Does the Price Level Adjust Faster to Aggregate Technology Shocks than to Monetary Policy Shocks?

LUIGI PACIELLO

EIEF, Rome

Abstract

This paper studies the speed of price adjustment to aggregate technology shocks and to monetary policy shocks in a Bayesian VAR model. Determining the speed of price adjustment to different types of shocks provides information on the ability of sticky price models to account for price level impulse responses. I show that, in the United States, the price level adjusts much faster to aggregate technology shocks than to monetary policy shocks. Results are robust to different identification assumptions and measures of aggregate prices. This evidence challenges existing models of price stickiness.

1 Introduction

This paper investigates whether the U.S. aggregate price level adjusts faster to aggregate technology shocks than to monetary policy shocks. Assessing the speed of price adjustment to different types of shocks is an important task in the macroeconomic literature, not only to establish the main sources of business cycle fluctuations, but also to understand the way different shocks transmit through the economy and to distinguish among available models. While a recent literature has quickly developed assessing the degree of price stickiness to sector-specific idiosyncratic shocks versus aggregate shocks, surprisingly little attention has been paid to differences in price stickiness within different types of aggregate shocks.[1]

Altig, Christiano, Eichenbaum and Linde (2005) and Dupor, Han and Tsai (2007) show that sticky price models resulting from staggered price setting have a hard time generating substantial differences in price adjustment speed to technology and monetary policy shocks. In these models the frequency of price adjustment is invariant to different shocks. Golosov and Lucas (2006) show that state-dependent models of price setting resulting from menu costs have difficulties generating different degree of price rigidity to different types of shocks. In these models when the firm pays the menu cost it can adjust prices to all realized shocks. As a consequence, large differences in the speed of price adjustment would favor, for instance, those theories that model price stickiness to monetary policy shocks mostly as the outcome of wage rigidity, rather than frictions in price setting, as suggested by Galí and Gertler (1999). By the same argument, large differences would also favor those theories that model frictions in price setting as the result of imperfect information rather than staggered price setting or menu costs. In fact, as suggested by Woodford (2002), if firms were better informed about technology shocks then about monetary policy shocks, prices

[1] See, for instance, Boivin, Giannoni and Mihov (2008) for an empirical investigation of price adjustment speed to sector-specific and aggregate shocks; Golosov and Lucas (2006); Gertler and Leahy (2008); Maćkowiak and Wiederholt (2008); Nakamura and Steinsson (2008b) for theoretical applications.

would adjust faster to technology shocks than to monetary policy shocks.

In order to assess the speed of price adjustment to technology and monetary policy shocks, I use a Bayesian VAR (BVAR) model with a large number of macroeconomic indicators and with standard Litterman priors. Recently Banbura, Giannone and Reichlin (2007) have shown that BVAR models including a large number of variables can be estimated, achieving relatively accurate forecasts and improving the structural analysis to monetary policy shocks. The importance of conditioning on large information set when identifying monetary policy shocks has also been shown in frameworks related to factor analysis by Bernanke, Boivin, and Eliasz (2005) and Giannone, Reichlin, and Sala (2004). In addition, I follow the structural VAR (SVAR) literature in making explicit identifying assumptions to isolate estimates of monetary policy and aggregate technology shocks while keeping the model free of the many additional restrictive assumptions needed to give every parameter and equation an economic interpretation. The model is estimated on U.S. data from 1960:I to 2007:II. I estimate explicit measures of price adjustment speed to aggregate technology and monetary policy shocks. Given these measures, I characterize the posterior probability distribution of the difference in price adjustment speed to technology and monetary policy shocks.

I obtain that the price level adjusts much faster to aggregate technology shocks than to monetary policy shocks. Under the benchmark specification of the model, it takes approximately 5.5 quarters less for the median price level response to accomplish half of its long-run adjustment to a permanent technology shock than to a monetary policy shock. Two years after a technology shock, the price level response has accomplished approximately two-thirds of its long-run adjustment, while, in the same period of time, the price level has accomplished only about one-fifth of its long-run adjustment to a monetary policy shock. The posterior probability that prices adjust faster to technology shocks than to monetary policy shocks is about 95 percent.

There is a large empirical literature investigating how aggregate macroeconomic variables respond to monetary policy shocks in the context of SVARs. These studies provide evidence of stickiness of the aggregate price level in response to monetary policy shocks.[2] A recent paper by Altig, Christiano, Eichenbaum and Linde (2005) estimates the responses of macroeconomic variables to both aggregate technology and monetary policy shocks within a SVAR. Interestingly, they show that point estimates of inflation impulse responses display substantially larger persistence to monetary policy shocks than to technology shocks. However, the relatively large error bands associated to inflation responses, and the price puzzle in inflation response to monetary policy shocks, make it difficult deriving sharp conclusions about differences in price adjustment speed to the two types of shocks.

This paper contributes to the existing literature on at least two dimensions. First, I estimate a model with a larger number of macroeconomic variables than in previous studies. The larger set of variables improves the structural analysis of impulse responses. For instance, more information helps solving the price puzzle following monetary policy shocks. This is important to properly quantify differences in price adjustment speed to the two types of shocks. Second, I assess robustness of findings against different identification assumptions and measures of aggregate prices. For instance, standard identification assumptions allow the price level to respond only with a lag to monetary policy shocks, but contemporaneously to technology shocks.[3] I show that estimated differences in price adjustment speed are robust to a different set of identification assumptions implying similar restrictions on the dynamic of prices to the two types of shocks.

The paper is organized as follows. Section 2 describes the BVAR model, the data, the prior and the identification assumptions, as well as deriving impulse responses to aggregate technology and monetary policy shocks. Section 3 studies measures of price adjustment speed and discusses results. Section 4 assesses robustness of findings against the main assumptions behind the procedure adopted in the paper. Section 5

[2] See Christiano, Eichenbaum and Evans (1999) for a review.

[3] See Christiano, Eichenbaum and Evans (1999) and Galí (1999).

concludes.

2 The benchmark BVAR model

This section describes the baseline empirical model consisting of a SVAR for a n-dimensional vector of variables, Y_t. The SVAR model is given by

$$A_0 Y_t = \upsilon + A_1 Y_{t-1} + ... + A_p Y_{t-p} + e_t, \tag{1}$$

where $Y_t = (y_{1,t}\ y_{2,t}\ ...y_{n,t})'$ is the set of time-series at period t, $\upsilon = (\upsilon_1\ \upsilon_2\ ...\ \upsilon_n)$ is a vector of constants, A_0, A_1,..A_p are $n \times n$ matrices of structural parameters, p is a non-negative integer, and e_t is an n-dimensional Gaussian white noise with unitary covariance matrix, $E\{e_t e_t'\} = I$, representing structural shocks.

The reduced form VAR model associated to (1) is given by

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + u_t, \tag{2}$$

where $c = A_0^{-1}\upsilon$, $B_s = A_0^{-1} A_s$ for $s = 1, ..p$, and $u_t = A_0^{-1} e_t$. It is assumed that all the roots of the VAR polynomial lie outside the unit circle. It follows that $\Upsilon \equiv E\{u_t u_t'\} = A_0^{-1}\left(A_0^{-1}\right)'$.

Following Banbura, Giannone and Reichlin (2007), Y_t includes a relatively large number of macroeconomic variables. Model (2) is estimated using the Bayesian VAR approach to overcome the curse of dimensionality. This approach consists in imposing prior beliefs on the parameters of (2). These priors are set according to the standard practice which builds on Litterman (1986)'s suggestions, which are often referred to as Minnesota priors. According to these priors, Y_t is assumed to evolve according to

$$Y_t = c + diag\left(\delta_1, ..., \delta_n\right) Y_{t-1} + u_t, \tag{3}$$

where the i^{th} equation in (2) is centered around a random walk with drift if the i^{th} element of Y_t is highly persistent, $\delta_i = 1$, and around a white noise otherwise, $\delta_i = 0$. In particular, prior beliefs are such that

$$
\begin{aligned}
E\left((B_s)_{ij}\right) &= \begin{cases} \delta_i, & if \quad i = j, s = 1 \\ 0, & \quad otherwise \end{cases}, \\
V\left((B_s)_{ij}\right) &= \frac{\lambda^2}{s^2}\frac{\sigma_i^2}{\sigma_j^2},
\end{aligned}
$$

for $i = 1, ..., n$, $j = 1, ..., n$, $s = 1, ..., p$, and the matrix Υ has prior expectation $E(\Upsilon) = diag\left(\sigma_1^2, ..., \sigma_n^2\right)$. The scale parameters σ_i^2 are set equal to the variance of the residual from a univariate autoregressive model of order p for the i^{th} element of Y_t. The hyper-parameter λ governs the overall tightness of the prior distribution around (3). Next subsection describes choices of λ and δ_i. Under these assumptions, the posterior distribution of $B = (B_1, ..., B_p, c)'$ and Υ is Normal inverted-Wishart. See Appendix B for more details.

2.1 Data and priors

Model (2) includes twenty-three U.S. macroeconomic indicators, among which there are four different indices of aggregate prices: GDP price deflator, consumer price index, producer price index and personal consumption expenditure deflator.[4] This allows the study of the dynamics of different aggregate price indices within the same model. The time span is from January 1960 through June 2007. Model (2) is esti-

[4] The model includes: labor productivity (GDPQ/LBMNU), hours worked (LBMNU), the nominal interest rate (FYFF), the GDP price deflator (PGDP), the Standard and Poor's stock price index (FSPCOM), the number of employees on non-farm payrolls (CES002), personal income (A0M051), real consumption (JQCR), real non-residential investments (IFNRER), real residential investments (JQIFRESR), industrial production (IPS10), capacity utilization (UTL11), unemployment rate (LHUR), housing starts (HSFR), the index of sensitive material prices (PSM99Q), the producer price index (PWFSA), the personal consumption expenditures price deflator (GDMC), the consumer price index (PUNEW), average hourly earnings (CES275), M1 monetary stock (FM1), M2 monetary stock (FM2), non-borrowed reserves (FMRRA) and total reserves (FMRNBA).

mated on a quarterly frequency, and the number of lags p is set equal to 4.

The model is specified so that the vector Y_t is stationary, ensuring that all the roots of the VAR polynomial lie outside the unit circle.[5] In particular, all the highly persistent variables enter Y_t in log-differences with the exception of the federal funds rate.[6] Given that persistent variables enter Y_t in log-differences, a white noise prior, $\delta_i = 0$, is assumed for all variables but the federal funds rate. This choice of $\delta = (\delta_1, ..., \delta_n)$ is consistent with Banbura, Giannone and Reichlin (2007) and Stock and Watson (2005). Results of this paper are robust to different specifications of δ. Finally, the hyper-parameter λ is chosen similarly to Banbura, Giannone and Reichlin (2007) and set equal to 0.065.[7]

2.2 Identification of the structural parameters

Identification of (1) amounts to putting enough restrictions on the model to be able to recover $A_0, A_1.., A_p$ and υ from the equations above, given estimates of the reduced form parameters, Υ, $B_1, ..., B_p$ and c. This is achieved in the benchmark specification of the model by appealing to the combination of standard identification assumptions for technology and monetary policy shocks. This choice has the advantage of making results easily comparable to the existing literature. The main disadvantage is that these standard identification assumptions restrict price level response to monetary policy shocks in the period of the shock. However, in section 4, I show that results are robust to different identification assumptions that allow for prices to respond contemporaneously to all shocks.

First, it is assumed that only technology shocks may have a permanent effect on the level of labor productivity, as originally proposed by Galí (1999). This restriction

[5] Stationarity of (2) is needed to implement the identification scheme in the next sub-section.

[6] The twenty-three indicators are entered in Y_t in levels, logarithms or log-differences depending on the persistence of each indicator. See Appendix A for details on how each indicator is entered in Y.

[7] The model includes a set of variables similar to Banbura, Giannone and Reichlin. Results are robust to different choices of λ. See Appendix C for more details on the choice of λ.

is satisfied by a broad range of business cycle models under standard assumptions. In particular, let's define the matrix $C \equiv (I - B_1 - ... - B_p)^{-1} A_0^{-1}$, and suppose that labor-productivity growth is the i^{th} element of vector Y_t, and that the technology shock is the j^{th} element of vector e_t. It is assumed that all the elements of the i^{th} row of C are zero except for the one associated to the j^{th} column.

Second, similarly to Christiano, Eichenbaum, and Evans (1999), it is assumed that monetary policy targets a policy instrument, S_t, according to

$$S_t = f(\mathcal{F}_t) + \omega e_t^s, \tag{4}$$

where $\mathcal{F}_t$ is the information available to the central bank as of time t, ω is a constant and e_t^s is the monetary policy shock. Following the Bernanke-Blinder assumption, S_t is set equal to the 3-month federal funds rate. Variables in Y_t are divided in four subsets, $Y_t = (X_t, S_t, Z_t, F_t)'$. Similarly to the recursive assumption of Christiano, Eichenbaum, and Evans (1999), it is assumed that variables in X_t, mainly quantities and prices, may respond to monetary policy shocks, e_t^s, with one period lag. It is also assumed that the FED targets the monetary policy instrument so that S_t is unresponsive to contemporaneous changes in Z_t, where Z_t includes M1 and M2 monetary stocks as well as non-borrowed and total reserves.[8] F_t is equal to the S&P stock price index and there is no restriction on the short-run relationship between F_t and the other variables in Y_t.[9]

Finally, the column of A_0^{-1} corresponding to the impact of monetary policy shocks on Y_t is normalized so that monetary policy shocks are associated to a contemporaneous increase in the federal funds rate; the column of A_0^{-1} corresponding to the impact of technology shocks is normalized so that such shocks are associated to a permanent

[8] Similarly to Christiano, Eichenbaum, and Evans (1999), results are robust to using non-borrowed reserves, M1 or M2 as the monetary policy instrument, S.

[9] This implies that the monetary policy instrument S_t is allowed to respond contemporaneously to F_t, as well as F_t is allowed to respond contemporaneously to S_t. See Appendix D for details.

increase in labor productivity.[10] Under this set of assumptions the impulse responses of Y_t to monetary policy and technology shocks are exactly identified.[11]

2.3 Impulse responses

Impulse responses are generated according to the methodology proposed by Ramirez, Waggoner and Zha (2007). In particular, the model reduced-form parameters $B_1, ...,$ B_p and Υ are drawn from the estimated Normal inverted-Wishart posterior distribution. For each draw of $B_1, ..., B_p$ and Υ, the model structural-form parameters $A_0, ...,$ A_p are computed according to the identification assumptions above. Given the structural parameters, the impulse responses of Y_t to a one standard deviation technology shock and to a one standard deviation monetary policy shock are computed for each draw.[12]

[Figures 1, 2 and 3 about here]

Figure 1 plots the median impulse responses to aggregate technology and monetary policy shocks, and the associated 68 and 90 percent confidence intervals, of the GDP price deflator (PGDP), the consumer price index (PUNEW), the personal consumption expenditure deflator (PCEPI) and the producer price index (PWFSA). Figure 2 plots the impulse responses of some key variables such as the federal funds rate, GDP, PGDP-inflation and labor productivity. Figure 3 plots the impulse responses of the remaining macroeconomic indicators of the model. Given the focus on price adjustment, this paper only discusses results about price impulse responses. However, the estimated impulse responses of the other variables in Y are consistent with results obtained in previous studies.[13] The main findings of this analysis are as follows.

[10] Results are robust to different normalization assumptions, and in particular to the likelihood preserving normalization proposed by Waggoner and Zha (2003).

[11] See Appendix D for details.

[12] Results are based on 5,000 draws and are robust to larger number of draws.

[13] See for instance Francis and Ramey (2005), Altig, Christiano, Eichenbaum and Linde (2005), Galì (1999).

First, the aggregate price level is more responsive to technology shocks than to monetary policy shocks. In particular, the median price level response to a monetary policy shock is approximately zero for the first 6 quarters, and only afterwards starts converging slowly towards its new long-run level. It takes about 15 quarters before 90 percent of the posterior distribution of price level response to a one standard deviation monetary policy shock is different from zero. In contrast, the median price level starts adjusting immediately to a technology shock, accomplishing most of its long run-adjustment within 8 quarters from the shock. Moreover, 90 percent of the posterior distribution of price level response is always below zero. This evidence suggests that price adjustment is substantially faster to technology shocks than to monetary policy shocks.

Second, the shape and the dynamic of price impulse responses do not change much across different measures of aggregate price. For a given shock, either to technology or monetary policy, the median responses of the consumer price index, the GDP deflator, the personal consumption expenditure deflator and the producer price index are very similar both in terms of magnitude and in terms of dynamics. This evidence is consistent, for instance, with empirical microeconomic studies of price adjustment which show that sectoral level finished good producer prices and consumer prices share similar distributions of frequency of price adjustment.[14]

Third, the estimated impulse responses of the price level to monetary policy shocks display no price puzzle. With the exception of the consumer price index, the median response of the price level to a tightening in monetary policy is negative at all horizons. The median consumer price index response to a monetary policy shock displays a mild price puzzle, lasting only two quarters. However, the consumer price index response is statistically zero for those quarters. The ability of the model to eliminate the price puzzle relies on two main ingredients. The first one is the inclusion in Y_t of a relatively large number of variables. As shown by Banbura, Giannone and Reichlin

[14] See for instance Nakamura and Steinsson (2008).

(2007), increasing the number of variables in the BVAR model helps substantially in solving the price puzzle. The second ingredient is allowing the central bank to respond to contemporaneous changes in the S&P stock price index. This permits the model to better distinguish monetary policy shocks from systematic responses of the monetary policy instrument to changes in asset prices.[15]

Fourth, technology shocks are much more important than monetary policy shocks in explaining inflation forecast error variance. Table 1 contains the forecast error variance decomposition of the four different measures of aggregate price inflation.

[Table 1 about here]

Technology shocks account for a relatively large fraction of the forecast error decomposition of inflation, at all horizons of forecast, ranging from a minimum of 20 percent for the producer price index at 2 quarters forecasting horizon, to a maximum of 46.7 percent for the GDP deflator at 16 quarters forecasting horizon. In contrast, monetary policy shocks explain a negligible fraction of the forecast error variance of inflation at all horizons and for all measures of aggregate prices.

3 Price adjustment speed

The impulse responses in the previous section provided valuable information on price adjustment speed to technology and monetary policy shocks. This section investigates price adjustment speed more in detail. Let's define price adjustment speed to shock

[15]This is also the interpretation of the price puzzle originally given by Sims (1992): the monetary policy authority may have better information than what is assumed by the model.

As a check on the importance of including asset prices into the information set by the central bank, I have identified the monetary policy shock by adopting the standard *recursiveness* scheme of Christiano, Eichenbaum and Evans (1999), as done in Banbura, Giannone and Reichlin (2007). In this exercise, Y_t has a large number of variables, but the monetary authority set rates without responding to contemporaneous change in asset prices. Under this identification scheme, the price impulse response to the monetary policy shock displays a price puzzle similar in magnitude to the one in Banbura, Giannone and Reichlin (2007).

x as the time it takes for the price level to complete fifty percent of its long-run adjustment to that shock. This measure of price adjustment speed is given by

$$\tau_x \equiv \min_j \left\{ j \in [0, 1, 2, ...) \ : \left|\gamma_{j,x}\right| \geq \frac{1}{2} \left|\bar{\gamma}_x\right| \right\}, \tag{5}$$

where $\gamma_{j,x}$ is the impulse response of the price level to shock x evaluated j periods after the shock, and $\bar{\gamma}_x$ is the long-run response of the price level to shock x. In the computation of $\tau_{\alpha,x}$, $\bar{\gamma}_x$ and $\gamma_{j,x}$ are normalized so that $\bar{\gamma}_x$ is negative. The long-run response $\bar{\gamma}_x$ is defined as the price level response 5 years after the shock. According to standard new-keynesian and real business cycle theories, both a permanent technology shock and a monetary policy shock to the nominal interest rate are expected to have a permanent impact on the price level.[16] However, in order to assess robustness of results against different shapes of price level impulse responses, I have considered different horizons in computing long-run response $\bar{\gamma}_x$.[17] Results are indeed robust. It follows that the difference in the price adjustment speed between monetary policy and technology shocks is given by

$$\tau \equiv \tau_s - \tau_z,$$

where z and s denote the technology and the monetary policy shocks, respectively. [18] The larger is τ, the faster the price level adjusts to technology shocks than to monetary policy shocks.

Let's define also a second measure of price adjustment speed as the fraction of the long-run price adjustment accomplished by the price level j periods after the shock. This measure is given by

$$\psi_x \equiv \frac{\gamma_{j,x}}{\bar{\gamma}_x}, \tag{6}$$

[16] See for instance Smets and Wouters (2007).

[17] If price level impulse responses were hump-shaped we should find results to be sensitive to this choice.

[18] Qualitative results are robust to different choices of α.

where $\gamma_{j,x}$ and $\bar{\gamma}_x$ are defined as above. According to this measure, the closer is the price level to its new long-run adjustment level, j periods after the shock, the faster it has adjusted to that shock. The difference in price adjustment speed is given by

$$\psi \equiv \psi_z - \psi_s,$$

where j is set equal to 8 quarters.[19] The larger is ψ, the faster the price level adjusts to technology shocks than to monetary policy shocks.

3.1 Results from posterior draws

This subsection reports main statistics about τ and ψ computed for the posterior draws of section 2. To better characterize price adjustment to the two types of shocks, for each measure of aggregate price level, draws are divided in four subsets depending on the sign of the long-run price response to the two types of shocks. In particular, draws are divided according to whether the associated long-run price response is negative to both types of shocks, to one or to none of the two types of shocks. The characterization of τ and ψ on the basis of the price level long-run response to the two types of shocks is useful when associated to predictions from standard new-Keynesian and real business cycle theories. According to these theories, prices in the long-run are expected to be permanently lower after a tightening in monetary policy, while the sign of the long-run price response to a positive technology shock depends on the parameterization of the model. However, under standard parameterization and behavior of monetary policy, the price level is also expected to drop in the long-run following the increase in productivity.[20] Figure 4 displays scatter plots for the draws of τ and ψ associated to each of the four measures of aggregate price. For each measure of aggregate price level, draws are labeled according to the sign of the price level long-run response to the two types of shocks. The main results from this analysis

[19] Qualitative results are robust to different choices of j.

[20] See Dedola and Neri (2006) and Uhlig (2006) on this point.

are as follows.

[Figure 4 about here]

First, the vast majority of draws is in the upper-right corner of the scatter plots for all measures of aggregate prices. This means that the posterior probability that the price level adjusts faster to technology shocks than to monetary policy shocks is : i) relatively high; ii) a similar across all four measures of aggregate price level.

Second, the vast majority of draws, about 95 percent of the total, displays negative sign in the long-run price response to both technology and monetary policy shocks. This is true across all four price indices. These results are consistent with standard economic theory. About 1.5 percent of draws displays positive sign in the long-run price response to technology shocks, while approximately 3.5 percent of draws displays positive sign in the long-run price response to monetary policy shocks.

Third, among the 5 percent of total draws for which prices adjust faster to monetary policy shocks than to technology shocks, about half of the draws displays positive sign in the long-run price response to monetary policy shocks.

[Table 2 about here]

Table 2 reports main statistics about the posterior distribution of τ and ψ. These statistics are very similar across the different measures of aggregate price level. On average it takes about 5.5 quarters more for the price level to accomplish half of the long-run response to a monetary policy shock than to a technology shock. Similarly, eight quarters after the shock, the average difference in the fraction of the long-run response accomplished by the price level is between 0.38 and 0.44, depending on the measure of aggregate price level. According to τ, the posterior probability that the price level adjusts faster to technology shocks than to monetary policy shocks ranges from a minimum of 0.94, for the personal consumption expenditure deflator, to a maximum of 0.97 for the producer price index. Similarly, according to ψ, the posterior probability that 8 quarters after the shock the price level has accomplished a larger fraction of the long-run adjustment to a technology shock than to a monetary policy shock ranges from a minimum of 0.93 to a maximum of 0.96.

When conditioning on the 95 percent of total draws with negative signs in the long-run response to both shocks, results about the difference in price adjustment speed are stronger than the ones obtained from all draws. In such a case, the posterior probability that the price level adjusts faster to technology shocks than to monetary policy shocks is between 0.98 and 0.99 according to τ, and between 0.97 and 0.98 according to ψ.

3.2 Interpretation of results

The fact that price adjustment speed differs substantially across different types of aggregate shocks implies that the degree of price stickiness to aggregate shocks — defined as the speed of price adjustment — appears to be conditional on the source of shocks. Large differences in the degree of price stickiness suggest that the frequency of price changes is not decisive for price level impulse responses. In fact, in models of price setting with Calvo-style staggered contracts, profit-maximizing prices are typically given by a markup over nominal marginal costs. In these models the price level can be sticky in response to a shock as the result of a combination of: i) relatively low frequency of price adjustment; ii) relatively high strategic complementarities in price setting; iii) sticky factor prices.[21] Everything else being equal, low frequency of price adjustment implies high price rigidity to all shocks. Similarly, higher strategic complementarities in price setting increase price rigidity to all aggregate shocks. Therefore it is unlikely that, in absence of other frictions, a combination of frequency

[21] The standard new-keynesian aggregate supply relation implies

$$\pi_t = \beta E_t \pi_{t+1} + \kappa s_t,$$

where π_t is inflation, κ is a coefficient depending on the frequency of price adjustment and strategic complementarities in price setting, s_t are real marginal costs in deviations from the steady state. See Woodford (2003) chapter 3 for more details.

of price adjustment and complementarities can generate substantially different price adjustment speed to technology and monetary policy shocks. This result poses a new challenge to existing models of sticky prices. In fact, as shown by Nakamura and Steinsson (2008b), increasing strategic complementarities in price setting helps standard sticky price models generating high price rigidity to aggregate shocks and low price rigidity to sector-specific idiosyncratic shocks. However, higher strategic complementarities would not explain different degrees of price rigidity to different aggregate shocks.[22]

A possibility to reconcile existing models with the empirical evidence on price adjustment speed is through sticky factor prices, such as real or nominal sticky wages.[23] In fact, marginal costs depend on factor prices as well as on the state of technology. If factor prices are sticky, marginal cost dynamics are mainly determined by technological innovations. It follows that, in absence of substantial frictions in price setting, the price level is sticky to monetary policy shocks but responsive to aggregate technology shocks. However, as shown by Del Negro and Schorfheide (2008), in absence of substantial frictions in price setting standard DSGE models may have a hard time explaining the joint behavior of inflation, output and labor share of production costs. With low price rigidities, movements in the labor share are dominated by mark-up shocks, which tend to generate a counterfactual negative correlation between labor share and inflation.

Differently from time-dependent models of price setting, menu cost models allow for state-dependent pricing. To the best of my knowledge there is no paper studying price responsiveness to aggregate technology and monetary policy shocks in a model of sticky prices with menu costs. In these models firms adjust prices faster in response to those shocks that have a larger impact on profit-maximizing prices. For

[22] Interestingly, Burstein and Hellwig (2007) show that estimated degree of strategic complementarities in price setting is too low to explain, in absence of other frictions, differences in price rigidity between sector specific and aggregate shocks.

[23] Galí and Gertler (1999) also suggest that wage rigidity is potentially important to account for inflation dynamics.

instance, everything else being equal, if technology shocks are larger than monetary policy shocks, firms decide to pay the menu cost and adjust prices, on average, more frequently in response to technology shocks than to monetary policy shocks. However, when firms pay the menu cost they can adjust prices to all realized shocks. Economic intuition suggests that, similarly to Golosov and Lucas (2006), if firms adjust prices frequently to aggregate technology shocks, or to other types of shocks, they adjust prices frequently as well to contemporaneous realizations of monetary policy shocks. It follows that, in such a case, the frequencies with which different shocks realize may matter in explaining differences in price adjustment speed.

Similarly to time- and state-dependent models of price setting, incomplete information theories have been popular in accounting for the sluggish price adjustment in response to monetary policy shocks. Such a framework can deliver prices responding more to aggregate technology shocks than to monetary policy shocks, if firms are relatively better informed about aggregate technology shocks than they are about monetary policy shocks. In particular, as suggested by Paciello (2008), a model in which firms make pricing decision under incomplete information, and allocate attention across different sources of uncertainty along the lines of Maćkowiak and Wiederholt (2008), can generate prices to be more responsive to aggregate technology shocks than to monetary policy shocks if, for instance, technology shocks are more volatile than monetary policy shocks.[24]

Exploring further the ability of different models of price setting to capture the behavior of prices in response to different types of aggregate shocks is in the author's view an important avenue for future research.

[24] Empirical estimations based on U.S. TFP growth suggest that technology shocks are approximately 2 times more volatile than innovations to the Federal Funds rate. See Fernald (2007) for estimates of TFP growth.

4 Robustness analysis

This section investigates to what extent results from the benchmark BVAR model are robust to several features of the estimation procedure, such as identification assumptions and subsample stability. The insights from these exercises reinforce the results obtained in the previous sections.[25]

4.1 A Solow-residual based identification for technology

One of the identifying assumptions in the previous sections is that the technology shock is the only shock affecting labor productivity in the long-run. This restriction holds in a wide range of business cycle models. However, there exist models that do not satisfy it. For example, this assumption is not true in an endogenous growth model where all shocks affect productivity in the long-run, nor is it true in a model where there are permanent shocks to the tax rate on capital income. To address these issues, this subsection adopts a different identification assumption for technology shocks, relying on a Solow-residual measure of quarterly total factor productivity (FTFP) growth estimated by Fernald (2007). Fernald's quarterly measure explicitly accounts for variable capital utilization and labor hoarding.[26] The FTFP series is added to Y and the posterior distribution of (B, Υ) is estimated as in section 2. Differently from section 2, in this subsection the identifying assumption is that a technology shock is the only shock affecting FTFP in the long-run, while the long-run response of labor productivity is unrestricted. Relative to the identification assumptions of section 2, the advantage of this procedure is that, by explicitly assum-

[25]Robustness analyses has been conducted also with respect to the tightness prior hyperparameter, λ, and frequency of the data, namely monthly instead of quarterly. Results are similar to the ones obtained under the benchmark specification and therefore omitted. These results are available on the author's web-page.

[26]The growth rate of FTFP is given by:

$$\Delta \ln(FTFP) = \Delta \ln(GDP) - \alpha \left(\Delta \ln(K) + \Delta \ln(Z)\right) - (1-\alpha) \left(\Delta \ln(QH) + \Delta \ln(E)\right),$$

where Z is capital utilization, K is capital input, E is labor effort per (quality-adjusted) hour worked, Q is labor quality (i.e., a labor composition adjustment), and H is hours worked.

ing an aggregate production function, it directly estimates total factor productivity growth.[27] This procedure has been originally applied by Christiano, Eichenbaum and Vigfusson (2004), suggesting there could be high frequency cyclical measurement error in Solow-residual based measures of total factor productivity, that the long-run restriction might clean out.[28] As long as the assumption about the aggregate production function holds at low frequencies, the model provides unbiased estimates of technology shocks. The remaining assumptions required to jointly identify the monetary policy shock are unchanged from section 2.

[Figures 5 and 6 about here]

Figure 5 plots technology shocks between 1961:II and 2007:II, estimated according both to the benchmark identification scheme of section 2 and to the identification scheme of this subsection. The time series of estimated technology shocks are very similar across the two identification assumptions, and have a high correlation equal to 0.96. This suggests that the two identification schemes deliver similar results in terms of price adjustment speed to technology and monetary policy shocks.

Figure 6 plots the impulse responses of the different measures of price level to the two types of shocks. The shape and dynamic properties of responses are very similar to the ones obtained under the benchmark identification scheme. Prices start adjusting to a technology shock right after the shock, and complete most of the adjustment within two years from the shock, while the response of prices to a monetary policy shock is approximately zero for about one year and a half following the shock, and only afterwards prices start slowly adjusting towards the new long-run equilibrium.

[Table 3 about here]

[27] See Chari, Kehoe and McGrattan (2008) for a criticism on long-run restrictions to labor productivity.

[28] The technology shock estimated trough long-run restrictions on FTFP, as in this subsection, has a 0.97 correlation with the residual of the equation associated to FTFP in the VAR. Therefore in this case long-run restrictions do not affect the estimates of technology shocks much.

Statistics about τ and ψ computed under the identification assumptions of this subsection are reported in column (1) of Table 3. These statistics are, both quantitatively and qualitatively, very similar to the ones obtained under the benchmark identification scheme.

4.2 Identification through sign restrictions

Under the benchmark identification scheme, the price level is allowed to respond contemporaneously to realizations of technology shocks, while it is allowed to respond to monetary policy shocks only with a lag. More generally, monetary policy shocks are identified through short-run type restrictions, while technology shocks are identified trough long-run type restrictions. This section adopts an agnostic method to identify both technology and monetary policy shocks. Such a method relies on imposing sign restrictions to the impulse responses of Y_t to each of the two types of shocks. This method has been originally proposed by Faust (1998) and then applied by Uhlig (2006) to the identification of monetary policy shocks, and by Dedola and Neri (2007) to the identification of technology shocks. Intuitively, this identification scheme treats price responses to the two types of shocks *symmetrically* from an identification standpoint. For instance, it allows prices to respond immediately to both types of shocks. Its main disadvantage is that it imposes relatively weak restrictions on the response of the economy to the two types of shocks and, as a consequence, impulse responses may be less tightly estimated than under the benchmark identification scheme. From a Bayesian point of view, sign restrictions amount to attributing probability zero to reduced-form parameters giving rise to impulse responses which contravene the restrictions. To the extent that these restrictions do not lead to over-identification, they impose no constraint on the reduced form of the VAR. Standard Bayesian methods can thus be used for estimation and inference. Apart from the different identification assumptions, the rest of the estimation procedure is as in the benchmark specification of the model.

Sign restrictions on the impulse responses to monetary policy shocks are similar to the ones adopted by Uhlig (2006), while sign restrictions on the impulse responses to technology shocks are similar to the ones adopted by Dedola and Neri (2006).[29] In general, these restrictions require prices, monetary aggregates and quantities to move in the opposite direction of the federal funds rate for at least two quarters in the case of a monetary policy shock, and require quantities and labor-productivity to move in the opposite direction of prices for a relatively large number of quarters in the case of a permanent technology shock. Sign restrictions are reported in more details in Table 4.[30]

[Table 4 about here]

Intuitively, this method distinguishes the two types of shocks on the basis of the facts that: i) permanent technology shocks have a more persistent impact on quantities than monetary policy shocks; ii) quantities and prices move in opposite directions following a technology shock, but move in the same direction following a monetary policy shock; iii) monetary policy shocks are associated to changes in monetary aggregates and interest rates. Finally, this subsection adopts the algorithm proposed by Ramirez, Waggoner and Zha (2007) to compute the posterior distribution of impulse responses.[31]

[Figure 7 about here]

Figure 7 plots the impulse responses of the four measures of aggregate price level to one standard deviation technology and monetary policy shocks. Although the identification scheme is very different from the one adopted under the benchmark specification, impulse responses to the two types of shocks are very similar to the ones reported in section 2. The price level response is faster to technology shocks

[29] I refer to these authors for a discussion of the ability of these restrictions to distinguish technology from monetary policy shocks as well as from other shocks.

[30] Results are robust to different specifications of sign restrictions, and in particular to different assumptions about the number of periods they are expected to hold for.

[31] For more details see Ramirez, Waggoner and Zha (2007) pp. 38-40.

than to monetary policy shocks. As a consequence, statistics about τ and ψ reported in column (2) of Table 3 confirm the findings of the benchmark specification. The posterior probability that the price level adjusts faster to technology shocks than to monetary policy shocks ranges from a minimum of 0.78 to a maximum of 0.89, depending on the measure of price level and price adjustment speed adopted. The average τ is about 4 quarters, while the average ψ is between 27 and 31 percentage points. Standard deviations of τ and ψ are larger than under the benchmark specification. The larger standard deviations and the slightly smaller median estimates of τ and ψ reflect the weaker identification assumptions.

An advantage of sign restrictions is that they do not require system (2) to be stationary. This property allows assessing robustness of results above against the specification of model (2) in levels. Prior beliefs are adjusted accordingly.[32] Results about price adjustment speed to the two types of shocks are very similar to the ones obtained under the benchmark specification and are therefore omitted.

4.3 Subsample stability

This subsection briefly discusses subsample stability of results. Galí, López-Salido and Vallés (2003) have found that the effects of technology shocks estimated with long-run restrictions differ drastically between the two periods before and after Volcker's tenure at the helm of the Federal Reserve System. Precisely, a positive technology shock causes inflation to be much more persistent in the subsample up to the early 1980's than afterwards. Boivin and Giannoni (2006) find that the impact of monetary policy shocks on the U.S. economy is less effective in the pre-1980 period than in the post-1980 one. The smaller impact of monetary policy shocks is particularly pronounced on inflation which displays a statistically zero response in the post-1980 period. A similar break in the sample is also suggested by Stock and Watson (2002)

[32] All variables that under the benchmark specification entered Y_t in log-differences are instead entered in logarithms, and are given a random walk prior, $\delta_i = 1$, instead of a white-noise prior.

who identify the beginning of the Great Moderation in the period between 1982:IV and 1985:III. As a consequence, this subsection studies price adjustment speed in two sub-sample starting and ending around the mid-80's.

[Figures 8 and 9 about here]

Figure 8 reports price level impulse responses estimated in the pre-83 period, while Figure 9 reports impulse responses estimated in the post-83 period.[33] Price level response to technology shocks is faster in the post-83 period than in the pre-83 period. This evidence is consistent with Galí, López-Salido and Vallés (2003). With 90 percent probability confidence, price level response to monetary policy shocks is not statistically different from zero in the post-83 period, while it is statistically different from zero in the pre-83 period, although only after several quarters. This evidence is consistent with Boivin and Giannoni's (2006) findings.

Columns (3) and (4) in Table 3 report the main statistics about τ and ψ computed in the two sub-samples.[34] These results show that price adjustment speed to technology shocks is larger than to monetary policy shocks in both subsamples. In the post-83 period, the average difference in price adjustment speed has slightly decreased for the consumer price index, the GDP and the personal consumption expenditure deflators, while it has increased for the producer price index. However, due to samples of smaller size, the standard deviations of τ and ψ are larger than under full sample specification. It follows that the differences in τ and ψ across the two subsamples are not statistically significant. Moreover, the posterior probability of $\tau > 0$ rises in the post-83 period, while the posterior probability of $\psi > 0$ drops in the post-83 period. Therefore, although price responsiveness to both technology and monetary policy shocks has changed over the two sub-samples, there is no strong evidence of a

[33] This choice coincides with the second appointment of Volcker at the helm of the Federal Reserve.

[34] Due to the smaller sample size, the procedure adopted in section 2 to compute prior tightness imply $\lambda = 0.1$ in both subsamples.

change in τ and ψ.

5 Concluding remarks

This paper answers the question of whether, by how much and how likely it is that the U.S. aggregate price level adjusts faster to aggregate technology shocks than to monetary policy shocks. Under the benchmark specification of the model, it takes on average about 5.5 quarters less for the price level response to accomplish half of its long-run adjustment to a technology shock than to a monetary policy shock. Two years after a technology shock, the median price level response has accomplished approximately two-thirds of its long-run adjustment, while two years after a monetary policy shock the median price level response has accomplished only about one-fifth of its long-run adjustment. According to the measures of price adjustment speed in the paper, the posterior probability that the price level adjusts faster to technology shocks than to monetary policy shocks is about 95 percent. The estimates of price adjustment speed to a given shock are similar across different indices of aggregate price level. These results are robust to different identification assumptions.

These facts challenge existing models of price stickiness. Sticky price models have a hard time matching different price level responsiveness to aggregate technology and monetary policy shocks. Two main line of research seem promising exploring. One line of research points toward wage rigidity as main source of price rigidity. The other line of research is related to recent development on price setting under incomplete information and rational inattention. Exploring further the ability of these models to explain the estimated differences in price adjustment speed is left for future research.

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Appendices

A Data

Mnemon	Series	Component of Y=(X,S,Z,F)	Lev	Log	d-Log
GDPQ/LBMNU	Labor productivity	X			v
LBMNU	Index total hours worked	X			v
FYFF	INTEREST RATE: FEDERAL FUNDS	S	v		
PGDP	GDP price deflator	X			v
FSPCOM	Standard and Poor's stock price index	F			v
CES002	Number of employees on non-farm payrolls	X			v
A0M051	Personal income (AR, BIL. CHAIN 2000 $)	X			v
JQCR	Real Personal Consumption Expenditures	X			v
IFNRER	Real non-residential investments	X			v
JQIFRESR	Real residential investments	X			v
IPS10	Industrial production	X			v
UTL11	Capacity utilization	X	v		
LHUR	Unemployment rate	X	v		
HSFR	Housing starts (NONFARM)	X		v	
PCOM	Index of sensitive material prices	X			v
PWFSA	Producer price index	X			v
PCPEPI	Personal consumption expenditures price deflator	X			v
PUNEW	Consumer price index	X			v
CES275	Average hourly earnings	X			v
FM1	M1 monetary stock	Z			v
FM2	M2 monetary stock	Z			v
FMRRA	Non-borrowed reserves	Z			v
FMRNBA	Total reserves	Z			v
FTFP	Fernald's (2007) TFP estimate	X			v

The source of most of the data is the DRI Basic Economics Database, available on-line at Northwestern University. Output, GDP deflator, residential and non-residential investments were obtained from the BEA website. Most data is available at a monthly frequency. Output, GDP deflator, residential and non-residential investments are not. When I estimate the model at the monthly frequency, I use Sims and Zha (2007) interpolated monthly series for these four time series. LBMNU is also not available at the monthly frequency. In the monthly frequency analysis, the latter is replaced by the BLS index for average weekly hours worked.

B Minnesota prior

Let's rewrite model (2) as a system of multivariate regressions:

$$\underset{T\times n}{Y} = \underset{T\times k}{X}\,\underset{k\times n}{B} + \underset{T\times n}{U},$$

where $Y = (y_1, ...y_T)'$, $X = (X_1, ..., X_T)'$ and with $X_t = \left(Y'_{t-1}, ..., Y'_{t-p}, 1\right)$, $U = (u_1, ..., u_T)'$, $B = (B_1, ..., B_p, c)'$, and $k = np + 1$. The prior beliefs are such that B and Ψ have a Normal inverted Wishart distribution, according to which

$$\Psi \backsim iW\left(S_0, \alpha_0\right) \quad \text{and} \quad B|\Psi \backsim N\left(B_0, \Psi \otimes \Omega_0\right).$$

The prior parameters S_0, α_0, B_0 and Ω_0 are chosen so that the coefficients in B_1, B_2,.., B_p, denoted by $(B_s)_{ij}$, $s = 1, ..p$, $i = 1, 2.., n$, $j = 1, 2, ..n$, have prior expectations and variances given by

$$\begin{aligned} E\left((B_s)_{ij}\right) &= \begin{cases} \delta_i, & if \quad i = j, s = 1 \\ 0, & otherwise \end{cases}, \\ V\left((B_s)_{ij}\right) &= \frac{\lambda^2}{s^2}\frac{\sigma_i^2}{\sigma_j^2}, \end{aligned}$$

and the matrix Ψ has prior expectation $E(\Psi) = diag\left(\sigma_1^2, ..., \sigma_n^2\right)$. For details see

Kadiyala and Karlsson (1997). The scale parameters σ_i^2 are set equal to the variance of the residual from a univariate autoregressive model of order p for the variable y_i.

The prior is implemented by adding T_0 dummy observations, Y_0 and X_0, to Y and X respectively. It can be shown that this is equivalent to imposing a normal inverted-Wishart prior with $B_0 = (X_0'X_0)^{-1} X_0'Y_0$, $\Omega_0 = (X_0'X_0)^{-1}$, $S_0 = (Y_0 - X_0B_0)'(Y_0 - X_0B_0)$ and $\alpha_0 = T_0 - k - n - 1$. It follows that the dummy-augmented VAR model is:

$$\underset{T_* \times n}{Y_*} = \underset{T_* \times k}{X_*} \underset{k \times n}{B} + \underset{T_* \times n}{U_*},$$

where $T_* = T + T_0$, $X_* = (X', X_0')$, $Y_* = (Y', Y_0')'$ and $U_* = (U', U_0')'$. To insure the existence of the prior expectation of Ψ it is necessary to add an improper prior $\Psi\tilde{}\ |\Psi|^{-(n+3)/2}$. The posterior distribution of (B, Ψ) is a Normal inverted-Wishart:

$$\Psi|Y \backsim iW(S_*, \alpha_*) \quad \text{and} \quad B|\Psi, Y \backsim N(B_*, \Psi \otimes \Omega_*),$$

where $B_* = (X_*'X_*)^{-1} X_*'Y_*$, $\Omega_* = (X_*'X_*)^{-1}$, $S_* = (Y_* - X_*B_*)'(Y_* - X_*B_*)$ and $\alpha_* = T_* - k + 2$. See Banbura, Giannone and Reichlin (2007) for more details.

C Parameterization of λ

Consider a n_1-dimensional subset of Y. Define the in-sample mean squared forecast error (MSFE) of the 1-step-ahead mean squared forecast as:

$$MSFE_i^{(\lambda,m)} = \frac{1}{T-p-1} \sum_{t=p+1}^{T} \left(\hat{y}_{i,t}^{(\lambda,m)} - y_{i,t} \right)^2,$$

where $i = 1, ..., n_1$ indices the variable the MSFE is computed for, T is the length of the sample, $\hat{y}_{i,t}^{(\lambda,m)}$ is the one-step-ahead forecast computed in model m with prior parameterization equal to λ. This analysis studies three types of models, depending on the number of variables included in the analysis and the value of λ. The first model, $m = 1$, includes n_1 variables and is estimated with a flat prior, $\lambda = \infty$. The

n_1 variables considered are: labor-productivity, hours worked, GDP price deflator, Federal Funds rate, M2 money stock, commodity price index, capacity utilization and average hourly earnings of production workers. This set of variables is similar to the one adopted by other authors in the study of the response of the U.S. economy to monetary policy and aggregate technology shocks[35]. The second model, $m = 2$, is the benchmark model. It includes all the n macroeconomic indicators and is estimated with the Minnesota prior described in the main text and depending on λ. The third model, $m = 3$, includes all the n variables and is estimated imposing the prior exactly, $\lambda = 0$. Following Banbura, Reichlin and Giannone (2007), I choose λ in model $m = 2$ so to minimize the difference in fit from model $m = 1$:

$$\lambda^* = \arg\min_{\lambda} \left| F - \frac{1}{n_1} \sum_{i=1}^{n_1} \frac{MSFE_i^{(\lambda,1)}}{MSFE_i^{(0,3)}} \right|,$$

where $F = \frac{1}{n_1} \sum_{i=1}^{n_1} \frac{MSFE_i^{(\infty,1)}}{MSFE_i^{(0,3)}} = 0.35$ is the measure of relative fit associated to the reference model. From this procedure λ^* is equal to 0.065.

C.1 Alternative measures of λ

Section 4 considers different values of λ. These values are chosen so to increase or reduce the fit under the benchmark specification, $\frac{1}{n_1} \sum_{i=1}^{n_1} \frac{MSFE_i^{(\lambda,1)}}{MSFE_i^{(0,3)}}$, by 0.05. At $\lambda = 0.04$ is associated a measure of fit approximately equal to 0.4. At $\lambda = 0.12$ is associated a measure of fit approximately equal to 0.3.

D Identification

Let's order the variables in the model as $Y_t = (X_t, S_t, Z_t, F_t)'$, where the first element of X_t and Y_t is log-labor productivity. Variables are entered in the VAR according to Appendix A. Following Ramirez, Waggoner and Zha (2007) let's express

[35] See for instance Christiano, Eichenbaum and Evans (1999) and Altig, Christiano, Eichenbaum and Linde (2005).

the set of linear restrictions onto the structural parameters of A_0 as

$$H(A_0) = \begin{bmatrix} A_0^{-1} \\ (I - B(1))^{-1} A_0^{-1} \end{bmatrix} \equiv D$$

where $B(1) = B_1 + ... + B_p$ and $B_1, ..., B_p$ are the estimates of the reduced form autoregressive matrices. D is a $2n \times n$ matrix of restrictions imposed on the impact and long-run responses to structural shocks. Let's define n_x and n_z as the number of variables in X and Z respectively. Let's order the technology and monetary policy shock as the n^{th} and $n_z^{th} + 1$ element of the vector of structural shocks e_t respectively. The identifying restrictions are zero restrictions on the matrix D given by

$$D^* = \begin{bmatrix} 0 & 0 & T_x & x \\ 0 & x & x & x \\ T_z & x & x & x \\ x & x & x & x \\ 0 & 0 & 0 & x \\ x & x & x & x \\ x & x & x & x \\ x & x & x & x \end{bmatrix}, \tag{7}$$

where T_z and T_x are $n_z \times n_z$ and $n_x \times n_x$ matrices respectively, and have the form of upper triangular matrices with an inverted order of columns:

$$T_i = \begin{bmatrix} 0 & \cdots & 0 & x_{1,n_i} \\ 0 & \cdots & x_{2,n_i-1} & x_{2,n_i} \\ 0 & / & \vdots & \vdots \\ x_{n_i,1} & \cdots & x_{n_i,n_i-1} & x_{n_i,n_i} \end{bmatrix},$$

where $i = z, x$. The zero restrictions on D^* satisfy both the necessary and sufficient (rank) conditions for exact identification derived by Ramirez, Waggoner and Zha (2007). In order to recover A_0 from the system of linear equations, $H(A_0) = D^*$ and $A_0^{-1}A_0^{-1\prime} = \Upsilon$, I recur to an algorithm proposed by Ramirez, Waggoner and Zha (2007). Let $\Sigma = SD^{\frac{1}{2}}$ be the $n \times n$ lower diagonal Cholesky matrix of the covariance of the residuals of the reduced form VAR, that is $SDS\prime = E[u_t u_t'] = \Upsilon$ and $D = diag(\Upsilon)$. Let's compute $H(\Sigma)$ and define matrices P_1 and P_2 as:

$$P_1 \equiv \begin{bmatrix} 0_{1\times n} & 1 & 0_{1\times n-1} \\ I_{n\times n} & 0_{n\times 1} & 0_{n\times n-1} \\ 0_{n\times n} & 0_{n\times 1} & I_{n-1\times n-1} \end{bmatrix}, \tag{8}$$

$$P_2 \equiv [i_n,\ i_{n-1}, ..., \ i_1], \tag{9}$$

where $I_{s\times s}$ is the s-dimensional identity matrix and i_s is an n-dimensional column vector of zeros with the sth element equal to 1.

Proposition 1 *For given estimates of B and Υ, let Σ be the Cholesky factor associated to Υ, and let $H(\cdot)$, P_1 and P_2 be defined as in $(8)-(9)$. Let P_3 be the Q factor associated with the QR decomposition of the matrix $P_1 H(\Sigma)$ and define $P = P_3 P_2'$. Let also A_0 satisfy the restriction $H(A_0) = D^*$ where D^* is defined as in (7). It follows that $A_0 = \Sigma^{-1}P$.*

For a proof see Ramirez, Waggoner and Zha (2007). These restrictions satisfy both the necessary and the rank conditions for exact identification. The structural shocks e_t are obtained from $e_t = A_0^{-1}u_t$. Finally, the order of the variables in X and Z can be arbitrarily changed without any effect on the identifications of the columns for technology and monetary policy shocks. To see these, consider the matrix A_0.

These assumptions impose the following zero restrictions on the matrix A_0,

$$A_0 = \begin{bmatrix} \underset{(n_x \times n_x)}{a_{11}} & \underset{n_x \times 1}{0} & \underset{(n_x \times n_z)}{0} & \underset{n_x \times 1}{a_{14}} \\ \underset{(1 \times n_x)}{a_{21}} & \underset{(1 \times 1)}{a_{22}} & \underset{(1 \times n_z)}{0} & \underset{(1 \times 1)}{a_{24}} \\ \underset{(n_z \times n_x)}{a_{31}} & \underset{(n_z \times 1)}{a_{32}} & \underset{(n_z \times n_z)}{a_{33}} & \underset{(n_z \times 1)}{a_{34}} \\ \underset{(1 \times n_x)}{a_{41}} & \underset{(1 \times 1)}{a_{42}} & \underset{(1 \times n_z)}{a_{43}} & \underset{(1 \times 1)}{a_{44}} \end{bmatrix}.$$

Then consider the $n \times n$ orthonormal matrix

$$W = \begin{bmatrix} W_{11} & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & W_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

where W_{11} and W_{33} are $n_x \times n_x$ and $n_z \times n_z$ orthonormal matrices respectively. If A_0 satisfies $H(A_0) = D^*$, any matrix $\tilde{A}_0 = W A_0$ also satisfies $H\left(\tilde{A}_0\right) = D^*$.

	Inflation Forecast Variance Decomposition					
	H=2		H=6		H=16	
	TECH	MP	TECH	MP	TECH	MP
PUNEW						
	25.7	0.3	33.9	0.7	34.4	2.3
	(1.6)	(0.5)	(3.0)	(0.7)	(4.3)	(1.6)
PWSFA						
	20.0	0.3	25.1	0.8	25.1	2.4
	(1.2)	(0.5)	(2.3)	(0.7)	(3.0)	(1.5)
PCEPI						
	36.2	0.2	42.4	0.6	41.9	2.1
	(1.8)	(0.4)	(3.5)	(0.7)	(5.1)	(1.7)
PGDP						
	39.7	0.2	46.7	0.6	44.8	2.5
	(2.1)	(0.4)	(4.0)	(0.8)	(5.9)	(1.9)

Table 1: Average forecast-error variance decomposition, % of total. Standard deviations in parenthesis. H: horizon of forecast. PUNEW: CPI level; PWSFA: PPI level; PCEPI: PCE deflator; PGDP: GDP deflator.

	τ			ψ		
	Subset N	Subset P	All draws	Subset N	Subset P	All draws
PUNEW						
Average	5.93	-1.01	5.61	0.47	-0.08	0.44
Median	6.00	-2.00	6.00	0.48	-0.19	0.48
Std	2.34	6.04	3.01	0.18	0.46	0.23
Pr(s>0 | Y)	0.99	0.37	0.96	0.98	0.34	0.95
PWSFA						
Average	5.67	-0.49	5.49	0.44	0.00	0.42
Median	6.00	-1.50	6.00	0.45	0.00	0.45
Std	2.23	7.01	2.50	0.18	0.40	0.21
Pr(s>0| Y)	0.98	0.47	0.97	0.98	0.45	0.96
PCEPI						
Average	5.50	-1.14	5.12	0.40	-0.13	0.37
Median	6.00	-2.00	5.00	0.41	-0.24	0.40
Std	2.47	5.80	3.10	0.18	0.42	0.24
Pr(s>0 | Y)	0.98	0.35	0.94	0.97	0.31	0.93
PGDP						
Average	5.67	-1.41	5.32	0.41	-0.13	0.38
Median	6.00	-3.00	6.00	0.41	-0.20	0.40
Std	2.35	5.41	2.8	0.17	0.40	0.22
Pr(s>0 | Y)	0.98	0.34	0.95	0.98	0.30	0.95

Table 2: Benchmark BVAR. Statistics about τ and φ. N: subset-of draws with negative long-run response to both Tech and MP shocks; P: subset-of draws with positive long-run response to at least one of the two shocks; Fraction of draws in N is 94%. Pr(s>0| Y) = Pr(τ>0 | Y) for columns 2-4 and Pr(s>0| Y)= Pr(ψ>0 | Y) for columns 5-7.

	(1)		(2)		(3)		(4)	
	τ	ψ	τ	ψ	τ	ψ	τ	ψ
PUNEW								
Average	5.38	0.45	3.92	0.27	4.29	0.36	1.71	0.11
Std	3.23	0.26	5.24	0.37	4.81	0.37	4.42	0.34
Pr(s>0 | Y)	0.95	0.94	0.81	0.78	0.84	0.83	0.79	0.36
PWSFA								
Average	5.22	0.44	3.92	0.27	3.59	0.31	6.65	0.46
Std	3.11	0.25	5.24	0.37	3.99	0.32	5.50	0.43
Pr(s>0 | Y)	0.95	0.94	0.81	0.78	0.88	0.85	0.90	0.81
PCEPI								
Average	5.01	0.39	4.11	0.27	4.22	0.35	3.94	0.20
Std	3.30	0.26	4.65	0.33	4.40	0.33	4.13	0.30
Pr(s>0 | Y)	0.94	0.93	0.85	0.81	0.86	0.84	0.91	0.78
PGDP								
Average	5.22	0.41	4.20	0.31	4.62	0.36	3.25	0.21
Std	3.20	0.25	3.92	0.27	4.56	0.33	4.17	0.30
Pr(s>0 | Y)	0.95	0.95	0.89	0.88	0.86	0.86	0.92	0.79

Table 3 : Robustness analysis. (1): FTFP identification of sect. 4.1; (2): Sign-restrictions identification of sect. 4.2; (3): Sub-sample 1960:I-1983:IV of sect. 4.3; (4): Sub-sample 1984:I-2007:II of sect. 4.4. Pr(s>0| Y) = Pr(τ>0 | Y) or Pr(ψ>0 | Y) depending on the column.

	MP		TECH	
	# of Quarters	Sign-Restriction	# of Quarters	Sign-Restriction
PGDP	2	≤ 0	20	≤ 0
M2	2	≤ 0	-	-
FYFF	2	≥ 0	-	-
IFNRER	2	≤ 0	10	≥ 0
JQCR	2	≤ 0	5	≥ 0
GDPQ/ LBMNU	-	-	20	≥ 0
LBMNU	2	≤ 0	-	-
GDPQ	2	≤ 0	10	≥ 0
CES275/PGDP	-	-	20	≥ 0

Table 4: Sign- Restrictions. The second and fourth columns contain the least number of quarters it is assumed to hold for. The third and fifth columns contain the sign restrictions. Remaining variables are unrestricted.

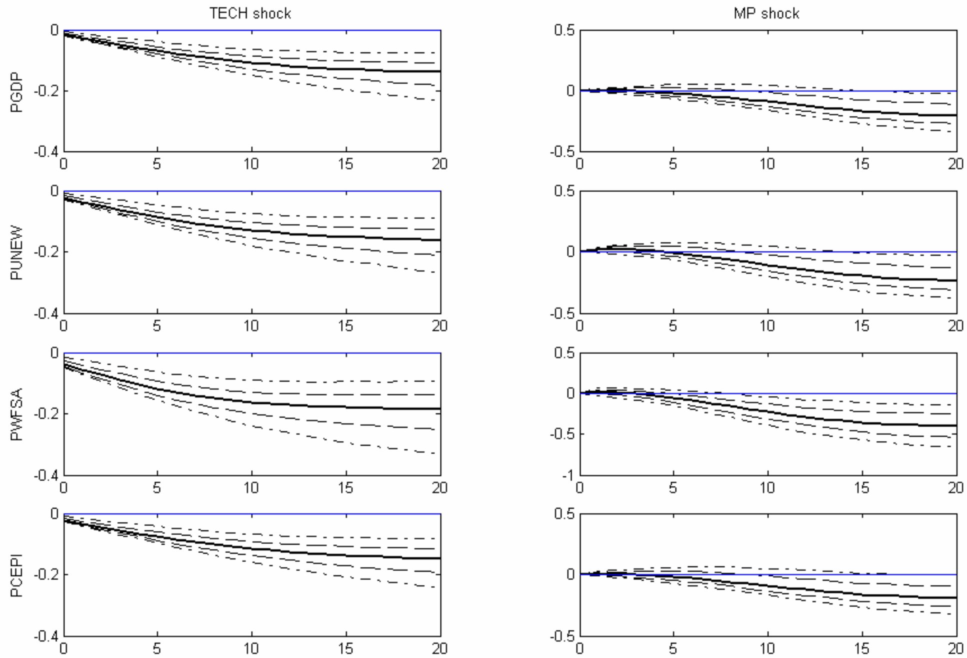

Figure 1 : Benchmark BVAR. Median, 68th and 90th percentiles impulse responses to one standard deviation shock. Horizontal Axis: quarters; Vertical Axis: percentage points. GDPQ: real GDP. FFR: annual FedFunds rate, PGDP: GDP deflator; PWFSA: producer price index; PCEPI: consumption expenditure deflator; PUNEW: CPI. Units are in basis points.

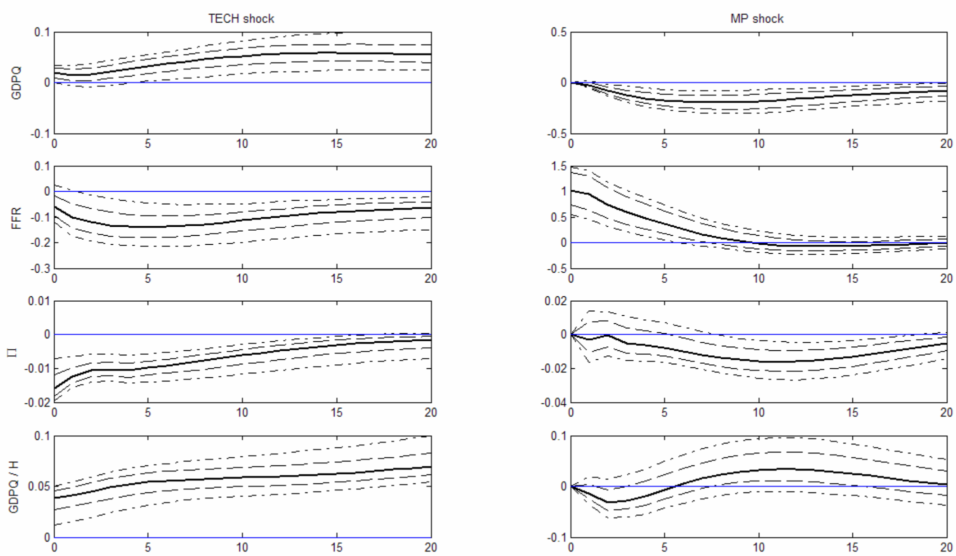

Figure 2 : Benchmark BVAR, Median, 68th and 90th percentiles impulse responses to one standard deviation shock. GDPQ: real GDP. FFR: annual FedFunds rate, Π: GDP deflator quarterly inflation, GDPQ/H: labor productivity.

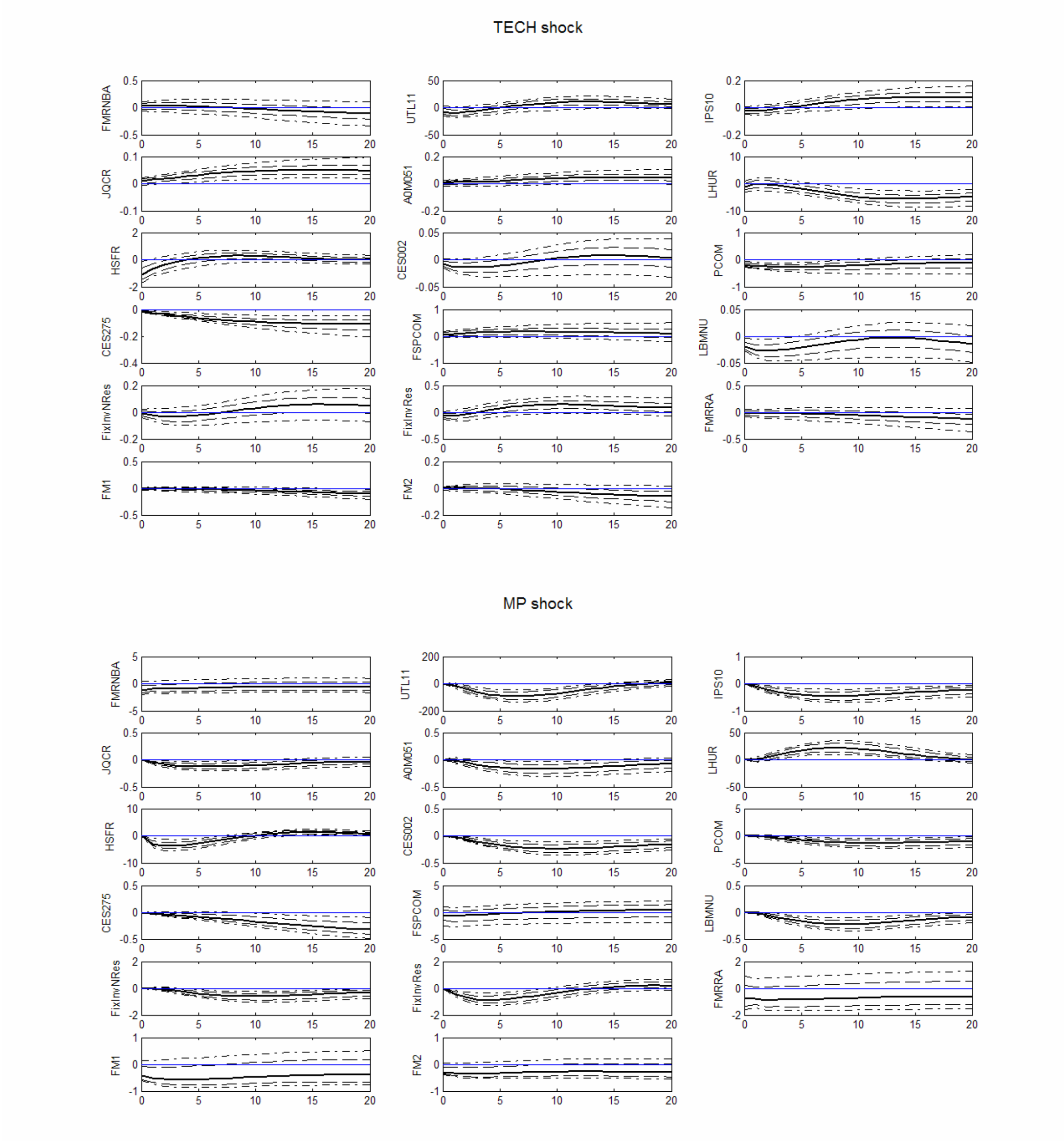

Figure 3 : Benchmark BVAR. Impulse response impulse responses to one standard deviation shock.

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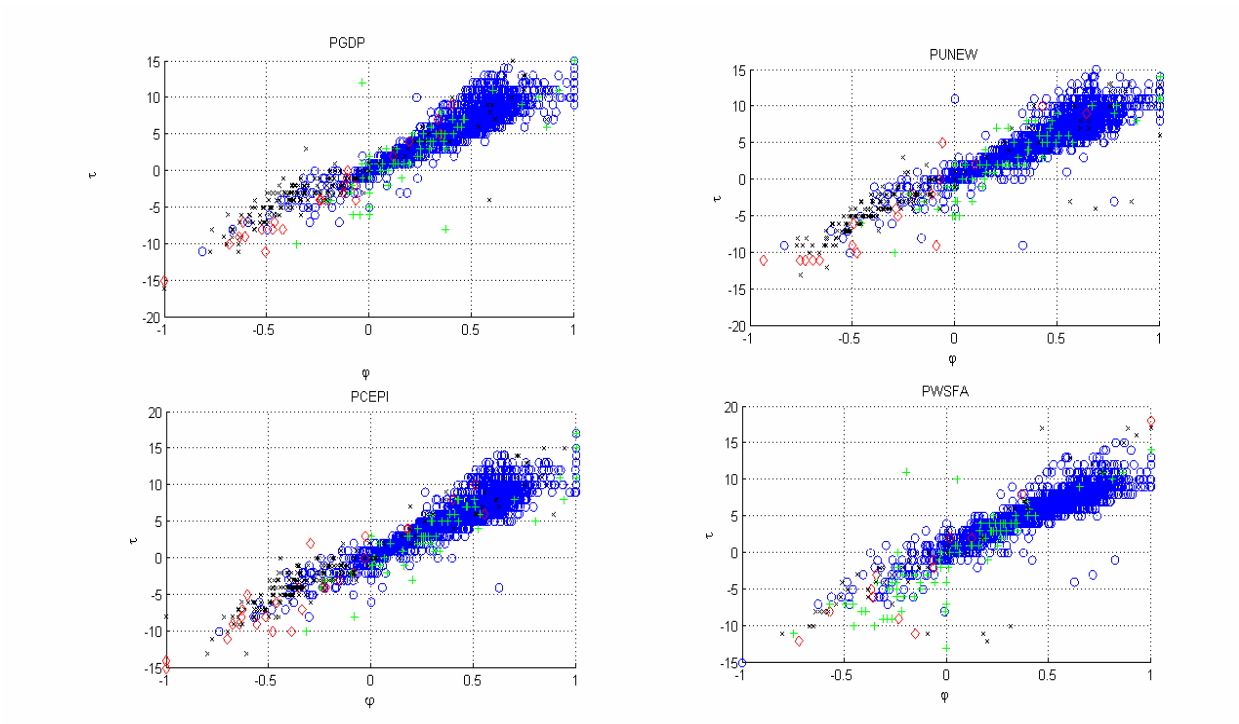

Figure 4 : Benchmark BVAR, difference in the speed of price adjustment. o: long-run price responses are negative to both shocks; ◊: long-run price responses are positive to both; x: long-run price response is positive to MP and negative to TECH; +: long-run price response is negative to MP and positive to TECH.

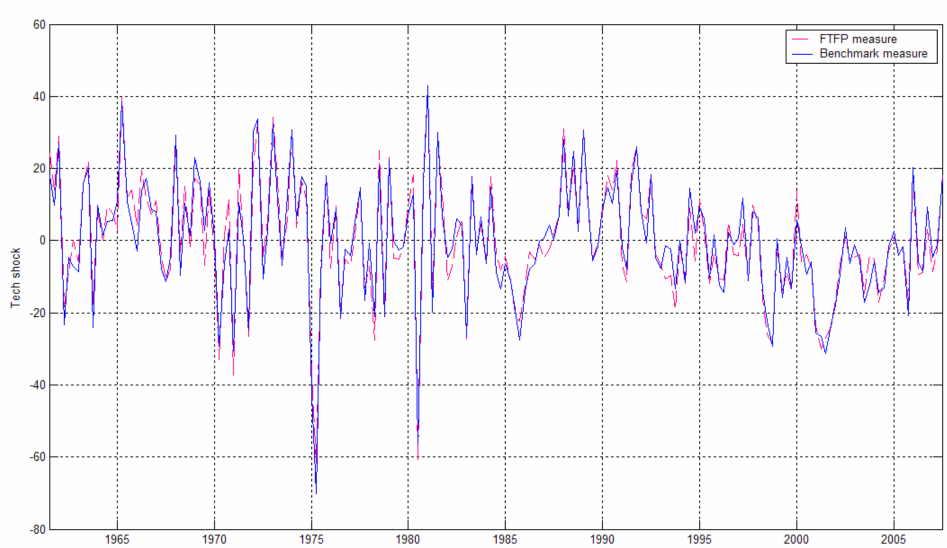

Figure 5 : Estimates of technology shocks. The solid-blue line is the benchmark identification scheme, the dashed-red line is the estimate obtained by imposing long-run restrictions on the FTFP series in the BVAR model.

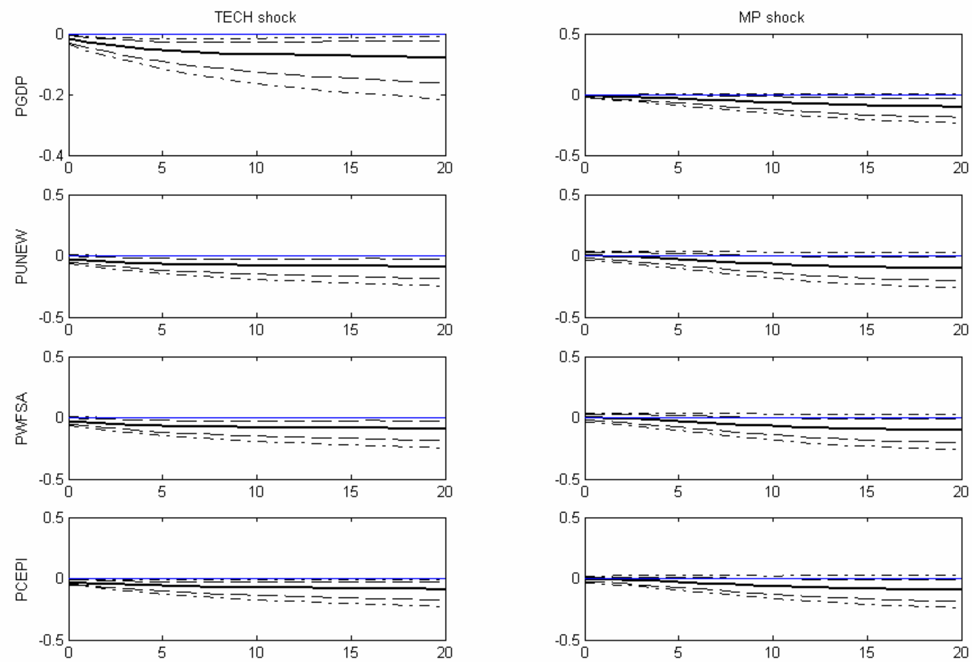

Figure 6 : FTFP identification. Median, 68th and 90th percentiles impulse responses to one standard deviation shock.

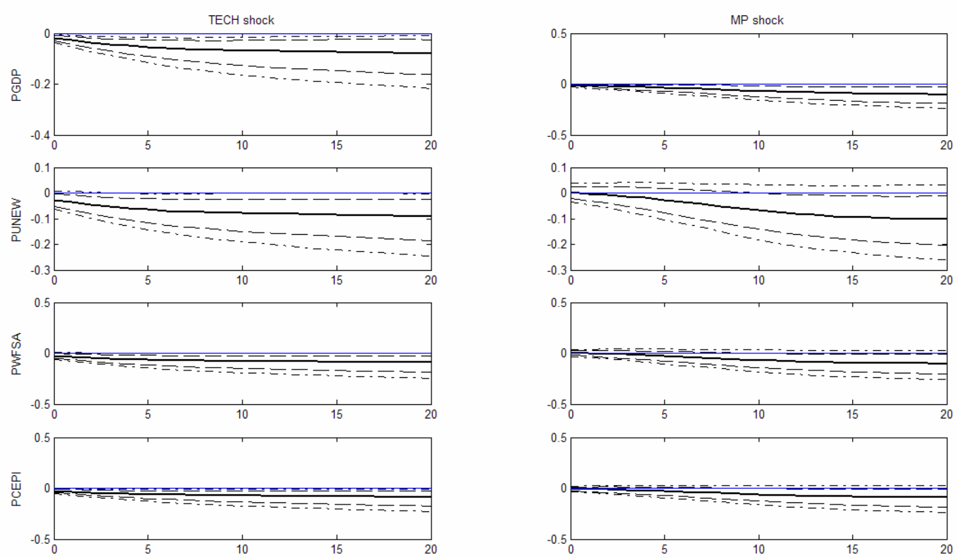

Figure 7 : Sign-restrictions identification. Median, 68th and 90th percentiles impulse responses to one standard deviation shock.

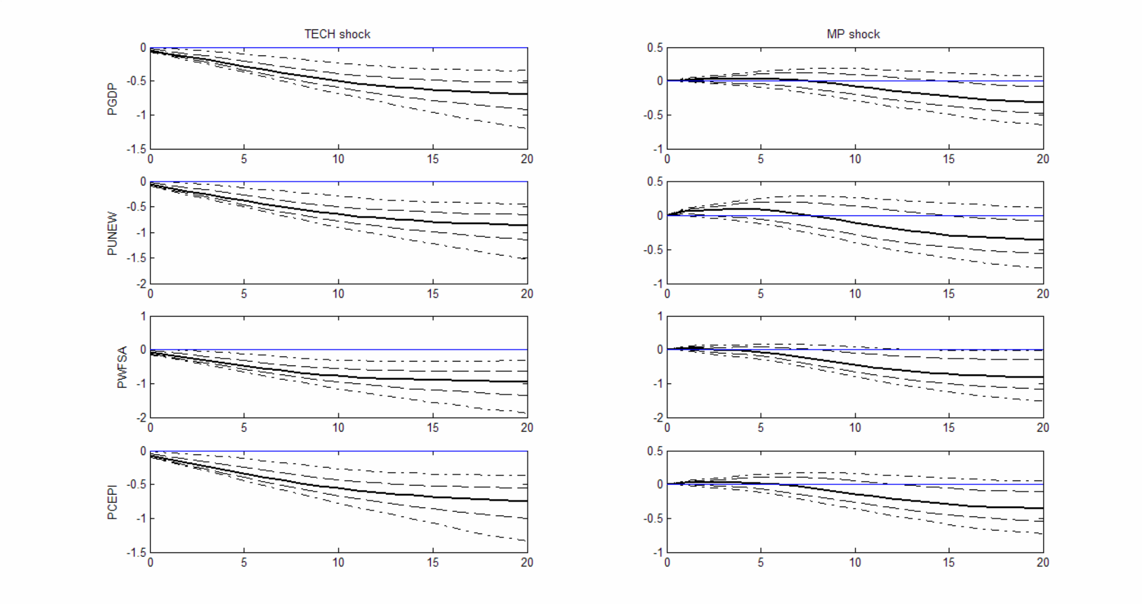

Figure 8 : Sub-sample 1960:I-1982:III. Median, 68th and 90th percentiles impulse responses to one standard deviation shock.

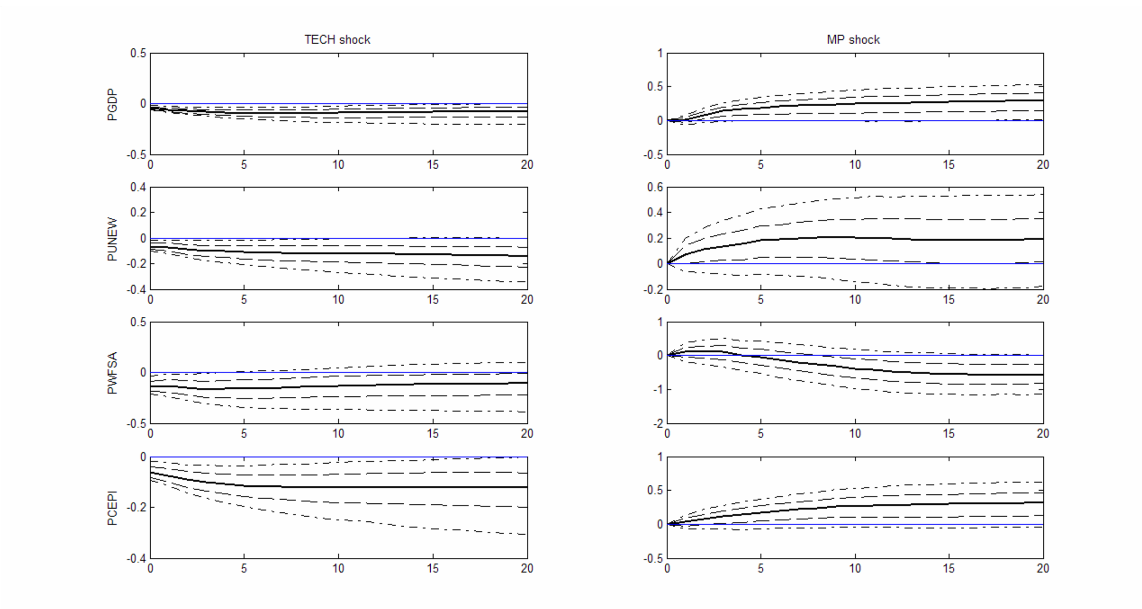

Figure 9 : Sub-sample 1982:IV-2007:II. Median, 68th and 90th percentiles impulse responses to one standard deviation shock.