a real exchange rate appreciation.

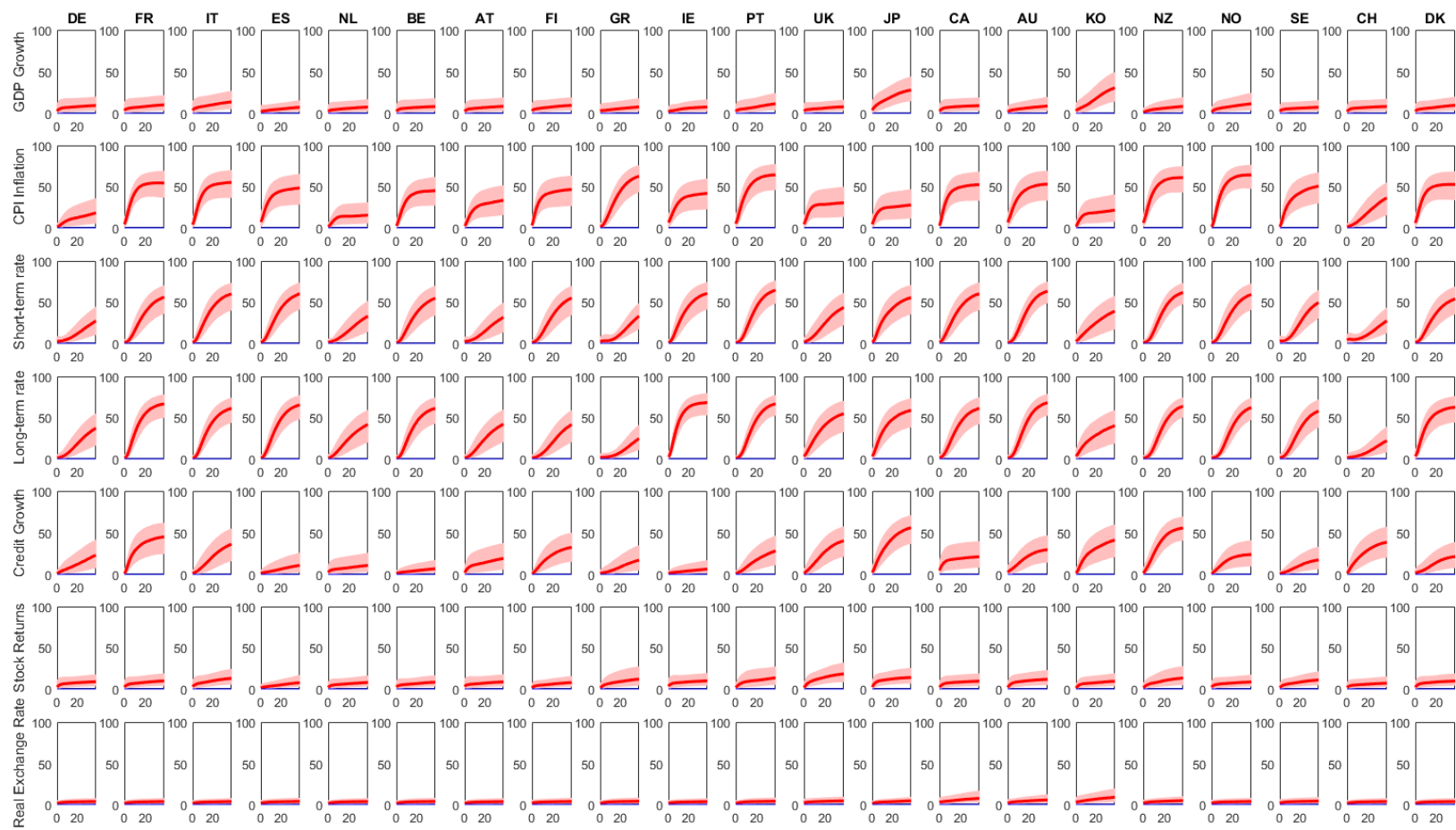


Figure 12: Contribution of US inflation target shock to FEV. See notes to figure 11.

### 3.2.2 Contribution of the shock

Figure 12 presents the contribution of the US target shock the FEV of the foreign variables discussed above. The contribution of the shock to fluctuations in the real exchange rate and GDP growth are relatively modest and average about 3 to 11 percent at the ten year horizon, respectively. Similarly, the average contribution of the shock to international stock returns is fairly small and is estimated to be about 10 percent at the ten year horizon. This shock appears more important for the FEV of inflation, short and long-term rates with a cross-country average contribution well above 40% at the ten year horizon.

To put these decompositions in historical context, figure 13 presents the contribution of the target shock to past movements in key international variables. The solid line in each panel of the figure presents an estimate of the common component across countries. In particular, the contribution of the structural shocks  $\varepsilon_t$  in the VAR given by 12 can be calculated by noting that deviations of each endogenous variable from a baseline trend at horizon  $H$  are given as:

$$\tilde{e}_t(H) = \sum_{h=0}^{H-1} \tilde{A}^h \varepsilon_{t+H-h} \quad (14)$$

where  $\tilde{A}^h$  denote the impulse responses at horizon  $h$  and  $\varepsilon_t = A_0^{-1} \tilde{v}_t$  where the contemporaneous impact matrix is obtained via the restrictions on the FEV of  $\hat{\pi}_{LH}$ . With  $\tilde{e}_t$  in hand, an estimate of the data net of the idiosyncratic error is easily obtained using the observation equation of the system:  $\tilde{X}_{it} = \Lambda \tilde{e}_t$ . The solid line in each panel of figure 13 is obtained using  $\tilde{X}_{it}$ . For example, the top left panel presents an estimate of ‘global inflation’ which is obtained as the first principal component of the inflation data for the 21 countries net of the idiosyncratic error:  $e_\pi \left( \tilde{X}_{it} \right)$  where  $e_\pi$  is a selection vector that extracts CPI inflation for each country. The dotted line represents the counterfactual estimate of this common component. It assumes that in equation 14 the element of the structural disturbances,  $\varepsilon_t$ , that corresponds to the US target shock equals zero at each horizon. The counterfactual principal component is then extracted using the data matrix built from equations 14 and 13 under this assumption.

Consider the top left panel. The estimate of global inflation follows a pattern very similar to that reported in Mumtaz and Surico (2012) and Ciccarelli and Mojon (2010). The 1970s were characterised by high inflation, with the level dropping post-1984. The dotted line represents the estimate of this global component assuming that the US inflation target shock equals zero at each point in time. In the absence of this shock, the phenomenon of global inflation during the 1970s and the early 1980s is largely absent suggesting that loose US monetary policy was an important driving force. Post-1990, this effect is reversed – the US target shock exerts a negative influence on international inflation rates. The results presented in the top right panel of the figure are starker – global long-term rates would have been substantially lower in the absence of US target shocks before the mid-1990s, with the counterfactual estimate not displaying the persistent decline observed after the mid-2000s. Results for the short-rate in the bottom left panel suggest very similar conclusions. In contrast, the shock makes a limited contribution to the historical common movements in stock returns. Taken together, these results provide support for two recent empirical observations in the literature. First, the results are consistent with the finding that global yields are characterised by a common level factor (see Diebold *et al.* (2008)) that has displayed a downward trend since the early 1990s. Our results suggest that the US inflation target shock is an important factor behind the behaviour of the ‘global yield curve’. Second, the sizeable contribution of the shock to short-term rates and inflation suggests that US monetary policy is an important determinant of policy

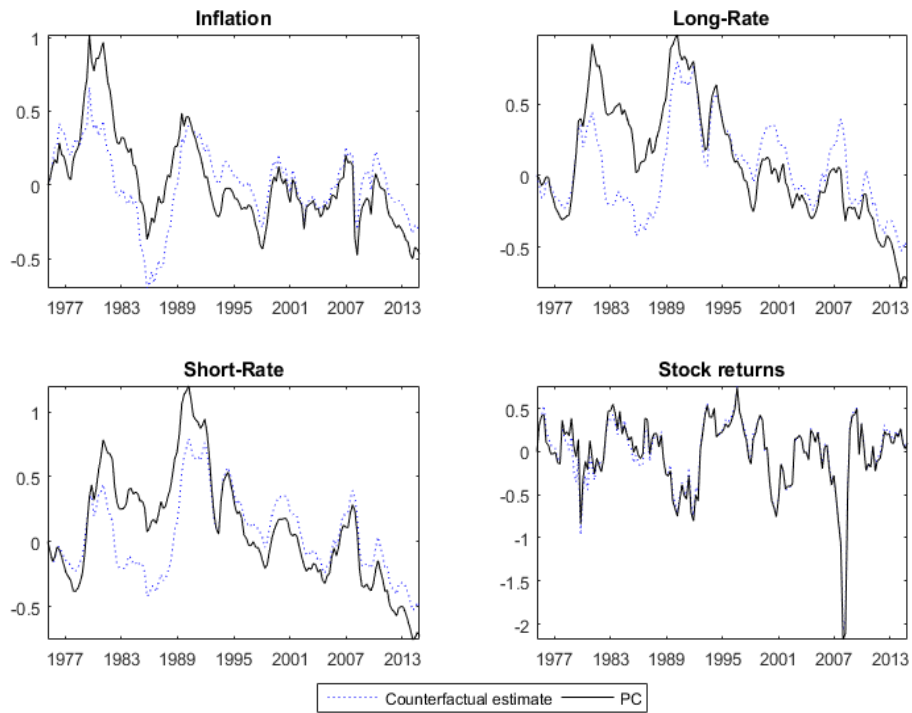


Figure 13: Historical decomposition. The solid line shows the first principal component of the (standardised) data excluding the idiosyncratic error and VAR implied trend. The dotted line plots the same object when the US inflation target shock is set to zero.

developments abroad (see Rey (2016)).

## 4 Conclusions

We propose to identify shocks to the Fed’s implicit inflation target as innovations in an SVAR that explain the bulk of the FEV of long-horizon inflation expectations. When this scheme is applied to data simulated from a DSGE model that features a time-varying inflation target, we are able to recover the target shock and estimate its transmission with precision. This result remains robust when the target is assumed to be unobserved by the agents in the model or the monetary policy rule is subject to regime shifts.

Application of this SVAR to US data suggests that the impact of a 1 percent positive inflation target shock is large with the peak effect on GDP growth and inflation, one year ahead, estimated to be 0.8 percent and 1.2 percent, respectively. The shock has its largest impact on both the short and the long-term interest rate. Decompositions from the SVAR indicate that this shock was the major driving force behind the great inflation of the 1970s and contributed substantially to the persistent decline observed in long-term interest rates. We also present evidence that suggests that the US target shock has a strong impact on interest rates and inflation in a panel of 21 developed economies. In the absence of this shock, global inflation would have been lower during the 1970s and early 1980s and the level of international yields would have been higher after the mid-1990s.

For researchers and policy makers our results offer two key insights. First, our analysis shows that systematic policy changes by the Fed matter for the economy as they can have persistent effects on key variables. Second, our results suggest that changes in the US target have international effects. Given the possibility of changes in the leadership and outlook of the Federal Reserve under the new US government, these conclusions can help in the analysis of OECD economic performance in the near future.

## A Appendix A: Data sources

FRED is Federal Reserve Economic data (<http://research.stlouisfed.org/fred2/>) and GFD refers to Global Financial Data (<http://www.globalfinancialdata.com/>).

### Data on inflation expectations

- PTR. Downloaded from FRB/US model webpage.
- Blue Chip/Livingstone survey. Available from the Philadelphia Fed.

### Macroeconomic/Financial data for the United States

- Real GDP: Real GDP (FRED series id GDPC96).
- CPI (FRED series id CPIAUCSL). We calculate inflation as the quarterly growth in CPI.
- 3 month Treasury Bill rate (FRED series id TB3MS).
- 10 Year government bond yield (GFD code IGUSA10D)

**International data** This is a version of the data set used in Mumtaz and Musso (2017). The set of countries in the panel include: Germany, France, Italy, Spain, Netherlands, Belgium, Austria, Finland, Greece, Ireland, Portugal, United Kingdom, Japan, Canada, Australia, South Korea, New Zealand, Norway, Sweden, Switzerland, Denmark. Table 1 presents details on the variables included for each country in the panel. In addition we include crude oil price, natural gas price, agricultural raw material price, food price, beverages price, fertilizer price, metals and mineral price and precious metals price. These indices are obtained from the World bank and included in log differences in the panel. The OECD data base can found at <https://data.oecd.org/>. BIS refers to the Bank for International Settlements (<https://www.bis.org/statistics/>) while the IMF and ECB data are located at <http://data.imf.org> and <https://www.ecb.europa.eu/stats/html/index.en.html>. LD equals log difference. All NSA series are adjusted using the X13 filter. Further details on the data are provided in Mumtaz and Musso (2017).

	Variable	Transformation	Source
1	REAL GDP	LD	OECD
2	CONSUMER PRICE INDEX	LD	OECD
3	SHORT-TERM INTEREST RATE	NA	BIS, IMF, OECD
4	STOCK PRICES	LD	BIS, IMF, OECD
5	CREDIT TO THE PRIVATE SECTOR	LD	BIS, IMF, OECD
6	BANK LOANS TO THE PRIVATE SECTOR	LD	BIS, IMF, OECD
7	HOUSE PRICES	LD	BIS, IMF, OECD
8	BROAD MONEY	LD	ECB, BIS, IMF, OECD
9	NARROW MONEY	LD	ECB, BIS, IMF, OECD
10	INDUSTRIAL PRODUCTION	LD	IMF, OECD
11	RETAIL SALES VOLUMES	LD	OECD,FRED
12	EMPLOYMENT	LD	BIS, OECD
13	UNEMPLOYMENT RATE	NA	OECD
14	REAL GROSS FIXED CAPITAL FORMATION	LD	OECD, BIS
15	REAL PRIVATE CONSUMPTION	LD	OECD, BIS
16	REAL EXPORTS	LD	OECD, BIS
17	REAL IMPORTS	LD	OECD, BIS
18	REAL EXCHANGE RATE	LD	GFD for exchange rates and authors' calculations
19	LONG-TERM INTEREST RATE	NA	BIS, IMF, OECD

Table 1: Variables included for each country

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# The Federal Reserve's implicit inflation target and Macroeconomic dynamics. (Technical Appendix: SVAR results and DSGE model)\*

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January 2018

## Abstract

Key words:

JEL codes: C5, E1, E5, E6

## 1 Estimation of the Bayesian VAR model

Consider the reduced form VAR

$$Y_t = \alpha \Gamma_t + \sum_{j=1}^P \beta_{t-j} Y_{t-j} + v_t, \text{var}(v_t) = \Omega$$

where  $\Gamma_t$  is  $1 \times M$  vector of exogenous regressors, which in our application includes an intercept. We adopt a Bayesian approach to estimation of the reduced form VAR model. We introduce a natural conjugate prior for the VAR parameters (see Banbura *et al.* (2010)):

$$Y_{D,1} = \begin{pmatrix} \frac{\text{diag}(\gamma_1 \sigma_1 \dots \gamma_N \sigma_N)}{\tau} \\ 0_{N \times (P-1) \times N} \\ \dots \\ \text{diag}(\sigma_1 \dots \sigma_N) \\ \dots \\ 0_{M \times N} \end{pmatrix}, \text{ and } X_{D,1} = \begin{pmatrix} \frac{J_P \otimes \text{diag}(\sigma_1 \dots \sigma_N)}{\tau} & 0_{NP \times M} \\ 0_{N \times NP+M} & \\ \dots & \\ 0_{M \times NP} & I_M \times c \end{pmatrix} \quad (1)$$

where  $\gamma_1$  to  $\gamma_N$  denotes the prior mean for the coefficients on the first lag,  $\tau$  is the tightness of the prior on the VAR coefficients and  $c$  is the tightness of the prior on the constant terms. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable using a training sample. We set  $\tau = 0.2$ . The scaling factors  $\sigma_i$  are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Finally we set  $c = 1/1000$  in our implementation indicating a flat prior on the

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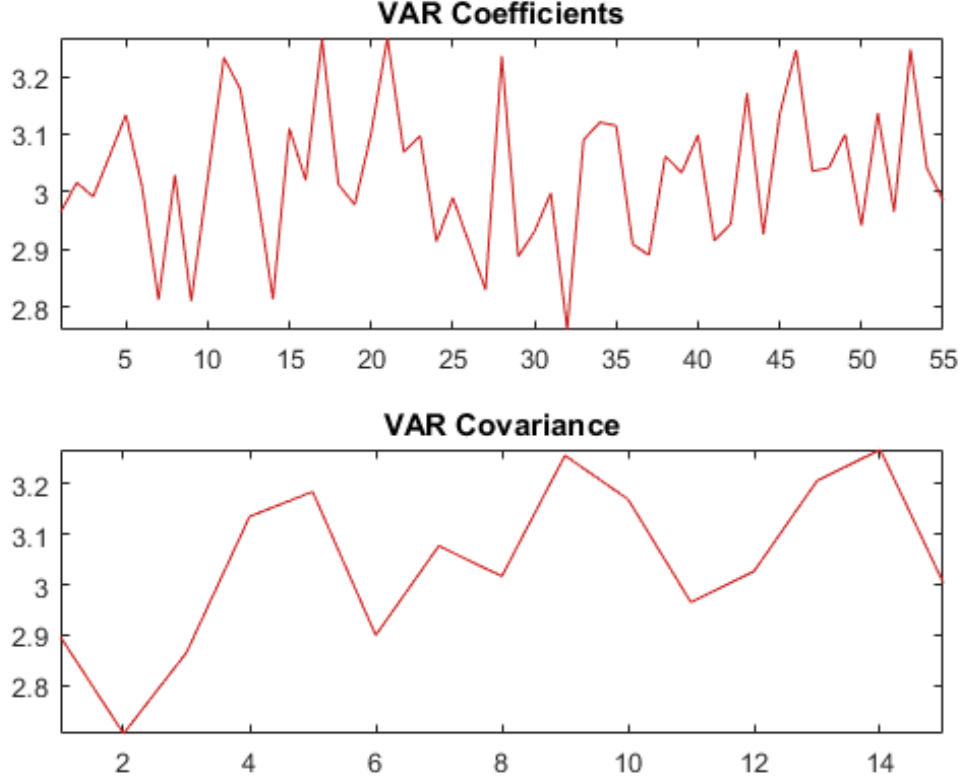


Figure 1: Inefficiency factors for the benchmark VAR model.

constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{\text{diag}(\gamma_1 \mu_1 \dots \gamma_N \mu_N)}{\lambda}, \quad X_{D,2} = \left( \frac{(1_{1 \times P}) \otimes \text{diag}(\gamma_1 \mu_1 \dots \gamma_N \mu_N)}{\lambda} \quad 0_{N \times M} \right) \quad (2)$$

where  $\mu_i$  denotes the sample means of the endogenous variables calculated using the training sample. As in Banbura *et al.* (2010), the tightness of this sum of coefficients prior is set as  $\lambda = 10\tau$ . Given the natural conjugate prior, the conditional posterior distributions of the VAR parameters  $B = \text{vec}([\alpha, \beta_1; \beta_2 \dots; \beta_j])$  and  $\Omega$  take a simple form and are defined as:

$$G(B|\Omega) \sim N(B^*, \Omega \otimes (X^*{}' X^*)^{-1}) \quad (3)$$

$$G(\Omega|B) \sim IW(S^*, T^*). \quad (4)$$

where  $X$  denotes the right hand side variables  $\Gamma_t, Y_{t-1}, \dots, Y_{t-P}$ . The posterior means are given by  $B^* = (X^*{}' X^*)^{-1} (X^*{}' Y^*)$  and  $S^* = (Y^* - X^* \tilde{B})' (Y^* - X^* \tilde{B})$ , where  $Y^* = [Y; Y_{D,1}; Y_{D,2}]$ ,  $X^* = [X; X_{D,1}; X_{D,2}]$  and  $\tilde{B}$  is the draw of the VAR coefficients  $B$  reshaped to be conformable with  $X^*$ .  $T^*$  denotes the number of rows of  $Y^*$ . A Gibbs sampler offers a convenient method to simulate the posterior distribution of  $B$  and  $\Omega$  by drawing successively from these conditional posteriors. We employ 25,000 iterations using the last 5000 for inference.

Figure 1 reports inefficiency factors for key parameters of the benchmark model calculated

using a Parzen window. The estimates are below the recommended level of 20 providing support for convergence.

Once the iterations are past the burn-in stage, we calculate the contemporaneous impact matrix. As described in the main text, the the VAR in structural moving average form is:

$$Y_t = B(L) A_0 \varepsilon_t$$

The  $k$  period ahead forecast error of the  $ith$  variable is given by:

$$Y_{it+k} - \hat{Y}_{it+k} = e_1 \left[ \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q \varepsilon_{t+k-j} \right]$$

where  $e_1$  is a selection vector that picks out  $\hat{\pi}^{LH}$  in the set of variables. Following Uhlig (2004a), the proposed identification scheme thus amounts to finding the column of  $Q$  that solves the following maximisation problem:

$$\arg \max_{Q_1} e_1' \left[ \sum_{k=0}^K \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q_1 Q_1' \tilde{A}_0' B_j' \right] e_1$$

such that  $Q_1' Q_1 = 1$ . Here  $Q_1$  is the column of  $Q$  that corresponds to the shock that explains the largest proportion of the FEV of the first variable in the VAR,  $\hat{\pi}^{LH}$ . This objective function can be written as

$$\arg \max_{Q_1} Q_1' S Q_1$$

where  $S = \sum_{k=0}^K \sum_{j=0}^{k-1} \tilde{A}_0' B_j' (e_1 e_1') B_j \tilde{A}_0$ . The maximisation problem can be expressed as a Lagrangian

$$L = Q_1' S Q_1 - \lambda (Q_1' Q_1 - 1)$$

The first order condition is  $S Q_1 = \lambda Q_1$ . As shown by Uhlig (2004b), this is an eigenvalue-eigenvector problem. The column  $Q_1$  that maximises the variance is the eigenvector associated with the largest eigenvalue  $\lambda$ . We use the matlab code written by Kurmann and Otrok (2013) to implement this solution.

## 2 Estimation of the Bayesian Mixed Frequency VAR model

The observation equation of the model is defined as

$$y_t = H_t \beta_t + V_t$$

where  $y_t = [\hat{\pi}_t^{LH} \ z_t]$  where  $z_t$  denotes the remaining  $N - 1$  endogenous variables in the VAR. As discussed in the text, the Blue Chip\Livingstone survey proxy for  $\hat{\pi}^{LH}$  is unavailable every quarter.  $\beta_t$  denotes the  $ns \times 1$  vector of state variables  $(\tilde{\pi}_t^{LH}, z_t, \tilde{\pi}_{t-1}^{LH}, z_{t-1})$  where  $\tilde{\pi}_t^{LH}$  denotes the unknown higher frequency data on inflation expectations. At time  $t$ , if  $\hat{\pi}_t^{LH}$  is missing, the matrix  $H_t$  is defined as

$$H_t = \begin{bmatrix} & 0_{1 \times ns} \\ 0_{N-1 \times 1} & I_{N-1} \ 0_{N-1 \times ns-N} \end{bmatrix}$$

and  $var(V_t) = 1e10$ .

At time  $t$ , if  $\hat{\pi}_t^{LH}$  is available and  $\hat{\pi}_{t-1}^{LH}$  is missing, we assume that  $\hat{\pi}_t^{LH}$  is an average of the

current and the previous quarters (unobserved) expectations data. Thus:

$$H_t = \begin{bmatrix} \frac{1}{2} & 0_{1 \times N-1} & \frac{1}{2} & 0_{1 \times N-1} \\ 0_{N-1 \times 1} & I_{N-1} & 0_{N-1 \times ns-N} \end{bmatrix}$$

and  $var(V_t) = 0$ .

For some periods both  $\hat{\pi}_t^{LH}$  and  $\hat{\pi}_{t-1}^{LH}$  are available. Then we assume that for that period inflation expectations are observed at the quarterly frequency:

$$H_t = \begin{bmatrix} 1 & 0_{1 \times ns-1} \\ 0_{N-1 \times 1} & I_{N-1} & 0_{N-1 \times ns-N} \end{bmatrix}$$

and  $var(V_t) = 0$ .

The transition equation is a  $VAR(2)$  written in companion form

$$\beta_t = \mu + F\beta_{t-1} + e_t$$

where  $var(e_t) = \Omega$ .

As in the standard VAR model, we assume a natural conjugate prior for the VAR parameters. Given  $\beta_t$ , the conditional posterior of the VAR coefficients  $\mu, F$  and the error covariance  $\Omega$  is as defined for the BVAR above and these parameters can be easily draw. Conditional on a draw for  $\Xi = \mu, F, \Omega$ , the Carter and Kohn (1994) algorithm is used to draw  $\beta_t$ . This conditional posterior is defined as

$$H(\tilde{\beta}_T \setminus \Xi) = H(\beta_T \setminus \tilde{z}_T) \prod_{t=1}^{T-1} H(\beta_t \setminus \beta_{t+1}, \tilde{z}_t)$$

where  $\tilde{\beta}_T = [\beta_1, \beta_2, \dots, \beta_T]$ ,  $\tilde{z}_T = [z_1, z_2, \dots, z_T]$ . The mean and variance of the normal density  $H(\beta_T \setminus \tilde{z}_T)$  can be obtained via the Kalman filter. Carter and Kohn (1994) provide the updating equations to obtain the mean and variance of the normal densities  $H(\beta_t \setminus \beta_{t+1}, \tilde{z}_t)$ . We use 25000 iterations of the Gibbs Sampler and retain the last 5000 iterations for inference.

Figure 2 presents the estimated posterior distribution of  $\hat{\pi}_t^{LH}$  and compares it with the observed low frequency data.

### 3 Sensitivity Analysis

In this section, we present a number of robustness checks regarding the benchmark VAR model. First, we expand the benchmark VAR model by adding the first three principal components extracted from a large panel of macroeconomic and financial data for the US (FRED-QD database provided by the St Louis Fed). This allows us to incorporate large amount information into the model and to potentially account for potential information insufficiency (see Forni and Gambetti (2014)). The impulse responses and FEV decomposition from this model are very similar to the benchmark case (see figure 3). When the model is estimated truncated the sample to 2007, the main conclusions are largely unaffected (see figure 4). Figures 5 and 6 show that altering the lag length to 1 and 4 respectively does not affect the benchmark results greatly. Figure 7 shows that the results are similar to benchmark when a horizon of 80 quarters is used for shock identification. Figure 8 shows that the results are not materially different if a flat prior for the VAR parameters is used. Figure 9 shows the variance decomposition using the mixed frequency VAR model.

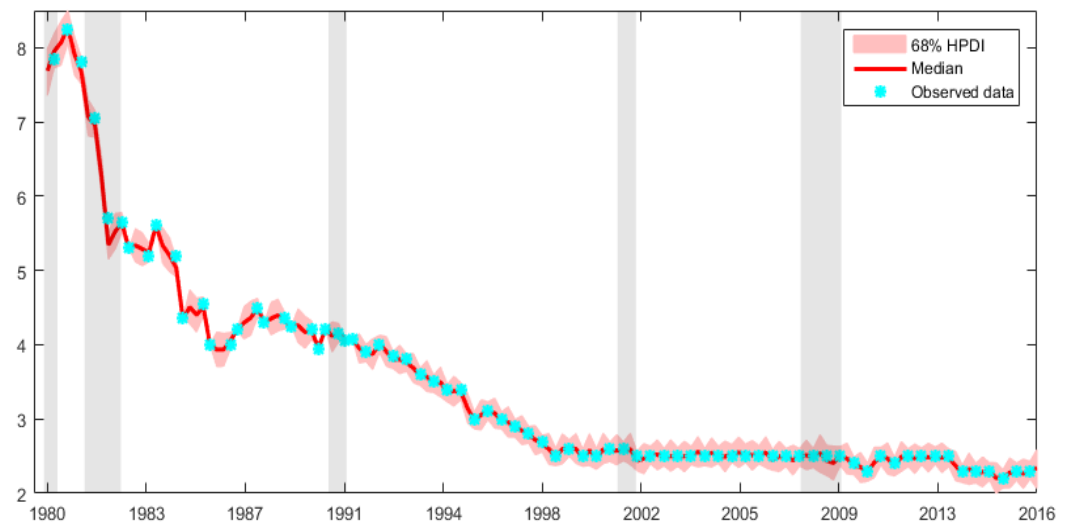


Figure 2: Estimated quarterly data for long-horizon blue chip/Livingstone survey inflation expectations.



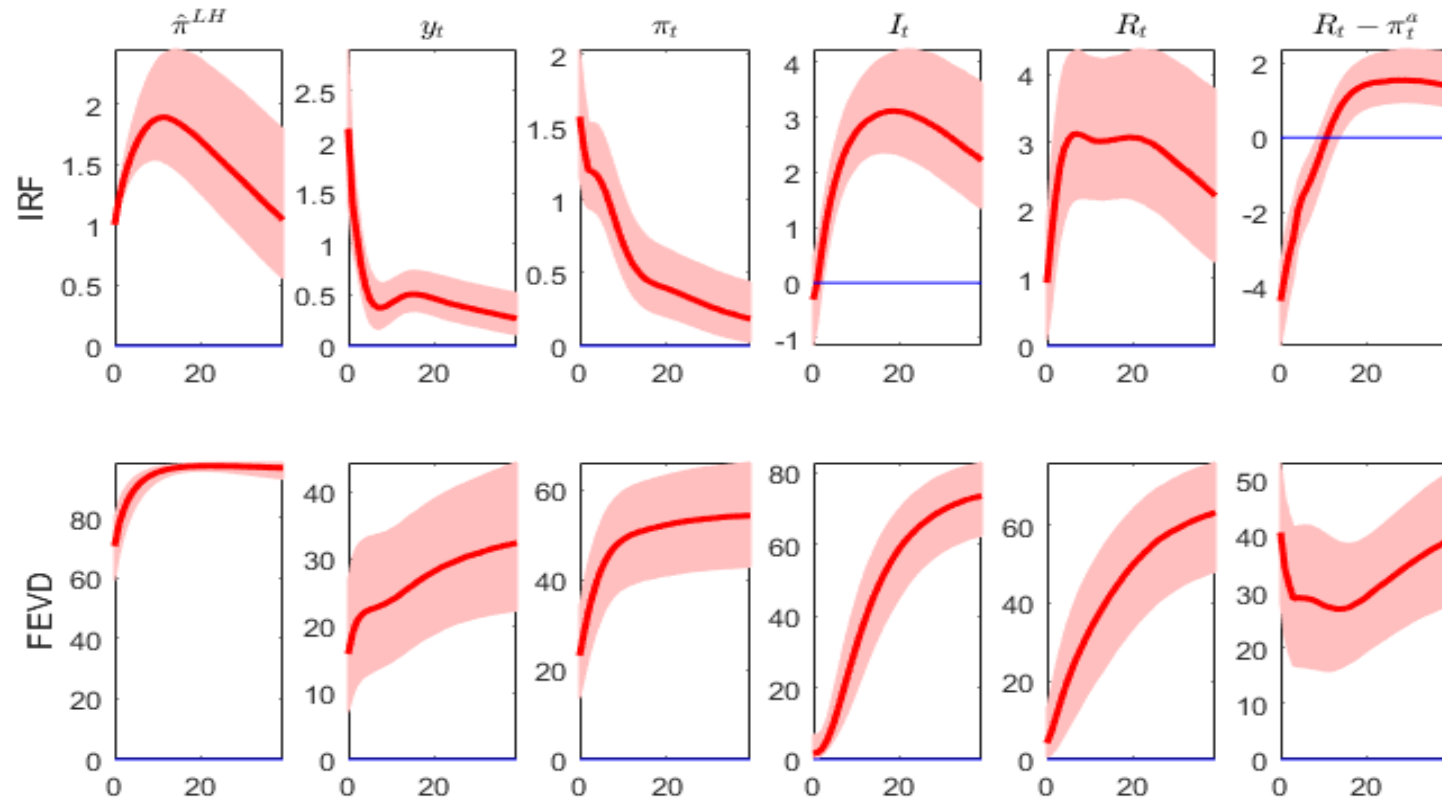


Figure 3: Response from a version of the benchmark model that includes principal components from a large data set.

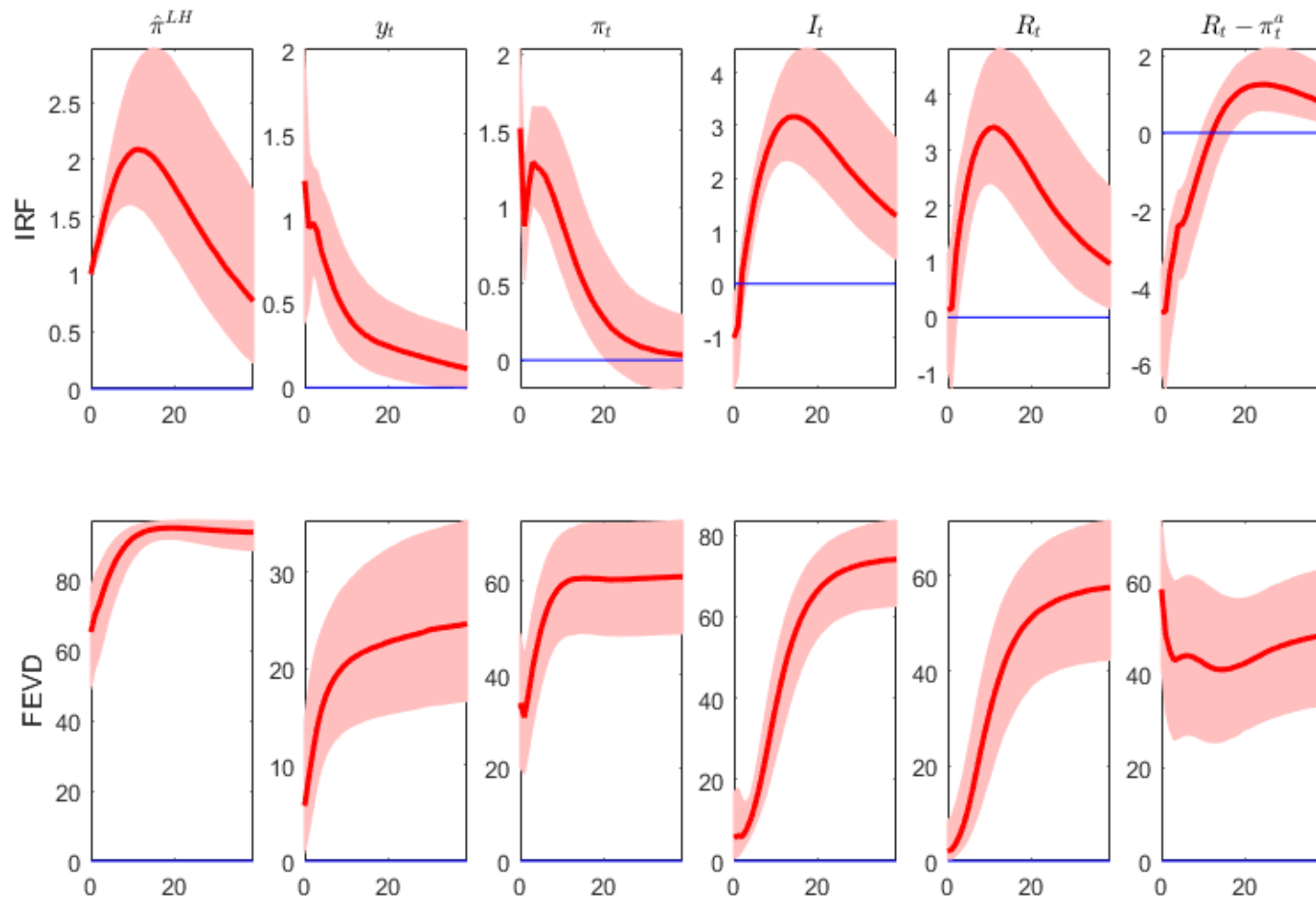


Figure 4: Response from a version of the benchmark model estimated using data up to 2006Q4.

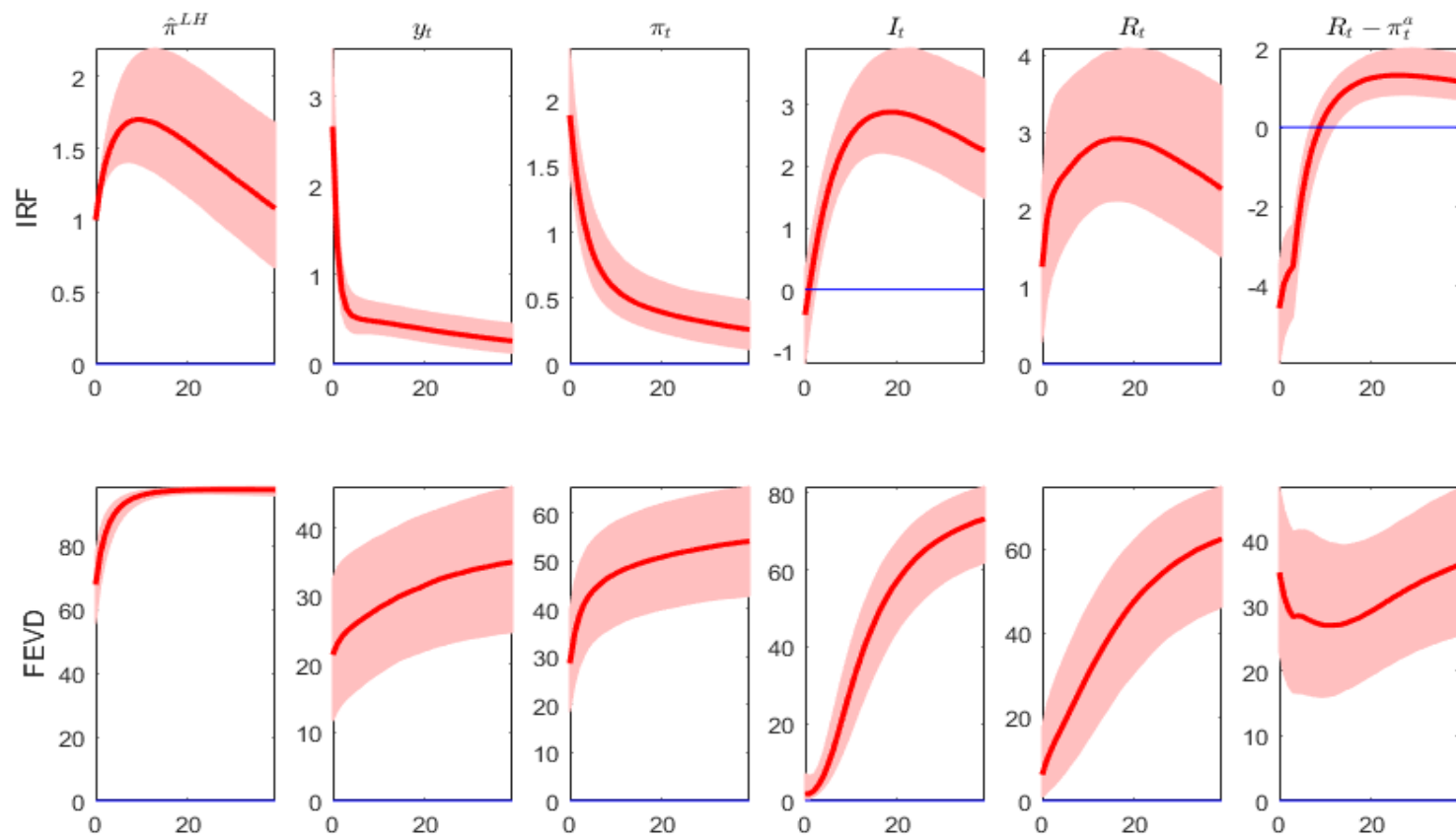


Figure 5: Response from a version of the benchmark model estimated using a lag length of 1.

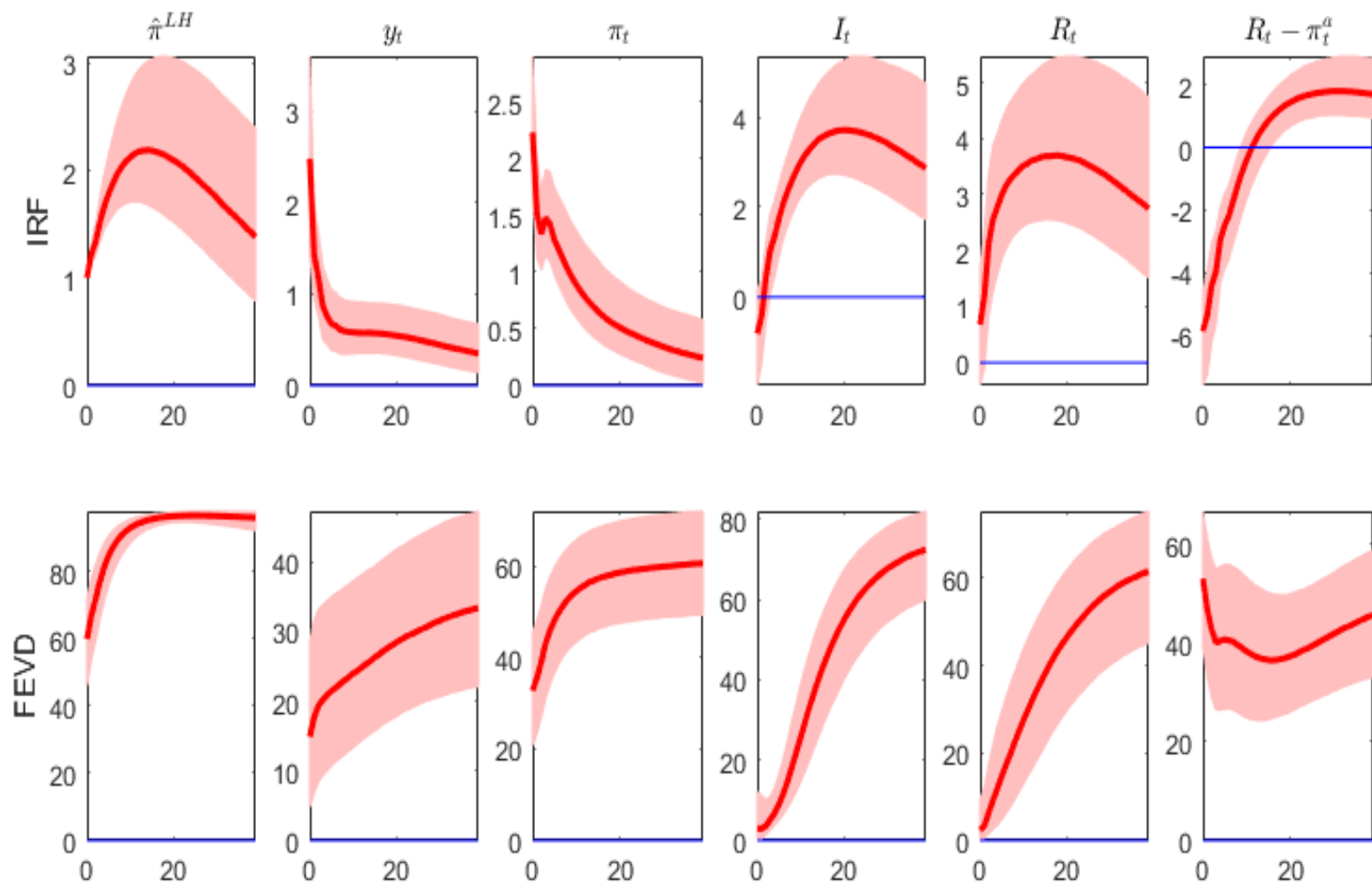


Figure 6: Response from a version of the benchmark model estimated using a lag length of 4.

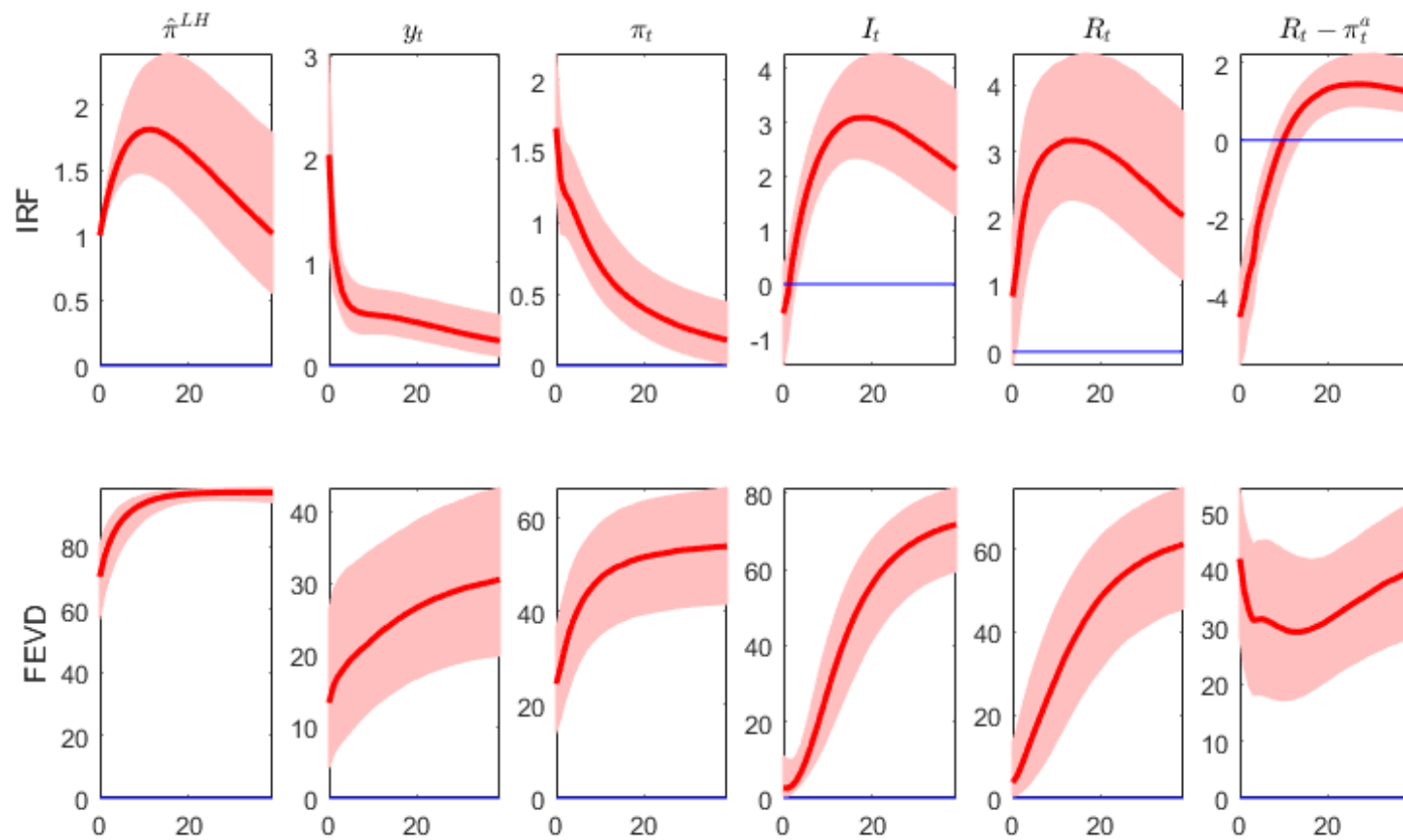


Figure 7: Response from a version of the benchmark model estimated using a horizon of 80 quarters to identify the target shock.

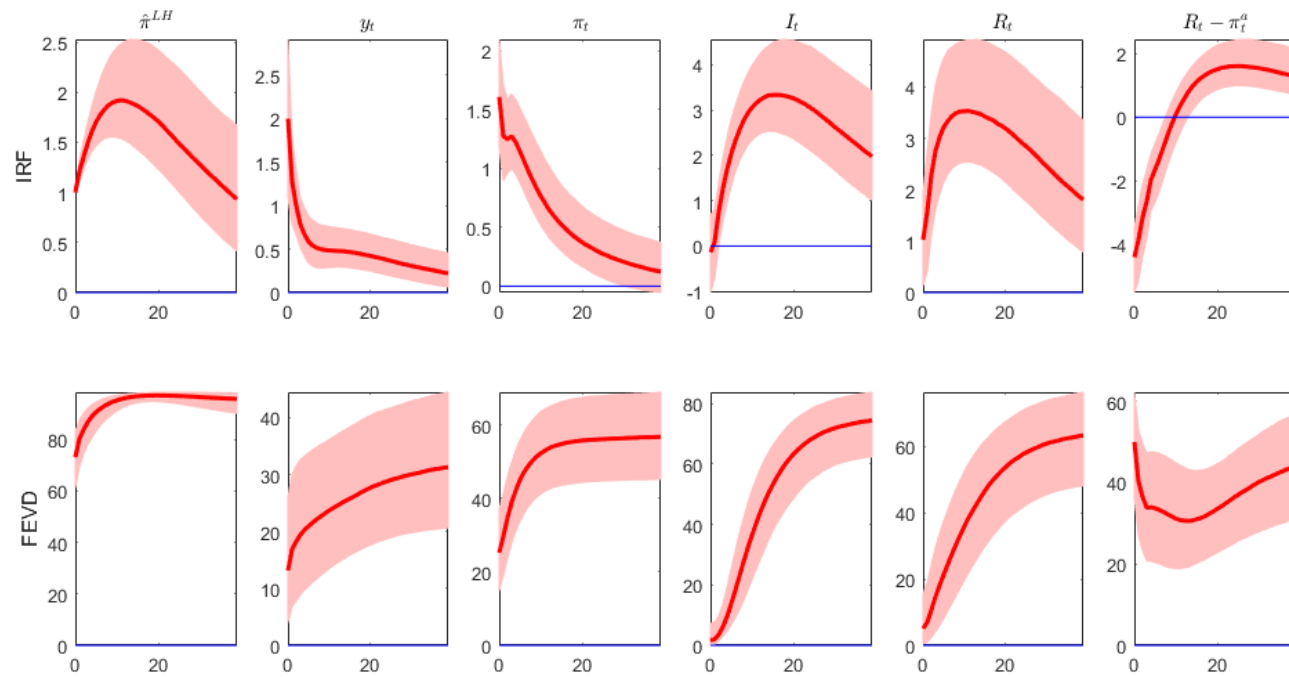


Figure 8: Response from a version of the benchmark model estimated using a flat prior.

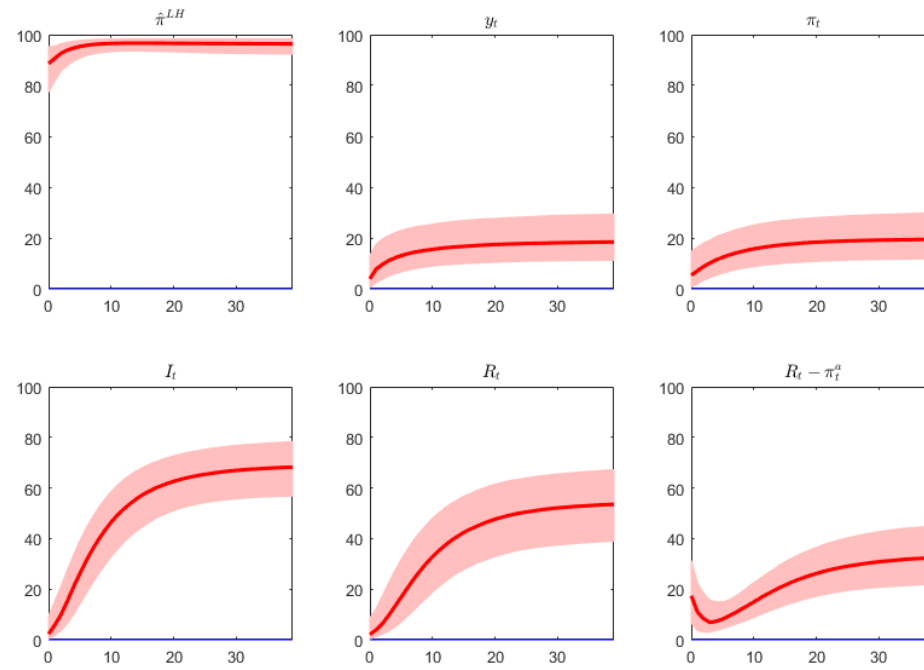


Figure 9: Contribution to FEV from the mixed-frequency VAR using Blue Chip/Livingstone survey expectations.

## 4 FAVAR Model

### 4.1 Estimation

Recall that the model is defined as

$$\begin{pmatrix} Y_t \\ X_{it} \end{pmatrix} = \begin{pmatrix} I_N & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Y_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ e_{it} \end{pmatrix}, \text{var}(e_{it}) = R = \text{diag}([r_1, r_2, \dots, r_M])$$

$$\tilde{Y}_t = \tilde{\alpha} + \sum_{j=1}^P \tilde{\beta}_j \tilde{Y}_{t-j} + \tilde{v}_t, \text{var}(\tilde{v}_t) = Q$$

where  $\tilde{Y}_t = \begin{pmatrix} Y_t \\ F_t \end{pmatrix}$ . The prior for the factor loadings  $\Lambda$  is normal  $N(\Lambda_{i0}, \Sigma_0)$  where  $\Lambda_0$  is obtained by estimating a linear regression of  $X_{it}$  on a principal component estimator of  $F_t$  and  $\Sigma_0$  is a diagonal matrix with diagonal elements equal to 10. The prior for the diagonal elements of  $R$  is inverse Gamma  $IG(T_0, D_0)$  where  $T_0 = 1$  and  $D_0 = 1e - 5$ . As in the simple VAR models above, we use a natural conjugate prior for the VAR parameters  $B = \text{vec}(\tilde{\beta}_j, \tilde{\alpha})$ ,  $Q$  with the tightness parameter  $\tau = 0.2$ .

The Gibbs sampling algorithm for this model is now standard in the literature and involves sampling from the following conditional posterior distributions:

1.  $H(\Lambda|F_t, R, B, Q)$ . Given the factors  $F_t$ , the observation equation is set of M independent linear regressions

$$X_{it} = F_t \Lambda'_i + e_{it}$$

where  $\Lambda_i$  denotes the  $i$ th row of the factor loading matrix. The conditional posterior is normal  $N(M, V)$ :

$$V = \left( \Sigma_0^{-1} + \frac{1}{r_i} F'_t F_t \right)^{-1}$$

$$M = V \left( \Sigma_0^{-1} \Lambda_{i0} + \frac{1}{r_i} F'_t X_{it} \right)$$

2.  $H(R|\Lambda, F_t, B, Q)$ . The conditional posterior for the diagonal elements of  $R$  is  $IG(T_0 + T, e'_{it} e_{it} + D_0)$  where  $T$  is the sample size.
3.  $H(B|\Lambda, F_t, R, Q)$ . The draw for the VAR coefficients is exactly as described in section 1.
4.  $H(Q|\Lambda, F_t, R, B)$ . The draw for the VAR error covariance is exactly as described in section 1.
5.  $H(F_t|\Lambda, R, B, Q)$ . Given the model parameters, the factors can be drawn using the Carter and Kohn (1994) algorithm.

We employ 200,000 iterations with a burn-in of 150,000 and save every 30th draw, leaving 5000 draws for inference. Figure 10 shows that for most parameters the estimated inefficiency factors are fairly low. Given the heavily parameterised nature of the model, this constitutes strong evidence in favour of convergence of the algorithm.

In order to select the number of factors we compute the marginal likelihood for models that allow the number of factors  $k = 2, 3, \dots, 8$ . The marginal likelihood is calculated via the Chib (1995)



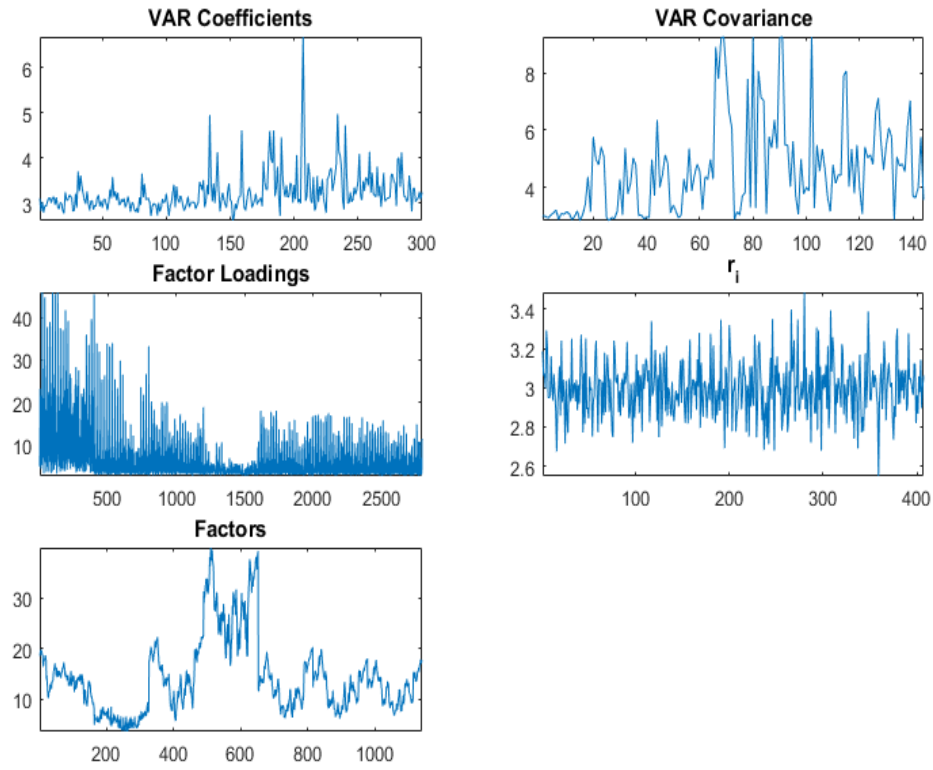


Figure 10: Inefficiency factors for the FAVAR model

Number of Factors $k$	Log Marginal Likelihood
2	-9039.86
3	-1678.23
4	2863.42
5	6899.23
6	11127.57
7	13162.74
8	10503.30

Table 1: Log Marginal Likelihood

estimator. In brief, this estimator is based on rearranging the Bayes theorem. Consider the Bayes Theorem in logs

$$\ln H(\Psi, F_t \setminus Z) = \ln F(Z \setminus \Psi, F_t) + \ln P(\Psi) - \ln H(Z)$$

where  $\Psi = \{\Lambda, R, B, Q\}$  i.e. parameters,  $Z$  denotes the data  $[X_{it}, Y_t]$ .  $\ln H(\Psi, F_t \setminus Z)$  is the log posterior that equals the log likelihood  $\ln F(Z \setminus \Psi, F_t)$  plus the log prior  $\ln P(\Psi)$  minus the log marginal likelihood  $\ln H(Z)$ . Thus

$$\ln H(Z) = \ln F(Z \setminus \Psi, F_t) + \ln P(\Psi) - \ln H(\Psi, F_t \setminus Z) \quad (5)$$

Because the parameters and the states do not appear in  $\ln H(Z)$ , this expression can be evaluated at any point in the posterior density for  $\Psi$ . Conventionally this point is chosen to be the posterior mean  $\Psi^*$ .

Thus, to estimate the marginal likelihood we need to evaluate eq 5.  $P(\Psi)$  is easiest to evaluate as it involves evaluating the prior for each parameter (at  $\Psi^*$ ) and then taking the product. The likelihood  $F(Z \setminus \Psi, F_t)$  can be evaluated using the Kalman filter. The key task is evaluating the posterior density  $H(\Psi, F_t \setminus Z)$ . This term can be factored as:

$$H(\Lambda, R, B, Q, F_t) = H(\Lambda|R, B, Q, F_t) \times H(R|B, Q, F_t) \times H(B|Q, F_t) \times H(Q|F_t)$$

Chib (1995) shows that a restricted version of the Gibbs sampler presented above can be used to evaluate each of the terms on the RHS of this expression. Table 1 shows that the estimated log marginal likelihood is maximised for  $k = 7$ .

Figure 11 plots the response of US variables to the target shock obtained from the FAVAR. The results are similar to the benchmark case. Figure 12 shows the response of the trade balance.

## 5 Theoretical Model

### 5.1 Firms

Three types of firms are operated in the domestic economy. The intermediate monopolistically competitive domestic firms use labour supplied by households to produce a differentiated good that is sold to a final good producer who employs a continuum of these differentiated goods in her constant elasticity of substitution – CES – production to deliver the final good. The monopolistically competitive importing firms use a costless technology and turn a homogeneous good – bought in the world market – into a differentiated good, which is then sold to the domestic consumers. The

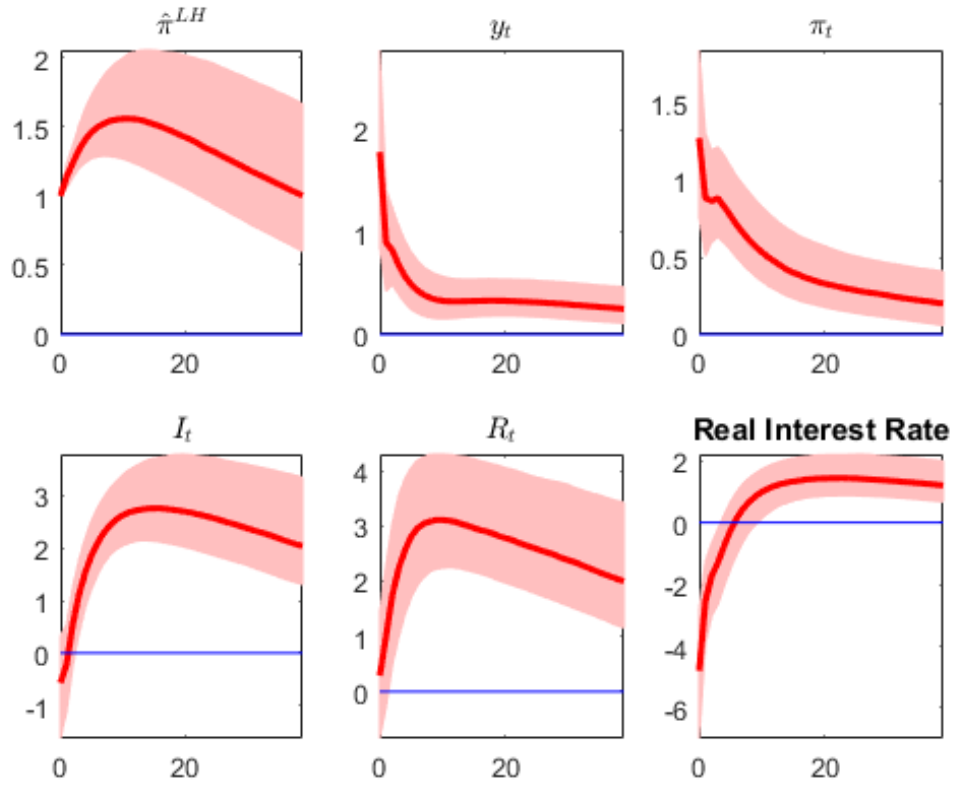


Figure 11: Response of US variables to an inflation target shock using the FAVAR model.

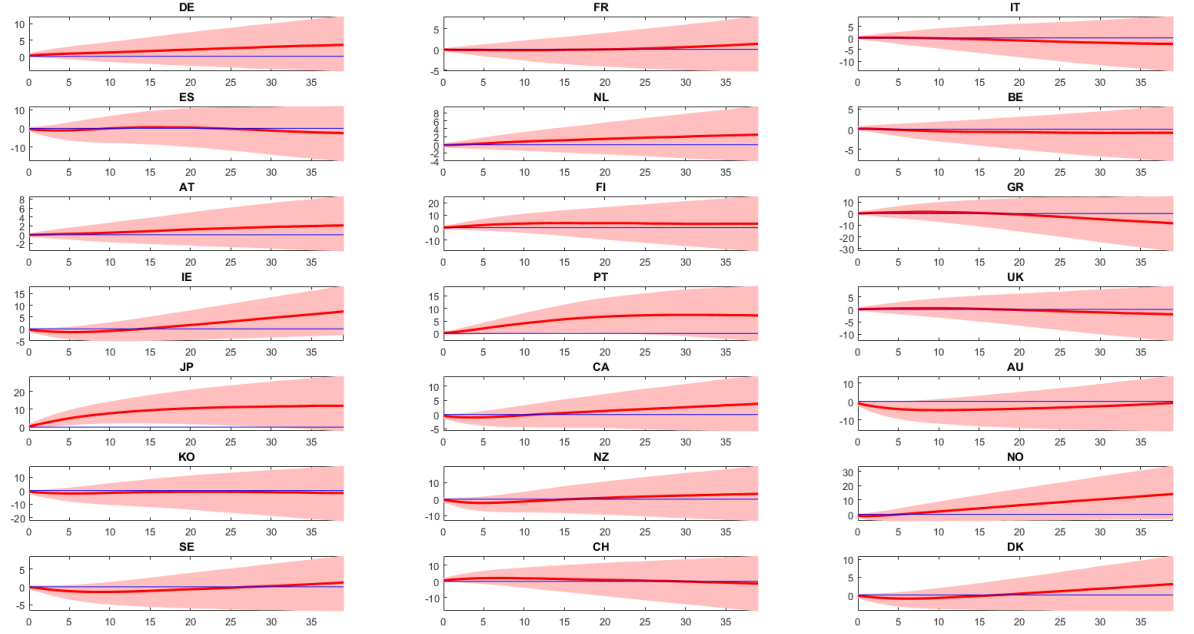


Figure 12: Response of the trade balance

exporting monopolistically competitive firms use similar ‘brand naming’ technology and transform the domestic final good into a differentiated product that is sold to foreign households.

This sector consists of three firms, the ‘labour packer’ who hires labour from households and transforms it into a homogeneous input good –  $h_t^d$ , a continuum of monopolistically competitive firms that buys  $h_t^d$  and produces an intermediate  $y_{i,t}$  and the final good producer who combines all these intermediate products into a single good consumed by households. The final good producer’s CES production function is given by

$$y_t^d = \left[ \int_0^1 y_{i,t}^{\frac{1}{\lambda_{y,t}}} di \right]^{\lambda_{y,t}} \quad (6)$$

where

$$\lambda_{y,t} = (1 - \rho_{\lambda_y}) \lambda_y + \rho_{\lambda_y} \lambda_{y,t-1} + \sigma_{\lambda_y} \omega_{\lambda_y,t} \quad (7)$$

denotes the time-varying mark-up in the domestic good market. The final good producer’s demand curve for  $y_{i,t}$  arises from the profit minimisation problem –  $\max_{y_{i,t}} \left\{ p_t \left[ \int_0^1 y_{i,t}^{\frac{1}{\lambda_{y,t}}} di \right]^{\lambda_{y,t}} - \int_0^1 p_{i,t} y_{i,t} \right\}$

$$y_{i,t} = \left( \frac{p_{i,t}}{p_t} \right)^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}} y_t^d \quad (8)$$

The final good price index is obtained by combining 6 and 8

$$p_t = \left[ \int_0^1 p_{i,t}^{\frac{1}{1-\lambda_{y,t}}} di \right]^{1-\lambda_{y,t}} \quad (9)$$

Intermediate good producers use the following production function

$$y_{i,t} = z_t \left( \Gamma_t h_{i,t}^d \right)^\alpha k_{i,t}^{1-\alpha} \quad (10)$$

where

$$z_t = (1 - \rho_z) z + \rho_z z_{t-1} + \sigma_z \omega_{z,t} \quad (11)$$

$$\gamma_t = \ln \left( \frac{\Gamma_t}{\Gamma_{t-1}} \right) = (1 - \rho_\gamma) \gamma + \rho_\gamma \gamma_{t-1} + \sigma_\gamma \omega_{\gamma,t} \quad (12)$$

is a stationary exogenous technological process and  $h_{i,t}^d$  is the amount of homogeneous labour rented by the firm  $i^{ih}$ . The intermediate firm select  $h_{i,t}^d$  in order to minimise its production cost

$$\min_{h_{i,t}^d} p_t w_t h_{i,t}^d + p_t r_t^k k_t + mc_{i,t} p_t \left[ y_{i,t} - z_t \left( \Gamma_t h_{i,t}^d \right)^\alpha k_{i,t}^{1-\alpha} \right] \quad (13)$$

The real marginal cost for the intermediate firms is given by the first order conditions of (13) with respect to  $h_{i,t}^d$  and  $k_{i,t}$

$$mc_{i,t} = \frac{w_t}{\alpha \frac{y_{i,t}}{h_{i,t}^d}} \quad (14)$$

$$mc_{i,t} = \frac{r_t^k}{(1 - \alpha) \frac{y_{i,t}}{k_{i,t}}} \quad (15)$$

A fraction  $-(1 - \xi_y)$  of intermediate firms receive a random signal and they are allowed to optimally reset their prices  $-p_{i,t}^{new}$ . The proportion  $-\xi_y$  of firms that cannot reoptimise prices will set  $p_t$  based on backward-looking rule

$$p_t = \pi_{t-1}^{\kappa_y} \bar{\pi}_t^{1-\kappa_y} p_{t-1} \quad (15)$$

where  $\pi_t = \frac{p_t}{p_{t-1}}$  is the gross inflation and  $\kappa_y$  is the indexation parameter. The pricing problem of firm  $i$  is then

$$\max_{p_{i,t}^{new}} E_t \sum_{j=0}^{\infty} (\beta \xi_y)^j \frac{\lambda_{t+j}}{\lambda_t} \left\{ \left( \prod_{s=1}^j \pi_{t+s-1}^{\kappa_y} \bar{\pi}_{t+s}^{1-\kappa_y} \frac{p_{i,t}^{new}}{p_{t+j}} - mc_{t+j} \right) y_{i,t+j} \right\} \quad (16)$$

subject to

$$y_{i,t+j} = \left( \prod_{s=1}^j \pi_{t+s-1}^{\kappa_y} \bar{\pi}_{t+s}^{1-\kappa_y} \frac{p_{i,t}^{new}}{p_{t+j}} \right)^{-\frac{\lambda_{y,t}}{\lambda_{y,t-1}}} y_{t+j}^d \quad (17)$$

The first-order condition is expressed as system of difference equations

$$f_{1,t} = \lambda_t m c_t y_t^d + \beta \xi_y E_t \left( \frac{\pi_t^{\kappa_y} \bar{\pi}_{t+1}^{1-\kappa_y}}{\pi_{t+1}} \right)^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}} f_{1,t+1} \quad (18)$$

$$f_{2,t} = \lambda_t \ddot{\pi}_t y_t^d + \beta \xi_d E_t \left( \frac{\pi_t^{\kappa_y} \bar{\pi}_{t+1}^{1-\kappa_y}}{\pi_{t+1}} \right)^{-\frac{1}{\lambda_{y,t}-1}} \left( \frac{\ddot{\pi}_t}{\ddot{\pi}_{t+1}} \right) f_{2,t+1} \quad (19)$$

$$0 = \lambda_{y,t} f_{1,t} - f_{2,t} \quad (20)$$

$$1 = \xi_y \left( \frac{\pi_{t-1}^{\kappa_y} \bar{\pi}_t^{1-\kappa_y}}{\pi_t} \right)^{-\frac{1}{\lambda_{y,t}-1}} + (1 - \xi_y) \bar{\pi}_t^{-\frac{1}{\lambda_{y,t}-1}} \quad (21)$$

where  $\ddot{\pi}_t \equiv \frac{p_t^{new}}{p_t}$ .

Market clearing condition in the domestic sector

$$y_t = \int_0^1 y_{i,t} di = \int_0^1 \left( \frac{p_{i,t}}{p_t} \right)^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}} di y_t^d = v_t^p y_t^d \quad (22)$$

where  $v_t^p = \int_0^1 \left( \frac{p_{i,t}}{p_t} \right)^{-\frac{\lambda_{d,t}}{\lambda_{d,t}-1}} di$  is the price dispersion term and it is given by

$$v_t^p = \xi_y \left( \frac{\pi_{t-1}^{\kappa_y} \bar{\pi}_t^{1-\kappa_y}}{\pi_t} \right)^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}} v_{t-1}^p + (1 - \xi_y) \bar{\pi}_t^{-\frac{\lambda_{y,t}}{\lambda_{y,t}-1}} \quad (23)$$

## 5.2 Households

The domestic economy is populated by a continuum of households that attain utility from consumption –  $c_{\kappa,t+j}$  – and leisure –  $h_{\kappa,t+j}$ . Household's preferences are separable

$$E_t \sum_{j=0}^{\infty} \beta^j \left\{ d_{t+j} \frac{(c_{\kappa,t+j} - b c_{\kappa,t+j-1})^{1-\sigma_c}}{1 - \sigma_c} - \psi_{t+j} \Gamma_{t+j}^{1-\sigma_c} \frac{h_{\kappa,t+j}^{1+\varphi}}{1 + \varphi} d\kappa \right\} \quad (24)$$

where  $d_t$  is a discount factor shock

$$d_t = (1 - \rho_d) d + \rho_d d_{t-1} + \sigma_d \omega_d \quad (25)$$

$\beta$  is the discount factor,  $\varphi$  the inverse of the Frisch elasticity,  $\sigma_c$  the inverse of intertemporal elasticity of substitution and  $b$  the habit formation parameter. They also invest on fiscal capital that is rented to firms, furthermore capital accumulation is subject to investment adjustment cost

$$\bar{k}_t = (1 - \delta) \bar{k}_{t-1} + \phi_t \left( 1 - \frac{\psi_I}{2} \left( \frac{i_t}{\gamma i_{t-1}} - 1 \right) \right) i_t \quad (26)$$

$$k_t = v_t \bar{k}_{t-1}$$

Household's real budget constraint is given by

$$D_{\kappa,t}^h + c_{\kappa,t} + i_{\kappa,t} + \Upsilon_{\kappa,t} = \frac{r_{t-1}^h}{\pi_t} D_{\kappa,t-1}^h + w_{\kappa,t} h_{\kappa,t} + r_t^k v_{\kappa,t} \bar{k}_{\kappa,t-1} - u(v_{\kappa,t}) \bar{k}_{\kappa,t-1} + F_{\kappa,t} - T_{\kappa,t} \quad (27)$$

The household  $\kappa$  uses its labour income  $-w_{\kappa,t} h_{\kappa,t}$ , net return on capital services  $-r_t^k v_{\kappa,t} \bar{k}_{\kappa,t-1} - u(v_{\kappa,t}) \bar{k}_{\kappa,t-1}$ , gross interest rate financial intermediary deposits  $-\frac{r_{t-1}^h}{\pi_t} D_{\kappa,t-1}^h$ , government transfers  $-T_{\kappa,t}$  and profits  $-F_{\kappa,t}$  to finance consumption, investment and new purchases of financial assets  $-c_{\kappa,t} + i_{\kappa,t} + D_{\kappa,t} + \Upsilon_{\kappa,t}$ . The household maximises (24) with respect to  $c_{\kappa,t}$ ,  $i_{\kappa,t}$ ,  $\bar{k}_{\kappa,t-1}$  and  $D_{\kappa,t}^h$  subject to (27) and (26)

$$\frac{d_t}{(c_{\kappa,t} - b c_{\kappa,t-1})^{\sigma_c}} - E_t \frac{\beta b d_{t+1}}{(c_{\kappa,t+1} - h c_{\kappa,t})^{\sigma_c}} = \lambda_{\kappa,t} \quad (28)$$

$$\lambda_{\kappa,t} = \beta E_t \left\{ \lambda_{\kappa,t+1} \frac{r_t^h}{\pi_{t+1}} \right\} \quad (29)$$

$$r_{\kappa,t}^k = u'(v_{\kappa,t}) \quad (30)$$

$$q_{\kappa,t} = \beta \frac{\lambda_{\kappa,t+1}}{\lambda_{\kappa,t}} \left[ r_{t+1}^k v_{\kappa,t+1} - u(v_{\kappa,t+1}) + (1 - \delta) q_{\kappa,t+1} \right] \quad (31)$$

$$1 = q_{\kappa,t} \left\{ 1 - \frac{\psi_I}{2} \left( \frac{i_t}{i_{t-1}} - \gamma \right)^2 - \psi_I \left( \frac{i_t}{i_{t-1}} - \gamma \right) \frac{i_t}{i_{t-1}} \right\} + \beta \frac{\lambda_{\kappa,t+1}}{\lambda_{\kappa,t}} q_{\kappa,t} \psi_I \left( \frac{i_{t+1}}{i_t} - \gamma \right) \left( \frac{i_{t+1}}{i_t} \right)^2 \quad (32)$$

### 5.3 Financial intermediary

The financial intermediary firm issues deposits to households paying a gross interest rate  $r_t^h$ . The firm then purchases a portfolio of short and long term government issued bonds paying interest  $r_t^S$  and  $r_t^L$ .

Similar to Andres *et al.* (2004), Chen *et al.* (2012), Harrison (2012) and Liu *et al.* (2014) we follow the formulation in Woodford (2001) and long-term bonds are perpetuities that cost  $p_{L,t}$  at time  $t$  and pay an exponentially decaying coupon  $\kappa^s$  at time  $t + s + 1$  where  $0 < \kappa \leq 1$ . As it is explained in Woodford (2001) and Chen *et al.* (2012) the advantage of this formulation is that the price in period  $t$  of a bond issued  $s$  periods ago  $p_{L-s,t}$  is a function of the coupon the current price  $p_{L,t}$

$$p_{L-s,t} = \kappa^s p_{L,t} \quad (33)$$

This relation allows to express the balance sheet equation and government budget constraint (below) in a familiar form that it is easy to work with it (see the discussion in Chen *et al.* (2012)). Furthermore, in order to keep things simple, we rule out the possibility of a secondary market for long-term bonds, meaning that agents who buy long-term debt must hold it until maturity.<sup>1</sup> Finally, for simplicity we assume that all government bonds issued are purchased by this firm.

The intermediary's balance sheet is given

$$b_{\kappa,t}^h = \frac{b_{\kappa,t}^S}{\varepsilon_t^b} + \frac{p_{L,t} b_{\kappa,t}^L}{\varepsilon_t^b}$$

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<sup>1</sup>See the discussion in Andres *et al.* (2004) for the advantages of that assumption.

or

$$b_{\kappa,t}^h = \frac{b_{\kappa,t}^S}{\varepsilon_t^{b^S}} + \frac{\bar{b}_{\kappa,t}^L}{\varepsilon_t^{\bar{b}^L}} \quad (34)$$

Motivated by the work of Smets and Wouters (2007) we assume the balance sheet equation is subject to two ‘financial’ shocks: a short and a long-term risk premium shocks denoted by  $\varepsilon_t^{b^S}$ ,  $\varepsilon_t^{\bar{b}^L}$  and  $\varepsilon_t^{\bar{b}^{L,*}}$ , respectively.

Intermediary’s profit function is then given by

$$\xi_t = \underbrace{b_{\kappa,t}^h + \frac{r_{t-1}^S}{\pi_t} b_{\kappa,t-1}^S + \frac{p_{L,t} r_t^L}{\pi_t} b_{\kappa,t-1}^L}_{\text{revenues}} - \underbrace{\frac{b_{\kappa,t}^S}{\varepsilon_t^{b^S}} - \frac{p_{L,t} b_{\kappa,t}^L}{\varepsilon_t^{\bar{b}^L}} - \frac{r_{t-1}^h}{\pi_t} b_{\kappa,t-1}^h - \frac{x}{2} (\delta_{\kappa,t-1}^B - \vartheta \delta_{t-2}^B - (1 - \vartheta) \delta^B)^2 \frac{\Gamma_{t-1}}{\pi_t}}_{\text{expenditures}}$$

where

$$\delta_{\kappa,t}^B = \frac{b_{\kappa,t}^S}{\bar{b}_{\kappa,t}^L}$$

Intermediary’s profits are subject to two adjustment costs. The first one captures the idea that altering the foreign debt held by domestic intermediaries to GDP ratio is costly.<sup>2</sup> The second term reflects the situation where although intermediaries prefer to hold more long than short-term debt that decreases ‘liquidity’.

Using the balance sheet equation the profit function becomes

$$\begin{aligned} E_t \xi_{t+1} &= \frac{r_t^S}{\pi_{t+1}} b_{\kappa,t}^S + E_t \left\{ \frac{r_{t+1}^L}{\pi_{t+1}} \frac{p_{L,t+1}}{p_{L,t}} \right\} \bar{b}_{\kappa,t}^L - E_t \left\{ \frac{r_t^h}{\pi_{t+1}} \right\} b_{\kappa,t}^h \\ &\quad - \frac{x}{2} [\delta_{\kappa,t}^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B]^2 \frac{\Gamma_t}{E_t \pi_{t+1}} \end{aligned} \quad (35)$$

Profit maximisation with respect to short, domestic and foreign long-term debt and subject to the balance sheet condition delivers an expression for the effective rate faced by the household, long-term interest rate and exchange rate

### Short-term debt

$$\begin{aligned} 0 &= \frac{r_t^S}{E_t \pi_{t+1}} - \frac{r_t^h}{\varepsilon_t^{b^S} E_t \pi_{t+1}} - x [\delta_{\kappa,t}^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B] \frac{\Gamma_t}{\bar{b}_{\kappa,t}^L E_t \pi_{t+1}} \\ \frac{r_t^h}{\varepsilon_t^{b^S}} &= r_t^S - x [\delta_{\kappa,t}^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B] \frac{\Gamma_t}{\bar{b}_{\kappa,t}^L} \end{aligned} \quad (36)$$

### Long-term domestic debt

$$\begin{aligned} 0 &= E_t \left\{ \frac{r_{t+1}^L}{\pi_{t+1}} \frac{p_{L,t+1}}{p_{L,t}} \right\} - \frac{r_t^h}{\varepsilon_t^{\bar{b}^L} E_t \pi_{t+1}} + x [v_{\kappa,t} - \vartheta v_{t-1} - (1 - \vartheta) v] \frac{\Gamma_t b_{\kappa,t}^S}{(\bar{b}_{\kappa,t}^L)^2 E_t \pi_{t+1}} \\ E_t \left\{ r_{t+1}^L \frac{p_{L,t+1}}{p_{L,t}} \right\} &= \frac{r_t^h}{\varepsilon_t^{\bar{b}^L}} - x [\delta_{\kappa,t}^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B] \frac{\Gamma_t b_{\kappa,t}^S}{(\bar{b}_{\kappa,t}^L)^2} \end{aligned} \quad (37)$$

<sup>2</sup>In our model this term is not required to make the net foreign asset position of the model stationary (see the discussion in Schmitt-Grohe and Uribe (2003)) as we properly model long-term debt in the foreign economy.



## 5.4 Wages

We follow Erceg *et al.* (2000) and assume that each monopolistically competitive household supplies a differentiated labour service to the production section. They set their nominal wage and supply any amount of labour demanded by the firms at that wage rate. For convenience, we assume that there exist a representative firm that combines households' labour inputs into a homogeneous input hood -  $h_t^d$  - using a CES production function

$$h_t^d = \left[ \int_0^1 h_{\kappa,t}^{\frac{1}{\lambda_w}} d\kappa \right]^{\lambda_w} \quad (39)$$

where  $\lambda_w$  is the wage mark-up. Taking  $w_t$  and  $w_{\kappa,t}$  as given the aggregator's demand for the labour hours of household  $\kappa$  results its profit maximisation  $\max_{h_{\kappa,t}} \left\{ w_t \left[ \int_0^1 h_{\kappa,t}^{\frac{1}{\lambda_w}} d\kappa \right]^{\lambda_w} - \int_0^1 w_{\kappa,t} h_{\kappa,t} \right\}$

$$h_{\kappa,t} = \left( \frac{w_{\kappa,t}}{w_t} \right)^{-\frac{\lambda_w}{\lambda_w-1}} h_t^d \quad (40)$$

The aggregate wage arise from the profit condition and the demand curve

$$w_t = \left[ \int_0^1 w_{\kappa,t}^{\frac{1}{1-\lambda_w}} d\kappa \right]^{1-\lambda_w} \quad (41)$$

In each period, a function  $1 - \xi_w$  of households receive a random signal and they are allowed to reset wages optimally -  $w_t^{new}$ . All other households can only partially index their wages by past inflation. The problem of setting wages can be described as follows

$$\max_{w_t^{new}} E_t \sum_{j=0}^{\infty} (\beta \xi_w)^j \left\{ -\psi_{t+j} \Gamma_{t+j}^{1-\sigma_c} \frac{h_{\kappa,t+j}^{1+\varphi}}{1+\varphi} + \lambda_{t+j} \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_t^{1-\kappa_w} \gamma}{\pi_{t+s}} w_{\kappa,t} h_{\kappa,t+j} \right\} \quad (42)$$

subject to

$$h_{\kappa,t+j} = \left( \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} \frac{w_{\kappa,t}}{w_{t+j}} \right)^{-\frac{\lambda_w}{\lambda_w-1}} h_{t+j}^d \quad (43)$$

Substituting labour demand into the former equation

$$\max_{w_{\kappa,t}} E_t \sum_{j=0}^{\infty} (\beta \xi_w)^j \left\{ -\frac{\psi_{t+j} \Gamma_{t+j}^{1-\sigma_c}}{1+\varphi} \left( \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} \frac{w_{\kappa,t}}{w_{t+j}} \right)^{-\frac{\lambda_w(1+\varphi)}{\lambda_w-1}} \left( h_{t+j}^d \right)^{1+\varphi} \right. \\ \left. + \lambda_{t+j} \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} w_{\kappa,t} \left( \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} \frac{w_{\kappa,t}}{w_{t+j}} \right)^{-\frac{\lambda_w}{\lambda_w-1}} h_{t+j}^d \right\}$$

which can be simplified further

$$\max_{w^{\kappa,t}} E_t \sum_{j=0}^{\infty} (\beta \xi_w)^j \left\{ -\frac{\psi_{t+j} \Gamma_{t+j}^{1-\sigma_c}}{1+\varphi} \left( \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} \frac{w_{\kappa,t}}{w_{t+j}} \right)^{-\frac{\lambda_w(1+\varphi)}{\lambda_w-1}} \left( h_{t+j}^d \right)^{1+\varphi} \right. \\ \left. + \lambda_{t+j} \left( \prod_{s=1}^j \frac{\pi_{t+s-1}^{\kappa_w} \bar{\pi}_{t+s}^{1-\kappa_w} \gamma}{\pi_{t+s}} \frac{w_{\kappa,t}}{w_{t+j}} \right)^{-\frac{1}{\lambda_w-1}} w_{t+j} h_{t+j}^d \right\}$$

The first order is summarised by the following recursive equations

$$v_{1,t} = \frac{1}{\lambda_w} (w_t^{new})^{\frac{1}{1-\lambda_w}} \lambda_t w_t^{\frac{\lambda_w}{\lambda_w-1}} h_t^d + \beta \xi_w E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w} \gamma}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_w}} \left( \frac{w_{t+1}^{new}}{w_t^{new}} \right)^{\frac{1}{\lambda_w-1}} v_{1,t+1} \quad (44)$$

$$v_{1,t} = \psi_t \gamma_t^{1-\sigma_c} \left( \frac{w_t}{w_t^{new}} \right)^{\frac{(1+\varphi)\lambda_w}{\lambda_w-1}} \left( h_t^d \right)^{1+\varphi} + \beta \xi_w E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w} \gamma}{\pi_{t+1}} \right)^{\frac{(1+\varphi)\lambda_w}{1-\lambda_w}} \left( \frac{w_{t+1}^{new}}{w_t^{new}} \right)^{\frac{(1+\varphi)\lambda_w}{\lambda_w-1}} v_{1,t+1} \quad (45)$$

$$w_t^{\frac{1}{1-\lambda_w}} = \xi_w \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_t^{1-\kappa_w} \gamma}{\pi_t} \right)^{\frac{1}{1-\lambda_w}} w_{t-1}^{\frac{1}{1-\lambda_w}} + (1 - \xi_w) (w_t^{new})^{\frac{1}{1-\lambda_w}} \quad (46)$$

The market clearing condition in the labour market is

$$h_t = \int_0^1 h_{\kappa,t} d\kappa = v_t^w h_t^d \quad (47)$$

where  $v_t^w = \int_0^1 \left( \frac{w_{i,t}}{w_t} \right)^{-\frac{\lambda_w}{\lambda_w-1}} d_i$  is the wage dispersion term and its evolution is described

$$v_t^w = \xi_w \left( \frac{\pi_{t-1}^{\kappa_w} \bar{\pi}_t^{1-\kappa_w} \gamma}{\pi_t} \right)^{\frac{\lambda_w}{1-\lambda_w}} \left( \frac{w_{t-1}}{w_t} \right)^{\frac{\lambda_w}{1-\lambda_w}} v_{t-1}^w + (1 - \xi_w) \left( \frac{w_t^{new}}{w_t} \right)^{\frac{\lambda_w}{1-\lambda_w}} \quad (48)$$

## 5.5 Government

Government's budget constraint adjusted for long-term debt is given by

$$b_t^S + \bar{b}_t^L + T_t = \frac{r_{t-1}^S}{\pi_t} b_{t-1}^S + \frac{r_t^L}{\pi_t} \frac{p_{L,t}}{p_{L,t-1}} \bar{b}_{t-1}^L + G_t$$

where the left hand side is the total (short plus long-term) debt issued by the government at time  $t$ . Finally, transfers are adjusted according to the following rule

$$T_t = \Phi \left( \frac{b_{t-1}^S + \bar{b}_{t-1}^L}{b^S + \bar{b}^L} \right)^\theta \quad (49)$$

$$G_t = g_t y_t \quad (50)$$

## 5.6 Monetary policy

The monetary authority sets its instrument short-term interest rate according to a Taylor rule

$$\frac{r_t}{r} = \left(\frac{r_{t-1}}{r}\right)^{\phi_R} \left(\frac{\pi_t}{\bar{\pi}_t}\right)^{(1-\phi_R)\phi_\pi} \left(\frac{y_t}{y}\right)^{(1-\phi_R)\phi_y} m_t \quad (51)$$

where  $m_t = m_{t-1}^{\rho_m} e^{\sigma_R \omega_{R,t}}$ . In other words, the policymaker adjusts the nominal interest rate in response to its lag value, to inflation deviations from the target

$$\bar{\pi}_t - 0.999\bar{\pi}_{t-1} = \rho_{\bar{\pi}} (\bar{\pi}_{t-1} - 0.999\bar{\pi}_{t-2}) + \sigma_{\bar{\pi}} \omega_{\bar{\pi},t} \quad (52)$$

(De Graeve *et al.* (2009)) and to trend output gap deviations from its long-run equilibrium  $-y$ .

## 5.7 Market clearing conditions

$$y_t^d = c_t + G_t + i_t \quad (53)$$

## 5.8 Stationary Equations

$$\frac{y_t}{\gamma_t} = \tilde{y}_t = z_t \left(h_t^d\right)^\alpha \tilde{k}_t^{1-\alpha} \quad (54)$$

$$\bar{k}_t = (1-\delta) \frac{\bar{k}_{t-1}}{\gamma_t} + \phi_t \left(1 - \frac{\psi_I}{2} \left(\frac{\tilde{i}_t \gamma_t}{\tilde{i}_{t-1}} - \gamma\right)^2\right) \tilde{i}_t \quad (55)$$

$$r_t^k = u'(\nu_t) \quad (56)$$

$$q_t = \beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t \gamma_{t+1}} \left[ r_{t+1}^k \nu_{t+1} - u(\nu_{t+1}) + (1-\delta) q_{t+1} \right] \quad (57)$$

$$1 = q_t \left\{ 1 - \frac{\phi_I}{2} \left(\frac{\tilde{i}_t \gamma_t}{\tilde{i}_{t-1}} - \gamma\right)^2 - \phi_I \left(\frac{\tilde{i}_t \gamma_t}{\tilde{i}_{t-1}} - \gamma\right) \frac{\tilde{i}_t \gamma_t}{\tilde{i}_{t-1}} \right\} + \beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t \gamma_{t+1}} q_{t+1} \phi_I \left(\frac{\tilde{i}_{t+1} \gamma_{t+1}}{\tilde{i}_t} - \gamma\right) \left(\frac{\tilde{i}_{t+1} \gamma_{t+1}}{\tilde{i}_t}\right)^2 \quad (58)$$

$$mc_t = \frac{\tilde{w}_t}{\alpha \frac{\tilde{y}_t}{h_t}} = \frac{\tilde{w}_t h_t}{\alpha \tilde{y}_t} \quad (59)$$

$$mc_t = \frac{r_t^k \nu_t}{\alpha \frac{\tilde{y}_t \gamma_t}{\tilde{k}_{t-1}}} \quad (60)$$

$$\frac{d_t}{\left(\tilde{c}_t - b \frac{\tilde{c}_{t-1}}{\tilde{\gamma}_t}\right)^{\sigma_c}} - E_t \frac{\beta b d_{t+1}}{\left(\tilde{c}_{t+1} \tilde{\gamma}_{t+1} - h \tilde{c}_t\right)^{\sigma_c}} = \tilde{\lambda}_t$$

$$\tilde{\lambda}_t = \beta E_t \left\{ \frac{\tilde{\lambda}_{t+1}}{\tilde{\gamma}_{t+1}^{\sigma_C}} \frac{r_t^h}{\pi_{t+1}^c} \right\} \quad (61)$$

$$\tilde{v}_{1,t} = \frac{1}{\lambda_w} (\tilde{w}_t^{new})^{-\frac{1}{\lambda_w-1}} \tilde{\lambda}_t \tilde{w}_t^{\frac{\lambda_w}{\lambda_w-1}} h_t^d + \beta \xi_w E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w} \gamma}{\pi_{t+1}} \right)^{\frac{1}{1-\lambda_w}} \left( \frac{\tilde{w}_{t+1}^{new} \tilde{\gamma}_{t+1}}{\tilde{w}_t^{new}} \right)^{\frac{1}{\lambda_w-1}} \tilde{v}_{1,t+1} \tilde{\gamma}_{t+1}^{1-\sigma_C} \quad (62)$$

$$\tilde{v}_{1,t} = \psi_t \left( \frac{\tilde{w}_t}{\tilde{w}_t^{new}} \right)^{\frac{(1+\varphi)\lambda_w}{\lambda_w-1}} \left( h_t^d \right)^{1+\varphi} + \beta \xi_w E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w} \gamma}{\pi_{t+1}} \right)^{\frac{(1+\varphi)\lambda_w}{1-\lambda_w}} \left( \frac{\tilde{w}_{t+1}^{new} \tilde{\gamma}_{t+1}}{\tilde{w}_t^{new}} \right)^{\frac{(1+\varphi)\lambda_w}{\lambda_w-1}} \tilde{v}_{1,t+1} \tilde{\gamma}_{t+1}^{1-\sigma_C} \quad (63)$$

$$\tilde{w}_t^{\frac{1}{1-\lambda_w}} = \xi_w \left( \frac{\pi_{t-1}^{\kappa_w} \bar{\pi}_t^{1-\kappa_w} \gamma}{\pi_t} \right)^{\frac{1}{1-\lambda_w}} \left( \frac{\tilde{w}_{t-1}}{\tilde{\gamma}_t} \right)^{\frac{1}{1-\lambda_w}} + (1 - \xi_w) (\tilde{w}_t^{new})^{\frac{1}{1-\lambda_w}} \quad (64)$$

$$\tilde{f}_{1,t} = \tilde{\lambda}_t m c_t \tilde{y}_t^d + \beta \xi_y E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w}}{\pi_{t+1}} \right)^{-\frac{\lambda_y}{\lambda_y-1}} \tilde{f}_{1,t+1} \tilde{\gamma}_{t+1}^{1-\sigma_C} \quad (65)$$

$$\tilde{f}_{2,t} = \tilde{\lambda}_t \ddot{\pi}_t \tilde{y}_t^d + \beta \xi_d E_t \left( \frac{\pi_t^{\kappa_w} \bar{\pi}_{t+1}^{1-\kappa_w}}{\pi_{t+1}} \right)^{-\frac{1}{\lambda_y-1}} \left( \frac{\ddot{\pi}_t}{\ddot{\pi}_{t+1}} \right) \tilde{f}_{2,t+1} \tilde{\gamma}_{t+1}^{1-\sigma_C} \quad (66)$$

$$0 = \lambda_y \tilde{f}_{1,t} - \tilde{f}_{2,t} \quad (67)$$

$$\frac{\tilde{b}_t^S}{\varepsilon_t^S} + \frac{\bar{b}_t^L}{\varepsilon_t^L} + \tilde{T}_t = \frac{r_{t-1}^S}{\pi_t^c} \frac{\tilde{b}_{t-1}^S}{\tilde{\gamma}_t} + \frac{r_t^L}{\pi_t^c} \frac{p_{L,t}}{p_{L,t-1}} \frac{\bar{b}_{t-1}^L}{\tilde{\gamma}_t} - \tilde{G}_t \quad (68)$$

$$\tilde{y}_t^d = \tilde{c}_t + \tilde{G}_t + \tilde{i}_t \quad (69)$$

$$\frac{r_t^h}{\varepsilon_t^S} = r_t^S - x [\delta_t^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B] \frac{1}{\bar{b}_{\kappa,t}^L} \quad (70)$$

$$E_t \left\{ r_{t+1}^L \frac{p_{L,t+1}}{p_{L,t}} \right\} = \frac{r_t^h}{\varepsilon_t^S} - x [\delta_t^B - \vartheta \delta_{t-1}^B - (1 - \vartheta) \delta^B] \frac{\tilde{b}_{\kappa,t}^S}{(\bar{b}_{\kappa,t}^L)^2} \quad (71)$$

## 5.9 Steady states

Household's Euler equation implies

$$r^h = \frac{\tilde{\gamma}^{\sigma_C} \pi^c}{\beta} \quad (72)$$

Household's effective interest rate spread is given by financial intermediary first order condition

$$\frac{r^h}{r^S} = r^S = r^L$$

Set  $y = 1$  and  $l = 1/3$

$$k = \left( \frac{\tilde{y}}{z h^\alpha} \right)^{\frac{1}{1-\alpha}} \quad (73)$$

$$i = \delta k \quad (74)$$

$$c = (1 - g) y - i \quad (75)$$

$$\tilde{\lambda} = \frac{d(\tilde{\gamma}^{\sigma_C} - \beta b)}{(\tilde{c} \tilde{\gamma} - b \tilde{c})^{\sigma_C}} \quad (76)$$

$$\begin{aligned}
mc &= \frac{wh}{\alpha y} = \frac{1}{\lambda_p} \\
w &= \frac{\alpha y}{h\lambda_p}
\end{aligned} \tag{77}$$

$$\tilde{w}^{new} = w \tag{78}$$

$$\tilde{v}_1 = \frac{\frac{1}{\lambda_w} \tilde{\lambda} \tilde{w} h}{1 - \beta \xi_w \tilde{\gamma}^{1-\sigma_C}} \tag{79}$$

$$\psi = \frac{(1 - \beta \xi_w \tilde{\gamma}^{1-\sigma_C})}{h^{1+\varphi}} \tag{80}$$

$$\tilde{f}_1 = \frac{\tilde{\lambda} mc \tilde{y}}{1 - \beta \xi_y \tilde{\gamma}^{1-\sigma_C}} \tag{81}$$

$$\tilde{f}_2 = \frac{\tilde{\lambda} \bar{\pi} \tilde{y}}{1 - \beta \xi_y \tilde{\gamma}^{1-\sigma_C}} \tag{82}$$

## 5.10 Linearised Equations

$$\hat{r}_t^h = \hat{r}_t^S + \hat{\varepsilon}_t^{b^S} - \tilde{x} \left( \hat{\delta}_t^B - \vartheta \hat{\delta}_{t-1}^B \right) \tag{83}$$

$$\hat{r}_{t+1}^L + \hat{p}_{L,t+1} - \hat{p}_{L,t} = \hat{r}_t^h - \hat{\varepsilon}_t^{b^L} - \frac{\tilde{x}}{\delta} \left( \hat{\delta}_t^B - \vartheta \hat{\delta}_{t-1}^B \right) \tag{84}$$

$$\hat{\delta}_t^B = \hat{b}_t^S - \hat{b}_t^L$$

$$\begin{aligned}
\hat{b}_t^S + \frac{\hat{b}_t^L}{\delta^B} &= \frac{1}{\beta} \left( \hat{b}_{t-1}^S + \frac{\hat{b}_{t-1}^L}{\delta^B} - \left( 1 + \frac{1}{\delta^B} \right) \hat{\gamma}_t \right) - \frac{T}{b^S} \hat{T}_t \\
&+ \frac{1}{\beta} \left\{ \hat{r}_{t-1}^S - \hat{\pi}_t^c + \frac{1}{\delta^B} \left( \hat{r}_t^L - \hat{\pi}_t^c + \hat{p}_{L,t} - \hat{p}_{L,t-1} \right) \right\} - \frac{gy}{b^S} (\hat{g}_t + \hat{y}_t)
\end{aligned} \tag{85}$$

$$\frac{T}{b^S} \hat{T}_t = \theta \left( \hat{b}_{t-1}^S + \frac{\hat{b}_{t-1}^L}{\delta^B} - (1 + \delta) \hat{\gamma}_t \right) \tag{86}$$

$$mc_t = \hat{w}_t + \hat{h}_t - \hat{y}_t \tag{87}$$

$$mc_t = \hat{w}_t + \hat{h}_t - \hat{y}_t$$

$$\hat{\lambda}_t = \hat{\lambda}_{t+1} - \sigma_C \hat{\gamma}_{t+1} + r_t^h - \hat{\pi}_{t+1} \tag{88}$$

$$\frac{\gamma^{\sigma_C} - \beta b}{\gamma^{\sigma_C}} \hat{\lambda}_t = \left[ \hat{d}_t - \frac{\beta \gamma}{\gamma^{\sigma_C}} \hat{d}_{t+1} \right] - \frac{\sigma_C}{1 - \frac{b}{\gamma}} \left\{ \begin{aligned} &\left( 1 + \frac{\beta b^2}{\gamma^{1+\sigma_C}} \right) \hat{c}_t - \frac{b}{\gamma} (\hat{c}_{t-1} - \hat{\gamma}_t) \\ &- \frac{\beta b}{\gamma^{\sigma_C}} (\hat{c}_{t+1} + \hat{\gamma}_{t+1}) \end{aligned} \right\} \tag{89}$$

$$\begin{aligned}
[\Delta \hat{w}_t + \hat{\gamma}_t + \hat{\pi}_t - \kappa_w \hat{\pi}_{t-1} + (1 - \kappa_w) \bar{\pi}_t] &= \beta \gamma^{1-\sigma_c} [\Delta \hat{w}_{t+1} + \hat{\gamma}_{t+1} + \hat{\pi}_{t+1} - \kappa_w \hat{\pi}_t - (1 - \kappa_w) \bar{\pi}_{t+1}] \\
&+ \frac{(1 - \beta \xi_w \gamma^{1-\sigma_c}) (1 - \xi_w) [\lambda_w - 1]}{[(\varphi + 1) \lambda_w - 1] \xi_w} \left\{ \hat{\psi}_t + \varphi \hat{h}_t - \hat{\lambda}_t - \hat{w}_t \right\} \\
&+ \hat{\lambda}_{w,t}
\end{aligned}$$

$$\hat{y}_t = \hat{z}_t + \alpha \hat{h}_t + (1 - \alpha) \hat{k}_t \quad (90)$$

$$\hat{k}_t = \hat{v}_t + \bar{k}_{t-1} - \hat{\gamma}_t \quad (91)$$

$$\hat{v}_t = \frac{1}{\psi_v} \hat{r}_t^k \quad (92)$$

$$\begin{aligned}
\bar{k}_t &= \left(1 - \frac{i}{\bar{k}}\right) (\bar{k}_{t-1} - \hat{\gamma}_t) + \frac{i}{\bar{k}} \hat{i}_t + \left(1 - \frac{1 - \delta}{\gamma}\right) (1 + \beta \gamma^{1-\sigma_c}) \gamma^2 \psi_I \hat{\phi}_t \\
\hat{p}_{L,t} &= -\frac{r}{r - \kappa} \hat{r}_t^L \quad (93)
\end{aligned}$$

$$\bar{b}_t^L = \hat{p}_{L,t} + \hat{b}_t^L \quad (94)$$

$$\hat{y}_t = \frac{c}{(1 - g)y} \hat{c}_t + \frac{g}{1 - g} g_t + \frac{i}{(1 - g)y} \hat{i}_t + \frac{r^k k}{(1 - g)y} \hat{v}_t \quad (95)$$

$$\begin{aligned}
\hat{\pi}_t - \hat{\pi}_t &= \frac{\beta}{1 + \beta \kappa_y} E_t (\hat{\pi}_{t+1} - \hat{\pi}_{t+1}) + \frac{\kappa_y}{1 + \beta \kappa_y} (\hat{\pi}_{t-1} - \hat{\pi}_t) - \frac{\beta \kappa_y}{1 + \beta \kappa_y} (\hat{\pi}_t^c - \hat{\pi}_{t+1}) \\
&+ \frac{(1 - \xi_y) (1 - \beta \xi_y)}{\xi_y (1 + \beta \kappa_y)} \widehat{m} c_t + \lambda_{y,t} \quad (96)
\end{aligned}$$

### 5.11 Estimation

A number of parameters (Table 2) is decided prior to the estimation of the model. The time discount factor ( $\beta = 0.99$ ), the steady state value of the productivity growth ( $\gamma = 1$ ) and the inflation target ( $\bar{\pi} = 1$ ) imply that the steady state value of the interest rate is 4%. We follow the literature and assume log consumption preferences ( $\sigma_C = 1$ , Justiniano *et al.* (2010)). Similar to Smets and Wouters (2007) steady-state price and wage markup are set equal to 20% and 10% respectively. The share of capital in the production ( $\alpha$ ) and its depreciation rate ( $\delta$ ) have been calibrated to 0.36 and 0.025, numbers typically used in the literature (Christiano *et al.* (2005), Trabandt and Uhlig (2011) and Jermann and Quadrini (2012)).  $\delta_B$  has been set equal to 1 to match the steady state short- to long-term debt ratio in the data (see De Graeve and Theodoridis (2016)). As in Smets and Wouters (2007), Leeper *et al.* (2010), and Traum and Yang (2011) the steady-state government spending to GDP ratio ( $g$ ), short-term to GDP ration ( $\frac{b^S}{y}$ ) and the lump-sum tax response coefficient to debt ( $\theta$ ) equal 0.18, 0.65 and 0.025, respectively.

Table 3 summarises the prior moments and density functions of the structural parameter vector estimated. The same prior moments are employed for the estimation of both full and limited information models. These moments are those employed by Smets and Wouters (2007).

Tables 4, 5, 6 and 7 report the posterior moments of the Full, Limited Information and Markov Switching models respectively. All set of estimates are very similar with each other but also with those in the literature. Figure 13 illustrate the evolution of the regimes in the data.

Table 2: Calibrated Parameters

Mnemonic	Description	Value
$\beta$	Time Discount Factor	0.990
$\gamma$	Steady State Productivity Growth	1.000
$\bar{\pi}$	Steady State Inflation Target	1.000
$\sigma_C$	Inverse Intertemporal Substitution Elasticity	1.000
$\lambda_y$	Steady State Price Markup	1.200
$\lambda_w$	Steady State Wage Markup	1.100
$\theta$	Tax Response to Debt	0.025
$\alpha$	Production Capital Share	0.360
$\delta$	Capital Depreciation Rate	0.025
$\frac{1}{\delta^B}$	Steady State Long to Short Term Debt Ratio	1.000
$h$	Steady State Hours	0.333
$g$	Steady State Government Spending to GDP Ratio	0.180
$\frac{b^S}{y}$	Steady State Short Term Debt to GDP Ratio	0.650

### 5.12 Noise Inflation Expectations Measured

The identification scheme is put through another test. Its performance is investigated when long-run inflation expectations are measured with an error

$$\begin{aligned}\pi_t^{Obs,LR-IE} &= E_t \pi_{t+40} + \epsilon_t \\ \epsilon_t &= 0.999\epsilon_{t-1} + \sigma_\epsilon \omega_{\epsilon,t}\end{aligned}$$

This noise process  $\epsilon_t$  has been calibrated to be two times more volatile than the long run inflation expectation series ( $E_t \pi_{t+40}$ ). The specification of the noise process captures the belief that agents stick with the “wrong” inflation target for a long-time.

## 6 Long Run Identification

Michelis and Iacoviello (2016) identify an inflation target shock using on VECM long-run restrictions. We use our model and the identification schemes proposed by Gonzalo and Ng (2001) to investigate the ability of long-run restriction to recover the true shock (Dison and Theodoridis (2017) illustrate how this scheme can be modified to allow for stationary variables to enter to the VECM model). The inflation target is the only shock that can have a permanent effect on the policy rate, inflation, long-term interest rate and zero long-run effect on GDP growth. Furthermore, the shock increases all the nominal variables by the same amount in the long run. We evaluate the performance of this identification scheme by using the artificial data generated from the benchmark DGP used in the Monte-Carlo experiments in the paper. The performance of the scheme is quite poor, even when additional short run restrictions (the shock increases all nominal variables contemporaneously) the performance of the identification procedure remains far from satisfactory in line with the analysis in Erceg *et al.* (2005). As shown in Figure 15, the response of output obtained by using the VAR is substantially different from the DSGE response. Moreover, the wide error bands indicate that there is a lot of variation in the estimates across the monte-carlo replications

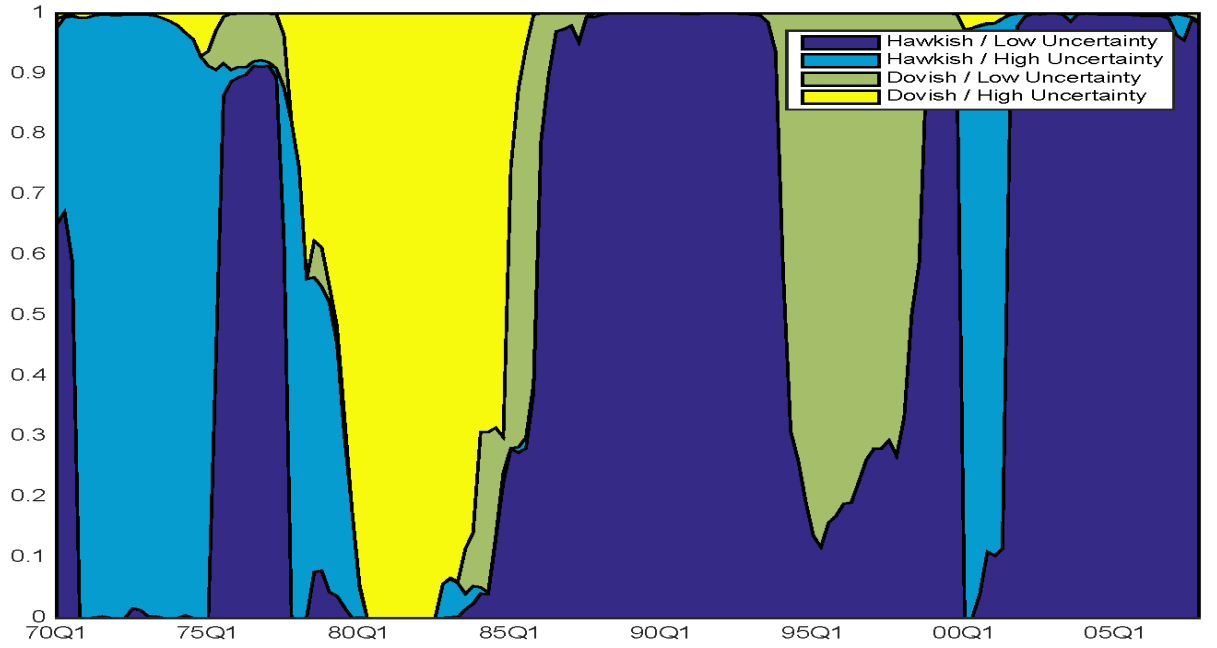


Figure 13: Smoothed Regime Probabilities

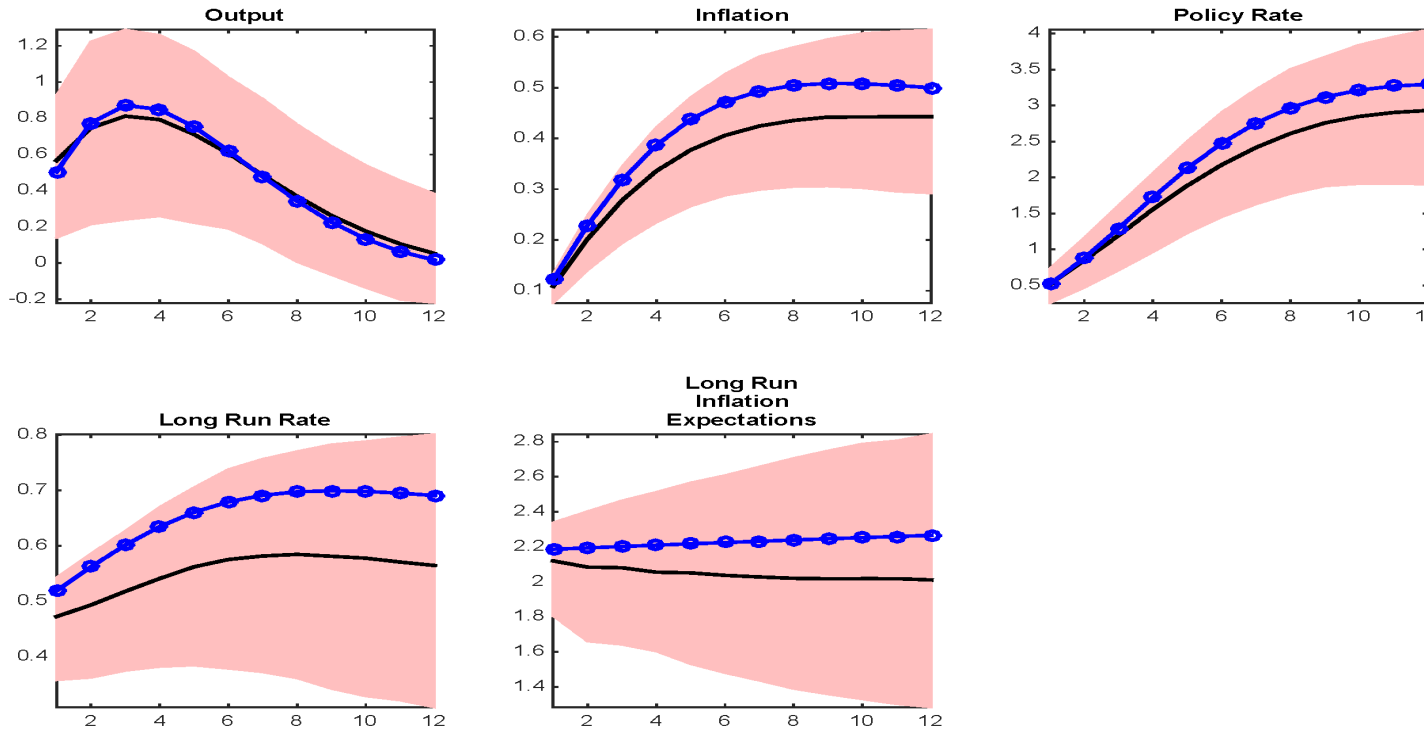


Figure 14: The black line and the shadow pink area correspond to the pointwise 50, 5 and 95 percentiles of the simulated distribution. The blue circle line represents the DSGE true response to an inflation target shock.



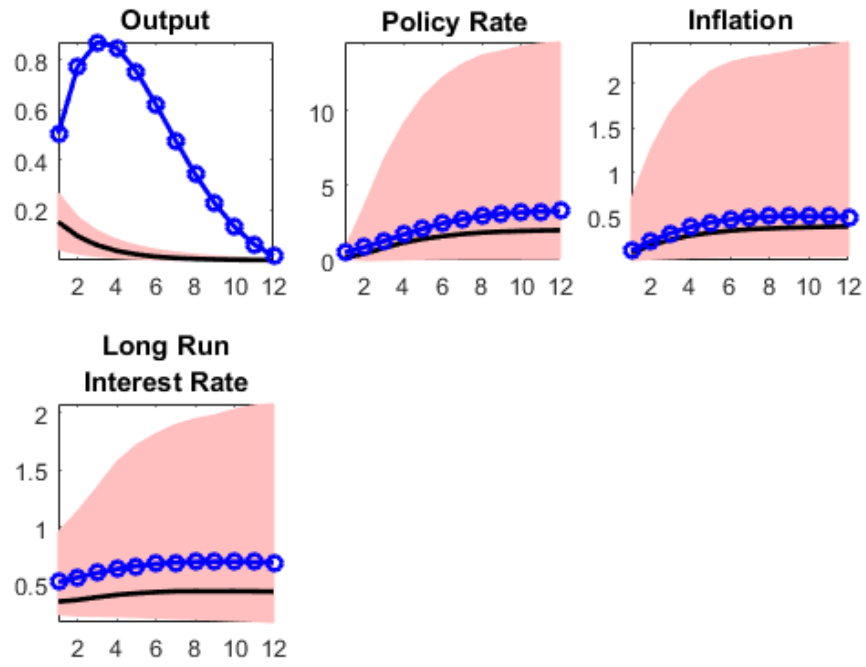


Figure 15: Response to target shocks using LR identification. Blue circle line is the true DSGE response.

implying that it is hard to distinguish this long-run stochastic trend.

Table 3: Estimated Parameters: Prior Moments

Mnemonic	Description	Density	Mean	STD
$\sigma_L$	Inverse Labour Supply Elasticity	Normal	1.50	0.25
$\chi$	Liquidity Adjustment Cost	Normal	5.00	0.25
$b$	Habit Smoothing	Beta	0.75	0.05
$\kappa_y$	Price Indexation	Beta	0.50	0.15
$\xi_y$	Calvo Price Reset Probability	Beta	0.50	0.10
$\kappa_w$	Wage Indexation	Beta	0.50	0.15
$\xi_w$	Calvo Wage Reset Probability	Beta	0.50	0.10
$\phi_R$	Policy Smoothing	Beta	0.75	0.10
$\phi_\pi$	Inflation Policy Response	Normal	1.50	0.10
$\phi_y$	Output Policy Response	Normal	0.12	0.05
$\psi_\nu$	Capital Utilisation Cost	Normal	5.00	0.50
$\phi_I$	Investment Adjustment Cost	Normal	4.00	0.50
$\rho_\gamma$	AR Persistence Non Stationary Productivity Process	Beta	0.50	0.20
$\rho_{b^S}$	AR Persistence of Short Term Debt Supply Process	Beta	0.50	0.20
$\rho_{\lambda_y}$	AR Persistence Price Markup Process	Beta	0.50	0.20
$\sigma_{\lambda_y}$	STD Price Markup Process	Beta	0.50	0.20
$\rho_{\lambda_W}$	AR Persistence Wage Markup Process	Beta	0.50	0.20
$\mu_{\lambda_W}$	MA Persistence Wage Markup Process	Beta	0.50	0.20
$\rho_{\bar{\pi}}$	AR Persistence Inflation Target Process	Beta	0.50	0.20
$\rho_m$	AR Persistence Monetary Policy Process	Beta	0.50	0.20
$\rho_g$	AR Persistence Government Spending Process	Beta	0.50	0.20
$\rho_\phi$	AR Persistence Investment Specific Process	Beta	0.50	0.20
$\sigma_\gamma$	STD Non Stationary Productivity Process	Inv-Gamma	0.10	2.00
$\sigma_{b^S}$	STD of Short Term Debt Supply Process	Inv-Gamma	0.10	2.00
$\mu_{\lambda_y}$	MA Persistence Price Markup Process	Inv-Gamma	0.10	2.00
$\sigma_{\lambda_W}$	STD Persistence Wage Markup Process	Inv-Gamma	0.10	2.00
$\sigma_{\bar{\pi}}$	STD Inflation Target Process	Inv-Gamma	0.10	2.00
$\sigma_{r^S}$	STD Monetary Policy	Inv-Gamma	0.10	2.00
$\sigma_g$	STD Government Spending Process	Inv-Gamma	0.10	2.00
$\sigma_\phi$	STD Investment Specific Process	Inv-Gamma	0.10	2.00

**Notes:** STD denotes the standard deviation and Inv-Gamma the inverse gamma distribution.

Table 4: Full Information Model Estimated Parameters: Posterior Moments

Mnemonic	Description	Mode	5 <sup>th</sup>	95 <sup>th</sup>
$\sigma_L$	Inverse Labour Supply Elasticity	1.53	0.83	1.81
$\chi$	Liquidity Adjustment Cost	4.05	4.12	5.40
$b$	Habit Smoothing	0.71	0.71	0.76
$\kappa_y$	Price Indexation	0.92	0.78	0.92
$\xi_y$	Calvo Price Reset Probability	0.89	0.89	0.92
$\kappa_w$	Wage Indexation	0.75	0.32	0.84
$\xi_w$	Calvo Wage Reset Probability	0.46	0.46	0.91
$\phi_R$	Policy Smoothing	0.74	0.76	0.87
$\phi_\pi$	Inflation Policy Response	1.90	1.87	2.11
$\phi_y$	Output Policy Response	0.14	0.13	0.31
$\psi_\nu$	Capital Utilisation Cost	5.17	4.21	5.84
$\phi_I$	Investment Adjustment Cost	5.45	4.63	5.99
$\rho_\gamma$	AR Persistence Non Stationary Productivity Process	0.29	0.14	0.39
$\rho_{bS}$	AR Persistence of Short Term Debt Supply Process	0.86	0.33	0.85
$\rho_{\lambda_y}$	AR Persistence Price Markup Process	0.89	0.84	0.94
$\sigma_{\lambda_y}$	STD Price Markup Process	1.00	0.99	1.00
$\rho_{\lambda_W}$	AR Persistence Wage Markup Process	0.95	0.71	0.97
$\mu_{\lambda_W}$	MA Persistence Wage Markup Process	0.83	0.60	0.87
$\rho_{\bar{\pi}}$	AR Persistence Inflation Target Process	0.17	0.15	0.57
$\rho_m$	AR Persistence Monetary Policy Process	0.41	0.12	0.41
$\rho_g$	AR Persistence Government Spending Process	0.95	0.95	1.00
$\rho_\phi$	AR Persistence Investment Specific Process	0.96	0.94	0.97
$\sigma_\gamma$	STD Non Stationary Productivity Process	1.03	0.94	1.13
$\sigma_{bS}$	STD of Short Term Debt Supply Process	0.99	1.12	4.00
$\mu_{\lambda_y}$	MA Persistence Price Markup Process	0.17	0.14	0.18
$\sigma_{\lambda_W}$	STD Persistence Wage Markup Process	1.08	0.90	1.15
$\sigma_{\bar{\pi}}$	STD Inflation Target Process	0.10	0.10	0.12
$\sigma_{rS}$	STD Monetary Policy	0.23	0.20	0.24
$\sigma_g$	STD Government Spending Process	0.59	0.55	0.65
$\sigma_\phi$	STD Investment Specific Process	0.31	0.29	0.39

**Notes:** The columns 5<sup>th</sup> and 95<sup>th</sup> refer to the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the posterior distribution of the structural parameter vector.

Table 5: Limited Information Model Estimated Parameters: Posterior Moments

Mnemonic	Description	Mode	5 <sup>th</sup>	95 <sup>th</sup>
$\sigma_L$	Inverse Labour Supply Elasticity	1.57	1.19	1.99
$\chi$	Liquidity Adjustment Cost	4.32	3.92	4.76
$b$	Habit Smoothing	0.65	0.62	0.68
$\kappa_y$	Price Indexation	0.89	0.81	0.92
$\xi_y$	Calvo Price Reset Probability	0.70	0.66	0.74
$\kappa_w$	Wage Indexation	0.79	0.61	0.91
$\xi_w$	Calvo Wage Reset Probability	0.29	0.23	0.36
$\phi_R$	Policy Smoothing	0.75	0.69	0.80
$\phi_\pi$	Inflation Policy Response	1.91	1.88	1.96
$\phi_y$	Output Policy Response	0.09	0.05	0.12
$\psi_\nu$	Capital Utilisation Cost	5.34	4.53	6.03
$\phi_I$	Investment Adjustment Cost	4.52	3.89	5.28
$\rho_\gamma$	AR Persistence Non Stationary Productivity Process	0.22	0.12	0.34
$\rho_{bS}$	AR Persistence of Short Term Debt Supply Process	0.86	0.82	0.88
$\rho_{\lambda_y}$	AR Persistence Price Markup Process	0.98	0.95	0.99
$\sigma_{\lambda_y}$	STD Price Markup Process	0.64	0.48	0.73
$\rho_{\lambda_W}$	AR Persistence Wage Markup Process	0.96	0.92	0.99
$\mu_{\lambda_W}$	MA Persistence Wage Markup Process	0.73	0.59	0.83
$\rho_{\bar{\pi}}$	AR Persistence Inflation Target Process	0.11	0.04	0.23
$\rho_m$	AR Persistence Monetary Policy Process	0.39	0.27	0.54
$\rho_g$	AR Persistence Government Spending Process	0.95	0.92	0.97
$\rho_\phi$	AR Persistence Investment Specific Process	0.95	0.92	0.97
$\sigma_\gamma$	STD Non Stationary Productivity Process	1.02	0.94	1.12
$\sigma_{bS}$	STD of Short Term Debt Supply Process	0.92	0.79	1.10
$\mu_{\lambda_y}$	MA Persistence Price Markup Process	0.16	0.14	0.18
$\sigma_{\lambda_W}$	STD Persistence Wage Markup Process	1.22	1.06	1.36
$\sigma_{\bar{\pi}}$	STD Inflation Target Process	0.10	0.10	0.11
$\sigma_{rS}$	STD Monetary Policy	0.24	0.23	0.27
$\sigma_g$	STD Government Spending Process	0.59	0.54	0.65
$\sigma_\phi$	STD Investment Specific Process	0.31	0.28	0.35

**Notes:** The columns 5<sup>th</sup> and 95<sup>th</sup> refer to the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the posterior distribution of the structural parameter vector.

Table 6: Markov Switch Model Estimated Parameters: Posterior Moments Deep Parameter

Mnemonic	Description	Mode	5 <sup>th</sup>	95 <sup>th</sup>
$\sigma_L$	Inverse Labour Supply Elasticity	1.60	1.58	1.64
$\chi$	Liquidity Adjustment Cost	4.67	4.64	4.73
$b$	Habit Smoothing	0.73	0.72	0.74
$\kappa_y$	Price Indexation	0.91	0.87	0.93
$\xi_y$	Calvo Price Reset Probability	0.86	0.84	0.88
$\kappa_w$	Wage Indexation	0.39	0.33	0.42
$\xi_w$	Calvo Wage Reset Probability	0.92	0.92	0.93
Hawkish Policy Regime				
$\phi_R$	Policy Smoothing	0.87	0.83	0.87
$\phi_\pi$	Inflation Policy Response	1.82	1.76	1.84
$\phi_y$	Output Policy Response	0.26	0.24	0.29
Dovish Policy Regime				
$\phi_R$	Policy Smoothing	0.73	0.69	0.78
$\phi_\pi$	Inflation Policy Response	0.91	0.89	0.94
$\phi_y$	Output Policy Response	0.33	0.32	0.34
$p_{1,2}^c$	Probability Switching from Hawkish to Dovish Regime	0.02	0.00	0.03
$p_{2,1}^c$	Probability Switching from Dovish to Hawkish Regime	0.05	0.03	0.08
$p_{1,2}^\sigma$	Probability Switching from Low to High Uncertainty Regime	0.03	0.01	0.04
$p_{2,1}^\sigma$	Probability Switching from High to Low Uncertainty Regime	0.03	0.02	0.06

**Notes:** The columns 5<sup>th</sup> and 95<sup>th</sup> refer to the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the posterior distribution of the structural parameter vector. The prior distribution of distribution of  $\phi_R$ ,  $\phi_y$  and the standard deviation of all shocks is the same across both regimes. Only the prior distribution of  $\phi_\pi$  is different in the Dovish regime ( $\phi_\pi \sim N(0.90, 0.025)$ ). The prior distribution of the switching probabilities is the Beta with mean and standard deviation of 0.1.

Table 7: Markov Switch Model Estimated Parameters: Posterior Moments Shock Parameters

Mnemonic	Description	Mode	5 <sup>th</sup>	95 <sup>th</sup>
$\rho_\gamma$	AR Persistence Non Stationary Productivity Process	0.30	0.24	0.33
$\rho_{b^S}$	AR Persistence of Short Term Debt Supply Process	0.44	0.42	0.50
$\rho_{\lambda_y}$	AR Persistence Price Markup Process	0.96	0.93	0.97
$\mu_{\lambda_y}$	STD Price Markup Process	0.99	0.99	1.00
$\rho_{\lambda_W}$	AR Persistence Wage Markup Process	0.79	0.74	0.82
$\mu_{\lambda_W}$	MA Persistence Wage Markup Process	0.73	0.67	0.77
$\rho_{\pi}$	AR Persistence Inflation Target Process	0.52	0.48	0.54
$\rho_m$	AR Persistence Monetary Policy Process	0.26	0.22	0.31
$\rho_g$	AR Persistence Government Spending Process	0.97	0.95	0.98
$\rho_\phi$	AR Persistence Investment Specific Process	0.93	0.91	0.95
Low Uncertainty Regime				
$\sigma_\gamma$	STD Non Stationary Productivity Process	0.59	0.56	0.62
$\sigma_{b^S}$	STD of Short Term Debt Supply Process	2.58	2.54	2.60
$\sigma_{\lambda_y}$	MA Persistence Price Markup Process	0.14	0.13	0.16
$\sigma_{\lambda_W}$	STD Persistence Wage Markup Process	0.74	0.68	0.75
$\sigma_{\pi}$	STD Inflation Target Process	0.10	0.10	0.11
$\sigma_{r^S}$	STD Monetary Policy	0.10	0.10	0.11
$\sigma_g$	STD Government Spending Process	0.44	0.41	0.47
$\sigma_\phi$	STD Investment Specific Process	0.31	0.29	0.33
High Uncertainty Regime				
$\sigma_\gamma$	STD Non Stationary Productivity Process	1.42	1.39	1.43
$\sigma_{b^S}$	STD of Short Term Debt Supply Process	4.00	3.69	4.00
$\sigma_{\lambda_y}$	MA Persistence Price Markup Process	0.28	0.25	0.31
$\sigma_{\lambda_W}$	STD Persistence Wage Markup Process	1.41	1.34	1.46
$\sigma_{\pi}$	STD Inflation Target Process	0.11	0.10	0.12
$\sigma_{r^S}$	STD Monetary Policy	0.32	0.30	0.36
$\sigma_g$	STD Government Spending Process	0.78	0.73	0.82
$\sigma_\phi$	STD Investment Specific Process	0.31	0.31	0.35

**Notes:** The columns 5<sup>th</sup> and 95<sup>th</sup> refer to the 5<sup>th</sup> and 95<sup>th</sup> percentiles of the posterior distribution of the structural parameter vector.

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