Does Inflation Adjust Faster to Aggregate Technology Shocks than to Monetary Policy Shocks?[*]

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Abstract

This paper studies U.S. inflation adjustment speed to aggregate technology shocks and to monetary policy shocks in a medium size Bayesian VAR model. According to the model estimated on the 1959-2007 sample, inflation adjusts much faster to aggregate technology shocks than to monetary policy shocks. These results are robust to different identification assumptions and measures of aggregate prices. However, by separately estimating the model over the pre- and post-1980 periods, this paper further shows that inflation adjusts much faster to technology shocks than to monetary policy shocks in the post-1980 period, but not in the pre-1980 period.

JEL Codes: E31, E4, C11, C3

Keywords: Bayesian VAR, inflation, monetary policy

1   Introduction

This paper investigates whether U.S. inflation adjusts faster to aggregate technology shocks than to monetary policy shocks. Technology and monetary policy shocks are particularly important as these shocks account together for a large fraction of business cycle fluctuations.[1] Assessing the speed of inflation adjustment to different types of shocks is an important task in macroeconomics, 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. For instance, Altig, Christiano, Eichenbaum and Linde (2011) and Dupor, Han and Tsai (2009) have recently shown that DSGE models of sticky prices have a hard time jointly explaining inflation responses to technology and monetary policy shocks.

In this paper I document inflation adjustment to technology and monetary policy shocks using a medium size Bayesian VAR (BVAR) model, estimated on the U.S. economy from 1959 to 2007. This is not the first paper studying inflation responses to technology and monetary policy shocks in the context of VARs. Altig et al. (2011), Edge, Laubach and Williams (2003) and Dupor, et al. (2009) have recently estimated structural VARs of the U.S. economy in the post second World War period, and found that inflation responds much faster to aggregate technology shocks than to monetary policy shocks. This paper contributes to this literature on three dimensions.

First, after measuring inflation adjustment speed in response to technology and monetary policy shocks, this paper derives the posterior probability associated to the hypothesis that inflation adjusts faster to aggregate technology shocks than to monetary policy shocks. For instance, when estimating the BVAR in the whole sample, I find that this posterior probability is high, ranging from 84 to 92 percent

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[1]See, for intance, Smets and Wouters (2007).

depending on the measure of price level and on the horizon of evaluation of adjustment speed.

Second, I show that the difference in inflation adjustment speed is not stable across different subsamples. In particular, I find that inflation adjusts faster to aggregate technology shocks than to monetary policy shocks in the post-1980 period, i.e. the period associated to Volcker and Greenspan at the helm of the Federal Reserve, but not in the pre-1980 period. Inflation adjustment speed has substantially increased to technology shocks in the Volcker-Greenspan period relatively to the pre-Volcker period, while it has changed less over time after a monetary policy shock. These results are consistent, for instance, with predictions of models of price setting under imperfect information as in Mackowiak and Wiederholt (2010) and Paciello (2010). According to these models, a policy that stabilizes more the price level induces firms to pay more attention to productivity shocks relatively to nominal shocks, inducing a faster response of inflation to the former than to the latter.[2] More generally, these results might pose a new challenge to DSGE models of sticky prices beyond the facts addressed by Altig et al. (2011) and Dupor et al. (2009).

Third, on the methodological side, this paper applies the methodology proposed by Banbura, Giannone and Reichlin (2010) for the estimation of potentially large BVAR models, and combines it with recent results by Ramirez, Waggoner and Zha (2007, 2010), to obtain identification of impulse responses to both aggregate technology and monetary policy shocks. This is important as recent studies (e.g. Bernanke et al. (2005), and Banbura et al. (2010)) have shown that larger information set improve the identification of monetary policy shocks and reduce the risk of omitted variables miss-specifications. In fact, I show that the benchmark specification of the BVAR predicts a higher posterior probability of inflation adjusting faster to technology than

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[2]See Clarida et al. (1999) for evidence about the evolution of monetary policy over time.

to monetary policy shocks relatively to a model of smaller size. Moreover, the paper shows that results about inflation adjustment speed are robust to several identification assumptions of the structural shocks. This is important as identification of monetary policy and technology shocks through short- and long-run restrictions as in Altig, et al. (2011) have recently been questioned by part of the macroeconomic literature.[3] I also show that whether inflation adjusts faster to technology than to monetary policy shocks is independent of the measure of price level, such as the GDP deflator, the consumer price index, the producer price index and the consumption deflator. This evidence supports the view that the difference in price adjustment speed to the two shocks is common to different sectors of the economy.

In a related literature, Galì, Lopez-Salido and Valles (2003) have shown that inflation adjustment speed has increased to technology shocks in the Volcker-Greenspan era. Boivin and Giannoni (2006) and Boivin, Kiley and Mishkin (2010) have shown that inflation responsiveness to monetary policy shocks has decreased in the Volcker-Greenspan period. Findings of this paper are consistent with results by those authors. Differently from those papers, I estimate inflation response to the two structural shocks within the same model, including a larger number of macroeconomic indicators. This approach allows a direct comparison of the evolution of inflation adjustment speed to technology and monetary policy shocks over time and reduces uncertainty in the posterior estimates.

The paper is organized as follows. Section 2 describes the BVAR model, the data, the prior and the identification assumptions. Section 3 derives impulse responses to aggregate technology and monetary policy shocks in the whole sample, and assesses subsample stability of results. Section 4 assesses robustness of findings against the

[3]See the reference list in Erceg, Guerrieri and Gust (2005) for most of the relevant references regarding identification of technology shocks. See Faust (1998) and references therein regarding identification of monetary policy shocks.

assumptions on the identification of aggregate technology and monetary policy shocks. Section 5 concludes.

2   The benchmark BVAR model

This section describes the baseline empirical model consisting of a structural vector autoregression (SVAR) for an 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 follows that $\Upsilon \equiv E\{u_t u_t'\} = A_0^{-1}\left(A_0^{-1}\right)'$.

Several authors (e.g. Bernanke et al. (2005) and Banbura et al. (2010)) have shown that larger information set help improving the identification of monetary policy shocks, as well as the model ability at forecasting inflation, output and short-term interest rate. The vector Y_t includes the same macroeconomic indicators considered in the VAR model of Altig et al. (2011), but augmented by some of the additional indicators considered by Banbura et al. (2010) in their "medium" size BVAR. These additional indicators help to reduce uncertainty in the estimate of inflation responses

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to technology and monetary policy shocks, while the Bayesian shrinkage helps addressing the curse of dimensionality.[4] The VAR is specified in terms of stationary variables. Stationarity of (2) is needed to implement the identification scheme in the next section.[5] To achieve stationarity I rescale the non-stationary economic variables similar to Altig et al. (2011).[6] The time span is from January 1959 through June 2007, and the model is estimated at a quarterly frequency with the number of lags p set equal to 4.

I assume a Normal inverted-Wishart prior for the parameters of (2) according to results by Kadilaya and Karlsson (1997) and similarly to Banbura et al. (2010). In particular, let $B \equiv (B_1, ..., B_p, c)'$, the Normal inverted-Wishart prior has the form

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

The prior parameters B_0, Ω_0, S_0 and α_0 are chosen consistently with the assumption that the prior mean can be associated to the following process

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

where the ith equation in (2) is centered around a random walk with drift if the ith element of Y_t is highly persistent, $\delta_i = 1$, and around a white noise otherwise, $\delta_i = 0$. This amounts to shrinking the diagonal elements of B_1 corresponding to the ith equation for which $\delta_i = 1$ toward one, and the remaining coefficients in $B_1, ..., B_p$ toward zero. I refer to Appendix B for more details on the prior.

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[4] The appendix provides details on the variables included in the model.

[5] All the roots of the VAR polynomial need to be ouside the unit circle. Draws with coefficients inside the unit circle are discarded.

[6] Details on the specification of the vector Y are given in the appendix. The price level and labor productivity enter the model in log-differences. Standard test of cointegration cannot reject the hypothesis of no cointegration among variables in Y.

I assume a white noise prior, $\delta_i = 0$, for all variables but the Federal funds rate which is entered in levels and characterized by substantial persistence. In fact, the other persistent variables are either rescaled or entered in first differences. The overall tightness of the prior distribution around model (3) is governed by an hyper-parameter, formally defined as λ in Appendix B. Banbura et al. (2010) suggest that prior tightness should be chosen in relation to the size of the system. De Mol, Giannone and Reichlin (2006) discuss this point in detail and show that as the number of estimated parameters increases, the overall tightness should increase as well in order to avoid over-fitting of the model to the data. In comparing VARs of different size, these authors suggest fixing a VAR model as a reference, and adjusting prior tightness associated to each model so that the different models are characterized by comparable in-sample mean squared forecast error for a selected group of variables. I follow this recommendation. I set prior tightness relative to a reference model that has flat prior and the size of a standard new-Keynesian model, including five macroeconomic indicators.[7] See Appendix C for more details on the choice of the hyper-parameter governing prior tightness. In section 4 I will assess robustness of results to this choice.

2.1 Identification of the structural parameters

Identification of model (1) amounts to putting enough restrictions on the model to be able to recover $A_0, A_1.., A_p$ and υ 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. These identification assumptions have the advantage of making results easily comparable to the existing literature. However, in section 4, I

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[7] The five variables are: labor productivity, per-capita hours worked, the Federal Funds rate, M2 and the GDP deflator. This model is similar to models studied by Galì et al. (2003) and Boivin and Giannoni (2006).

will show that results about inflation responses are robust to different identification assumptions.

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 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 ith element of vector Y_t, and that the technology shock is the jth element of vector e_t. It is assumed that all the elements of the ith row of C are zero but the one associated to the jth column.

Second, similarly to Christiano et al. (2005), it is assumed that monetary policy targets a policy instrument, S_t, according to

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

where 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-months average 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 et al. (2005), it is assumed that variables in X_t 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 money velocity. F_t is equal to the interest rate on Treasury bonds with ten years maturity in difference from the the 3-months average Federal Funds rate, and there is no short-run restriction on the relationship between F_t and the other variables in Y_t.[8]

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[8]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.

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 increase in labor productivity.[9] Under this set of assumptions the impulse responses of Y_t to monetary policy and technology shocks are exactly identified.[10]

3   Impulse responses and inflation adjustment speed

Impulse responses are generated according to the methodology proposed by Ramirez, Waggoner and Zha (2007, 2010). More details are given in Appendix D. 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.[11] I consider four different measures of inflation: the GDP deflator, the CPI, the PPI and the consumption expenditure deflator. I separately estimate the BVAR for each of these measures.

Inflation adjustment speed is measured according to the methodology proposed by Cogley, Primiceri and Sargent (2010). Relative to other measures of inflation persistence, such as half-lives, this measure has the advantage of not relying on the monotonicity of responses. Given that inflation response to monetary policy shocks is characterized by a hump-shape dynamic, this property is very appealing. In par-

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

[10]See Appendix D for details.

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

ticular, inflation persistence to shock i, j periods after the shock, is measured as

$$r_i^j \equiv 1 - \frac{\sum\limits_{s=0}^{j} (\hat{\pi}_{s,i})^2}{\sum\limits_{s=0}^{\infty} (\hat{\pi}_{s,i})^2}, \tag{5}$$

where $\hat{\pi}_{s,i}$ is the response of the inflation rate to shock $i \in \{TECH, \ MP\}$, evaluated s periods after the shock. According to this measure, inflation is weakly persistent when the effects of shocks decay quickly, and it is strongly persistent when they decay slowly. When the effects of shock i die quickly, r_i^j is close to zero at relatively short horizon. But when the effects of shock i decay slowly, r_i^j remains far from zero for longer horizon. Thus, for small or medium $j \geq 0$, a small r_i^j signifies high adjustment speed, and a large r_i^j implies low adjustment speed.

3.1 Results from the whole sample

This section evaluates inflation responses in the 1959:Q1-2007:Q2 sample, with particular emphasis on inflation adjustment speed.[12] Figure 1 displays scatter plots for the values of r_i^j obtained from the posterior draws of the structural parameters of the BVAR model; r_i^j is evaluated at one year horizon of responses, i.e. $j = 4$.[13] Each plot is associated to one of the four measures of prices. The vertical axis of each plot reports values of r_i^j associated to the monetary policy shock, and the horizontal axis values of r_i^j associated to the technology shock. By definition of r_i^j, draws above (below) the 45 degree line mean that inflation adjustment is faster (slower) to technology shocks than to monetary policy shocks.

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[12]Impulse responses of inflation, as well as other economic variables, are provided in an on-line appendix available on the author's website.

[13]Results are qualitatively similar for other horizon j. More details are in the on-line appendix.

In Figure 1, the vast majority of draws is above the 45 degree line for all measures of prices. The posterior probability that inflation adjusts faster to technology shocks than to monetary policy shocks, i.e. $r_{TECH}^{j=4} < r_{MP}^{j=4}$, is relatively high across all four measures of aggregate price level, ranging from about 0.87 for the GDP deflator to 0.91 for the CPI. Figure 2 evaluates the same measure but across different horizons j for r_i^j, holding fixed the measure of prices to the GDP deflator. The shorter the horizon of evaluation, the higher the posterior probability of inflation adjusting faster to technology shocks, ranging from a low of 0.85 at an evaluation horizon of 3 years to a maximum of 0.93 for a horizon of 2 quarters.

Table 2 reports the median, 16th and 84th percentiles of the posterior distribution of r_i^j for the technology and the monetary policy shocks respectively, evaluated at $j = 2, 4, 8, 12, 16$. From this table we can draw the following conclusions. First, inflation adjustment speed to technology shocks is much faster than to monetary policy shocks, independently of the horizon of the response at which we measure r_i^j, and independently of the measure of aggregate prices. For instance, two years after the shock, GDP deflator inflation has accomplished at the median about 85 percent of total adjustment to the technology shock, but only 18 percent of total adjustment to the monetary policy shock.[14] In addition, it takes 2 quarters for median inflation response to accomplish half of its response to the technology shock, while it takes more than 2 years in response to the monetary policy shock.

3.2 Subsample analysis

Boivin and Giannoni (2006) and Boivin et al. (2010) have documented that the impact of monetary policy shocks on the U.S. economy has became less effective

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[14]Notice that the fraction of inflation adjustment accomplished j quarters after the shock is measured by $1 - r_{j,i}$.

in the Volcker-Greenspan period compared to the pre-Volcker one. Similarly, Galí et al. (2003) have found that the effects of technology shocks on inflation differ drastically between the two periods. This section answers the following questions: (i) Does inflation adjust faster to technology shocks than to monetary policy shocks in all subsamples? (ii) Does the difference in inflation adjustment speed quantitatively similar in the different subsamples?

I evaluate and compare inflation adjustment speed to the two shocks in the periods before and after Volcker's tenure, i.e. 1959:Q1-1979:Q3 and 1979:Q4-2006:Q1, as well as in the periods including Volcker's second mandate and/or Greenspan, i.e. 1983:Q4-2006:Q1 and 1987:Q3-2006:Q1.[15] Hence, I label these subsamples as "pre-Volcker", "Volcker I - Greenspan", "Volcker II - Greenspan" and "Greenspan" respectively.

Figure 3 displays scatter plots for the values of r_i^j obtained from the posterior draws of the structural parameters of the BVAR model in the different periods; r_i^j is evaluated at one year horizon of responses.[16] These figures show that the difference between inflation adjustment speed to the two shocks has changed over time. In fact, in the 1959:Q1-1979:Q3 subsample, the majority of draws is below the 45 degree line, indicating that inflation adjusts faster to monetary policy shocks than to technology shocks. In contrast, in the 1979:Q4-2006:Q1 subsamples, the majority of draws is above the 45 degree line, indicating that inflation adjusts faster to technology shocks than to monetary policy shocks.

To better quantify inflation adjustment speed in the different subsamples, Table 3 reports the median, 16th and 84th percentiles of the posterior distribution of r_i^j in the different subsamples. Inflation adjustment speed to technology shocks has

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[15]The parameter λ is set in each subsample according to the algorithm in Appendix C.

[16]There statistics refer to the CPI. Similar statistics are obtained for the GDP deflator, but the shape of median impulse responses of the CPI to a monetary policy shock in the post 80's subsamples display a less pronounced "price puzzle". See the Online Appendix for more details on the shape of impulse responses.

substantially increased over time. This is true across all horizons of evaluation of inflation adjustment speed. For instance, two years after the shock, inflation accomplishes about 17 versus 85 percent of overall adjustment to technology shocks under the "pre-Volcker" and "Volcker - Greenspan" subsamples respectively. In contrast, inflation adjustment speed to monetary policy shocks is lower in the last two decades than in the pre-Volcker subsample. The latter is consistent with findings by Boivin and Giannoni (2006).

4   Robustness analysis

This section investigates to what extent results from the benchmark BVAR model are robust to several features of the identification assumptions. While extensively adopted, identification of monetary policy shocks through the *recursive* assumption of Christiano et al. (2005), and identification of technology shocks through long-run restrictions as in Gali (1999) have been recently criticized by part of the macroeconomic literature. In fact, zero restrictions on the contemporaneous responses of economic variables to monetary policy shocks might be particularly restrictive when frequency of observations is quarterly.[17] Furthermore, long-run restrictions on the response of economic variables to technology shocks might give biased results in a VAR with a finite number of lags.[18] This section investigates to what extent results from the benchmark BVAR model are robust to several features of the identification assumptions. I identify the two structural shocks of interest through a different method relying on sign restrictions of impulse responses, and I consider a different identification assumption of technology shocks based on a Solow-residual measure of

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[17]See Faust (1998) and references therein regarding identification of monetary policy shocks.

[18]See the reference list in Erceg, et al.(2005) for most of the relevant references regarding identification of technology shocks.

quarterly total factor productivity growth. The insights from these exercises reinforce the results obtained in the previous sections. Below I discuss some of these results more in detail.

In addition, Table 4 and Figure 4 also assess robustness of results to prior tightness, and to estimating the model on monthly data. While relaxing the weight on the prior may increase uncertainty in posterior estimates, it does not change the prediction about inflation adjusting faster to technology shocks. Results are robust to estimating the model at a monthly frequency.

4.1 Identification through sign restrictions

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 (2006) to the identification of technology shocks. These sign restrictions are robust in the sense that they are consistent with a wide range of DSGE models.[19] 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. Differently from the benchmark identification assumptions, this procedure does not require stationarity of the vector Y. Therefore, I can leave the non-stationary variables of the model in levels.[20] Given the specification in levels, I can include in the VAR different measures of price level and money supply, as reported in the appendix. Apart from the different identification

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[19]Canova, Gambetti and Pappa (2007), Dedola and Neri (2006) provide detailed examples of standard DSGE models where these restrictions hold. Moreover, these restrictions are consistent with impulse responses estimated in a DSGE model by Smets and Wouters (2007). I refer to these authors for more details.

[20]The specification of δ is changed accordingly. For instance in the benchmark specification $\delta = 0$ for inflation, in the specification in levels $\delta = 1$.

assumptions, the rest of the estimation procedure is as in the benchmark specification of the model. I adopt the algorithm proposed by Ramirez et al. (2007, 2010) to compute the posterior distribution of impulse responses.[21]

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).[22] 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.[23]

Results in Table 4 and Figure 4 confirm main findings from the benchmark model, i.e. that inflation adjustment speed is higher to technology shocks than to monetary policy shocks.

4.2 A Solow-residual based identification for technology

As an additional robustness check on identification of technology shocks, this subsection adopts a different identification assumption for technology shocks, relying on

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

[22] 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.

[23] More specifically, sign restrictions to a monetary policy shock are such that: the impulse responses of M2, investments, consumption, GDP and hours worked are non-positive for the first 2 periods at least; the Federal Funds rate is non-negative for the first 2 periods at least; the impulse responses of CPI is negative in at least one quarter within the first 12 quarters from the shock.

Restrictions to a technology shock are such that: the impulse responses of GDP and investments are non-negative in the first 10 quarters; the impulse responses of labor productivity non-negative; the impulse responses of the real wage and consumption are non-negative for at least 5 quarters; the impulse responses of CPI is negative in at least one quarter within the first 12 quarters from the shock.

a Solow-residual measure of quarterly total factor productivity (FTFP) growth esti-
mated by Fernald (2007). Fernald's quarterly measure explicitly accounts for variable
capital utilization and labor hoarding.[24] The FTFP series is added to Y and the pos-
terior 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. Relative to the identification assumptions of section
2, the advantage of this procedure is that, by explicitly assuming an aggregate pro-
duction function, it directly estimates total factor productivity growth.[25] 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.
According to Table 4, inflation adjustment speed to technology shocks is higher than
to monetary policy shocks. The associated posterior probability is about 0.86.

4.3   Smaller VAR

Table 4 and Figure 4 report results from the estimation of the smaller size VAR used
as reference model. This model includes GDP, the Federal Funds rate, inflation, per-
capita hours worked and money velocity. The model has the same size of a standard
new-Keynesian model, and a similar version has been studied in the context of VARs
by Galì et al. (2003) or Boivin and Giannoni (2006). When analyzing impulse
responses obtained from the small size model, I obtain no clear answer on whether

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[24]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.

[25]This procedure has been originally applied by Christiano, Eichenbaum and Vigfusson (2004) sug-
gesting 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.

inflation adjusts faster to technology shocks than to monetary policy shocks. In fact, uncertainty in the estimates of impulse responses is higher.[26] This uncertainty reflects in the estimate of the posterior probability of inflation adjusting faster to technology shocks, which drops substantially to about 0.47. In fact, the difference in median estimates of inflation adjustment speed to the two shocks is much smaller than under the benchmark model. Therefore, allowing for more information in the VAR helps identifying the response of the economy to the two shocks, and reduces uncertainty in the estimation of inflation adjustment speed.

5   Concluding remarks

This paper answers the question of whether, by how much and how likely it is that U.S. inflation adjusts faster to aggregate technology shocks than to monetary policy shocks. According to a BVAR model for the 1959-2007 sample, this paper finds that U.S. inflation adjusts much faster to technology shocks than to monetary policy shocks. This paper also finds that this result is robust to different identification assumptions. However, when investigating more in detail over subsamples, this paper finds that inflation adjusts faster to technology shocks than to monetary policy shocks in the Volcker-Greenspan period, but the opposite is true in the pre-Volcker subsample. This result is due to the fact that inflation adjustment speed in the later subsample has substantially increased to technology shocks, while it has changed much less to monetary policy shocks. These results are interesting, for instance, from the perspective of models of price setting under rational inattention. Paciello (2010) and Mackowiak and Wiederholt (2010) show in fact that the allocation of attention by firms, and hence the speed of inflation adjustment, crucially depend on the systematic

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[26]Impulse responses are available in the on-line appendix.

response of monetary policy to expected inflation and output fluctuactions.

Increasing the number of macroeconomic indicators in the VAR helps reducing the uncertainty in the estimation of inflation responses to technology and monetary policy shocks. Reducing the uncertainty might help to evaluate the ability of available models of price setting to account for the different speed of inflation adjustment to the two structural shocks.

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A Data

TABLE 1

Model data

Mnemon	Series	Y=(X,S,Z,F)	Units
GDPQ/LBMNU	Labor productivity	X	$\Delta \log$
LBMNU/P16	Index total hours worked per person	X	log
FYFF	Interest rate: Federal Funds rate	S	Level
(LBCPU+LBMNU)/GDP	Labor share of GDP	X	log
FYGT10	Interest rate: 10-YR U.S. Treasury	F	Level
(GCN+GCS+GGE)/GDP	Consumption share of GDP	X	log
(GCD+GPI)/GDP	Investment share of GDP	X	log
IPS10/QGDP	Industrial production relative to GDP	X	log
UTL11	Capacity utilization	X	Level
LHUR	Unemployment rate	X	Level
HSFR	Housing starts index	X	log
MZMSL/GDP	Money velocity	Z	log
PGDP	GDP price deflator (PGDP)	X	$\Delta \log$
PUNEW	Consumer price index (CPI)[a; b]	X	log
PCPEPI	Personal cons. expend. deflator (PCE)[a; b]	X	log
PWFSA	Producer price index (PPI)[a; b]	X	log
FM1	M1 monetary stock[a]	Z	log
FMRRA	Non-borrowed reserves[a]	Z	log
FMRNBA	Total reserves[a]	Z	log

Notes: The source of most of the data is the DRI Basic Economics Database, available on-line at Northwestern University. Output, GDP deflator were obtained from the BEA website; "[a]" denotes those variables that are included in the model only under sign restrictions identification; "[b]" denotes the price indeces that are entered in the benchmark specification of Y one at the time.

B   Kadiyala and Karlson (1997) 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

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

The prior parameters S_0, α_0, B_0 and Ω_0 are chosen so that the prior expectaxtion of Ψ is equal to $E(\Psi) = diag\left(\sigma_1^2, ..., \sigma_n^2\right)$, and the prior expectactions and variances of the elements of $vec(B)$ coincide with

$$E\left((B_s)_{ij}\right) = \begin{cases} \delta_i, & if \ \ i = j, s = 1 \\ 0, & otherwise \end{cases},$$

$$V\left((B_s)_{ij}\right) = \frac{\lambda^2}{s^2}\frac{\sigma_i^2}{\sigma_j^2},$$

where $(B_s)_{ij}$ is the i, j element of B_s for $s = 1, ..p$, $i = 1, 2.., n$, $j = 1, 2, ..n$. Notice that the unconditional distribution of B is matricvariate t. For details see Kadiyala and Karlsson [28] and Banbura, Giannone and Reichlin (2010) at pages 74-75. 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. The vectors Y_0 and X_0 are defined as in eq. 5 of Banbura et al. (2010).

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 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 $\alpha_* = T_* - k + 2$.

C   Parameterization of λ

Consider an 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 two types of models, depending on the number of variables included in the analysis and the value of λ. The first model, $m = 1$, is similar to the model by Galì et al. [26], including $n_1 < n$ variables

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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 and M2 money stock. The second model $m = 2$ is the benchmark model with n variables. Following Banbura, Reichlin and Giannone (2010), I choose λ in model $m = 2$ so to minimize the difference in fit from model $m = 1$ over the n_1 variables:

$$\lambda^* = \arg\min_\lambda \left| F - \frac{1}{n_1} \sum_{i=1}^{n_1} \frac{MSFE_i^{(\lambda,2)}}{MSFE_i^{(0,1)}} \right|,$$

where $F = \frac{1}{n_1} \sum_{i=1}^{n_1} \frac{MSFE_i^{(\infty,1)}}{MSFE_i^{(0,1)}} = 0.17$ is the measure of relative fit associated to the reference model. From this procedure λ^* is equal to 0.07.

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 et al. [31], [32] let's express 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 nth and $(n_z + 1)^{th}$ elements of the vector of structural shocks e_t respec-

tively. In particular, the identifying restrictions are zero restrictions such that the matrix D is given by

$$D^* = \begin{bmatrix} \underset{(n_x \times n_z)}{0} & \underset{(n_x \times 1)}{0} & \underset{(n_x \times n_x)}{T_x} & \underset{(n_x \times 1)}{x} \\ \underset{(1 \times n_z)}{0} & \underset{(1 \times 1)}{x} & \underset{(1 \times n_x)}{x} & \underset{(1 \times 1)}{x} \\ \underset{(n_z \times n_z)}{T_z} & \underset{(n_z \times 1)}{x} & \underset{(n_z \times n_x)}{x} & \underset{(n_z \times 1)}{x} \\ \underset{(1 \times n_z)}{x} & \underset{(1 \times 1)}{x} & \underset{(1 \times n_x)}{x} & \underset{(1 \times 1)}{x} \\ \underset{(1 \times n_z)}{0} & \underset{(1 \times 1)}{0} & \underset{(1 \times n_x)}{0} & \underset{(1 \times 1)}{x} \\ \underset{(n-1 \times n_z)}{x} & \underset{(n-1 \times 1)}{x} & \underset{(n-1 \times n_x)}{x} & \underset{(n-1 \times 1)}{x} \end{bmatrix}, \quad (6)$$

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:

$$T_i = \begin{bmatrix} 0 & \cdots & 0 & x \\ 0 & \cdots & x & x \\ 0 & \diagup & \vdots & \vdots \\ x & \cdots & x & x \end{bmatrix},$$

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 [31] and [32]. In order to recover A_0 from the system of linear equations, $H(A_0) = D^*$

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and $A_0^{-1} A_0^{-1\prime} = \Upsilon$, I recur to an algorithm proposed by Ramirez, Waggoner and Zha [31] and [32]. Let $\Sigma = S D^{\frac{1}{2}}$ be the $n \times n$ lower diagonal Cholesky matrix of the covariance of the residuals of the reduced form VAR, that is $S D S\prime = E[u_t u_t'] = \Upsilon$ and $D = diag(\Upsilon)$. Let's compute $H\left(\Sigma^{-1}\right)$ and define matrices P_1 and P_2 as:

$$
P_1 \equiv \begin{bmatrix} 0_{1\times n} & 1 & 0_{1\times n-1} \\ I_{n\times n} & 0_{n\times 1} & 0_{n\times n-1} \\ 0_{n-1\times n} & 0_{n-1\times 1} & I_{n-1\times n-1} \end{bmatrix}, \tag{7}
$$

$$
P_2 \equiv \begin{bmatrix} i_n, & i_{n-1}, & \ldots, & i_1 \end{bmatrix}, \tag{8}
$$

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. This means that the structural shocks are ordered so that all variables in X do not respond contemporaneously to the monetary policy shock. The Federal Funds rate, i.e. the $(n_x + 1)^{th}$ element of Y, does not respond contemporaneously to variables in Z. To be more specific, the structrual shocks are ordered in the following way:

$$
e_t' = \begin{bmatrix} e_t^{z\prime} & e_t^{s\prime} & e_t^{x\prime} & e_t^{f\prime} & e_t^{a\prime} \\ (1 \times n_z) & (1 \times 1) & (1 \times n_x) & (1 \times 1) & (1 \times 1) \end{bmatrix},
$$

where $e_t^{s\prime}$ and $e_t^{a\prime}$ are the monetary policy and technology shocks respectively.

Proposition 1 *For given estimates of B and Υ, let Σ be the Cholesky factor associated to Υ, and let $H\left(\cdot\right)$, P_1 and P_2 be defined as in $(7) - (8)$. Let P_3 be the Q factor associated with the QR decomposition of the matrix $\left(P_1 H\left(\Sigma^{-1}\right)\right)'$ and define $P = P_3 P_2'$. Let also A_0 satisfy the restriction $H\left(A_0\right) = D^*$ where D^* is defined as in (6). It follows that $A_0 = \Sigma^{-1} P$.*

For a proof see Ramirez, Waggoner and Zha [31] and [32]. 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, notice that 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.

TABLE 2

Benchmark BVAR. Measures of inflation adjustment speed

	Horizon of impulse response, quarters				
	2	4	5	12	16
Type of shock					
Panel A. PGDP					
TECH	50	34	15	7	4
	(40,74)	(23,61)	(6,41)	(2,28)	(1,15)
MP	97	92	82	47	14
	(84,99)	(62,98)	(47,91)	(24,61)	(5,25)
Panel B. CPI					
TECH	33	18	6	4	2
	(21,65)	(9,51)	(1,33)	(1,23)	(0,13)
MP	96	90	71	31	6
	(79,99)	(65,97)	(45,82)	(16,44)	(2,13)
Panel C. PPI					
TECH	35	18	7	4	2
	(17,68)	(7,50)	(1,33)	(1,22)	(0,12)
MP	97	79	44	16	3
	(82,99)	(56,89)	(25,60)	(6,30)	(1,10)
Panel D. PPCE					
TECH	37	23	11	7	4
	(22,69)	(11,57)	(3,40)	(2,29)	(1,16)
MP	97	89	66	26	5
	(78,99)	(60,96)	(37,80)	(12,40)	(1,12)

Notes : Median, and $(16^{th}, 84^{th})$ statistics from the posterior distribution of inflation adjustment speed r_i^j for different horizons of evaluation j, and conditional on type of shock i. Values are in % units. Each panel refers to a different price index. PGDP: GDP deflator; PPCE: personal consumption expenditure deflator.

TABLE 3

Sub-sample stability. Measures of inflation adjustment speed

	Horizon of impulse response, quarters				
	2	4	5	12	16
Type of shock					
Panel A. Pre-Volcker, 1959:Q1 – 1979: Q3					
TECH	96	94	83	53	25
	(90,99)	(86,98)	(70,90)	(39,67)	(16,37)
MP	89	56	37	19	3
	(81,95)	(44,73)	(22,58)	(11,34)	(2,13)
Panel B. Volcker – Greenspan, 1979:Q4– 2006:Q1					
TECH	50	34	15	8	4
	(27,82)	(16,69)	(4,48)	(2,35)	(1,22)
MP	83	63	34	18	9
	(52,98)	(31,88)	(12,64)	(5,49)	(1,31)
Panel C. Volcker II – Greenspan, 1983:Q4– 2006:Q1					
TECH	50	42	29	22	13
	(23,85)	(18,76)	(10,63)	(5,54)	(2,36)
MP	98	61	31	16	6
	(89,99)	(38,86)	(10,63)	(5,35)	(1,21)
Panel D. Greenspan, 1987:Q3– 2006:Q1					
TECH	28	19	13	10	7
	(12,67)	(7,52)	(4,38)	(2,30)	(1,21)
MP	95	69	27	14	6
	(83,99)	(47,86)	(9,52)	(3,33)	(1,18)

Notes : Median, and $(16^{th}, 84^{th})$ statistics from the posterior distribution of inflation adjustment speed r_i^j for different horizons of evaluation j, and conditional on type of shock i. Values are in % units. Each panel refer to a different subsample.

TABLE 4

Robustness analysis. Measures of inflation adjustment speed

	Horizon of impulse response, quarters				
	2	4	5	12	16
Type of shock					
Panel A. Sign-restrictions identification					
TECH	49	32	14	8	3
	(22,79)	(12,62)	(4,42)	(1,26)	(0,14)
MP	61	49	32	14	5
	(24,89)	(18,81)	(8,64)	(3,38)	(1,19)
Panel B. Solow-residual identification					
TECH	52	36	13	5	2
	(41,74)	(25,62)	(6,39)	(1,25)	(0,14)
MP	93	83	76	47	15
	(82,99)	(59,95)	(43,89)	(23,60)	(5,25)
Panel C. Smaller size VAR					
TECH	72	64	40	23	11
	(67,83)	(58,76)	(33,57)	(17,37)	(7,19)
MP	88	64	53	42	26
	(70,98)	(32,90)	(16,80)	(8,65)	(5,42)
Panel D. $\lambda = 0.03$					
TECH	55	40	18	8	3
	(43,78)	(27,66)	(9,47)	(2,30)	(0,16)
MP	95	90	79	41	10
	(85,99)	(71,97)	(59,87)	(26,54)	(4,19)
Panel E. $\lambda = 0.15$					
TECH	54	39	20	11	5
	(41,73)	(27,60)	(11,40)	(5,25)	(2,12)
MP	85	63	31	19	10
	(61,98)	(30,89)	(8,66)	(3,49)	(1,30)

Notes : Median, and $(16^{th}, 84^{th})$ statistics from the posterior distribution of inflation adjustment speed r_i^j for different horizons of evaluation j, and conditional on type of shock i. Values are in % units. Each panel refers to a different specification of the model.
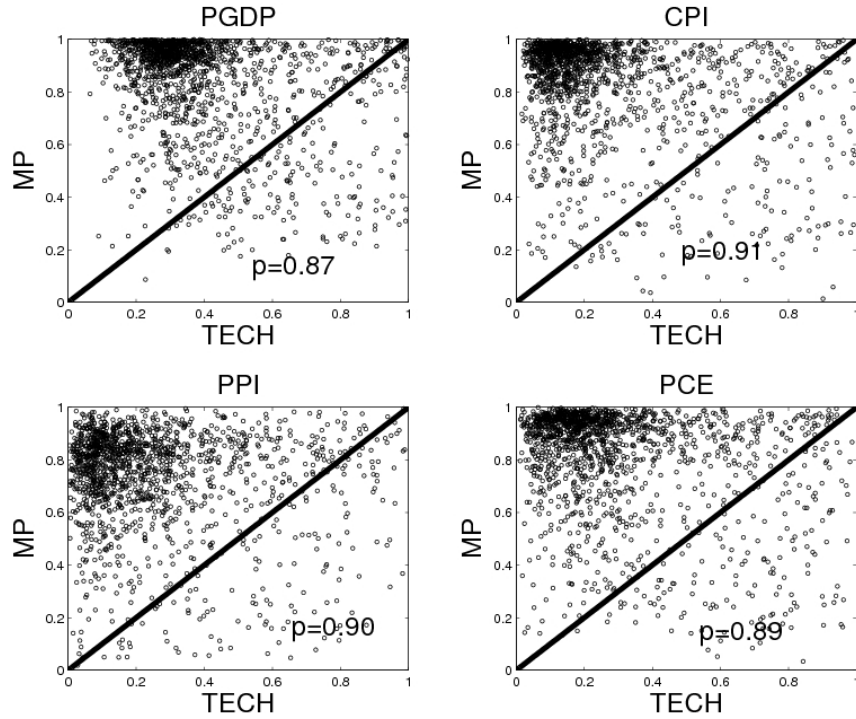
Figure 1: Draws of inflation adjustment speed, r_i^j, to TECH (horizontal axis) and MP (vertical axis) shocks, for different measures of prices, evaluated at 1 year horizon; p is the posterior probability that inflation adjusts faster to technology than to monetary policy shocks.
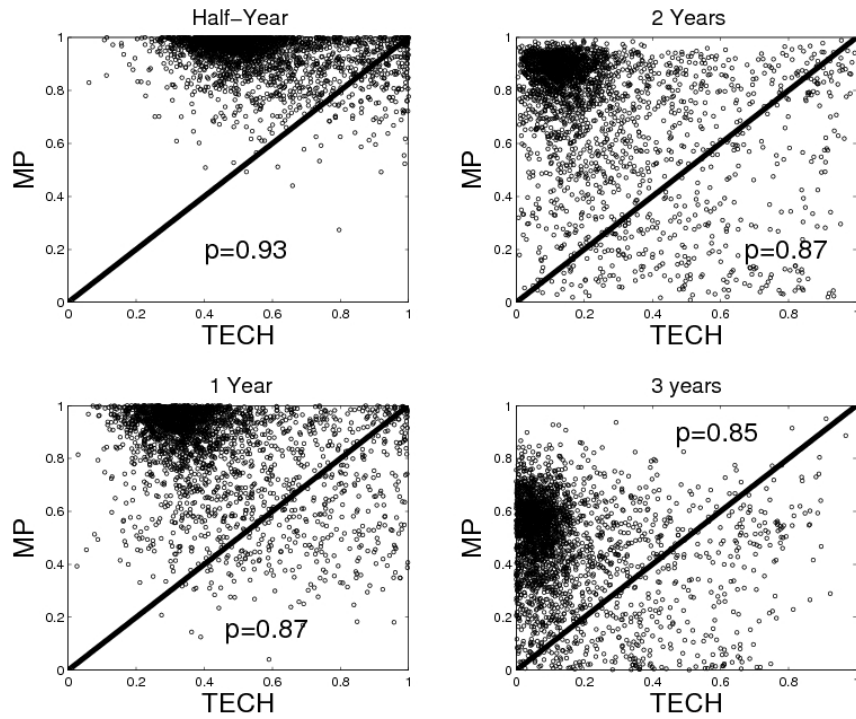
Figure 2: Draws of inflation adjustment speed, r_i^j, to TECH (horizontal axis) and MP (vertical axis) shocks, for different horizons of evaluation, under the GDP deflator; p is the posterior probability that inflation adjusts faster to technology than to monetary policy shocks.
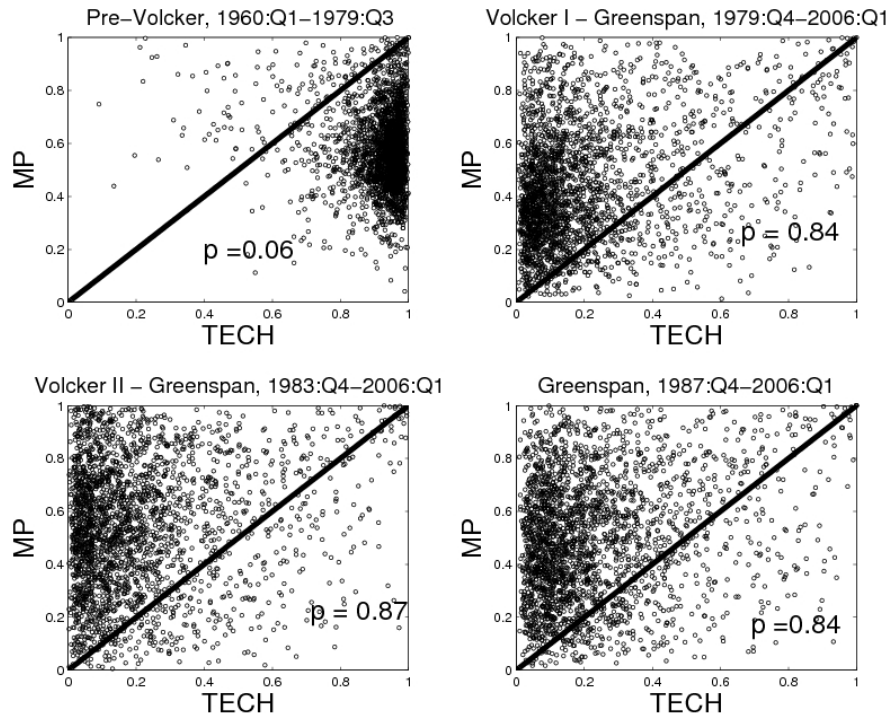
Figure 3: Subsample stability. Draws of inflation adjustment speed, r_i^j, to TECH (horizontal axis) and MP (vertical axis) shocks, at 1 year horizon of evaluation; p is the posterior probability that inflation adjusts faster to technology than to monetary policy shocks.
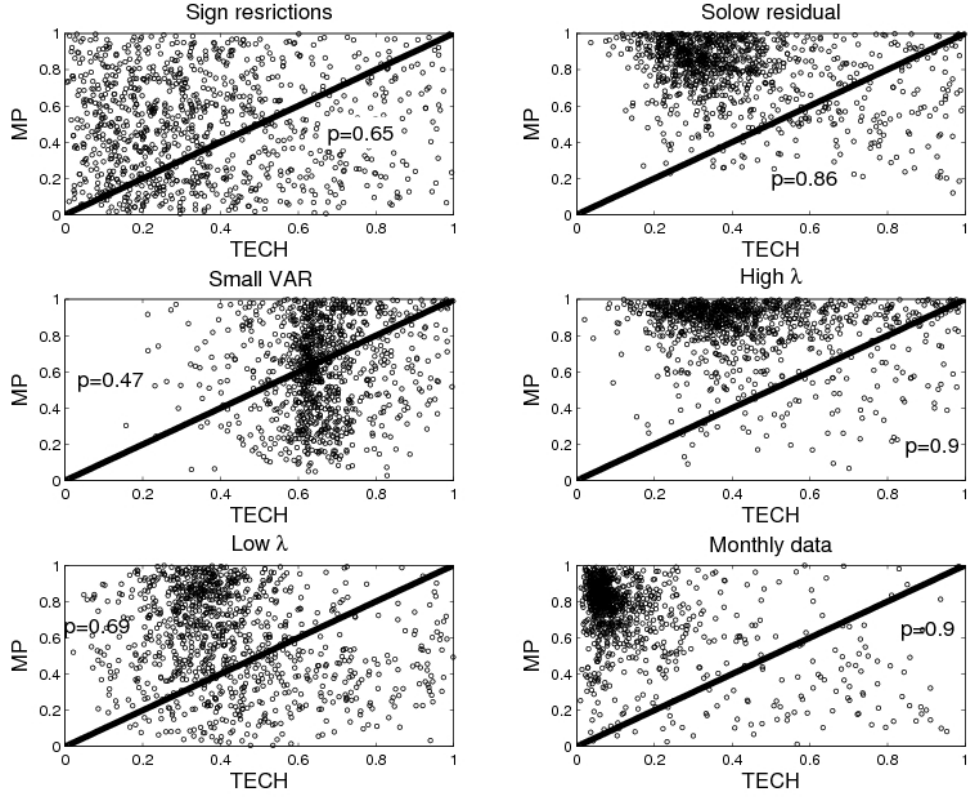
Figure 4: Robustness analysis. Draws of inflation adjustment speed, r_i^j, to TECH (horizontal axis) and MP (vertical axis) shocks, at 1 year horizon of evaluation; p is the posterior probability that inflation adjusts faster to technology than to monetary policy shocks.