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The Responsiveness of Prices to Aggregate Technology Shocks and Monetary Policy Shocks

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ABSTRACT

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I show that the speed of price adjustment to aggregate technology shocks is substantially larger than to monetary policy shocks. In the context of large Bayesian Vector Autoregression models, I establish that aggregate and disaggregate prices adjust very quickly to technology shocks, while they only respond sluggishly to monetary policy shocks. I derive explicit measures of difference in price responsiveness. Under the benchmark specification, aggregate prices accomplish half of their long-run response to a permanent technology shock 6 quarters before they accomplish half of their long-run response to a monetary policy shock. I show that these results are very robust across different identification schemes, models specifications and data definitions. Looking at disaggregated producer prices responses

to the two aggregate shocks, I find that prices adjust faster to technology shocks in about 85% of industries. I also find that industries where prices are more volatile tend to be the industries with the smaller difference in price responsiveness to the two shocks.

I show that the difference in the speed of price adjustment to the two types of shocks arises naturally in a model where price setting firms optimally decide what to pay attention to, subject to a constraint on information flows. In my model, firms pay more attention to technology shocks than to monetary policy shocks when the former affects profits more than the latter. Furthermore, strategic complementarities in price setting generate complementarities in the optimal allocation of attention. Therefore, each firm has an incentive to acquire more information on the variables that the other firms are, on average, more informed about. These complementarities induce a powerful amplification mechanism of the difference in the speed with which prices respond to technology shocks and to monetary policy shocks. Finally, I show that the monetary policy rule may influence substantially the difference in price responsiveness by affecting the allocation of attention decision by firms. I compare the implications about relative price responsiveness to the two shocks from my model to the ones from a more standard model of nominal price rigidities. I show that these two classes of models have potentially very different implications for monetary policy in terms of relative price responsiveness.

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CHAPTER 1

Do Aggregate Prices to Adjust Faster to Aggregate Technology Shocks than to Monetary Policy Shocks?

1.1. Introduction

Assessing the speed of price adjustment to different type of shocks impacting on the economy is an important task in the macroeconomic literature. This debate is relevant not only to establish the main source of business cycle fluctuations but also to understand the way different shocks transmit through the economy.

There is a large empirical literature investigating how aggregate macroeconomic variables respond to monetary policy shocks in the context of structural vector autoregression (SVAR) models. In this literature, there is large consensus that inflation and prices respond slowly to monetary policy shocks. For instance, after an unexpected monetary policy tightening, aggregate price indices are commonly found to remain unchanged for about a year and a half, and start declining thereafter[1]. A relatively more recent literature investigates the effects of neutral technology shocks using SVAR models. Papers in this literature consistently find that in the United States prices respond in general very quickly to neutral technology shocks[2]. There is a relatively small number of papers estimating and identifying jointly the responses of prices to neutral technology and monetary policy shocks[3]. Although these papers generally recognize the different dynamic behavior of prices to the two types of shocks, this fact is not addressed systematically. For instance, there is not a quantitative and statistical measure of the difference in price responsiveness to these two aggregate shocks. In this paper I construct different measures of speed of price adjustment to shocks. I use these measures to evaluate the difference in price responsiveness to the technology and monetary policy shocks. For each measure I compute the probability associated to the event that prices adjust faster to neutral technology shocks than to monetary policy shocks. This exercise provides sharp evidence that prices adjust much faster to technology shocks.

Studying price responsiveness to monetary policy shocks and neutral technology shocks is important because it gives information on the role of each shock in

[1]See for example Christiano, Eichenbaum and Evans (1999).
[2]See for example Basu et al. (1995) or Altig et al. (2005).
[3]See Gali (1992) or Altig et al. (2005).

accounting for business cycle fluctuations. Some authors have argued that nominal demand shocks, and therefore monetary policy shocks[4], account for a large fraction of business cycle fluctuations, while other authors have pointed to neutral technology shocks as the main drivers of economic fluctuations[5]. An important part of the debate relies on determining price responsiveness to each of these two types of shocks. For instance according to the standard new-Keynesian literature, everything else being equal, the slower prices respond to monetary policy shocks, the larger the real effect of such shocks are. On the inverse, the slower prices respond to neutral technology shocks the smaller is the impact of the latter on real output, investments and consumption. For instance, Dupor, Han and Tsai (2007) have argued that standard sticky price models have an hard time accounting for the response of the economy to neutral technology and monetary policy shocks under the same calibration of the model.

Applications studying the responses of the economy to technology and monetary policy shocks are typically based on systems of small dimensions, matching the dimension of the typical structural macroeconomic model[6]. However, the structural analysis may be affected by informational assumptions[7]. For example, when

[4]See Gali (1999).
[5]See Finn E. Kydland and Edward C. Prescott (1982).
[6]They range from four variables in Gali (1992), to about ten variables in the richest specification (as, for example, in Altig, Christiano, Eichenbaum, and Evans, 1999).
[7]See for example Forni, Giannone, Lippi, and Reichlin (2005) and Giannone and Reichlin (2006).

identifying the monetary shock, it is important to condition on the relevant information set of the central bank, possibly containing many conjunctural indicators and financial variables. The empirical relevance of taking into account such information has been shown in frameworks related to factor analysis[8]. Bambura, Giannone and Reichlin (2007) show that standard Bayesian VAR models are an appropriate tool for large panels of data and constitutes a valid alternative to factor models for dealing with the curse of dimensionality problem. I therefore estimate a Bayesian VAR model with a large number of variables. This paper follows the structural VAR literature in making explicit identifying assumptions to isolate estimates of monetary policy and aggregate technology behavior and its effects on the economy, while keeping the model free of the many additional restrictive assumptions needed to give every parameter and equation a behavioral interpretation. I adopt several identification schemes for the two structural shocks to assess the robustness of the findings to different assumptions about the impact of monetary policy and neutral technology shocks on the economy.

Finally, recent empirical evidence on the disaggregated frequency of price adjustment has casted doubts on the belief that prices are generally adjusted with low frequency and has therefore opened the question of whether existing models

[8]See Bernanke, Boivin, and Eliasz (2005), Favero, Marcellino, and Neglia (2005), Giannone, Reichlin, and Sala (2004) and Stock and Watson (2005b).

of price rigidity provide a good representation of firms pricing behavior[9]. Boivin, Giannoni and Mihov (2008) reconcile the contrasting evidence from aggregate and disaggregate data suggesting that prices may indeed adjust with different speeds and frequencies to aggregate and sectorial level shocks. This paper provides evidence that even within aggregate shocks there is substantial difference in the speed of price adjustment.

The paper is organized as follows. In section 2 I describe the Bayesian VAR model, the data and the associated prior assumptions. In section 3 I state the benchmark identification assumptions about the two structural shocks and describe the impulse responses of aggregate prices to each of them. In section 4 I define the measures of price responsiveness and use them to answer the question of wether, by how much and with what probability prices adjust faster to neutral technology shocks than to monetary policy shocks. In section 5 I assess the robustness of my findings against the main assumptions behind my procedure. Section 6 concludes.

1.2. BVAR model

I consider the following VAR(p) model:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + u_t, \tag{1.1}$$

[9]See Blinder, Canetti, Lebow, and Rudd (1998) and Bils and Klenow (2004).

where $Y_t = (y_{1,t}\ y_{2,t}\ ...y_{n,t})'$ is the vector of observations at period t, u_t is an n-dimensional white noise with covariance matrix $Eu_t u_t' = \Psi$, $c = (c_1\ c_2\ ...\ c_n)$ is a vector of constant and B_1, B_2,.., are the $n \times n$ autoregressive matrices.

The vector Y_t can potentially include a large number of variables. I therefore follow Bambura et al. (2007) and estimate the model (3.1) using the Bayesian VAR approach to overcome the curse of dimensionality. I therefore impose priors beliefs on the parameters of the model. These priors are set according to the standard practice which builds on Litterman (1986)'s suggestions and it is often referred as Minnesota priors. Let us write the VAR (3.1) as a system of multivariate regressions:

$$\underset{T\times n}{Y} = \underset{T\times k}{X}\ \underset{k\times n}{B} + \underset{T\times n}{U}, \tag{1.2}$$

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 belief is that (B, Ψ) have a normal inverted-Wishart distribution:

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

The parameters S_0, α_0, B_0 and Ω_0 are chosen so that all the coefficients of B_1, B_2,.., B_p, denoted by $\left(B_k\right)_{ij}$, $k = 1, ..p$, $i = 1, 2.., n$, $j = 1, 2, ..n$, are independent and normally distributed with means and variances given by

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

$$V\left((B_k)_{ij}\right) = \frac{\lambda^2}{k^2}\frac{\sigma_i^2}{\sigma_j^2}$$

and with the matrix of variance covariance of residuals u_t, Ψ, having a mean of $E(\Psi) = diag(\sigma_1^2, ..., \sigma_n^2)$. The prior on the intercept is diffuse. The idea of such prior beliefs is that each component i of Y_t follows a random walk with drift, $\delta_i = 1$, if the variable i has high persistence, or a white noise, $\delta_i = 0$, otherwise. The parameter λ controls the tightness of the prior distribution and defines the weight given in the posterior distribution to the priors beliefs relative to the information coming from the data. The larger is λ, the smaller is the weight of priors into the posterior distribution. The factor k adjusts the prior variance for the lag length, while $\frac{\sigma_i^2}{\sigma_j^2}$ controls for the variability of different data. I set the scale parameters σ_i^2 equal the variance of a residual from a univariate autoregressive model of order p for the variables y_i. The prior is implemented by adding T_0 dummy observations[10], Y_0 and X_0 to the system in (3.2). This is equivalent to imposing a normal inverted-Wishart prior with $B_0 = (X_0'X_0)^{-1} X_0'Y_0$,

[10]See Bambura, Giannone and Reichlin (2007) for more details.

$\Omega_0 = (X_0' X_0)^{-1}$, $S_0 = (Y_0 - X_0 B_0)' (Y_0 - X_0 B_0)$ and $\alpha_0 = T_0 - k - n - 1$. It follows that the dummy-augmented VAR model is:

$$\underset{T_* \times n}{Y_*} = \underset{T_* \times k}{X_*} \underset{k \times n}{B} + \underset{T_* \times n}{U_*}, \tag{1.3}$$

where $T_* = T + T_0$, $X_* = (X', X_0')$, $Y_* = (Y', Y_0')'$ and $U_* = (U', U_0')'$. The posterior distribution of (B, Ψ) is a normal inverted-Wishart[11]:

$$\Psi | Y \backsim iW (S_*, \alpha_*) \quad \text{ and } \quad B | \Psi, Y \backsim N (B_*, \Psi \otimes \Omega_*), \tag{1.4}$$

where $B_* = (X_*' X_*)^{-1} X_*' Y_*$, $\Omega_* = (X_*' X_*)^{-1}$, $S_* = (Y_* - X_* B_*)' (Y_* - X_* B_*)$ and $\alpha_* = T_* - k + 2$.

1.2.1. Data and priors

I consider two different VAR models. The first model is a parsimonious 5 variables VAR (small VAR), including labor productivity (GDPQ/LBMNU) and hours worked (LBMNU) as a measure of real activity, the nominal interest rate (FYFF) as a proxy for the monetary policy instrument, the GDP price deflator (PGDP) as a measure of aggregate prices and the Standard and Poor's stock price index

[11] To insure the existence of the prior expectation of Ψ it is necessary to add an improper prior $\Psi \tilde{} \, |\Psi|^{-(n+3)/2}$.

(FSPCOM) as an indicator for the financial markets. The parsimonious model has the advantage of being less exposed to the curse of dimensionality problem than larger models. This allows me to set a diffuse prior on the reduced form autoregressive matrices. This is equivalent to set λ to ∞.

The disadvantage of the small model is that it may be missing relevant information and provide unreliable estimates of the structural shocks[12]. Therefore I also study a larger VAR model with 23 macroeconomic indicators (large VAR).

In addition to the variables of the small VAR, the large VAR includes 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).

[12]Giannone and Reichlin (2006) shows the potential shortcomings of estimating structural parameters into a VAR with missing information.

I deal with the curse of dimensionality problem associated to the large number of variables by setting λ to 0.1 similarly to Bambura et al. (2007)[13]. Variables are transformed so to have a stationary VAR. The appendix contains details on whether variables are entered in levels, logarithms or log-differences. The need of stationarity comes from the fact that the identification strategy of structural parameters adopted in the paper requires the matrix $(I - B(1))^{-1}$ to be finite, where $B(1) = B_1 + ... + B_p$. The time span is from January 1960 through June 2007. I estimate the reduced form VAR in (3.3) on a quarterly frequency[14] and set the number of lags p to 4. I use the white noise prior, $\delta_i = 0$, for all but one variable. This is because all the variables for which there is high persistence are entered in the VAR in log-differences to preserve stationarity[15]. The only variables for which I set a random walk prior is the nominal interest rate, which has high enough persistence but is stationary and therefore enters the model in levels[16].

[13] Later in the paper I consider different values for λ.

[14] Whenever the original data is at the monthly frequency I transorm it into quarterly taking the average of the months over the quarter.

[15] The choice of these priors is consistent with BGR and Stock and Watson (2005). I set a white noise prior any time a variables that enter in levels in BGR, and has a random walk prior there, is entered in differences in my model. The other priors are set as in BGR.

[16] I also considered the case where interest rates have a white noise prior. The results of the paper are unchanged.

1.3. Identification and Impulse responses

The structural VAR associated to (3.1) can be written as

$$A_0 Y_t = \upsilon + A_1 Y_{t-1} + ... + A_p Y_{t-p} + e_t, \tag{1.5}$$

where $\upsilon = A_0 C$ is the vector of constant variables, $A_s = A_0 B_s$ is the s^{th} order autoregressive matrix of the structural model, and $e_t = A_0 u_t$ is the vector of structural shocks realizations at time t. In order to recover the parameters of the structural model from the estimated reduced form (3.1), I impose restrictions on the matrix of structural parameters A_0. I am interested in the impulse responses of the system defined in (3.5) to two of the n structural shocks. This means that I need only to impose enough restrictions so to be able to recover the columns of A_0^{-1} relative to the neutral technology and monetary policy shocks, independently of the response of the system to the remaining shocks.

The first identifying assumption is that only neutral technology shocks may have a permanent effect on the level of labor productivity, as originally proposed in Gali (1999). This restriction is satisfied by a broad range of business cycle models, under standard assumptions.

The other assumptions specify the monetary policy rule according to the popular recursive identification scheme in Christiano, Eichenbaum, and Evans (1999).

In particular the monetary policy shock is identified as the residual to the following equation

$$S_t = f(\Omega_t) + \sigma^s \varepsilon_t^s, \tag{1.6}$$

where Ω_t is the information available to the central bank as of time t, S_t is the monetary policy instrument and ε_t^s is the monetary policy shock. I follow Christiano, Eichenbaum, and Evans (1999) and set S_t equal to the 3-months Federal Funds rate[17]. I then order the variables in the model as $Y_t = (\Delta_t, X_t, S_t, Z_t, F_t)'$, where Δ_t is the growth rate in labor-productivity, X_t contains slow-moving variables, S_t is the monetary policy instrument, Z_t and F_t contains fast-moving variables. The identifying assumption is that slow-moving variables and labor productivity do not respond contemporaneously to a monetary policy shock and that the fast moving variables Z_t are not part of the information set Ω_t, which is equivalent to say that the monetary policy instrument is not set in response to contemporaneous realizations of this subset of variables. There is no restriction on F_t in the sense that F_t is included in Ω_t but at the same time it is allowed to respond to contemporaneous changes in the monetary policy instrument S_t. Similarly to

[17]Results are invarian to using different varables as monetary policy instruments as non-borrowed reserves or M1 and M2 money growth. This is consistent with the results obtained by Christiano, Eichenbaum and Evans (1999).

Christiano, Eichenbaum and Evans (1999) Z_t includes both M1 and M2 monetary stock, non-borrowed reserves and total reserves. The variables in Z_t enter Ω_t only with a lag. The S&P stock price index is instead included in F_t allowing in principle the monetary authority to respond contemporaneously to changes in asset prices. All the other variables are included in X_t. I finally impose the following sign restrictions: I normalize the diagonal elements of A_0^{-1} so that the monetary policy shock is associated to an increase in the Federal Funds rate in the period of the shock, while the neutral technology shock is associated to a permanent increase in labor productivity. With this set of restrictions the monetary policy and neutral technology shocks are exactly identified[18].

1.3.1. Drawing from the posterior and the associated impulse responses

In this section I compute the median, the 68^{th} and the 90^{th} quantiles associated to the posterior distribution of the impulse responses to neutral technology and monetary policy shocks. Given the restrictions above, and given the estimates of the reduced form VAR parameters (B, Ψ), the matrix of structural parameters A_0 is obtained through the procedure described in Ramirez, Waggoner and Zha (2007). Given the estimates of the reduced form VAR parameters (B, Ψ) I can

[18] See the Appendix for details.

draw from the posterior distribution in (3.4). For each draw of (B, Υ) I compute the associated A_0 and obtain the impulse responses to the two identified shocks.

Tables 1 plots the median impulse responses, and the associated 68 and 90 percent confidence intervals, of the Federal Fund rate, the GDP price deflator, output and inflation to aggregate neutral technology and monetary policy shocks. In the small model, the responses of the price level and inflation to the monetary policy shock are never statistically different from zero. The median response of the price level to such a shock is approximately zero for about 15 quarters before turning negative. In the large model the median price level response to such a shock is zero for the first 8 quarters, and only after turns negative and starts converging to the new long-run level. Relatively to the smaller model, however, in the large model inflation and price response to the monetary policy shock become statistically different from zero after approximately 8 and 12 quarters respectively. This evidence confirms the results of the existing empirical literature on the response of aggregate prices to monetary policy shocks. Similarly to Bambura et al. (2007) the larger model reduces substantially the uncertainty surrounding impulse responses to the monetary policy shock when compared with the small model. This is due mostly to the greater amount of information available in the large model[19]. The

[19] When I set λ to 0.1 for the small model as well, I do not get a reduction in uncertainty about impulse responses. This suggests that tighter priors are not the cause of the better performance of the large model over the small one.

fact that the aggregate prices response to the monetary policy shock is not statistically different from zero in the small model provides support for the view that the stickiness in the response of prices to the monetary policy shock obtained in the large BVAR model is not the outcome of the Minnesota priors imposed on the system.

Turning to the impulse responses to the neutral technology shock, both inflation and the price level responses are statistically different from zero in the quarters immediately after the shock. This suggest that prices start adjusting to these shocks immediately. The persistency in inflation reflects the persistence in labor productivity growth. The price level has already accomplished most of its long run-response to the technology shock 8 quarters after the shock. This suggests that the adjustment in prices is substantially faster to this type of shock than to the monetary policy shock. This evidence holds in both large and small models.

Tables 2 plots the responses of the other variables of the large VAR to the two shocks. The impulse responses of the other measures of prices to the two shocks resemble the ones obtained for the GDP price deflator.

Tables 1 and 2 contain the forecast error variance decompositions for different measures of aggregate prices in the large model and for the GDP price deflator in the small model. No matter what the index of aggregate prices is or what the model we look at is, the neutral technology shock accounts for a large fraction of the forecast error decomposition at all horizons of forecast, ranging from a minimum of 16 percent for the PPI with 2 quarters forecasting horizon, to a maximum of 46 percent for the PGDP at 16 quarters forecast horizon. In contrast the impact of the monetary policy shock on the forecast error variance of prices is negligible at all horizons and for all measures of prices.

1.4. Difference in price responsiveness

The previous section provided information on the responsiveness of aggregate prices to the two types of shocks. Here I take a more systematic approach to the measurement of price responsiveness and derive two different measures for this purpose. These two measures are meant to capture the relative speed with which prices adjust to their long-run price level, taking into account for the fact that these two shocks have potentially different impacts on the economy and therefore on prices.

The first measure of price responsiveness is defined as the time it takes for prices to complete the fraction α of the long-run adjustment to a particular shock. It is given by

$$\tau_{\alpha,s} = \min_{j} \left\{ j \in [0, 1, 2, ...) \, | \gamma_{j,s} \leq \alpha \bar{\gamma}_s \right\}, \tag{1.7}$$

where $\alpha \in (0,1)$, $\gamma_{j,s}$ is the impulse response of the price level to shock s evaluated j periods after the shock, while $\bar{\gamma}_s$ is the long-run response of the price level to shock s. For simplicity, the signs of $\gamma_{j,s}$ and $\bar{\gamma}_s$ are normalized so that $\bar{\gamma}_s$ is always negative. The long-run response $\bar{\gamma}_s$ is defined as the price level response 5 years after the shock[20]. I label the neutral technology and the monetary policy shocks z and r respectively, so that the measure of difference in price responsiveness is $\tau_\alpha = \tau_{\alpha,r} - \tau_{\alpha,z}$. Finally I set α equal to 0.5 and drop the subscript from τ_α.[21] Intuitively τ measures how many quarters more it takes for the price level response to accomplish half of the long-run response to the monetary policy shock than to accomplish half of the long-run response to the neutral technology shock.

The second measure of price responsiveness is defined as the fraction of the long-run price adjustment accomplished by the price level j periods after the shock. It is given by

$$\psi_{j,s} = \frac{\gamma_{j,s}}{\bar{\gamma}_s}. \tag{1.8}$$

where $\gamma_{j,s}$ and $\bar{\gamma}_s$ are defined as above. According to this measure, the closer is the price level to its long-run level when evaluated j periods after the shock, the

[20]Th results that follow are unaffected by this choice. If I consider a longer horizon to measure the long-run price response, I get very similar answers in terms of differences in price responsiveness.
[21]The results are qualitatively unchanged for different values of α.

faster it has adjusted to that shock. The difference in price responsiveness is then measured as $\psi_j = \psi_{j,z} - \psi_{j,r}$. I set j to 8 quarters[22].

1.4.1. Results from the posterior draws

I draw 5,000 times from the posterior distribution of (B, Υ) in (3.4). For each draw I compute τ and ψ. According to the large model, at the median it takes 6 quarters more for the GDP price deflator to accomplish half of the long-run response to the monetary policy shock than to the neutral technology shock. Similar considerations hold for the other measure of difference in speed of prices adjustment ψ : 8 quarters after the shock, the median difference in the fraction of the long-run response accomplished by the GDP price deflator to the two shocks is 0.44. Therefore the GDP price deflator adjusts in median much faster to the neutral technology shock than to the monetary policy shock. Furthermore I can reject the null hypothesis that prices adjust to monetary policy shocks at least as fasts as they do to neutral technology shocks with a 95 percent probability according to both types statistics. These results hold not only for the GDP price deflator but also for the other measures of aggregate prices such as consumer and producers price indices, or personal consumption price deflator. There is therefore a large difference in the

[22]The results are qualitatively unchanged for different values of j.

speed with which prices adjust to the two structural shocks. This difference is independent of the index used to measure speed of adjustment.

I characterize the draws on the basis of the sign of the long-run price response. According to standard new-Keynesian and real business cycle models, prices in the long-run are expected to be permanently lower after both a positive permanent neutral technology shock and a positive shock to the Federal Fund rate. I therefore consider the price response to have the *wrong sign* anytime its long-run value is positive, and right otherwise. To better characterize the responsiveness of prices to the two structural shocks I distinguish the draws that deliver long-run impulse responses $\bar{\gamma}_s$ with the *right sign*, from those that fail to deliver that to at least one shock. The former subset of draws is labeled R, while the latter is labeled W. Tables 3 and 4 contain the relevant statistics for τ and ψ. The fraction of draws in R is much higher in the large model than in the small one, 0.94 and 0.58 respectively. More information is therefore useful in bringing price impulse responses closer to what predicted by standard theory. Furthermore, the fraction of draws in W due exclusively to monetary policy shocks drops from 0.89 in the small model to 0.53 in the large model. According to the measure of relative price responsiveness τ, the posterior probability that the GDP price deflator adjusts faster to the neutral technology shock than to the monetary policy shock is 0.95 in the large model and 0.64 in the small one. Most of the difference in the results across the two models is due to fewer draws in the small model that have the *right sign*. In fact, when I consider only draws within the subset R, the probability that the GDP price deflator adjusts faster to the neutral technology shock rises to 0.98 and 0.83 in the large and small model respectively. Therefore almost all of the events in which prices adjust faster to the monetary policy shock are when the price long-run response to at least one of the two shocks has the *wrong sign*.

1.5. Robustness analysis

In this subsection I investigate to what extent results above are robust to several features of my procedure, such as the identification assumptions, the way data is entered into the model and the frequency of the observations. The insights from these exercises reinforce the results obtained in the previous sections. To save on space I will only report results for the aggregate GDP price deflator as the other three measures of aggregate prices share very similar results.

1.5.1. A Solow-residual based identification for technology

The identifying assumption adopted for the neutral technology shock in the benchmark model requires that the technology shock is the only shock affecting labor productivity in the long-run. This restriction holds in a wide class of business cycle models. An advantage of this approach is that I do not need to make all the usual assumptions required to construct Solow-residual based measures of neutral technology shocks. Examples of these assumptions include corrections for labor hoarding, capital utilization, and time-varying markups. Of course there exist models that do not satisfy my identifying assumption. For example, the assumption is not true in an endogenous growth model where all shocks affect productivity in the long run. Nor is it true in an otherwise standard model when there are permanent shocks to the tax rate on capital income. To address the plausibility of my identification scheme I compare the results above with the ones obtained through a different identification assumption for the neutral technology shock. In particular I use a measure of quarterly total factor productivity growth (FTFP) estimated by Fernald (2007) on the basis of the annual equivalent estimated in Basu et al.(2006) using conventional growth accounting methods. This is a Solow-residual measure of productivity growth which explicitly accounts for variable capital utilization and labor hoarding. The identifying assumption for the neutral technology shock here is that the latter is the only shock affecting FTFP in the long-run. This procedure has been originally applied by Christiano et al. (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[23]. The

[23]I get similar results in this paragraph if I do not impose long run restrictions on FTFP but assume instead that FTFP is true measure of TFP growth and therefore exogenous.

restrictions required to jointly identify the monetary policy shock are unchanged from above[24]. I apply these identifying restrictions to the large model.

First of all there is a 0.94 positive correlation between the estimates of technology shocks from the benchmark identification scheme and the estimates of technology shocks obtained with the Solow-residual based identification. This result by itself should be enough to argue that the properties relative to the difference in price responsiveness are unchanged from what showed above. Tables 3 plots the two series of estimates for the neutral technology shocks which indeed almost overlap for the entire sample. The labor productivity based identification provides a slightly more volatile estimate of the shock, most likely reflecting more idiosyncratic noise associated with such a measure. Tables 4 plots the impulse responses of output, inflation, prices and interest rates to the two shocks. The shape and dynamic properties of the responses are very similar to the ones obtained from the benchmark identification scheme. Prices start adjusting to the neutral technology shock right after the shock and complete most of the adjustment within 2 years from the shock, while the response of prices to the monetary policy shock is approximately zero for the first 2 years and only afterwards prices starts adjusting towards the new long-run equilibrium. The statistics for τ and ψ in Table 4 are

[24]In practice I add FTFP to the system in (3.1) and order the variable first in Y. Then I apply the same identification algorithm from above. Of course now the long-run restrictions are imposed on FTFP and not on labor productivity growth.

extremely similar to the ones relative to the benchmark identification scheme and confirm the fact that according to τ and ψ prices adjust faster to technology than to monetary policy shocks with a 95 percent probability at least.

1.5.2. Identifying the monetary policy and neutral technology shocks through sign restrictions

In this paragraph I assess the robustness of the results above to a different identification scheme for both the neutral technology and the monetary policy shock. In particular, I use an agnostic method which relies on imposing sign restrictions to the impulse responses to each of the two types of shocks. This method has been applied by Uhlig (2006) to the identification of the monetary policy shock, and by Dedola and Neri (2007) to the identification of the neutral technology shock. It has the advantage of not imposing a zero restriction on the contemporaneous response of aggregate prices to the monetary policy shock. Intuitively this identification scheme treats the price responses to the two shocks *symmetrically* from an identification standpoint. This is important to assess the robustness of the results from the benchmark large BVAR model. In that model the assumed white-noise prior on inflation coupled with the zero identification restriction on the contemporaneous response of prices to the monetary policy shock was equivalent to assume ex-ante that prices do not respond at all to the monetary policy shock. On the inverse the same prior, coupled with the long-run restriction to the neutral technology shock, supposes that the response of prices to the neutral technology shock is an immediate jump to the new equilibrium price level. Although I have already addressed the role of the prior for the results on the different price responsiveness when comparing the impulse responses from the small and the large model, in this paragraph I provide an additional check of the robustness of the results. I therefore use only sign restrictions to identify the two shocks. These restrictions, coupled with the Minnesota-type prior on aggregate prices, do not impose ex-ante any asymmetry in the responsiveness of prices to the two types of shocks: according to these assumptions prices are expected to adjust to both structural shocks with an immediate jump to new long-run price level. Any difference in the posterior distribution of price impulse responses to the two shocks has to come from the observed data. From a Bayesian point of view, sign restrictions amount to attributing probability zero to reduced-form parameter realizations 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. I can thus use standard Bayesian methods for estimation and inference, obtaining measures of the statistical reliability of estimated impulse responses. Therefore the posterior distribution of the reduced form parameters is the same as in (3.4). The algorithm to compute the posterior distribution of the impulse responses associated to each shock is the same proposed by Ramirez et al. (2007)[25]. The sign restrictions imposed on the impulse responses to the monetary policy and neutral technology shocks are in Table 7 and are similar to the ones imposed by Uhlig (2006), and Dedola and Neri (2006) respectively[26].

Although I have adopted a very different identification scheme from the benchmark one, the answer to the question of whether prices adjust faster to neutral technology shocks than to monetary policy shocks is unchanged. According to both τ and ψ, the posterior probability that prices adjust faster to neutral technology shocks is 91 percent. The medians for τ and ψ reported in Table 6 are 5 quarters and 39 percent respectively. The impulse responses for the price level in Tables 5 show that the median price response to the monetary policy shock is zero for the first 2 quarters, and only after that starts very slowly going below zero towards the long run response. The price response to the neutral technology shock is much faster, so that 4 quarters after the shock prices have accomplished almost all of the adjustment towards the new long-run equilibrium. Notice that I have not imposed sign restrictions on the other measures of aggregate prices. However, given the high correlation in the data between these measures and the GDP price

[25] I draw 5,000 times from the posterior distribution and for each draw of reduced form parameters I draw A_0.

[26] I refer to these authors for a discussion of the ability of these restrictions to distinguish the neutral technology and monetary policy shocks from the other shocks.

deflator, they will be indirectly influenced to some extent by the sign restriction on the latter. In any case, statistics for τ and ψ relative to consumer and producer price indices are very similar to the ones obtained for the GDP price deflator.

Another advantage of the sign restrictions identification scheme over the more standard identification adopted in the sections above is that it does not require the system to be specified in terms of stationary variables. I have therefore estimated the system in (3.3) with the following change: all variables that were entered in log-differences are instead entered in logs, and have an associated random walk prior, $\delta_i = 1$, instead of the white-noise prior. Results about the difference in price responsiveness to the two shocks are very similar to the ones obtained from the model specified in terms of stationary variables and therefore are omitted. All these results are very supportive of the thesis that prices adjust much faster to neutral technology than to monetary policy shocks.

1.5.3. Monthly frequency

The empirical literature investigating the response of macroeconomic variables to monetary policy shocks in the context of structural vector autoregression models makes often use of monthly frequency data[27]. The advantage of using monthly

[27] For instance Christiano et al. (1999) uses quarterly data while Bambura et al (2007), Bernanke et al. (2004) and Uhling (2006) use monthly data.

data over lower frequencies is that the benchmark identification for the monetary policy shock one requires variables not to respond to the monetary policy shock for a month instead of a quarter. Unfortunately some of the economic variables needed to identify the two shocks are unavailable at the monthly frequency, for instance real output. In this paragraph I use interpolated variables anytime the monthly observation is unavailable[28] and estimate the VAR at the monthly frequency. I therefore set the number of lags p to 13 and the hyper-parameter λ to 0.1. Data is available from January 1964 to June 2006. The estimation and identification method is identical to the benchmark version of the model.

Tables 6 plots the impulse responses for output, inflation, prices and FedFunds rates to monetary policy and neutral technology shocks. Interestingly, the median inflation following a neutral technology shock is substantially larger in the first month after the shock relative to the following months, suggesting an even greater speed of price adjustment to such a shock than estimated in the quarterly model. This different behavior of inflation is not explained by the difference in sample period: when I run the quarterly VAR on the same sample of the monthly model, I obtain impulse responses very similar to the full sample. Therefore the difference

[28]Variables unavailable at the monthy frequency are: real GDP, real non-residential and residential investments and GDP price deflator. I therefore use Sims and Zha (2007)'s interpolated equivalents. The sample at the montlhy frequency is 1964:1-2006:6. See the appendix for more details.

has to be attributed simply to the fact that by construction the quarterly model deliver an average of the response for the quarter, but for a given mean inflation can be large in the first month and small in the following two.

The response of inflation to monetary policy shocks is not statistically different from zero for about 2 years after the shock, and only after start to become negative. This is as in the benchmark quarterly model. The medians for τ and ψ, reported in Table 8, are 19 months and 53 percent respectively. The posterior probability that prices adjust faster to neutral technology than to monetary policy shocks according to τ and ψ is at least 0.93.

1.5.4. Priors tightness

In the benchmark large VAR model I choose a value of λ equal to 0.1. This has helped dealing with the curse of dimensionality problem. This value is also close to the one adopted by Bambura et al. (2007) in a similar model. In this paragraph I investigate the robustness of the results above to several values of λ.[29] Tabless 7 and 8 plot the impulse responses of inflation, FedFunds rates, prices and output for λ equal to 0.07 and 0.5 respectively. In both cases prices adjust faster to neutral technology shocks than to monetary policy shocks. In general,

[29] Following Bambura et al. (2007), I derive the value of λ that minimizes the difference in the in-sample fit of the large model from the small one ($\lambda = \infty$). This method controls for overfitting while keeping the models comparable. According to this procedure λ is 0.07.

price impulse responses resemble the ones obtained in the benchmark specification. However for the case of a looser prior ($\lambda = 0.5$) there is more uncertainty associated with the impulse responses. This is a consequence of the combination of the relatively small data sample with the loose prior, and is therefore due to the curse of dimensionality problem. Tables $9 - 12$ contain the main statistics regarding τ and ψ estimated in the large model for different values of λ. Independently from the value of λ adopted, aggregate prices adjust faster to neutral technology shocks than to monetary policy shocks. As λ increases however the fraction of draws with the *right sign* in R decreases.

1.6. Conclusions

This paper answers the question of whether, by how much and how likely it is that prices adjust faster to aggregate technology than to monetary policy shock. I find that prices adjust much faster to aggregate technology shocks than they do to monetary policy shocks with a very large probability. For instance, it takes in median about 6 quarters less for the aggregate GDP deflator to accomplish half of its long-run response to a permanent technology shock than it takes to accomplish half of its long-run response to a monetary policy shock. The difference in price responsiveness is statistically significant and robust to different identification assumptions, model specifications and priors. The estimated probability from a large Bayesian VAR model that aggregate prices adjust faster to technology shocks ranges from 0.91 percent to 0.99 percent depending on the identification assumptions, data definition and measure used.

CHAPTER 2

The Responsiveness of Prices to Technology and Monetary Policy Shocks under Rational Inattention

2.1. Introduction

I study the responsiveness of prices to aggregate total factor productivity (TFP) and monetary policy shocks in the context of a general equilibrium model in which price setters have limited information processing capabilities and allocate attention across the different types of shocks impacting on profit-maximizing prices, along the lines of Mackoviak and Wiederholt (2007). The responsiveness of prices to different types of shocks has received considerable attention in the last decade. A recent literature has developed trying to account contemporaneously for the slow response of prices to aggregate nominal shocks and for the quick response of prices to firm specific idiosyncratic shocks[1]. The high frequency with which firms change their prices has called into question the ability of standard new-Keynesian

[1]See for instance Altig, Christiano Eichenbaum and Linde (2005), Golosov and Lucas (2006), Midrigan (2006), Mackoviak and Wiederholt (2007).

sticky price models in accounting for both aggregate and disaggregate behavior of prices[2]. A relatively more recent literature has focused on price responsiveness to two fundamental aggregate shocks, TFP and monetary policy shocks. According to empirical evidence from structural vector autoregression models, prices adjust much faster to aggregate TFP shocks than to monetary policy shocks: it takes about 19 months more for prices to reach 50 percent of the long-run price response to a monetary policy shock than to reach 50 percent of the long-run price response to an aggregate TFP shock[3]. This evidence is hard to reconcile with standard new-Keynesian sticky price models[4].

In this paper I derive the conditions under which models of price setting under rational inattention can generate substantial differences in price responsiveness to aggregate TFP and monetary policy shocks. I characterize analytically the role of monetary policy and strategic complementarities in price setting in influencing the difference in price responsiveness to the two types of shocks. I compare price responsiveness in such a model with the one obtained in more standard new-Keynesian models of price stickiness. I show that the same monetary policy can have very different implications in terms of price responsiveness to the two types of shocks across the two different classes of models. These differences arise because

[2]See Bils and Klenow (2004).
[3]See Paciello (2008a, 2008b) for empirical evidence on aggregate and disaggregate prices.
[4]See Dupor, Han and Tsai (2007).

of the additional impact monetary policy has on price responsiveness through the attention allocation decision. For instance, if the monetary policy is more accommodating towards TFP shocks, it reduces the responsiveness of the price level to this type of shocks both in models with price setting under rational inattention and in models with sticky prices. In the former, however, it also reduces price responsiveness to the TFP shocks by causing a smaller allocation of attention to such a shock. Everything else being equal, if the fraction of profit-maximizing price volatility due to aggregate TFP shocks is larger (smaller) than the one due to monetary policy shocks, the monetary policy has to be relatively more (less) accommodating towards TFP shocks to achieve a given target for price responsiveness to the two types of shocks when compared with the monetary policy needed in more standard sticky prices models.

The paper also deals with the impact of strategic complementarities in price setting on price responsiveness. I show that these complementarities have different implications for price responsiveness to the two aggregate shocks across the different classes of price setting models. In particular, more complementarities in price setting magnify the asymmetry in price responsiveness to the two types of shocks in models with attention allocation, while they reduce this asymmetry in more standard models of price rigidity. In fact, if firms allocate attention across the different types of shocks, there is an additional channel through which complementarities in price setting influence price responsiveness: more strategic complementarities in price setting imply more complementarities in the allocation of attention decision[5]. Each firm has higher incentives to allocate attention to one type of shock when its competitors allocate more attention to that shock. These incentives generate a coordination in the allocation of attention decision toward the same type of shock and away from the other one. Therefore more complementarities amplify the asymmetry in price responsiveness to the two aggregate shocks.

These results are important because the different predictions about the impact of a change in monetary policy and in strategic complementarities in price setting on the difference in price responsiveness to the two types of shocks offer powerful tests of models of price setting under rational inattention against more standard models of price rigidity[6].

I consider a simple general equilibrium model with a representative household, a private sector and a central bank. There is a large number of monopolistically competitive firms which set prices under rational inattention and decide how much attention to pay to the response of profit-maximizing prices to each type of shock. In general, they will pay more attention to the shock that accounts for the larger

[5]Hellwig and Veldkamp (2007) show that strategic complementarities in price setting imply complementarities in the acquisition of information.
[6]Paciello (2008b) studies empirically the impact of strategic complementarities in price setting on price responsiveness to TFP and monetary policy shocks.

fraction of the profit-maximizing price volatility. Everything else being equal, the more attention firms pay to a type of shock the faster prices adjust to that shock. There are only two types of shocks in the economy, an aggregate TFP shock and a monetary policy shock. Each monopolistically competitive firm has a production technology that mixes labor and intermediate inputs similarly to Basu (1995) and Nakamura and Steinsson (2007). There is therefore a round-about type supply according to which each unit of output can be used both as a final good and as an intermediate input. The larger is the share of intermediate inputs into nominal marginal costs the larger strategic complementarities in price setting are. Once I approximate the dynamics of the economy around the non-stochastic steady state I solve analytically for the rational inattention problem and derive the equilibrium price responsiveness to each type of shock.

The paper is organized as follows. Section 2 introduces the model. Section 3 describes the solution of the model and implications for relative price responsiveness. Section 4 consider how a Taylor type monetary policy rule affects the difference in price responsiveness to technology and monetary policy shocks. Section 5 contains interesting extensions to the benchmark model. Section 6 concludes.

2.2. Model

There is a measure 1 of different intermediate goods, indexed by $i \in [0, 1]$, each produced by one monopolistic firm using labor and intermediate inputs as the only factors of production. Along the lines of Basu (1995) and Nakamura and Steinsson (2007), there is an aggregate composite good, which can be used both for consumption by households and for production by intermediate good producers. The aggregate composite good is produced by a perfectly competitive sector using a continuum of intermediate goods according to a Dixit-Stiglitz technology with constant return to scale. The assumption that intermediate good producers use the composite good as an input increases strategic complementarities in price setting. On the consumption side, there is an infinitely-lived representative household, with preferences defined over the final consumption good and labor supply in each period. There is a risk free zero coupon bond traded by the household, with zero initial supply. A central bank controls the nominal rate of interest in a cashless economy.

The information structure of the economy is modeled along the lines of Maćkoviak and Wiederholt (2007), with prices set under rational inattention. Intermediate good producers have limited information processing capabilities and therefore make their price choices under rational inattention. I assume for simplicity that the other agents of the economy take their decisions under complete information. Each intermediate good producer sets the nominal price on the basis of its own information, and intermediate goods are traded at the posted prices. Production factors are hired to satisfy the incoming demand.

Household preferences: The representative household's preferences over sequences of the composite consumption good and labor supply $\{C_{t+\tau}, L_{t+\tau}\}_{\tau=0}^{\infty}$ are given by:

$$U_t = E_t \sum_{\tau=0}^{\infty} \beta^{\tau} \left(\log\left(C_{t+\tau}\right) - \frac{\psi_0}{1+\psi_l}\, L_{t+\tau}^{1+\psi_l} \right), \tag{2.1}$$

where $\beta \in (0,1)$ is the discount factor, and $\mathrm{E}_t(\cdot)$ denotes the household's expectations conditional on the realizations of all variables up to period t. The household has therefore complete information. The household's objective is to maximize (2.1) subject to its sequence of flow budget constraints, for $\tau = 0, 1, ...$

$$p_{t+\tau} C_{t+\tau} + \frac{B_{t+\tau}}{R_{t+\tau}} = B_{t+\tau-1} + w_{t+\tau} L_{t+\tau} + \pi_{t+\tau}, \tag{2.2}$$

where $B_{t+\tau}$ denotes the household' s demand of nominal bonds, $R_{t+\tau}$ the risk free nominal interest rate, $p_{t+\tau}$ the price of the consumption good, $w_{t+\tau}$ the nominal wage rate and $\pi_{t+\tau}$ the nominal aggregate profits rebated to the household. In addition, the household is subject to the following borrowing constraint that prevents it from engaging in Ponzi schemes:

$$\lim_{\tau \to \infty} E_t q_{t+\tau+1} B_{t+\tau} \geq 0, \tag{2.3}$$

at all dates and under all contingencies. The variable q_t represents the period-zero price of one unit of currency to be delivered in a particular state of period t divided by the probability of occurrence of that state given information available at time 0 and is given by $q_t = \frac{1}{R_1 R_2 ... R_t}$, with $q_0 = 1$.

Composite good producers: The composite good, Y_t, is produced by a large number of producers through a constant returns to scale technology given by

$$Y_t = \left[\int_0^1 (y_{it})^{\frac{\theta-1}{\theta}} \, di \right]^{\frac{\theta}{\theta-1}}. \tag{2.4}$$

The demand for intermediate good i follows from the maximization of profits of the composite goods producers and it is given by

$$y_{it} = y\left(p_{it}\right) = Y_t \left(\frac{p_{it}}{p_t} \right)^{-\theta}. \tag{2.5}$$

It follows also that the composite good price p_t is given by the Dixit-Stiglitz aggregator

$$p_t = \left[\int_0^1 (p_{it})^{1-\theta} \right]^{\frac{1}{1-\theta}} . \tag{2.6}$$

Composite goods can be used both for consumption and for production. The aggregate demand for composite goods is therefore given by the sum of demand for consumption and for production purposes,

$$Y_t = C_t + \int_0^1 X_{it} di, \tag{2.7}$$

where X_{it} is the demand for intermediate inputs by firm i.

Central bank: The central bank sets the target nominal interest rate R_t^*. The effective nominal interest rate is then given by

$$R_t = R_t^* e^{\varepsilon_{rt}}, \tag{2.8}$$

where ε_{rt} is an iid and normally distributed monetary policy shock, $\varepsilon_{rt} \backsim N\left(0, \sigma_r^2\right)$.

Intermediate good producers: Each intermediate good producer combines labor and intermediate inputs according to the production function

$$y_{it} = \left(A_t L_{it}\right)^{1-\mu} \left(X_{it}\right)^{\mu}, \tag{2.9}$$

where A_t denotes the exogenous aggregate productivity variable, L_{it} and X_{it} respectively the labor and intermediate inputs of production. Aggregate productivity is stationary and follows the process

$$A_t = e^{\varepsilon_{at}} \tag{2.10}$$

where ε_{at} is an *iid* and normally distributed shock, $\varepsilon_{at} \backsim N\left(0, \sigma_a^2\right)$. Firm i's nominal profits are given by

$$\pi_{it} = p_{it} y\left(p_{it}\right) - w_t L_{it} - p_t X_{it}. \tag{2.11}$$

For simplicity I define x_{it} as the ratio of intermediate inputs to labor inputs,

$$x_{it} = \frac{X_{it}}{L_{it}}. \tag{2.12}$$

Substituting (2.12) into (2.9) and then substituting the resulting equation into (2.11), I can express without loss of generality nominal profits as a function of firm i's two control variables, prices and per-capita intermediate inputs

$$\pi_{it} = \pi\left(p_{it}, x_{it}\right) = \left(p_{it} - \frac{w_t x_{it}^{-\mu} + p_t x_{it}^{1-\mu}}{A_t^{1-\mu}}\right) y\left(p_{it}\right), \tag{2.13}$$

The price that maximizes (2.13) is given by

$$p_{it}^{\dagger} = \frac{\theta}{\theta - 1} \frac{w_t^{1-\mu} p_t^{\mu}}{A_t^{1-\mu}}, \tag{2.14}$$

while the profit-maximizing per-capita level of intermediate inputs is given by

$$x_{it}^{\dagger} = \frac{w_t}{p_t}. \tag{2.15}$$

As shown by Basu (1995) and Nakamura and Steinsson (2007) a larger share of intermediate inputs into production, μ, increases strategic complementarities in price setting. Everything else being equal, a larger μ implies a larger impact of the price level on intermediate good producer i's profit-maximizing price $p_{it}^{\dagger}$.

For simplicity, I assume that within each intermediate good producer there are two decision makers[7]. A purchasing department is in charge of choosing the optimal per-capita level of intermediate inputs, x_{it}. A sales department chooses the price, p_{it}. Although the purchasing department acts with perfect information, the sales department has limited information processing capabilities, which means that it cannot process more than κ_i bits of information per period on average[8]. Therefore the price decision is taken under rational inattention. The assumption

[7]Mankiw and Reis (2006) make a similar assumption.
[8]In information theory the flow of information is measured in bits.

of two separate decision makers within each firm allows to solve analytically for the dynamics of the model around the non-stochastic steady state, and therefore offers valuable insights on the role of different parameters for the dynamic of prices. Nevertheless, later in the paper, I will solve numerically the case with a unique decision maker choosing both p_i and x_i under rational inattention.

In order to study the allocation of attention within each firm across the two sources of uncertainty, ε_a and ε_r, I make the following assumption. Similar to Maćkoviak and Wiederholt (2007) I assume that information about ε_a and ε_r is processed separately. This means that the firm's total information processing capability, κ_i, is allocated optimally across these two separate information processing activities. It also means that no information is revealed about the realization of a process from acquiring and processing information about the other process. The advantage of this assumption is introducing a trade-off in the allocation of attention across the two types of shocks in a very simple way. It is however not the only way. In section 5 I show a case where this assumption does not hold but there is still an allocation of attention between across the two types of shocks. Given the multiplicative form of the equation for the profit-maximizing price in (2.14), $\left\{p_{it}^{\dagger}\right\}$ can be expressed as the product of two independently distributed components, $\left\{p_{ait}^{\dagger}\right\}$ and $\left\{p_{rit}^{\dagger}\right\}$. The processes $\left\{p_{ait}^{\dagger}\right\}$ and $\left\{p_{rit}^{\dagger}\right\}$ represent respectively the profit-maximizing price responses to the sequence of realizations of ε_{at} and ε_{rt}.

The firm's rational inattention problem is to maximize at period zero the expected discounted sum of future profits

$$\max_{\{p_{ait},p_{rit}\}} E_0 \sum_{t=1}^{\infty} q_t \pi_{it}, \tag{2.16}$$

subject to the constraint

$$I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right)+I\left(\left\{p^{\dagger}_{rit}\right\};\{p_{rit}\}\right)\leq \kappa_i, \tag{2.17}$$

where $I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right)$ and $I\left(\left\{p^{\dagger}_{rit}\right\};\{p_{rit}\}\right)$ denote the average amount of information contained in the price processes, $\{p_{ait}\}$ and $\{p_{rit}\}$, about profit-maximizing prices, $\left\{p^{\dagger}_{ait}\right\}$ and $\left\{p^{\dagger}_{rit}\right\}$, respectively.

The average flow of information $I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right)$ is defined as

(2.18)

$$I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right)=\lim_{T\to\infty}\frac{1}{T}\left[\begin{array}{c} H(p^{\dagger}_{ai0},p^{\dagger}_{ai1},......,p^{\dagger}_{aiT}) \\ -H(p^{\dagger}_{ai0},p^{\dagger}_{ai1},......,p^{\dagger}_{aiT}\mid p_{ai0},p_{ai1},......,p_{aiT}) \end{array}\right],$$

where $H(\cdot)$ denotes the entropy of a vector of realizations of random variables[9]. For instance the entropy of the random vector $p^{\dagger,T}=\left(p^{\dagger}_{ai0},p^{\dagger}_{ai1},......,p^{\dagger}_{aiT}\right)$ with

[9]For a definition of entropy see Cover and Thomas (1991). The average flow of information between $\left\{p^{\dagger}_{rit}\right\}$ and $\{p_{rit}\}$ is defined similarly and therefore I omit its description.

density $f\left(p_{ai0}^{\dagger}, p_{ai1}^{\dagger}, ..., p_{aiT}^{\dagger}\right)$ is defined as

$$H\left(p_{ai0}^{\dagger}, p_{ai1}^{\dagger}, ..., p_{aiT}^{\dagger}\right) = -\int f\left(p^{\dagger,T}\right) \log_2 f\left(p^{\dagger,T}\right) dp^{\dagger,T}. \tag{2.19}$$

The larger is the entropy associated with a random vector, the larger is the uncertainty about its realizations. Therefore, following the rational inattention literature, the information flow $I\left(\left\{p_{ait}^{\dagger}\right\}; \{p_{ait}\}\right)$ measures the reduction in uncertainty about $\left\{p_{ait}^{\dagger}\right\}$ as the difference between the value of the entropy before processing information and the value of the entropy conditional on the information processed. Intuitively the problem the firm faces is to choose the joint probability density function of the stochastic process for the profit-maximizing variable, $\left\{p_{ait}^{\dagger}\right\}$, and the stochastic process for variable it actually controls, $\{p_{ait}\}$. Ideally the firm would like to set the decision variables equal to their profit-maximizing levels in each period, but it is limited by the upper bound on the average flow of information it can process per period.

I finally assume that the noise in the decision is independent across firms. This assumption accords well with the idea that the constraint is the decision-makers limited attention rather than the availability of information.

Resource constraints: The resource constraints are given by

$$C_t + \int_0^1 X_{it} di = \int_0^1 y_{it} di, \tag{2.20}$$

$$\int_0^1 L_{it} di = L_t \tag{2.21}$$

Equilibrium Definition: I consider stationary equilibria in which all endogenous variables at time t are a function only of period t realization of the two shocks, ε_{at} and ε_{rt}. Such an equilibrium exists given the assumptions about the stochastic process for labor productivity, A_t, and assuming that the monetary policy rule, R_t^*, is a function only of period t realizations of the two shocks, $R_t^* = R^*(\varepsilon_{at}, \varepsilon_{rt})$. In what follows, $R^*(\cdot)$ denotes $R^*(\varepsilon_{at}, \varepsilon_{rt})$.

Definition 1. *For a given monetary policy,* $R^*(\cdot)$, *a symmetric, stationary equilibrium is a set of functions* $C(\cdot)$, $L(\cdot)$, $B(\cdot)$, $p(\cdot)$, $w(\cdot)$, $p_i(\cdot)$ *and* $x_i(\cdot)$, *such that:*

(i) $\{C(\cdot), L(\cdot), B(\cdot)\}$ *maximize* (2.1) *subject to* $(2.2) - (2.3)$.

(ii) $p(\cdot)$ *is given by* (2.6).

(iii) $x_i(\cdot)$ *is given by* (2.15).

(iv) $p_i(\cdot)$ *maximizes* (2.16) *subject to* (2.17).

(v) Each intermediate good producer i satisfies its incoming demand at $p_i(\cdot)$.

(vi) All other markets clear.

(vii) The resource constraints (2.20) – (2.21) *are satisfied.*

2.2.1. Solving the price setting problem

I characterize the equations describing the dynamics of the endogenous variables in the economy in log-deviations from the non-stochastic steady state. I then use these results to characterize the stochastic process for the profit-maximizing price in deviations from the non-stochastic steady state. Once I have this process I can solve the rational inattention problem. Variables with a hat denotes log-deviations from the non-stochastic steady state. The price level in the non-stochastic steady state is normalized to one. The household's first order conditions for consumption and labor supply are given by

$$\hat{C}_t = E_t\left(\hat{C}_{t+1} + \hat{p}_{t+1} - \hat{p}_t\right) - \hat{R}_t, \tag{2.22}$$

$$\hat{L}_t = \frac{1}{\psi_l}\left(\hat{w}_t - \hat{p}_t - \hat{C}_t\right). \tag{2.23}$$

The inputs ratio, $\hat{x}_{it}$, is set at the profit-maximizing level, $\hat{x}_{it}^{\dagger}$, in each period:

$$\hat{x}_{it} = \hat{x}_{it}^{\dagger} = \hat{w}_t - \hat{p}_t. \tag{2.24}$$

It follows from (2.12) that the dynamics of aggregate intermediate inputs are given by

$$\hat{X}_t = \hat{L}_t + \hat{w}_t - \hat{p}_t. \tag{2.25}$$

The production function in (2.9), the resource constraint in (2.20) and the definition of Y_t in (2.4) imply the following equations

$$\hat{L}_t = \hat{C}_t - \hat{A}_t, \tag{2.26}$$

$$\hat{Y}_t = (1-\mu)\,\hat{C}_t + \mu \hat{X}_t. \tag{2.27}$$

Price level dynamics equal the integral over intermediate good producers prices,

$$\hat{p}_t = \int_0^1 \hat{p}_{it} di. \tag{2.28}$$

From (2.14) it follows that the dynamics of profit-maximizing prices are given by

$$\hat{p}_{it}^{\dagger} = (1-\mu)\left(\hat{w}_t - \hat{A}_t\right) + \mu \hat{p}_t. \tag{2.29}$$

By substituting equation (2.26) into (2.23) I obtain an expression for the wage dynamics:

$$\hat{w}_t = (1 + \psi_l)\, \hat{C}_t - \psi_l \hat{A}_t + \hat{p}_t. \tag{2.30}$$

I then substitute (2.30) into(2.29) and obtain the dynamics for the profit-maximizing price in log-deviations from non-stochastic steady state as a function of the price level, real demand and productivity:

$$\hat{p}_{it}^{\dagger} = \hat{p}_t + \xi \left(\hat{C}_t - \hat{A}_t \right), \tag{2.31}$$

where the coefficient ξ is given by

$$\xi = (1 - \mu)\,(1 + \psi_l)$$

The parameter ξ represents the degree of strategic complemetarity in price setting as defined in Woodford (2003)[10]. The coefficient ξ decreases in the share of intermediate inputs in gross output, μ, and increases in the inverse of the Frisch elasticity of labor supply. When the share of intermediate inputs in production increases,

[10]The larger is ξ, the smaller are complementarities.

the share of the price level in nominal marginal costs increases relative to nominal wages. Therefore, everything else being equal, the profit-maximizing price is affected relatively more by the dynamics of the price level. Notice also that A_t coincides with the definition of potential output typically given in the New-Keynesian literature[11], and that in this economy consumption coincides with value added output. Therefore equation (2.31) is consistent with the New-Keynesian framework, where profit-maximizing prices adjust to deviations of output from potential and ξ denotes the magnitude of the adjustment.

In the equilibrium defined above, all economic variables are only a function of the current realizations of shocks, which are *iid* over time by assumption. Therefore I guess that in equilibrium the expectations of future deviations of prices and consumption from the steady state are such that

$$E_t\left[\hat{C}_{t+1}\right] = 0, \tag{2.32}$$

$$E_t\left[\hat{p}_{t+1}\right] = 0. \tag{2.33}$$

The guess will be verified in section 3. After substituting equation (2.22) into (2.31) and imposing the guess stated above, the dynamics of the profit-maximizing price

[11]The level of output that would prevail in an economy with fully flexible prices and complete information.

can be expressed as

$$\hat{p}_{it}^{\dagger} = (1 - \xi)\,\hat{p}_t - \xi\left(\hat{A}_t + \hat{R}_t\right). \tag{2.34}$$

From equations (2.8) and (2.10) it follows that

$$\hat{R}_t = \hat{R}_t^{*} + \varepsilon_{rt}, \tag{2.35}$$

$$\hat{A}_t = \varepsilon_{at}. \tag{2.36}$$

I finally assume that the monetary policy rule has a generic linear form given by

$$\hat{R}_t^{*} = \eta_a \varepsilon_{at} + \eta_r \varepsilon_{rt}. \tag{2.37}$$

In section 4 I will consider the case of a Taylor-type policy rule. It follows from (2.34) – (2.37) that the dynamics of the profit-maximizing price can be expressed as a function of the price level and the two fundamental shocks only

$$\hat{p}_{it}^{\dagger} = (1 - \xi)\,\hat{p}_t - \xi\,(1 + \eta_a)\,\varepsilon_{at} - \xi\,(1 + \eta_r)\,\varepsilon_{rt}. \tag{2.38}$$

Notice that if the price level and nominal rates respond identically to the two shocks, then also profit-maximizing prices respond identically.

I solve the model with the method of undetermined coefficients. First, I make the guess that the price level expressed in log-deviations from the non-stochastic steady state is a linear function of the two fundamental shocks:

$$\hat{p}_t = \gamma_a \varepsilon_{at} + \gamma_r \varepsilon_{rt}. \tag{2.39}$$

where γ_a and γ_r are undetermined coefficients representing the responsiveness of the price level to the two shocks. This guess satisfies (2.33). I will solve for γ_a and γ_r, and show that (2.39) is an equilibrium in section 3. As I am interested in the relative price responsiveness to the two types of shocks, I define the variable

$$\gamma = \frac{\gamma_a}{\gamma_r}, \tag{2.40}$$

as a measure for the responsiveness of the price level to aggregate productivity shocks relative to the responsiveness of the price level to the monetary policy shock.

Rational inattention problem: In order to obtain an analytical solution of the model, I consider a second order Taylor expansion around the non-stochastic steady state of intermediate good producers' objective (2.16). After the approximation and using stationarity, the objective (2.16) becomes[12]

$$-\lambda_p E\left[\left(\hat{p}_{ait}-\hat{p}^{\dagger}_{ait}\right)^2+\left(\hat{p}_{rit}-\hat{p}^{\dagger}_{rit}\right)^2\right], \tag{2.41}$$

where $\lambda_p=\beta\frac{\theta-1}{1-\beta}\frac{\bar{Y}}{2}$ is a constant and $\bar{Y}$ is the level of output in the non-stochastic steady state. The price setter's problem can be then interpreted as minimizing the sum over the mean square errors in pricing decisions relative to each shock. In the stationary equilibrium, the constraint on the average flow of information can be expressed in terms of the correlation between the profit-maximizing prices and the actual decisions[13], so that the intermediate good producer i minimizes (2.41) over the distribution for the decision variables, $\{\hat{p}_{ait},\hat{p}_{rit}\}$, subject to the constraint that

$$\frac{1}{2}\log_2\left(\frac{1}{1-\rho^2_{ai}}\right)+\frac{1}{2}\log_2\left(\frac{1}{1-\rho^2_{ri}}\right)\leq\kappa_i, \tag{2.42}$$

where ρ_{ai} is the correlation between the profit-maximizing price response, $\hat{p}^{\dagger}_{ait}$, and the actual price response, $\hat{p}_{ait}$, to the aggregate productivity shock, and ρ_{ri} is

[12]See the Appendix A for more details. Maćkoviak and Wiederholt (2007) show in a similar framework that the solution to the rational inattention probelm obtained with a quadratic approximation to the objective is very similar to the one obtained without any approximation when κ is large enough.

[13]See Appendix B for more details.

the correlation between the profit-maximizing price response, $\hat{p}^{\dagger}_{rit}$, and the actual price response, $\hat{p}_{rit}$, to the monetary policy shock. The larger is such a correlation, the larger is the amount of information processed. Intuitively, equation (2.42) imposes an upper bound on how correlated the decisions can be with their profit-maximizing counterparts. The price setter faces a trade-off in allocating attention between productivity and monetary policy shocks. By using (2.39) , (2.38), and (2.41)−(2.42), I can approximate the rational inattention problem in (2.16)−(2.17) as

$$\underset{(\rho_{ai},\,\rho_{ri})}{Max} - \lambda_p \left[\left(1-\rho_{ai}^2\right)\omega_a^2\sigma_a^2 + \left(1-\rho_{ri}^2\right)\omega_r^2\sigma_r^2 \right], \tag{2.43}$$

$$s.t.$$

$$i \;:\; \text{eq. } (2.42) \text{ holding}$$

$$ii \;:\; \rho_{ai} \leq 1,\ \rho_{ri} \leq 1 \tag{2.44}$$

where ω_a and ω_r are coefficients given by

$$\omega_a = \omega\left(\gamma_a, \eta_a\right) = (1-\xi)\,\gamma_a - \xi\eta_a - \xi, \tag{2.45}$$

$$\omega_r = \omega\left(\gamma_r, \eta_r\right) = (1-\xi)\,\gamma_r - \xi\eta_r - \xi. \tag{2.46}$$

The price setter's objective (2.43) depends on the correlations between the profit-maximizing price responses and the actual price responses to each shock. The larger are the correlations, the larger are expected profits. Everything else being equal, the larger is the weight associated to a type of shock, the larger is the loss in profits the firm would face from an error in the response of prices to that shock. The weights ω_a and ω_r depend on the degree of strategic complementarity in price setting, ξ, on the parameters of the monetary policy rule, η_a and η_r, and on the response of the price level to each shock, γ_a and γ_r. The function $\omega(\cdot)$ is strictly increasing (decreasing) in its first argument, γ, if and only if $\xi < 1$ $(\xi > 1)$. Intuitively, with $\xi < 1$, the fact that the competitors of intermediate good producer i are more responsive to a shock, makes it more worthwhile for intermediate good producer i to pay attention to that shock. In contrast, with $\xi > 1$, the fact that the competitors of intermediate good producer i are more responsive to a shock, makes it less worthwhile for intermediate good producer i to pay attention to that shock. In other words if price decisions are strategic complements also the attention allocation decisions are strategic complements: price setters will have incentives to process more information on the same variables its competitors process more information about[14]. The optimal allocation of attention at an interior solution

[14]Hellwig and Veldkamp (2007) study the conditions under which strategic complementarities in price-setting lead to complementarities in the acquisition of information.

implies

$$1-\left(\rho_{ai}^{*}\right)^{2} = 2^{-\kappa}\frac{\omega_r}{\omega_a}\frac{\sigma_r}{\sigma_a}, \tag{2.47}$$

$$1-\left(\rho_{ri}^{*}\right)^{2} = 2^{-\kappa}\frac{\omega_a}{\omega_r}\frac{\sigma_a}{\sigma_r}. \tag{2.48}$$

The price setter at intermediate good producer i chooses a price process which has a correlation with the profit-maximizing price that is increasing in the average amount of information the firm can process per period, κ. The optimal correlation associated to a type of shock is increasing in the relative weight that particular shock has in the objective function (2.43).

Flexible price benchmark: As a benchmark I derive the equilibrium dynamics of the model under complete information and flexible prices, i.e. when price setters have unlimited information processing capability, $\kappa_i \to \infty$. In this case, intermediate good prices are at their profit-maximizing levels, $\hat{p}_{it} = \hat{p}_{it}^{\dagger}$ for all t and i. It follows from (2.38) and $\hat{p}_{it} = \hat{p}_{it}^{\dagger} = \hat{p}_t$ that the aggregate price level is given by

$$\hat{p}_t = -\left(1+\eta_a\right)\varepsilon_{at} - \left(1+\eta_r\right)\varepsilon_{rt}, \tag{2.49}$$

and that the relative price responsiveness to the two shocks is given by

$$\gamma = \eta, \tag{2.50}$$

where $\eta \equiv \frac{1+\eta_a}{1+\eta_r}$ is an indicator of the relative responsiveness of the monetary policy rule, R_t^*, to the two shocks. For instance, if $\eta_a = \eta_r = -1$ the price level will be unresponsive to both shocks. In contrast, if $\eta_a \neq -1$ and $\eta_r \neq -1$ the price level will respond to both shocks. The closer are η_a and η_r to -1, the less responsive the price level is to productivity and monetary policy shocks respectively.

Corollary 2. *Under unlimited information processing capability and flexible prices,*

(1) *The relative price responsiveness to productivity and monetary policy shocks, γ, is equal to the relative responsiveness the monetary policy rule to the two shocks, η.*
(2) *The degree of strategic complementarities in price setting does not influence γ.*

Therefore, an asymmetry in the response of the price level to the two shocks is generated only by an asymmetry in the monetary policy.

Sticky price benchmark: As a second benchmark, I derive the equilibrium of the model when, in any period t, a fraction α of intermediate good producers sets $\hat{p}_{it} = \hat{p}^{\dagger}_{it}$ and $\hat{p}_{it+\tau} = E_t\left(\hat{p}^{\dagger}_{it+\tau}\right) = 0$ for all $\tau \geq 1$, while the remaining fraction of intermediate good producers sets $\hat{p}_{it+\tau} = 0$ for all $\tau \geq 0$. This is equivalent to say that only a fraction α is allowed to change a time-contingent pricing plan[15]. This type of friction is very similar to standard Calvo-type staggered pricing, where however firms are allowed to change only the current price with frequency α. The slightly departure from the standard Calvo framework allows for a stationary equilibrium where the adjustment of the economy to any shock happens within the period of the shock and allows for an analytical solution and a direct comparison with the rational inattention counterpart model. However the results derived about asymmetry in price responsiveness would absolutely hold also in the more standard Calvo-type sticky price model. In fact, this framework preserves the relevant characteristic of the Calvo-type sticky price model, which is that the frequency of prices adjustment is exogenous and equal across the two types of shocks. The dynamics of the price level in equilibrium is such that $\hat{p}_t = \alpha\hat{p}^{\dagger}_{it}$, which together with equation (2.38) implies

$$\hat{p}_t = -\frac{\alpha\xi}{1-\alpha\left(1-\xi\right)}\left[\left(1+\eta_a\right)\varepsilon_{at} + \left(1+\eta_r\right)\varepsilon_{rt}\right]. \tag{2.51}$$

[15]Burstein (2006) and Mankiw and Reis (2006) consider a similar case.

The relative price responsiveness to the two shocks is therefore given by

$$\gamma = \eta. \tag{2.52}$$

Corollary 3. *Under unlimited information processing capability and sticky prices,*

(1) *The relative price responsiveness to productivity and monetary policy shocks, γ, is equal to the relative responsiveness the monetary policy rule to the two shocks, η.*
(2) *The degree of strategic complementarities in price setting does not influence γ.*

The relative responsiveness under sticky prices is completely determined by the monetary policy rule as in the flexible price benchmark. Strategic complementarities in price setting and price rigidity do affect the price level response to the two shocks but do not affect the relative response. Intuitively, a change in the degree of strategic complementarity in price setting, ξ, or in the frequency of prices adjustment, α, affects price responsiveness independently of the type of shock.

2.3. Equilibrium characterization under rational inattention

In this section I characterize the equilibrium of the economy when price setters have limited information processing capabilities. Solving for the equilibrium of this economy requires solving for a fixed point. The rational inattention problem in equations (2.43) – (2.46) depends on the stochastic process for the profit-maximizing price, defined in (2.38), which in turn depends on the stochastic process for the price level in (2.39), that is an average over all intermediate good prices and therefore depends itself on the solution to the rational inattention problem.

Proposition 4. *There is a unique stationary equilibrium in which the log-deviations from non-stochastic steady state of all endogenous variables in period t are a linear function of the realization of the two shocks, ε_{at} and ε_{rt}. In this equilibrium, the price level is given by*

$$p_t = \gamma_a \varepsilon_{at} + \gamma_r \varepsilon_{rt}, \tag{2.53}$$

where

$$(2.54)\qquad \gamma_a = \begin{cases} -\xi\left(1+\eta_a\right)\bar{\gamma} & if \quad \eta\sigma > \varphi \\ -\xi\left(1+\eta_a\right)F\left(\frac{1}{\eta\sigma}\right) & if \quad \frac{1}{\varphi} \leq \eta\sigma \leq \varphi \\ 0 & if \quad \eta\sigma < \frac{1}{\varphi} \end{cases}$$

$$(2.55)\qquad \gamma_r = \begin{cases} 0 & if \quad \eta\sigma > \varphi \\ -\xi\left(1+\eta_r\right)F\left(\sigma\eta\right) & if \ \frac{1}{\varphi} \leq \eta\sigma \leq \varphi \\ -\xi\left(1+\eta_r\right)\bar{\gamma} & if \quad \eta\sigma < \frac{1}{\varphi} \end{cases}$$

and where the parameters $\bar{\gamma}$ *and* φ*, and the function* $F\left(\cdot\right)$ *are given by*

$$(2.56)\qquad \bar{\gamma} = \frac{1-2^{-2\kappa}}{1-\left(1-\xi\right)\left(1-2^{-2\kappa}\right)},$$

$$(2.57)\qquad F\left(\varkappa\right) = \frac{\xi + 2^{-2\kappa}\left(1-\xi\right) - 2^{-\kappa}\varkappa}{\xi^2 - 2^{-2\kappa}\left(1-\xi\right)^2}$$

$$(2.58)\qquad \varphi = 2^{\kappa_i}\frac{\xi}{1-\xi}$$

Proof: See Appendix D.

The equilibrium dynamics of the other aggregate variables in log-deviations from the non-stochastic steady state, $\hat{C}_{t,}$ $\hat{L}_t$, $\hat{w}_t$, and $\hat{X}_t$ can be easily obtained by substituting (2.53) respectively into (2.22) , (2.26) , (2.30) and (2.24) . In particular consumption is given by

$$\hat{C}_t = -\left(\eta_a + \gamma_a\right) \varepsilon_{at} - \left(1 + \eta_r + \gamma_r\right) \varepsilon_{rt}, \tag{2.59}$$

where γ_a and γ_r are defined in $(2.54) - (2.55)$. Finally notice that (2.53) and (2.59) satisfy the initial guesses (2.32) , (2.33) and (2.39) .

Aggregate prices are unresponsive to either productivity shocks or monetary policy shocks whenever $\eta\sigma > \varphi$ or $\eta\sigma < \frac{1}{\varphi}$ respectively. In these cases the attention allocation problem in $(2.43) - (2.46)$ has a corner solution where attention is paid only to one shock. Proposition 2 describes instead the interior solution to the rational inattention problem in terms of the correlations ρ_{ai} and ρ_{ri}.

Proposition 5. *At the interior solution of the problem in* $(2.43) - (2.46)$ *, the optimal allocation of attention implies*

$$\frac{1 - \left(\rho_{ri}^*\right)^2}{1 - \left(\rho_{ai}^*\right)^2} = \left[\Gamma\left(\sigma\eta, \kappa_i\right) \sigma\eta\right]^2, \tag{2.60}$$

where the function $\Gamma(\cdot,\cdot)$, *and the parameters* σ *and* η *are given by*

$$\Gamma(\sigma\eta,\kappa_i) \equiv \frac{1-(1-\xi)\left(1+2^{-\kappa_i}\frac{1}{\sigma\eta}\right)}{1-(1-\xi)\left(1+2^{-\kappa_i}\sigma\eta\right)}, \tag{2.61}$$

$$\sigma \equiv \frac{\sigma_a}{\sigma_r}, \tag{2.62}$$

$$\eta \equiv \frac{1+\eta_a}{1+\eta_r} \tag{2.63}$$

Proof: Substitute (2.54) – (2.55) into (2.47) – (2.48).

The ratio of correlations in equation (2.60) is a measure of the relative allocation of attention to the two shocks. Whenever this ratio is different from one there is an asymmetry in the allocation of attention. The asymmetry in the allocation of attention to the two shocks depends on the relative volatility of the two shocks, σ, and on the relative responsiveness of the nominal rate to the shocks, η. If $\sigma\eta = 1$, the two shocks receive exactly the same amount of attention, $\frac{\kappa_i}{2}$. In contrast if $\sigma\eta > 1$ $(\sigma\eta < 1)$, the productivity shock receives relatively more (less) attention than the monetary policy shock, implying a larger (smaller) correlation with the profit-maximizing behavior in the response of prices to the productivity shock relative to the monetary policy shock, $\rho^*_{ai} > \rho^*_{ri}$ $(\rho^*_{ai} < \rho^*_{ri})$. Therefore, the attention a shock receives increases when its volatility increases relatively to the other shock, and when the monetary policy is *less responsive* to it relatively to the other shock, where less responsive means a monetary policy that offset less the impact of a shock on the price level. Intuitively and everything else being equal, a shock with larger volatility accounts for a larger fraction of profit-maximizing prices volatility and increases the incentives to process information about that shock. Similarly, when the central bank reduces the responsiveness of the price level to a shock relatively more, it also reduces the fraction of the profit-maximizing price volatility caused by that shock, and therefore reduces the incentive to process information about that shock. For instance, if the central bank completely accommodates the productivity shock, $\eta_a = -1$, both aggregate and profit-maximizing prices do not respond to the productivity shock, their volatility is zero, and there is no incentive to acquire and process information on that shock. The further away $\sigma\eta$ is from 1,the more asymmetries in the allocation of attention; eventually reaching a corner solution, where information is processed only about one of the two shocks. At the corner solution one of the two correlation is zero.

The difference in allocation of attention depends also on the degree of strategic complementarity in price setting, ξ. Analytically this influence works through the function $\Gamma(\cdot,\cdot)$. At an interior solution, when prices are strategic complements, $\xi < 1$, the function $\Gamma(\cdot,\cdot)$ is increasing in $\sigma\eta$. This magnifies the impact of a change in $\sigma\eta$ on the difference in the allocation of attention to the two shocks. In contrast, when price decisions are strategic substitutes, $\xi > 1$, the function $\Gamma(\cdot,\cdot)$ is decreasing in $\sigma\eta$. This dampens the impact of a change in $\sigma\eta$ on the difference in the allocation of attention to the two shocks. The economic intuition behind this mechanism is that when prices are strategic complements (substitutes), the attention allocation decisions are also strategic complements (substitutes). In the case $\xi < 1$ firms have incentive to process more information about the same shock the other firms process more information about. This creates a magnification effect on the difference in allocation of attention to the two shocks and therefore on relative price responsiveness. This amplification can be so large that this model is always capable to generate a relatively large difference in the allocation of attention to the two shocks, no matter how small the *initial incentives,* given by the value of $\sigma\eta$, to allocate more attention to one shock are. Proposition 3 formalizes this idea.

Proposition 6. *For any value of $\sigma\eta \neq 1$, there exist a degree of strategic complementarity in price setting, $\bar{\xi} \in [0,1]$, such that the allocation of attention problem has a corner solution for any $\xi \leq \bar{\xi}$.*

Proof: See Appendix E.

By increasing strategic complementarities in price setting, i.e. decreasing ξ, the difference in allocation of attention increases monotonically towards an upper bound where one of the two shocks receives κ_i bits of attention and the other zero. For instance, let's focus on the case $\eta\sigma > 1$. Then as $\xi \to \frac{\eta\sigma 2^{-\kappa_i}}{1+\eta\sigma 2^{-\kappa_i}}$, it follows that

$\Gamma(\eta\sigma, \kappa_i) \rightarrow \infty$, which means that when complementarities are large enough, the coordination in the allocation of attention toward the same shock is so large that the impact of a small difference of $\eta\sigma$ from 1 can get endogenously highly magnified onto the difference in the volatilities of the profit-maximizing price processes due to each shock.

Finally the optimal attention allocation depends also on the amount of information processed per period, κ. As firms are allowed to process more information the difference in allocation of attention to the two shocks decrease. In fact, the function $\Gamma(\cdot, \cdot)$ is decreasing in κ when $\eta\sigma > 1$, and increasing in κ when $\eta\sigma < 1$. As the amount of information processed per period converges to infinity, the price responses to the two shocks converge to the responses obtained under flexible prices and complete information in (2.49).

2.3.1. The asymmetry in price responsiveness

It follows from equations $(2.54) - (2.55)$ that relative price responsiveness to the two types of shocks is given by

$$\gamma = \begin{cases} \infty & if \quad \eta\sigma > \varphi \\ \frac{F\left(\frac{1}{\eta\sigma}\right)}{F(\eta\sigma)}\,\eta & if \quad \frac{1}{\varphi} \leq \eta\sigma \leq \varphi \\ 0 & if \quad \eta\sigma < \frac{1}{\varphi} \end{cases} \tag{2.64}$$

An asymmetry in relative prices responsiveness to productivity and monetary policy shocks comes either from an asymmetry in standard deviations, σ, or from an asymmetry in monetary policy responsiveness to the two shocks, η, or from a combination of both. Strategic complementarities in price setting have a non-trivial impact on price responsiveness through the attention allocation decision. Proposition 4 captures the relationship between γ, η and ξ.

Proposition 7. *At an interior solution to the attention allocation problem,*

(1) *The relative price responsiveness to the two shocks, γ, is strictly increasing in the parameter representing relative volatility of the two shocks, σ.*

(2) *The relative price responsiveness to the two shocks, γ, is strictly increasing in the parameter representing relative monetary policy responsiveness to the two shocks, η. The relationship between γ and η is non-linear.*

(3) *The relative price responsiveness to the two shocks, γ, is strictly decreasing in the degree of strategic complementarity in price setting, ξ, if $\sigma\eta > 1$, and strictly incresing if $\sigma\eta < 1$.*

Proof: See Appendix F.

The first point of proposition 4 captures one of the main insight of Maćkoviak and Wiederholt (2007). For a given monetary policy relative response to shocks, η, firms pay relatively more attention to more volatile shocks. Therefore prices become relatively more responding to productivity shocks when the latter are relatively more volatile.

The second point captures the role of the monetary policy in the determination of relative price responsiveness to the two aggregate shocks. For a given relative volatility, σ, firms pay relatively more attention to shocks to which nominal rates are less responsive, η larger. Therefore prices are relative more responding to productivity shocks the larger is η. This result is similar to the one obtained in the benchmark models under flexible- and sticky- prices. In those models there was a linear positive relationship between relative price responsiveness and relative monetary policy responsiveness to the two shocks. Under rational inattention, instead, the relationship is non-linear. The non-linearity comes from the fact that a change in monetary policy affects relative price responsiveness also through the attention allocation decision. For instance, if the nominal rate is relatively less responding to productivity shocks, η larger, prices have to respond more to it for a given response of real rates. This is the reason behind the relationship between relative price and monetary policy responsiveness in the benchmark models. Under rational inattention, on top of the increased responsiveness to productivity shocks implied by the channel described above, there is a reallocation of attention in favor of the productivity shocks which further increases relative price responsiveness to such a shock. Therefore a change in relative monetary policy responsiveness to shocks has a larger impact on relative price responsiveness in models of price setting under rational inattention than in more standard models of flexible and sticky prices.

The third point of proposition 4 describes another key result of the paper. The relative price responsiveness depends on the degree of strategic complementarity in price-setting, ξ, through the attention allocation decision. For a given monetary policy and relative volatility of the two shocks, the more relative price responsiveness, γ, is the further away from 1 the smaller is ξ. More complementarities, i.e. lower ξ, increase the difference in the allocation of attention to the two shocks. This then affects directly the relative responsiveness. The fact that relative responsiveness depends on the degree of strategic complementarity in price setting through the attention allocation decision is an important point of departure from more standard sticky prices models.

2.3.2. Discussion on the role of monetary policy

In this model there is no trade-off between stabilizing the consumption gap and reducing price dispersion. A perfectly informed central bank can achieve full stabilization of the price level, reducing price dispersion to zero, while keeping consumption at potential. With this policy, profit-maximizing prices are constant, and there is no need of processing information for the price setter. At the optimal policy there is no difference between a model of price setting under rational inattention and more standard models of sticky prices. Output is always at potential while the price level is constant. However, if the monetary policy is not at the optimum, the predictions of standard sticky prices models about price responsiveness to the two shocks, and therefore real variable responses, may be substantially different from the predictions of a model of price setting under rational inattention. In the latter, a change in monetary policy affects price responsiveness also through the attention allocation decision. This means that the same change in policy may have substantially larger impact on the differential responses of prices to the two shocks under rational inattention. The smaller the degree of strategic complementarity in price setting is, the larger the impact of a change in monetary policy on relative price responsiveness. For instance, a given change in policy that reduces (not completely) price responses to productivity shocks and contemporaneously increases output response will cause a larger drop in price volatility and a larger increase in output volatility due to productivity shocks in an economy where prices are set under rational inattention than in a more standard economy with sticky prices.

2.4. The case of a Taylor rule type monetary policy

Taylor rules are widely used as representations of actual monetary policy rules. It is, therefore, an interesting exercise studying the interaction between the parameterization of this rule, and the incentives to allocate attention across the two types of shocks. Hence I consider the case where the nominal rate is set according to a Taylor-type rule,

$$\hat{R}_t^* = \phi_p \hat{p}_t + \phi_c \left(\hat{C}_t - \hat{C}_t^* \right), \tag{2.65}$$

which implies that the nominal rate is given by

$$\hat{R}_t = \phi_p \hat{p}_t + \phi_c \left(\hat{C}_t - \hat{C}_t^* \right) + \varepsilon_{rt}, \tag{2.66}$$

where $\hat{C}_t^*$ is the log-deviation of potential consumption from the non stochastic steady state. Potential consumption is defined as the level of consumption that would hold in the benchmark economy under complete information and flexible prices.

Flexible prices benchmark: With perfectly informed price setters and flexible prices each firm sets its price to the profit maximizing level, $\hat{p}_{it} = \hat{p}_{it}^{\dagger}$. It follows from (2.66), (2.34) and $\hat{p}_t = \hat{p}_{it} = \hat{p}_{it}^{\dagger}$ that the price level is given by

$$\hat{p}_t = -\frac{1}{1+\phi_p}\left(\varepsilon_{at} + \varepsilon_{rt}\right). \tag{2.67}$$

It follows that relative price responsiveness is always equal to 1,

$$\gamma = 1.$$

Intuitively, the Taylor rule in equation (2.65) treats the two shocks symmetrically. It is equivalent to a state contingent policy where $\eta_a = \eta_r = -\frac{\phi_p}{1+\phi_p}$. Therefore it implicitly implies $\eta = 1$. Notice that from (2.22), (2.32), (2.33), (2.66), (2.67), and from the definition of $\hat{C}_t^*$, $\hat{C}_t^* = \hat{C}_t$, it follows that the dynamics of aggregate consumption is given by

$$\hat{C}_t = \hat{C}_t^* = \varepsilon_{at}. \tag{2.68}$$

Sticky prices benchmark: Under sticky prices, the price setter chooses a time-contingent pricing plan in any period he receives a favorable draw, as in section 2. Therefore in each period t a fraction α of firms change its time-contingent plan, so that $\hat{p}_{it} = \hat{p}_{it}^{\dagger}$ and $\hat{p}_{it+\tau} = E_t\left(\hat{p}_{it+\tau}^{\dagger}\right) = 0$ for all $\tau \geq 1$. From (2.22), (2.32), (2.33) , (2.66) , and (2.68) it follows that aggregate consumption is given by

$$\hat{C}_t = -\frac{1+\phi_p}{1+\phi_c}\hat{p}_t + \frac{\phi_c}{1+\phi_c}\varepsilon_{at} - \frac{1}{1+\phi_c}\varepsilon_{rt}. \tag{2.69}$$

It follows from (2.31) and (2.69) and the fact that $\hat{p}_t = \alpha\hat{p}_{it}^{\dagger}$ that the price level is given by

$$\hat{p}_t = -\frac{\alpha\xi}{1-\alpha\left(1-\xi\frac{1+\phi_p}{1+\phi_c}\right)}\frac{1}{1+\phi_c}\left(\varepsilon_{at}+\varepsilon_{rt}\right). \tag{2.70}$$

It follows that relative price responsiveness is always equal to 1,

$$\gamma = 1.$$

Corollary 8. *If the monetary authority sets R_t^* according to a Taylor type rule as in* (2.65) *, and if firms set prices under complete information and flexible or sticky prices, the response of the price level to the productivity shock equals the response of the price level to the monetary policy shock.*

Rational inattention model: As emphasized in section 3, when price setters allocate attention to the two shocks, the monetary policy rule affects γ through the allocation of attention decision. Proposition 5 describes the interior solution to the rational inattention problem of intermediate good producer i when the nominal rate is given by (2.66).

Proposition 9. *If the nominal rate is given by* (2.66), *at the interior solution of problem* $(2.43)-(2.46)$*, the optimal allocation of attention implies*

$$\frac{1-\left(\rho_{ri}^{*}\right)^{2}}{1-\left(\rho_{ai}^{*}\right)^{2}}=\left[\tilde{\Gamma}\left(\sigma,\kappa_{i}\right)\sigma\right]^{2} \tag{2.71}$$

where the function $\tilde{\Gamma}(\cdot,\cdot)$ *is given by*

$$\tilde{\Gamma}\left(\sigma,\kappa_{i}\right)\equiv\frac{1-(1-\xi\phi)\left(1+2^{-\kappa_{i}}\frac{1}{\sigma}\right)}{1-(1-\xi\phi)\left(1+2^{-\kappa_{i}}\sigma\right)}, \tag{2.72}$$

$$\phi\equiv\frac{1+\phi_{p}}{1+\phi_{c}} \tag{2.73}$$

Proof: See Appendix G.

The monetary policy rule affects γ *indirectly* through the function $\tilde{\Gamma}(\cdot,\cdot)$. If $\sigma\neq1$, a more aggressive policy on prices (consumption), decreases (increases) the asymmetry in price responsiveness. Intuitively, the Taylor rule affects the degree of complementarity in the allocation of attention across different price setters. The degree of complementarity in the allocation of attention is no longer equal to the degree of strategic complementarity in price setting, ξ, but instead is the outcome of the combination of the latter with the monetary policy rule, $\xi\phi$. For instance, for a given allocation of attention, a monetary policy more aggressive on prices reduces the feedback on profit-maximizing prices coming from the allocation of attention decisions of the other price setters, reducing therefore complementarities in the allocation of attention decision. A policy more aggressive on consumption, instead, implies a more responding price level for any allocation of attention. This increases complementarity in allocation of attention. Proposition 6 derives the difference in price responsiveness under the Taylor rule specified in (2.65).

Proposition 10. *If the nominal rate is given by* (2.66), *the asymmetry in price responsiveness to the two shocks is given by*

$$\gamma = \begin{cases} \infty & if \quad \sigma > \tilde{\varphi} \\ \frac{\tilde{F}\left(\frac{1}{\sigma}\right)}{\tilde{F}(\sigma)} & if \quad \frac{1}{\varphi} \leq \sigma \leq \tilde{\varphi} \\ 0 & if \quad \sigma < \frac{1}{\tilde{\varphi}} \end{cases} \tag{2.74}$$

where the parameter $\tilde{\varphi}$ *and the function* $\tilde{F}(\cdot)$ *are given by*

$$\tilde{\varphi} = 2^{\kappa_i} \frac{\phi\xi}{1-\phi\xi}$$

$$\tilde{F}(\varkappa) = \frac{\phi\xi + 2^{-2\kappa}(1-\phi\xi) - 2^{-\kappa}\varkappa}{(\phi\xi)^2 - 2^{-2\kappa}(1-\phi\xi)^2}$$

Proof: See Appendix G.

The monetary policy rule affects relative price responsiveness only through its effect on the allocation of attention decision: γ is decreasing in ϕ_p and increasing in ϕ_c at an interior solution to the rational inattention problem, while it is independent of the Taylor rule parameters at the corner solutions. Differently from prices in the benchmark models in equations (2.67) and (2.70), the monetary authority can influence the asymmetry in price responsiveness through a simple Taylor rule as long as there is an allocation of attention decision.

2.5. Extensions

In this section I consider several extensions of the benchmark model presented in section 2. First I consider a different set of assumptions about information channels. Second I remove the assumption of separate decision makers within the firm allowing for both price and input decisions to be taken by the same decision maker under rational inattention. The insights from these exercises reinforce the results obtained in the previous sections.

2.5.1. Processing information without distinguishing between shocks

So far I have assumed that attending to productivity and monetary policy shocks are separate activities. In this section I make a different assumption about the way information is acquired and processed. Specifically, I assume that each price setter can receive the following signals,

$$s_{it} = \begin{cases} \hat{C}_t + \nu_c u_{it}^c \\ \hat{P}_t + \nu_p u_{it}^p \\ \hat{R}_t + \nu_r u_{it}^r \\ \hat{L}_t + \nu_l u_{it}^l \end{cases}, \tag{2.75}$$

where u_{it}^j is assumed to be *iid* across both time and individuals and normally distributed with zero mean and unitary variance. This signal structure conveys the idea that each firm processes information about realizations of variables that are usually available in the real world. It is realistic to assume that price setters have access to information on aggregate demand, prices, nominal rates and employment from public sources of information[16]. It is generally harder to find direct sources of information on the realizations of the shocks. I am ruling out, therefore, direct signals on productivity and monetary policy shocks. However, the price setter can always extract information about the realizations of fundamental shocks from the set of signals available in the economy. This is in the spirit of the signal-extraction literature[17]. Given that the price setter is interested in extracting information

[16]These statistics conatin no public noise. Information is therefore published and available with no error. The noise in the signals has to be inetrpreted exclusively as firm specific errors in processing the information.

[17]See Lucas (1972).

about the realization of the profit-maximizing price, $\hat{p}_{it}^{\dagger}$, he will pay attention to the different signals accordingly. Differently from the signal-extraction literature, and in the spirit of the rational inattention literature, the price setter chooses the precisions of the signals, $(\nu_c, \nu_p, \nu_r, \nu_l)$, to maximizes the objective

$$-\lambda_p E\left[\left(\hat{p}_{it} - \hat{p}_{it}^{\dagger}\right)^2\right],$$

subject to the constraint on the average amount of information processed per period,

$$I\left(\left\{\hat{p}_{it}^{\dagger}\right\};\{\hat{p}_{it}\}\right) \leq \kappa_i, \tag{2.76}$$

and to the constraint reflecting the restriction on the set of signals available to him,

$$\hat{p}_{it} = E\left[\hat{p}_{it}^{\dagger}|s_{it}\right], \tag{2.77}$$

where s_{it} is defined in (2.75). I assume that the monetary policy rule is given by (2.65). Differently from section 2, where the price setter was assumed to respond separately to the two shocks, here he chooses the price response to the new arrival of information without distinguishing between the two types of shocks. This does not mean that there is no allocation of attention to the two shocks. In fact, by choosing how precisely to acquire information about the different signals, the price setter implicitly chooses to have its price respond more accurately to one of the two shocks. For instance, the covariance between the profit-maximizing price with consumption conditional on the productivity shock has the opposite sign than the same covariance when we condition on the monetary policy shock. In fact, after a positive productivity shock, the profit-maximizing price drops while aggregate demand increases. In contrast, after a monetary policy shock, profit-maximizing prices and aggregate consumption move in the same direction. What matters for the price setter is the overall covariance of aggregate consumption with the profit-maximizing price. The sign of this covariance is the result of the combination of the covariances conditional on each shock. If, for example, the productivity shock has the larger volatility, $\sigma > 1$, then the covariance of the price level with aggregate demand is negative, as such a shock accounts for a larger fraction of the overall covariance than the monetary policy shocks. Therefore, everything else being equal, whenever the price setter observes a signal providing information of an increase (decrease) in consumption he decreases (increases) the price level. In such a case, $\sigma > 1$, by responding to the arrival of information on aggregate consumption, the price setter responds with the right sign to the productivity shock, but with the wrong sign to the monetary policy shock. Not all type of signals imply however a *trade-off* in the sign of the response of prices to shocks. For example, the price level is always positively correlated with the profit-maximizing price response, independently from the type of shock. If $\sigma > 1$ ($\sigma < 1$) by processing more information on aggregate consumption relative to the price level, the price setter implicitly allocates more (less) attention to the dynamics of $p_{it}^{\dagger}$ due to productivity shocks than to the dynamics of $p_{it}^{\dagger}$ due to monetary policy shocks.

Table 9 plots γ as a function of the degree of strategic complementarity in price setting. As an example, the model is calibrated so that there are incentives to process more information about technology shocks, $\sigma > 1$.[18] As complementarities increase, the asymmetry in price responsiveness increases. Therefore similarly to the benchmark model more complementarities exacerbate the difference in price responsiveness to the two shocks.

2.5.2. Choosing production inputs under rational inattention

In section 2 I assumed that only price decisions are taken under rational inattention, while per-capita intermediate inputs, x, are chosen under perfect information.

[18]The same results would apply to the case $\sigma < 1$.

In this section I assume instead that both decisions are taken under rational inattention. A quadratic approximation of (2.16) gives

(2.78)
$$-\lambda_p E\left[\left(\hat{p}_{ait}-\hat{p}_{ait}^{\dagger}\right)^2+\left(\hat{p}_{rit}-\hat{p}_{rit}^{\dagger}\right)^2\right]-\lambda_w E\left[\left(\hat{x}_{ait}-\hat{x}_{ait}^{\dagger}\right)^2+\left(\hat{x}_{rit}-\hat{x}_{rit}^{\dagger}\right)^2\right],$$

where $\hat{x}_{ait}^{\dagger}$ and $\hat{x}_{rit}^{\dagger}$ are the profit-maximizing responses to productivity and monetary policy shocks, and $\lambda_w = \beta\frac{(\theta-2)\mu(1-\mu)}{(1-\beta)(\theta-1)}\bar{Y}$ is a constant. Similarly to section 3 (2.78) can be further simplified in

$$-\left[\left(1-\rho_{ai}^2\right)\left(\lambda_p\omega_a^2+\lambda_w\delta_a^2\right)\sigma_a^2+\left(1-\rho_{ri}^2\right)\left(\lambda_p\omega_r^2+\lambda_w\delta_r^2\right)\sigma_r^2\right], \tag{2.79}$$

where δ_a and δ_r are obtained by substituting (2.30), (2.39), and (2.59) into (2.24), and are given by

$$\delta_a = -\left(\gamma_a+\eta_a+1\right)\xi, \tag{2.80}$$

$$\delta_r = -\left(\gamma_r+\eta_r+1\right)\xi, \tag{2.81}$$

The coefficients ω_a and ω_r are defined as in (2.45) − (2.46). Intermediate good producer i chooses ρ_{ai} and ρ_{ri} to maximize (2.79) subject to the constraint on the average amount of information processed per period,

$$\frac{1}{2}\log_2\left(\frac{1}{1-\rho_{ai}^2}\right)+\frac{1}{2}\log_2\left(\frac{1}{1-\rho_{ri}^2}\right)\leq\kappa_i. \tag{2.82}$$

The interior solution to this problem implies

$$1-(\rho_{ai}^*)^2 \quad = \quad 2^{-\kappa}\left(\frac{\lambda_p\omega_r^2+\lambda_w\delta_r^2}{\lambda_p\omega_a^2+\lambda_w\delta_a^2}\right)^{\frac{1}{2}}\frac{\sigma_r}{\sigma_a}, \tag{2.83}$$

$$1-(\rho_{ri}^*)^2 \quad = \quad 2^{-\kappa}\left(\frac{\lambda_p\omega_a^2+\lambda_w\delta_a^2}{\lambda_p\omega_r^2+\lambda_w\delta_r^2}\right)^{\frac{1}{2}}\frac{\sigma_a}{\sigma_r}. \tag{2.84}$$

The optimal allocation of attention depends also on the impact that each shock has on profits through the ratio of inputs. Comparing the solution to the rational inattention problem in section 3, $(2.47)-(2.48)$, with the solution in equations $(2.83)-(2.84)$, we should notice two things. First, the two decision share the same incentives to allocate attention to the two shocks, $|\omega_a|\lesseqgtr|\omega_r|\iff|\delta_a|\lesseqgtr|\delta_r|$. Second, the relative importance of the inputs ratio decision depends on the relative magnitude of λ_w. The ratio of λ_w to λ_p is substantially small for standard calibrations of μ and θ. Therefore the solution to the allocation of attention problem in equations $(2.83)-(2.84)$ is very similar to the one obtained in section 3 as the inputs ratio affects relatively little the volatility of profits. Given the non-linearity of equations $(2.83)-(2.84)$, it is not possible to solve analytically for the price level.

I therefore use to numerical methods. Table 10 plots γ against ξ for different values of η, holding $\sigma = 1$. As expected, there is no noticeable difference to the results from the model in section 2. More complementarities magnify the asymmetry in price responsiveness. For example, if $\eta > 1$, a decrease in ξ increases γ further away from 1.

2.6. Concluding remarks

I have shown that there are substantial differences in the properties of price responsiveness to aggregate productivity and monetary policy innovations across different models of price setting. In a simple general equilibrium model with nominal rigidities *a la* Calvo, higher strategic complementarities in price setting have no impact on relative price responsiveness to the two types of shocks. In contrast, in the same model but with price set under rational inattention, higher complementarities increase the asymmetry in relative price responsiveness to the two shocks. The same monetary policy may have very different implications for the asymmetry in price responsiveness across the two class of models.

The rational inattention model of price setting is better suited to account for differences in price responsiveness to different aggregate shocks. In general prices will be more responding to more volatile shocks, will be less responding to shocks which are *accommodated* more by the monetary policy authority.

CHAPTER 3

A Cross-Sectional Study of the Responsiveness of Disaggregated Prices to Aggregate Neutral Technology and Monetary Policy Shocks

3.1. Introduction

I study the responsiveness of disaggregated prices to neutral technology shocks and unanticipated changes in monetary policy. I document the differences in price responsiveness to the two shocks in 6-digits NAICS industries. I derive the empirical relationship between several industry specific statistics and price responsiveness to the two shocks. This analysis sheds some more light on the microeconomic behavior of prices setters[1]. The results help distinguishing between different classes of price-setting models, and eventually improve the ability to predict the behavior of aggregate prices.

In a companion paper, Paciello (2008b), I show that aggregate technology and monetary policy shocks account for a large fraction of aggregate prices volatility.

[1]See Paciello (2008b) for an analysis of aggregate prices responsiveness to neutral technology and moneary policy shocks in the U.S.

Furthermore aggregate prices adjust much faster to technology than to monetary policy shocks. Standard new-Keynesian sticky price models have an hard time reconciling the observed responses of aggregate prices to the two types of shocks. Dupor, Han and Tsai (2007) conjecture that these models may infact be deficient in capturing important aspects of the price setting behavior. More information on the behavior of disaggregated prices may therefore help exploring those aspects that standard sticky price models fail to address, and determining the economic forces behind the difference in price responsiveness to the two aggregate shocks. For instance, Boivin, Giannoni and Mihov (2007) have shown that disaggregated prices respond much faster to sector-specific shocks than to aggregate variables dynamics. This evidence has helped reconciling the empirical macroeconomic evidence that aggregate prices respond very slowly to aggregate nominal shocks[2], with the results from microeconomic empirical studies, according to which there is a high frequency of price changes at the firm level[3]. The differences in inflation persistence at aggregate and disaggregate level may be due to different degrees of responsiveness to macroeconomic and sector-specific shocks. Yet these results do not distinguish at the macroeconomic level between different sources of price volatility and different

[2]See Christiano, Eichenbaum and Evans (1999) for instance.
[3]See Bils and Klenow (2004).

aggregate shocks. In this paper I study two fundamental aggregate shocks, neutral technology and monetary policy shocks.

I estimate a large Bayesian VAR model, containing a large number of macroeconomic indicators[4] and 6-digits NAICS producer price series[5]. The macroeconomic time-series capture the dynamics of the aggregate economy, and allow to disentangle the aggregate technology shocks from the monetary policy innovations. The disaggregated prices provide information on the responsiveness of prices to the two shocks in each sector and on the fraction of disaggregated price volatility explained by each type of shock. I relate the cross-section of prices responsiveness and volatilities to several sector specific characteristics, such as revenues and labor-productivity. I compute second moments in the cross-section and evaluate the ability of standard sticky-prices models on one side and rational inattention models of price-setting on the other to generate those moments. For instance, I find that in sectors where prices are more volatile, there is a smaller difference in price responsiveness to the two aggregate shocks, and there is a smaller comovement with aggregate prices. In addition, sectors where there is a larger difference in price responsiveness to the two aggregate shocks, are characterized by larger price comovement with aggregate producer price index and by larger price volatility.

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[4]These are the same macroeconomic variables used by Paciello (2008b).
[5]These are the same series considered by Boivin, Giannoni and Mihov (2007).

I impose Minnesota priors on the autoregressive matrices of the reduced form VAR. This helps reducing the curse of dimensionality problem induced by the large number of time series in the model and the relatively small sample. Bambura, Giannone and Reichlin (2007) show that standard Bayesian VAR models are an appropriate tool for large panels of data and constitutes a valid alternative to factor models for dealing with the curse of dimensionality problem.

I interpret the results from the analysis of the cross-section of price responsiveness to the two shocks with a simple model. In this model I consider alternatively two different price-setting behaviors: a Calvo-style standard price setting model, and a rational inattention model of price setting. I then evaluate the ability of each of these two price-setting models in generating the observed moments.

The paper is organized as follows. In section 2 I describe the Bayesian VAR model, the data, the associated prior and identification assumptions about the two structural shocks, and describe the impulse responses of aggregate prices to each shock. In section 3 I define the measures of price responsiveness and use them to analyze in how many sectors and by how much disaggregated prices respond faster to neutral technology than to monetary policy shocks. In section 4 I study the cross-section of disaggregated prices responsiveness and volatilities. In section 5 I assess the robustness of my findings against the main assumptions behind my procedure. In section 6 I introduce a simple model to interpret the results of the previous sections. Section 7 concludes.

3.2. The BVAR model

I consider the following VAR(p) model:

$$Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + u_t, \tag{3.1}$$

where $Y_t = (y_{1,t}\ y_{2,t}\ ...y_{n,t})'$ is the vector of observations at period t, u_t is an n-dimensional white noise with covariance matrix $Eu_t u_t' = \Psi$, $c = (c_1\ c_2\ ...\ c_n)$ is a vector of constant and B_1, B_2,.., are the $n \times n$ autoregressive matrices.

The vector Y_t can potentially include a large number of variables. I therefore follow Bambura et al. (2007) and estimate the model (3.1) using the Bayesian VAR approach to overcome the curse of dimensionality. I therefore impose prior beliefs on the parameters of the model. These priors are set according to the standard practice which builds on Litterman (1986)'s suggestions and it is often referred as Minnesota priors. Let us write the VAR in (3.1) as a system of multivariate regressions:

$$\underset{T\times n}{Y} = \underset{T\times k}{X}\ \underset{k\times n}{B} + \underset{T\times n}{U}, \tag{3.2}$$

where $Y = (y_1, ...y_T)'$, $X = (X_1, ..., X_T)'$ and with $X_t = \left(Y'_{t-1}, ..., Y'_{t-p}, 1\right)$, $U = (u_1, ..., u_T)'$, $B = (B_1, ..., B_T, c)'$, and $k = np + 1$. The prior belief is that (B, Ψ) have a normal inverted-Wishart distribution:

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

The parameters S_0, α_0, B_0 and Ω_0 are chosen so that all the coefficients of B_1, B_2,.., B_p, denoted by $(B_k)_{ij}$, $k = 1, ..p$, $i = 1, 2.., n$, $j = 1, 2, ..n$, are independent and normally distributed with means and variances given by

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

and with the matrix of variance covariance of residuals u_t, Ψ, having a mean of $E(\Psi) = diag\left(\sigma_1^2, ..., \sigma_n^2\right)$. The prior on the intercept is diffuse. The idea of such prior beliefs is that each component i of Y_t follows either a random walk with drift, $\delta_i = 1$, if the variable i has high persistence, or a white noise, $\delta_i = 0$, otherwise. The parameter λ controls the tightness of the prior distribution and defines the weight given to the priors beliefs relative to the information coming from the data in the posterior distribution. The larger is λ, the smaller is the weight of priors into the posterior distribution. The factor k adjusts the prior variance for the lag length, while $\frac{\sigma_i^2}{\sigma_j^2}$ controls for the variability of different data. I set the scale parameters σ_i^2 equal the variance of a residual from a univariate autoregressive model of order p for the variables y_i. The prior is implemented by adding T_0 dummy observations[6], Y_0 and X_0, to the system in (3.2). 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:

$$\underset{T_* \times n}{Y_*} = \underset{T_* \times k}{X_*} \underset{k \times n}{B} + \underset{T_* \times n}{U_*}, \tag{3.3}$$

where $T_* = T + T_0$, $X_* = (X', X_0')$, $Y_* = (Y', Y_0')'$ and $U_* = (U', U_0')'$. The posterior distribution of (B, Ψ) is a normal inverted-Wishart[7]:

$$\Psi | Y \backsim iW(S_*, \alpha_*) \quad \text{and} \quad B | \Psi, Y \backsim N(B_*, \Psi \otimes \Omega_*), \tag{3.4}$$

where $B_* = (X_*'X_*)^{-1} X_*'Y_*$, $\Omega_* = (X_*'X_*)^{-1}$, $S_* = (Y_* - X_*B_*)'(Y_* - X_*B_*)$ and $\alpha_* = T_* - k + 2$.

[6]See Bambura, Giannone and Reichlin (2007) for more details.
[7]To insure the existence of the prior expectation of Ψ it is necessary to add an improper prior $\Psi \sim |\Psi|^{-(n+3)/2}$.

3.2.1. Data and priors

I study a large VAR model containing 23 macroeconomic indicators and 154 disaggregated producer price indices (PPI). The list of macroeconomic variables is in the appendix. In a companion paper, this set of variables has proven very effective in capturing the macroeconomic dynamics of the U.S. economy[8]. The disaggregated PPI series are at the 6-digit level of NAICS codes (corresponding to 4-digit SIC codes) and correspond to the data used by Boivin et al. (2007). The time span is from January 1976 through June 2005. All data have been transformed to induce stationarity. The need of stationarity comes from the fact that the identification strategy of structural parameters through long-run restrictions, imposed throughout the paper, requires $(I - B(1))^{-1}$ to be finite, where $B(1) = B_1 + ... + B_p$. The appendix contains details on whether variables are entered in levels, logarithms or log-differences. I estimate the reduced form VAR in (3.3) on a monthly frequency[9] and set the number of lags p to 13. Regarding the choice of the priors, I follow Bambura et al. (2007) and set a white noise prior, $\delta_i = 0$, for all but one variable. This is because all the variables for which there is high persistence are entered in

[8]See Paciello (2008b).

[9]Variables not available at the montlhy frequency are replaced with the interpolated equivalent from the quarterly frequency. See the appendx for more details.

the VAR in log-differences to preserve stationarity[10]. The only variables for which I set a random walk prior are interest rates, which have high enough persistence but are stationary and therefore enter the model in levels[11]. I finally set λ to 0.03 which is in between the values chosen by Bambura et al. (2007) for similar BVAR models with 20 and 131 macroeconomic indicators respectively.

3.2.2. Identification and Impulse responses

The structural VAR associated to (3.1) can be written as

$$A_0 Y_t = \upsilon + A_1 Y_{t-1} + ... + A_p Y_{t-p} + e_t, \tag{3.5}$$

where $\upsilon = A_0 C$ is the vector of constant variables, $A_s = A_0 B_s$ is the s^{th} order autoregressive matrix of the structural model, and $e_t = A_0 u_t$ is the vector of structural shocks realizations at time t. In order to recover the parameters of the structural model from the estimated reduced form, I impose restrictions on the matrix of structural parameters A_0. I am interested in the impulse responses of the system defined in (3.5) to two of the n structural shocks. This means that I need only to impose enough restrictions so to be able to recover the columns of

[10] All the variables that in Bambura et al. (2007) enter the model in logs and have a random walk prior, are entered in lod-differences and have a white noise prior in my model. The remaining variables and associated priors are as in in Bambura et al. (2007).

[11] I also considered the case where interest rates have a white noise prior. The results of the paper are unchanged.

A_0^{-1} relative to the technology and monetary policy shocks, independently of the response of the system to the remaining shocks.

The first identifying assumption is that only technology shocks may have a permanent effect on the level of labor productivity, as originally proposed in Gali (1999). This restriction is satisfied by a broad range of business cycle models, under standard assumptions. The remaining identifying assumptions specify the monetary policy rule according to the popular recursive identification scheme in Christiano, Eichenbaum, and Evans (1999). I order the variables in the model as $Y_t = (\Delta_t, X_t, S_t, Z_t, F_t)'$, where Δ_t is the growth rate in labor-productivity, X_t contains slow-moving variables, S_t is the monetary policy instrument, Z_t and F_t contains fast-moving variables. The identifying restriction is that slow-moving variables and labor productivity do not respond contemporaneously to a monetary policy shock and that the fast moving variables Z_t are not part of the monetary authority information set at time t, which is equivalent to say that the monetary policy instrument is not set in response to contemporaneous realizations of this subset of variables. There is no restriction on F_t. Similarly to Christiano, Eichenbaum and Evans (1999) Z_t includes M1 and M2 monetary stock, and non-borrowed and total reserves. The Standard & Poors price index is included in F_t. The monetary policy instrument adopted, S_t, is the 3-months Federal Funds rate. All the remaining macroeconomic indicators and the 154 disaggregated PPI series are included in X_t. Under the assumptions above, the columns of A_0^{-1} relative to the neutral technology and monetary policy shocks are exactly identified[12].

Table 11 plots the mean impulse responses of the 23 macroeconomic indicators and the associated quantiles to one standard deviation aggregate neutral technology and monetary policy shocks. Macroeconomic variables responses are very similar to the ones displayed by Paciello (2008b) in a similar BVAR model estimated without the disaggregated data. All aggregate price measures in fact display a high level of rigidity following the monetary policy shock, while start adjusting immediately to the technology shock.

Table 12 plots the mean impulse responses of the 154 disaggregated price level series, of their average and of the aggregate producer price index to technology and monetary policy shocks. The average impulse responses across industries are very similar to the aggregate producer price index responses. This means that the set of industries included in the sample is well representative of the entire universe of firms. This also suggests that the weights used in aggregate price indices do not play an important role in characterizing the response in the overall price indices. On average disaggregated prices are more responsive to technology shocks than

[12] See Paciello (2008b) for details.

to monetary policy shocks, confirming the empirical evidence from the study of aggregate price indices dynamics.

Table 1 reports the main statistics about inflation volatilities of the four aggregate price indices and the 154 disaggregate indices, with associated forecast-error variance decompositions relative to the technology and monetary policy shocks. As shown by Boivin et al. (2007) the disaggregated price series are substantially more volatile than the aggregate ones. The technology and monetary policy shocks account for a small fraction of the disaggregate prices forecast-error variance decomposition, confirming that in general aggregate shocks explain little of disaggregate prices volatility. Comparing technology and monetary policy shocks at the disaggregated level, the former accounts for a fraction of the forecast error variance which is more than 20 times the fraction due to the monetary policy shock. Therefore both shock together play a small role for disaggregated prices volatility but the monetary policy shock plays a relatively much smaller role.

3.3. Difference in price responsiveness

In this section I study the price responsiveness to technology and monetary policy shocks in the cross-section of 154 industries included in the BVAR model. In order to do that I need to specify measures of price responsiveness. The first measure of price responsiveness I consider is associated to the time it takes for prices to complete the fraction α of the long-run adjustment to a particular shock. It is defined as

$$\tau_{\alpha,s} = \min_{j} \left\{ j \in [0, 1, 2.....) \; |\gamma_{j,s} \leq \alpha \bar{\gamma}_s \right\}, \tag{3.6}$$

where $\alpha < 1$, $\gamma_{j,s}$ is the impulse response of the price level to shock s j periods after the shock, and $\bar{\gamma}_s$ is the long-run response of the price level to shock s. For simplicity, the signs of $\gamma_{j,s}$ and $\bar{\gamma}_s$ are normalized so that $\bar{\gamma}_s$ is always negative. The long-run response $\bar{\gamma}_s$ is defined as the price-level response 5 years after the shock[13]. The measure of difference in price responsiveness is given by the difference in $\tau_{\alpha,s}$ across the two shocks, $\tau = \tau_{\alpha,MP} - \tau_{\alpha,NT}$. Finally, I set α equal to 0.5.[14] Intuitively τ measures how many quarters more it takes for the price-level response to accomplish half of its long-run response to the monetary policy shock than to accomplish half of the long-run response to the technology shock. The larger is τ, the faster prices adjust to technology shocks than to monetary policy shocks.

The second measure of price responsiveness is defined as the fraction of the long-run price adjustment accomplished by the price level j periods after the shock, and

[13]Th results that follow are unaffected by this choice. If I consider a longer horizon to measure the long-run price response, I get very similar answers in terms of differences in price responsiveness.
[14]The qualitative results about the cross-section of τ are independent of α.

it is given by

$$\psi_{j,s} = \frac{\gamma_{j,s}}{\bar{\gamma}_s}. \tag{3.7}$$

According to this measure, the closer the price level is to its long-run level j periods after a shock, the faster it has adjusted to that shock. The difference in price responsiveness is then measured as $\psi = \psi_{j,NT} - \psi_{j,MP}$. I set j to 8 quarters but the statistical properties of $\psi_{j,s}$ hold for other choices of j.

3.3.1. Statistics from the estimated BVAR model

It is useful to distinguish across industries on the basis of the sign of their long-run price responses to positive technology and monetary policy shocks. According to standard macroeconomic theory, price impulse responses are expected to be negative after both a positive permanent shock to technology and a positive monetary policy shock to the Federal Funds rate. I therefore divide the set of all industries into two subsets R and W. In the subset R I include those industries that display estimated long-run price impulse responses $\bar{\gamma}_s$ with the *right sign* to both structural shocks according to theory. Industries which display the *wrong sign* long-run price response are instead assigned to W.

The subset R contains the vast majority of industries, 82 percent of total. Among the 28 industries in W (about 18 per cent of total industries), 24 display the *wrong sign* long-run price response only to the monetary policy shock. The remaining 4 have a *wrong sign response* to both shocks. All of the long-run price responses to the monetary policy shock in W are not statistically different from zero according to their posterior distribution. The subset W can therefore be interpreted as the set of industries that have a statistically zero price response to the monetary policy shock.

Tables 13-16 and Table 2 provide details about the cross-sections of τ and ψ. According to τ and ψ respectively, 92 and 84 percent of the industries in R adjust prices faster to technology than to monetary policy shocks. Across all industries the median value of τ is 12 months, meaning that at the median industry accomplishes half of the long-run price response to the technology shock a year earlier than to the monetary policy shock. Similarly, the estimated cross-section of ψ implies that 2 years after the shock the difference in the fraction of long-run price response accomplished to the two shocks is in median 26 percentage points in favor of the technology shock. In the subset of industries W there is much more dispersion in τ and ψ, reflecting the uncertainty in the price impulse responses to the monetary policy shock.

3.4. Cross-sectional analysis

Tables 3 and 4 report the cross-sectional correlations, with associated p-values[15], between several industry-specific statistics. I report statistics computed on all the 154 industries and in the subset R respectively.

There is a negative correlation between the disaggregated price volatility, Σ, and the ratio of 1 year-forecast error variance decompositions due to technology shocks relative to monetary policy shocks, $\frac{\Sigma^{NT}}{\Sigma^{MP}}$. Also, there is a strong negative relationship between Σ and the industry level price correlation with the aggregate PPI, ρ, and a negative relationship of Σ with the two measures of difference in price responsiveness τ and ψ. According to these correlations, in industries in which prices are more volatile, the technology and monetary policy shocks have a smaller difference in the share of forecast error variance decomposition that each shock accounts for. Industries with more volatile prices are also characterized by a smaller difference in the responsiveness of prices to the two structural shocks and display a smaller correlation of their price level with the aggregate PPI index. There is also a positive correlation between $\frac{\Sigma^{NT}}{\Sigma^{MP}}$ and τ in the subset R, implying that in industries where there is a smaller asymmetry in the fraction of price volatility due to the two aggregate shocks there is also a smaller asymmetry in

[15]The p-value is the probability of a zero correlation.

price responsiveness to the two shocks. Finally there is a positive correlation between the difference in price responsiveness and the price-correlation ρ.

3.4.1. Difference in price responsiveness and industry characteristics

Tables 5 and 6 report the results from the linear regressions of the two measures of difference in price responsiveness τ and ψ on a constant and several industry specific characteristics. All industry specific variables, but the concentration ratio $C4$, are the 5-digits equivalent to the 6-digits NAICS disaggregated price series. Infact most of the industry specific variables are unavailable at 6-digits. The regressions include proxies for the dimension of industries, such as the 2002-2006 averages of total production hours worked and revenues. From these regressions there is some evidence, although relatively weak, that larger firms tend to have smaller differences in the speed of prices adjustment to the two aggregate shocks. There is no role instead for the inverse of the concentration ratio in predicting the cross-section of difference in price responsiveness. The latter is often associated to product market competition. Boivin et al. (2007) also found no explanatory power for the responsiveness to monetary policy shocks of C4. These results show that the C4 ratio contains no information about the difference in the speed of price adjustment to shocks. Finally, there is weak evidence that more productive firms have larger speed of price adjustment. Although the slope coefficient on the latter is positive for both τ and ψ, it is statistically different from zero only for τ in the cross-section of all 154 industries, but even then it explains a small fraction of the variance in difference speed of price adjustment.

3.5. Robustness analysis

In this section I assess the sensitivity of the results above to some key assumptions in my empirical method. In particular I study wether the assumed priors influence the results. I also study price responsiveness through the FAVAR method described in Bernanke et al. (2005).

3.5.1. Robustness to prior choice

In choosing the tightness prior parameter λ the econometrician faces a trade-off. Decreasing λ reduces the uncertainty on the posterior distribution impulse response functions that might be caused by the shortage of data relative to the dimension of the system under study. On the other side, however, a smaller λ reduces also the overall weight given in the posterior distribution of parameters to the actual data. Given the results of Bambura et al. (2007) a value of λ set to 0.033 seemed appropriate. Nevertheless I report in Tables 7-8 and 9-10, respectively, the results from the estimation of the BVAR with λ set to 0.1 and 0.02.

As the prior gets tighter, λ decreases, the fraction of industries which display a statistically zero response to the monetary policy shock dramatically increases. This fraction goes from 0.08 when λ is equal to 0.1, to 0.44 when λ is set to 0.02. The reason for the latter is that in the data the evidence for a statistically non-zero response of prices to monetary policy shocks is relatively weak in many industries. On the other side the white-noise prior on inflation, coupled with the zero restriction imposed on the contemporaneous response of prices to the monetary policy shock, pushes towards a zero response of the price level to the monetary policy shock.

A looser prior, λ larger, reduces, on average, the difference in price responsiveness to the two aggregate shocks and reduces the fraction of industries for which prices adjust faster to technology shocks than to monetary policy shocks.

3.5.2. FAVAR model

Factor models have been shown to be successful at forecasting macroeconomic variables with a large number of predictors. It is therefore natural to compare the results relative to the difference in price responsiveness based on the Bayesian VAR with those produced by factor models where factors are estimated by principal components. Furthermore the FAVAR methodology has the advantage of not requiring economic priors on the reduced form parameters of the economic system. I therefore apply the FAVAR method described in Bernanke et al. (2005). I consider a small VAR model augmented by principal components extracted from a potentially large panel of data. I only provide here a general description of my implementation of the empirical framework and refer these authors for additional details. I assume that the economy is affected by a vector Y_t of common components to all variables entering the data set. Since I will be interested in characterizing the effects of monetary policy and technology shocks, this vector of common components includes a measure of the monetary policy instrument, the Federal Funds rate R_t, and of aggregate technology growth, Fernald (2007)'s measure of total factor productivity growth[16] A_t. The rest of the common dynamics are captured by a K $\times$ 1vector of unobserved factors F_t, where K is relatively small. These unobserved factors may reflect general economic conditions such as economic activity, the general level of prices, the level of productivity, which are not easily captured by a few time series, but rather by a wide range of economic variables. The vector of variables in the system of equations (3.1) is $Y_t = (A_t, R_t, F_t)'$. The K factors are unobservable. I denote by X_t the N $\times$1 vector of informational variables, where X_t contains all the

[16]This series is available at the quarterly frequency. The montlhy equivalent has been obtained through Chow-Lin interpolation.

variables included in the BVAR system described in section 2. The large set of observable informational series X_t is related to the common factors according to

$$X_t = \Lambda Y_t + e_t, \tag{3.8}$$

where Λ is an N $\times$(K + 2) matrix of factor loadings, and the N $\times$1 vector e_t contains (mean-zero) sector-specific components that are uncorrelated with the common components Y_t. These sector-specific components are allowed to be serially correlated and weakly correlated across indicators. The estimation procedure consists of two steps. In the first step the K common components are estimated through the first K principal components of X_t. In the second step the reduced form VAR in (3.1) is estimated.

The identification assumptions for the two structural shocks are similar to the ones applied to the Bayesian VAR. I assume that the only shock having a long-run impact on the measure of productivity A_t is the technology shock. I further assume that A_t and the last K-1 principal components do not respond contemporaneously to realizations of the monetary policy shock. Similarly to Bernanke et al. (2005) I remove from the last K-1 principal components the common contemporaneous dynamics with the monetary policy instrument. Given the relatively short length of the data sample and the relatively small number of macroeconomic indicators in X_t I set K equal to 3.

3.5.2.1. Disaggregated PPI responses. Table 17 displays the mean impulse responses of the 154 disaggregated PPI series, their average and the aggregate producer price index to positive technology and monetary policy shocks. The average impulse responses across industries are very similar to the aggregate producer price index responses. As in the benchmark BVAR model, on average disaggregated prices are more responsive to technology shocks than to monetary policy shocks. Disaggregated prices are constant on average following both the technology and monetary policy shocks for about one and two years respectively. The fraction of industries in the subset W is slightly smaller than in the benchmark BVAR model, about 12 percent of all industries. The fraction of industries that adjust faster to the technology shock than to the monetary policy shock in the subset R are 78 and 74 percent according respectively to τ and ψ. The medians for τ and ψ are smaller than in the benchmark BVAR model but still indicate a faster adjustment to technology shocks. In the subset R, industries accomplish half of the long run response to the technology shock in median 4 months before the monetary policy shock. Table 13 contains most of the relevant statistics about τ and ψ.

The FAVAR model also attributes a larger fraction of the forecast error variance decomposition to the technology and monetary policy shocks, both at the aggregate and the disaggregate level. It however confirms the order of importance in explaining price volatilities between the two aggregate shocks. The technology shock accounts for a larger fraction of aggregate and disaggregate price volatility. More details are in Table 11.

Table 12 reports the correlations and the associated p-values between several industry specific statistics. The sign and significance levels of these correlations confirm the results described for the benchmark BVAR. In addition, given the structure of the FAVAR model, I am able to distinguish between aggregate and idiosyncratic variations. The former associated to ΛY_t, the latter to e_t. Boivin et al. (2007) interestingly found that in industries with more idiosyncratic volatility there is a larger responsiveness of prices to monetary policy shocks. Here I find that more idiosyncratic volatility is associated to a larger difference in speed of price adjustment to the two shocks but this relation is weak and not statistically different from zero. Therefore there is no much of a role for sectorial specific shocks volatilities in accounting for the observed difference in the speed of prices adjustment to the two aggregate shocks.

In conclusion, the FAVAR model substantially confirms the results from the BVAR model. These results are also robust to the number of factors used and to the number of macroeconomic indicators included in X_t.

3.6. A simple model

From the analysis of the disaggregated price dynamics and their cross-section I obtained a series of interesting relationship between several statistics and measures of prices responsiveness and volatility. In this section I interpret these results with the help of a simple partial equilibrium model where the price-setting behavior is modeled either as in a sticky prices Calvo-style framework, along the lines of the new-Keynesian literature, or as a rational inattention setup along the lines of Maćkoviak and Wiederholt (2007) and Paciello(2008a). The model is not meant to capture all the dynamics of the economic variables, but to provide instead helpful insights about the role of several industry-specific characteristics for price responsiveness and price volatility. This helps understanding what type of price-setting behavior more naturally generates the relationships observed in the data.

I assume there is a final sector which assembles goods produced by a mass 1 of monopolistically competitive sectors according to the following technology

$$Y_t = \left(\int_0^1 (Y_{jt})^{\frac{\eta-1}{\eta}} \, dj \right)^{\frac{\eta}{\eta-1}}, \tag{3.9}$$

where j is the index for the sectors, η is the demand elasticity of substitution across sectors. Sector j produces its output, Y_{jt}, aggregating over a large number of monopolistically competitive firms, indexed by i, according to the following production technology

$$Y_{jt} = \left(\int_0^1 \left(Y_{ijt} \right)^{\frac{\theta - 1}{\theta}} di \right)^{\frac{\theta}{\theta - 1}}. \tag{3.10}$$

I assume for simplicity there is no friction in the price setting at the aggregate and sectorial level. It follows that aggregate and sectorial prices are given by

$$\begin{aligned} P_t &= \left(\int_0^1 \left(P_{jt} \right)^{\eta - 1} dj \right)^{\frac{1}{\eta - 1}}, \\ P_{jt} &= \left(\int_0^1 \left(P_{ijt} \right)^{\theta - 1} di \right)^{\frac{1}{\theta - 1}}. \end{aligned}$$

Finally, I assume that the profit-maximizing price dynamic of firm i in sector j is given by

$$\hat{P}^*_{ijt} = \left(1 - \xi_j\right) \hat{P}_t + \lambda_j^m \xi_j \hat{M}_t + \lambda_j^a \xi_j \hat{A}_t, \tag{3.11}$$

where all variables are expressed in deviations from the steady state; $\hat{P}_t$ is the log-deviation of aggregate final sector prices, $\hat{M}_t$ is the log-deviation of aggregate nominal demand, which is exogenously controlled by the monetary authority, and $\hat{A}_t$ is the exogenous aggregate productivity variable, common to all firms and sectors. The profit-maximizing price equation in (3.11) can be obtained as the outcome of a general equilibrium model where aggregate nominal demand is endogenously determined[17] and each firm i has a standard Cobb-Douglas production function. Here for simplicity I treat $\hat{M}_t$ as exogenous and interpret any change as a monetary policy shock. Both $\hat{M}_t$ and $\hat{A}_t$ are iid and normally distributed with mean zero and variances σ_m^2 and σ_a^2. The parameter ξ_j represent the degree of strategic complementarity in price setting in sector j, while λ_j^a and λ_j^a capture the heterogeneity in the relative responsiveness of profit-maximizing prices to aggregate productivity and nominal shocks. The profit-maximizing price (3.11) can be expressed as $\hat{P}_{ijt}^{*} = \hat{P}_{ijt}^{a,*} + \hat{P}_{ijt}^{m,*}$, where $\hat{P}_{ijt}^{a,*} = \left(1 - \xi_j\right) \hat{P}_t^a + \lambda_j^a \hat{A}_t$ and $\hat{P}_{ijt}^{m,*} = \left(1 - \xi_j\right) \hat{P}_t^m + \lambda_j^m \xi_j \hat{M}_t$, and where $\hat{P}_t^a$ and $\hat{P}_t^m$ are the impulse responses of aggregate prices to the productivity and nominal shocks respectively.

I assume there are frictions in the price-setting behavior at the firm level. In particular I consider two types of frictions. The first is along the lines of Calvo-style price setting models, widely applied in the new-Keynesian literature. The second is instead following the more recent literature which models the price-setting behavior under rational inattention[18]. I am interested in the moments implied by each of these models about the statistics obtained from the data in the sections above.

[17]See Paciello (2008a) for an example.
[18]See Paciello (2008a).

Sticky prices model: I derive the price setting behavior of firm i in sector j when it is allowed to change a time contingent pricing rule with an exogenous frequency $\alpha_j \in (0,1)$ under complete information. This type of friction is very similar to standard Calvo-type staggered pricing, where however firms are allowed to change only the current draw with frequency α_j. The slightly departure from the standard Calvo framework allows for a stationary equilibrium where the adjustment of the economy to any shock happens within the period of the shock and allows for an analytical solution and a direct comparison with the rational inattention counterpart model. However the results derived about asymmetry in price responsiveness would absolutely hold also in the more standard Calvo-type sticky price model. In fact, this framework preserves the relevant characteristic of the Calvo-type sticky price model, which is that the frequency of prices adjustment is exogenous and equal across the two types of shocks. Given these assumptions the dynamics of sectorial and firm level prices are given by

$$\hat{P}_{ij,t} = \begin{cases} \hat{P}^*_{ij,t} & \text{with probability } \alpha_j \\ 0 & \text{otherwise} \end{cases}, \tag{3.12}$$

$$\hat{P}_{j,t} = \alpha_j \hat{P}^*_{ij,t}. \tag{3.13}$$

Aggregate price dynamics are then given by

$$\hat{P}_t = \gamma_a \hat{A}_t + \gamma_m \hat{M}_t, \tag{3.14}$$

$$\gamma_a = \frac{\int_0^1 \alpha_j \xi_j \lambda_j^a dj}{1 - \int_0^1 \alpha_j \left(1 - \xi_j\right) dj}, \tag{3.15}$$

$$\gamma_m = \frac{\int_0^1 \alpha_j \xi_j \lambda_j^m dj}{1 - \int_0^1 \alpha_j \left(1 - \xi_j\right) dj}. \tag{3.16}$$

Rational inattention model: I assume that each firm i in sector j has limited information processing capabilities and therefore cannot process more than κ_j bits of information per period. According to the rational inattention literature, information is measured through the entropy concept. I assume there is an allocation of attention problem between the two aggregate shocks which is modeled by imposing that firms process information separately about the two shocks. In this case the dynamics of sectorial and firm level prices are given by

$$\hat{P}_{ij,t} = k_j^a \hat{P}_{ij,t}^{a,*} + u_{ij,t}^a + k_j^m \hat{P}_{ij,t}^{m,*} + u_{ij,t}^m \tag{3.17}$$

$$\hat{P}_{j,t} = k_j^a \hat{P}_{ij,t}^{a,*} + k_j^m \hat{P}_{ij,t}^{m,*}, \tag{3.18}$$

where the disturbance $u_{ij,t}^a$ and $u_{ij,t}^m$ are *iid* across firms and their volatility is associated to the quantity of information processed about each shock, and where

k_j^a and k_j^m are given by

$$k_j^a = \frac{1}{1+\frac{1}{2^{\kappa_j^a}-1}}, \tag{3.19}$$

$$k_j^m = \frac{1}{1+\frac{1}{2^{\kappa_j^m}-1}}, \tag{3.20}$$

$$\kappa_j^a = 2^{\kappa_j}\frac{\left(1-\xi_j\right)\gamma_a +_j \lambda_j^a \xi}{\left(1-\xi_j\right)\gamma_m + \lambda_j^m \xi_j}\frac{\sigma_a}{\sigma_m} \tag{3.21}$$

$$\kappa_j^m = \frac{2^{2\kappa_j}}{\kappa_j^a}. \tag{3.22}$$

Aggregate price dynamics are then given by

$$\hat{P}_t = \gamma_a \hat{A}_t + \gamma_m \hat{M}_t, \tag{3.23}$$

$$\gamma_a = \frac{\int_0^1 \kappa_j^a \xi_j \lambda_j^a dj}{1-\int_0^1 \kappa_j^a \left(1-\xi_j\right) dj}, \tag{3.24}$$

$$\gamma_m = \frac{\int_0^1 \kappa_j^m \xi_j \lambda_j^m dj}{1-\int_0^1 \kappa_j^m \left(1-\xi_j\right) dj}. \tag{3.25}$$

3.6.1. The cross section

In the model above there are four possible sources of heterogeneity across sectors. First the degree of strategic complementarity in price setting, ξ_j, second the responsiveness of profit-maximizing prices to productivity shocks, λ_j^a, third the responsiveness of profit-maximizing prices to productivity shocks, λ_j^m, and fourth the frequency of prices adjustment in the Calvo-style model, α_j, or amount of information processed per period, κ_j, in the rational inattention model.

I study how the change in each of these sector-specific variables affect the volatility of sector level prices, Σ_j, the relative volatility of prices due to each shock, $\frac{\Sigma_j^a}{\Sigma_j^m}$, the correlation between sector level prices and aggregate prices, ρ_j, and the relative price responsiveness to the two shocks in each sector, $\Delta_j = \frac{\hat{P}_{j,t}^a}{\hat{P}_{j,t}^m}$.

The first column of Table 14 reports the sign of the cross-correlations of the elements of the vector $Z_j = \left(\Sigma_j, \frac{\Sigma_j^a}{\Sigma_j^m}, \rho_j, \Delta_j\right)$ observed in the data[19]. The 2^{nd}-4^{th} columns of Table 14 report the signs of the correlations of the elements of Z_j generated in the rational inattention model of price-setting, when the source of heterogeneity across sectors is κ_j, ξ_j, λ_j^a and λ_j^m respectively[20]. The 5^{th}-7^{th} columns of Table 14 report instead the signs of the correlations induced by the Calvo-style price-setting model when the source of heterogeneity across sectors is α_j, ξ_j, λ_j^a and λ_j^m respectively. Throughout the analysis I assume without loss of generality that $\sigma_a > \sigma_m$.

[19] The correlations are reported in tables 3-4.

[20] The correlations are computed in the case of an interior solution in the allocation of attention decision. When in fact firms in a sector only pay attention to one type of shock, the rational inattention model behaves exactly as the Calvo-style price-setting model and therefore it is observationally equivalent in terms of correlations of the elements in Z_j.

Sticky prices model: In the Calvo-style price setting model the elements of the vector Z_j are given by

$$(3.26)\ \Sigma_j = \alpha_j^{0.5}\left(\left[\left(1-\xi_j\right)\gamma_a+\lambda_j^a\xi_j\right]^2\sigma_a^2+\left[\left(1-\xi_j\right)\gamma_m+\lambda_j^m\xi_j\right]^2\sigma_m^2\right)^{0.5},$$

$$(3.27)\ \rho_j = \frac{\alpha_j\left[\left(1-\xi_j\right)\gamma_a+\lambda_j^a\xi_j\right]\gamma_a\sigma_a^2+\alpha_j\left[\left(1-\xi_j\right)\gamma_m+\lambda_j^m\xi_j\right]\gamma_m\sigma_m^2}{\Sigma\Sigma_j}$$

$$(3.28)\ \frac{\Sigma_j^a}{\Sigma_j^m} = \frac{\left(1-\xi_j\right)\gamma_a+\lambda_j^a\xi_j}{\left(1-\xi_j\right)\gamma_m+\lambda_j^m\xi_j}\frac{\sigma_a}{\sigma_m},$$

$$(3.29)\ \Delta_j = \frac{\left(1-\xi_j\right)\gamma_a+\lambda_j^a\xi_j}{\left(1-\xi_j\right)\gamma_m+\lambda_j^m\xi_j},$$

where $\Sigma=\left[\gamma_a\sigma_a^2+\gamma_m\sigma_m^2\right]^{0.5}$, γ_a and γ_m are given by $(3.15)-(3.16)$.

In the cross-section of firms, there is a unitary correlations between $\frac{\Sigma_j^a}{\Sigma_j^m}$ and Δ_j : if prices are more responding to a shocks, then also the relative variance of the price components is larger for that shock. In the data, in fact, $\frac{\Sigma_j^a}{\Sigma_j^m}$ and Δ_j are positively correlated. The second thing to notice is that both $\frac{\Sigma_j^a}{\Sigma_j^m}$ and Δ_j vary in the cross-section only there is heterogeneity in λ_j^a and λ_j^m. If for instance, λ_j^a $=\lambda^a$ and $\lambda_j^m=\lambda^m$ for all j, then Δ_j and $\frac{\Sigma_j^a}{\Sigma_j^m}$ are equal respectively to 1 and $\frac{\sigma_a}{\sigma_m}$, independently of the cross-section of the degree of strategic complementarity in price setting, ξ_j, and of the frequency of prices adjustment, α_j. Therefore to have heterogeneity in the cross-section of sectors responses there has to be heterogeneity in the way each shock affects profit-maximizing prices across firms. The Calvo price setting model would generate the fact that sectors in which prices are more volatile are the ones in which there is a smaller difference in price responsiveness if there is heterogeneity in the profit-maximizing price responses to monetary policy shocks. In fact in sectors in which, λ_j^m is larger the price response to monetary policy shocks is relatively larger, implying Δ_j smaller, and everything else being equal the sector price volatility, Σ_j, is larger. It is less clear instead if this type of model is able to generate a positive comovement between ρ_j and Δ_j. In fact Δ_j is always increasing in λ_j^a and decreasing in λ_j^m, but the impact of λ_j^a and λ_j^m on ρ_j is not clear: ρ_j has an inverse-U relationship with λ_j^a and λ_j^m.

Rational inattention model: In the rational inattention model the elements of the vector Z_j are given by

$$\Sigma_j = \left(\left(k_j^a \left[\left(1-\xi_j\right) \gamma_a + \lambda_j^a \xi_j \right] \sigma_a \right)^2 + \left(k_j^m \left[\left(1-\xi_j\right) \gamma_m + \lambda_j^m \xi_j \right] \sigma_m \right)^2 \right)^{0.5}, \tag{3.30}$$

$$\rho_j = \frac{k_j^a \left[\left(1-\xi_j\right) \gamma_a + \lambda_j^a \xi_j \right] \gamma_a \sigma_a^2 + k_j^m \left[\left(1-\xi_j\right) \gamma_m + \lambda_j^m \xi_j \right] \gamma_m \sigma_m^2}{\Sigma \Sigma_j}, \tag{3.31}$$

$$\frac{\Sigma_j^a}{\Sigma_j^m} = \frac{k_j^a}{k_j^m} \frac{\left(1-\xi_j\right) \gamma_a + \lambda_j^a \xi_j}{\left(1-\xi_j\right) \gamma_m + \lambda_j^m \xi_j} \frac{\sigma_a}{\sigma_m} \tag{3.32}$$

$$\Delta_j = \frac{k_j^a}{k_j^m} \frac{\left(1-\xi_j\right) \gamma_a + \lambda_j^a \xi_j}{\left(1-\xi_j\right) \gamma_m + \lambda_j^m \xi_j}. \tag{3.33}$$

where $\Sigma = \left[\gamma_a \sigma_a^2 + \gamma_m \sigma_m^2\right]^{0.5}$, γ_a, γ_m, k_j^a and k_j^m are given by $(3.19) - (3.23)$. The main difference from the Calvo-style model is in the fact that here in place of the exogenous α_j there are the endogenous k_j^a and k_j^m which can be therefore different from each other. This introduces an additional channel through which create comovement across the four statistics in the cross-section of sector.

As in the Calvo price setting model, there is a unitary correlation between $\frac{\Sigma_j^a}{\Sigma_j^m}$ and Δ_j. Also the impact of heterogeneity in λ_j^a and λ_j^m on the cross-sectional comovement between the elements of Z_j is the same as in the more standard sticky price model.

In contrast from the Calvo price setting model, however, the rational inattention model generates enough heterogeneity in the pricing behavior towards the two types of shocks even in the absence of heterogeneity in λ_j^a and λ_j^m. Interestingly enough, heterogeneity in the degree of strategic complementarity in price setting, ξ_j, is able alone to explain all the heterogeneity observed in the data. In sectors where there are higher complementarities in price setting, the asymmetry in price responsiveness to the two types of shocks tend to be larger because of the larger asymmetry in attention allocation, therefore a decrease in ξ_j increases Δ_j. More complementarities, however, also increase the comovement with aggregate prices, ρ_j, being aggregate prices more responding to productivity shocks on average. Finally, more strategic complementarities within the sector increase the sector level price volatility because make firm responding more to the shock with the larger volatility.

3.7. Conclusions

I have shown that disaggregate prices respond faster to aggregate neutral technology shocks than to monetary policy shocks. Neutral technology shocks account for a larger fraction of disaggregate prices volatility than monetary policy shocks, but are both a small fraction of the total variance. There are interesting and statistically significant correlations between different sectorial statistics about price responsiveness and volatilities in the cross-section of 6-digits industries. These correlations provide useful guidance for the choice of the underlying price-setting model. Rational inattention models of price setting seem better suited to account for the observed heterogeneity in price responsiveness although more research is needed.

CHAPTER 4

References

4.1. References to Chapter 1

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CHAPTER 5

Appendix

5.1. Appendix to Chapter 1

5.1.1. A Data

Mnemon	Series	Entering Order in Y	Small	Large	d-Log
GDPQ/LBMNU	Labor prod.	X	v	v	v
LBMNU	Index total hours worked	X	v	v	v
FYFF	:FEDERAL FUNDS	S	v	v	
PFDIGDP	GDP price deflator	X	v	v	v
FSPCOM	S&Poor's stock price index	F	v	v	v
CES002	Number of employees	X		v	v
A0M051	Personal income	X		v	v
JQCR	Real Personal Consumption	X		v	v
IFNRER	Real non-residential investments	X		v	v
JQIFRESR	Real residential investments	X		v	v
IPS10	Industrial production	X		v	v
UTL11	Capacity utilization	X		v	
LHUR	Unemployment rate	X		v	
HSFR	Housing starts (NONFARM)	X		v	
PSM99Q	Index of sensitive material prices	X		v	v
PWFSA	Producer price index	X		v	v
GDMC	PCE deflator	X		v	v

PUNEW	Consumer price index	X	v	v
CES275	Average hourly earnings	X	v	v
FM1	M1 monetary stock	Z	v	v
FM2	M2 monetary stock	Z	v	v
FMRRA	Non-borrowed reserves	Z	v	v
FMRNBA	Total reserves	Z	v	v
FTFP	Fernald (2007)'s TFP growth estimate	X	v	v

Most data is available at a monthly frequency. Output, GDP deflator, residential and non-residential investments are not. When monthly frequency is needed I use Sims and Zha (2007) interpolated monthly series for those 4 time series. Also LBMNU is not available at the monthly frequency and in that case it is replaced with BLS index for average weekly hours worked.

5.1.2. B Identification

Let's order the variables in the model as $Y_t = (\Delta_t, X_t, S_t, Z_t, F_t)'$. Following Ramirez et al. (2007) I express the set of linear restrictions onto the structural parameters as

$$H\left(A_0\right) = \begin{bmatrix} A_0^{-1} \\ \left(A_0^{-1} - B\left(A_0\right)\right)^{-1} \end{bmatrix} = D \tag{5.1}$$

where $B\left(A_0\right) = A_0 B_1 + ... + A_0 B_p$ 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 the structural shocks. The identifying restrictions in section 3 are zero restrictions on D:

$$D^{*} = \begin{array}{c} \\ [\Delta, X']' \\ S \\ Z \\ F \\ \Delta \\ X \\ S \\ Z \\ F \end{array} \begin{array}{c} \begin{array}{cccc} \varepsilon^{z} & \varepsilon^{s} & \varepsilon^{x} & \varepsilon^{a} \end{array} \\ \begin{bmatrix} 0 & 0 & T_x & x \\ 0 & x & x & x \\ T_z & x & x & x \\ x & x & x & x \\ 0 & 0 & 0 & x \\ x & x & x & x \\ x & x & x & x \\ x & x & x & x \\ x & x & x & x \end{bmatrix} \end{array} \tag{5.2}$$

where ε^s and ε^a are respectively the monetary policy and technology shock, and ε^z and ε^x are the $n-2$ non-identified structural shocks. If n_x and n_z are the number of variables in X and Z respectively, then ε^z is $(n_z - 1) \times 1$ while ε^x $(n_x + 1) \times 1$. F contains only one variable. 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:

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

The zero restrictions on D^* satisfy both the necessary and sufficient (rank) conditions derived by Ramirez et al. (2007) for exact identification. 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 et al (2007). Let $\Sigma = CD^{\frac{1}{2}}$ be the $n \times n$ lower diagonal Cholesky matrix of the covariance of the residuals of the reduced form VAR (see eq. 1), that is $CDC\prime = E[u_t u_t^{\prime}] = \Psi$ and $D = diag(\Psi)$. Compute $H(\Sigma)$

and define the matrices P_1 and P_2 as:

$$P_1 = \begin{bmatrix} 0_{1\times n} & 1 & 0_{1\times n-1} \\ I_{n\times n} & 0_{n\times 1} & 0_{n\times n-1} \\ 0_{n\times n} & 0_{n\times 1} & I_{n-1\times n-1} \end{bmatrix}, \tag{5.3}$$

$$P_2 = [e_n,\ e_{n-1}, ...,\ e_1], \tag{5.4}$$

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

Proposition 11. *For given estimates of B and Ψ, let Σ be the Cholesky factor associated to Υ, and let $H(\cdot)$, P_1 and P_2 be defined as in $(5.1)-(5.4)$. 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 5.2. It follows that $A_0 = \Sigma^{-1} P$.*

Proposition 1 provides the exact identification of the impulse responses of Y to monetary policy and aggregate technology shocks[1]. The structural shocks e_t are obtained from $e_t = A_0 u_t$. The first and last elements of e_t are the monetary policy and technology shocks respectively. Finally, the order of the variables in X and Z

[1]For a proof see Ramirez, Waggoner and Zha (2007). These restrictions satisfy both the necessary and the rank conditions for exact identification.

can be aribtrarily changed without any effect on the identifications of the columns for technology and monetary policy shocks. To see these, consider the matrix A_0. The restrictions imposed on A_0^{-1} are equivalent to the following zero restrictions on A_0 :

$$A = \begin{array}{c|cccc} & [\Delta, X'] & S & Z' & F \\ [\Delta, X]' & a_{11} & 0 & 0 & a_{14} \\ S & a_{21} & a_{22} & 0 & a_{24} \\ Z & a_{31} & a_{32} & a_{33} & a_{34} \\ F & a_{41} & a_{42} & a_{43} & a_{44} \end{array},$$

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 $(n_x + 1) \times (n_x + 1)$ and $n_z \times n_z$ orthonormal matrices. Then any matrix $\tilde{A}_0 = W A_0$ satisfies both the short-run and long-run restrictions, without any effect on the estimated monetary policy rule structural parameters.

5.2. Appendix to Chapter 2

5.2.1. A Derivation of firms' objective

Without loss of generality, define the real profit function of firm z at time t as

$$\pi_{it}^{r}=\pi\left(\frac{p_{it}}{p_t},x_{it},w_t^r,A_t,Y_t\right)=\left(\frac{p_{it}}{p_t}-\frac{w_t^r x_{it}^{-\mu}+x_{it}^{1-\mu}}{A_t}\right)\left(\frac{p_{it}}{p_t}\right)^{-\theta}Y_t, \tag{5.5}$$

where w_t^r is the real wage rate. Real profits, π_{it}^r, can be expressed in terms of log-deviations from the non-stochastic steady state,

$$\begin{aligned}\pi_{it}^{r} &= \breve{\pi}\left(\hat{p}_{it}-\hat{p}_t,\hat{x}_{it},\hat{w}_t^r,\hat{A}_t,\hat{Y}_t\right)\\ &= \bar{Y}e^{(1-\theta)(\hat{p}_{it}-\hat{p}_t)}-(1-\mu)\frac{\theta-2}{\theta-1}\bar{Y}e^{\hat{w}_t^r-\mu\hat{x}_{it}-\hat{A}_t}-\mu\frac{\theta-2}{\theta-1}\bar{Y}e^{(1-\mu)\hat{x}_{it}-\hat{A}_t}+\frac{1}{\theta-1}\bar{Y}e^{\hat{Y}_t}.\end{aligned}$$

Firm i chooses the allocation of attention so as to maximize the expected discounted sum of profits expressed in terms of log-deviations from the non-stochastic steady state,

$$\Pi_{i0}=E\left[\sum_{t=1}^{\infty}e^{q_t}\breve{\pi}\left(\hat{p}_{it}-\hat{p}_t,\hat{x}_{it},\hat{w}_t^r,\hat{A}_t,\hat{Y}_t\right)\right]. \tag{5.6}$$

Similarly Maćkoviak and Wiederholt (2007), I compute a second-order Taylor approximation around the non-stochastic steady state of Π_{it}. Afterwards, I deduct from the quadratic objective the value of the quadratic objective at the profit-maximizing behavior $\left\{\hat{p}^{\dagger}_{it+\tau}, \hat{x}^{\dagger}_{it+\tau}\right\}_{\tau=0}^{\infty}$. This yields the following expression for the expected discounted sum of losses in profits due to suboptimal behavior:

$$-\beta\frac{1}{2}\frac{\theta-1}{1-\beta}\bar{Y}E\left(\hat{p}_{it+\tau}-\hat{p}^{\dagger}_{it+\tau}\right)^2-\beta\frac{(\theta-2)\,\mu\,(1-\mu)}{(1-\beta)\,(\theta-1)}E\left(\hat{x}_{it+\tau}-\hat{x}^{\dagger}_{it+\tau}\right)^2.$$

5.2.2. B Derivation of the information flow constraint in terms of correlations

In section 3, all endogenous variables expressed in log-deviations from the non-stochastic steady state are a linear function of the realizations of the two shocks. The information flows between $\hat{p}_{ait}$ and $\hat{p}^{\dagger}_{ait}$ and between $\hat{p}_{rit}$ and $\hat{p}^{\dagger}_{rit}$ can be expressed as

$$\begin{aligned}
I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right) &= I\left(\left\{\hat{p}^{\dagger}_{ait}\right\};\{\hat{p}_{ait}\}\right)=H\left(\hat{p}^{\dagger}_{ai}\right)-H\left(\hat{p}^{\dagger}_{ai}|\hat{p}_{ai}\right)\\
&= \frac{1}{2}\log_2\sigma^2_{\hat{p}^{\dagger}_{ai}}-\frac{1}{2}\log_2\left(\sigma^2_{\hat{p}^{\dagger}_{ai}}-\frac{\sigma^2_{\hat{p}^{\dagger}_{ai}\hat{p}_{ai}}}{\sigma^2_{\hat{p}_{ai}}}\right)\\
&= \frac{1}{2}\log_2\frac{1}{1-\rho^2_{\hat{p}^{\dagger}_{ai}\hat{p}_{ai}}}=\frac{1}{2}\log_2\frac{1}{1-\rho^2_{ai}},
\end{aligned}$$

where $\sigma^2_{\hat{p}^{\dagger}_{ai}}$ and $\sigma^2_{\hat{p}_{ai}}$ are respectively the variances of the profit-maximizing and actual prices conditional on the productivity shock, while $\sigma_{\hat{p}^{\dagger}_{ai}\hat{p}_{ai}}$ is the covariance among them. Similarly it can be derived $I\left(\left\{p^{\dagger}_{ait}\right\};\{p_{ait}\}\right)=\frac{1}{2}\log_2\frac{1}{1-\rho^2_{ri}}$.

Maćkoviak and Wiederholt (2007) show that the problem (2.43) $-$ (2.46) can be expressed in temrs of signals on the fundamental shocks

$$\begin{aligned}
& && \max_{\upsilon_a,\upsilon_r} -\lambda_p E\left[\left(\hat{p}_{ait}-\hat{p}^{\dagger}_{ait}\right)^2+\left(\hat{p}_{rit}-\hat{p}^{\dagger}_{rit}\right)^2\right] \\
& && s.t. \\
i) &\quad : && \hat{p}_{ait}=E\left[\hat{p}^{\dagger}_{ait}\mid s_{ait}\right], \\
ii) &\quad : && \hat{p}_{rit}=E\left[\hat{p}^{\dagger}_{rit}\mid s_{rit}\right], \\
iii) &\quad : && s_{ait}=\varepsilon_{at}+\upsilon_a u_{ait} \\
iv) &\quad : && s_{rit}=\varepsilon_{rt}+\upsilon_r u_{rit} \\
v) &\quad : && I\left(\{\varepsilon_{at}\};\{s_{ait}\}\right)+I\left(\{\varepsilon_{rt}\};\{s_{rit}\}\right)\leq\kappa_i.
\end{aligned}$$

where u_{ait} and u_{rit} are idiosyncratic noise, iid across firms and time, and normally distributed with mean zero and unitary variance. By substituting i)-iv) into v) and into the objective, the rational inattention problem becomes:

$$\max_{\upsilon_a,\upsilon_r} -\lambda_p \left[\frac{\sigma^2_{\hat{p}^\dagger_{ai}}}{1+\frac{\sigma_a^2}{\upsilon_a^2}} + \frac{\sigma^2_{\hat{p}^\dagger_{ri}}}{1+\frac{\sigma_r^2}{\upsilon_r^2}} \right]$$

$$s.t.$$

$$i) \quad : \quad \frac{1}{2}\log_2\left(1+\frac{\sigma_a^2}{\upsilon_a^2}\right) + \frac{1}{2}\log_2\left(1+\frac{\sigma_r^2}{\upsilon_r^2}\right) \leq \kappa_i.$$

Therefore it follows from above that $1+\frac{\sigma_a^2}{\upsilon_a^2} = \frac{1}{1-\rho_{ri}^2}$, and that the objective of the rational inattention problem can be expressed as

$$-\lambda_p \left[\left(1-\rho_{ai}^2\right)\sigma^2_{\hat{p}^\dagger_{ai}} + \left(1-\rho_{ri}^2\right)\sigma^2_{\hat{p}^\dagger_{ri}} \right].$$

5.2.3. C Derivation of price level dynamics in the benchmark model with sticky prices

Each firm i receives information in period t with probability α. Given that $p^\dagger_{it}$ is an *iid* process, when a firm changes its time-contingent plan at time t it does it so that $\hat{p}_{it} = \hat{p}^\dagger_{it}$ and $\hat{p}_{it+\tau} = E_t\left(\hat{p}^\dagger_{it+\tau}\right) = 0$ for all $\tau \geq 1$. Therefore the price level is given by $\hat{p}_t = \alpha \hat{p}_{it}^{\dagger}$. By substituting the latter into equation (2.38) I get equation (2.51).

5.2.4. D Proof of Proposition 1

Interior Solution

The response of the aggregate price to the two shocks is given by

$$\begin{aligned} \hat{p}_{at} &= \int_0^1 \hat{p}_{ait} di, \\ \hat{p}_{rt} &= \int_0^1 \hat{p}_{rit} di. \end{aligned}$$

We saw from Appendix B that $\hat{p}_{ait}$ and $\hat{p}_{rit}$ can be expressed as the conditional expectactions of profit-maximizing prices, conditioning on signals,

$$\begin{aligned} \hat{p}_{ait} &= \frac{\sigma_a^2}{\upsilon_a^2 + \sigma_a^2} \left(\varepsilon_{at} + \upsilon_a u_{ait}\right) \omega_a, \\ \hat{p}_{rit} &= \frac{\sigma_r^2}{\upsilon_r^2 + \sigma_r^2} \left(\varepsilon_{rt} + \upsilon_r u_{rit}\right) \omega_r, \end{aligned}$$

where $\frac{\sigma_a^2}{\upsilon_a^2+\sigma_a^2}$ and $\frac{\sigma_r^2}{\upsilon_r^2+\sigma_r^2}$ are equal respectively to ρ_a^{*2} and ρ_r^{*2}, which are defined in $(2.47) - (2.48)$, and where ω_a and ω_r are the profit-maximizing price responses to technology and monetary policy shocks in $(2.45)-(2.46)$. It follows that

$$\begin{aligned}
\hat{p}_{at} &= \int_0^1 \frac{\sigma_a^2}{\upsilon_a^2+\sigma_a^2}\left(\varepsilon_{at}+\upsilon_a u_{ait}\right)\omega_a di = \rho_a^{*2}\omega_a\varepsilon_{at}, \\
\hat{p}_{rt} &= \int_0^1 \frac{\sigma_r^2}{\upsilon_r^2+\sigma_r^2}\left(\varepsilon_{rt}+\upsilon_r u_{rit}\right)\omega_r di = \rho_r^{*2}\omega_r\varepsilon_{rt}.
\end{aligned}$$

Then the fixed point problem is solving for γ_a and γ_r in the guess (2.39) :

$$\begin{aligned}
\gamma_a &= (1-2^{-\kappa}\frac{\omega_r}{\omega_a}\frac{\sigma_r}{\sigma_a})\omega_a, \\
\gamma_r &= (1-2^{-\kappa}\frac{\omega_a}{\omega_r}\frac{\sigma_a}{\sigma_r})\omega_r.
\end{aligned}$$

The by substituting $(2.45)-(2.46)$ in the two equations above I solve for γ_a and γ_r :

$$\begin{aligned}
\gamma_a &= -\xi\left(1+\eta_a\right)F\left(\frac{1}{\eta\sigma}\right) \\
\gamma_r &= -\xi\left(1+\eta_r\right)F\left(\sigma\eta\right)
\end{aligned}$$

where the function $F(\cdot)$ is given by

$$F\left(\varkappa\right)=\frac{\xi+2^{-2\kappa}\left(1-\xi\right)-2^{-\kappa}\varkappa}{\xi^2-2^{-2\kappa}\left(1-\xi\right)^2}.$$

Corner solutions

At a corner where attention is paid only to technology shocks, the fixed point problem is

$$\begin{aligned}\gamma_a &= (1-2^{-2\kappa})\omega_a, \\ \gamma_r &= 0.\end{aligned}$$

It follows that the solution to γ_a is such that

$$\begin{aligned}\gamma_a &= -\xi\,(1+\eta_a)\,\frac{1-2^{-2\kappa}}{1-(1-\xi)\,(1-2^{-2\kappa})} \\ \gamma_r &= 0.\end{aligned}$$

Similarly, at the corner where attention is paid only to monetary policy shocks, the solution to the fixed point problem for γ_a amd γ_r is

$$\begin{aligned}\gamma_a &= 0 \\ \gamma_r &= -\xi\,(1+\eta_r)\,\frac{1-2^{-2\kappa}}{1-(1-\xi)\,(1-2^{-2\kappa})}.\end{aligned}$$

Derivation of φ

I derive the interval for $\eta\sigma$ in which there is an interior solution to the rational inattention problem. The conditions for an interior solution are given by (2.43).

Using (2.47), (2.48), (2.45), (2.46), (2.54) and (2.55) it follows that

$$\begin{aligned}
\rho_{ia}^{*2} &= \frac{\left(1-\frac{1}{\eta\sigma}\right)\left(\xi+2^{-\kappa_i}\left(1-\xi\right)\right)}{\xi-2^{-\kappa_i}\left(1-\xi\right)\frac{1}{\eta\sigma}} \\
\rho_{ir}^{*2} &= \frac{\left(1-\eta\sigma\right)\left(\xi+2^{-\kappa_i}\left(1-\xi\right)\right)}{\xi-2^{-\kappa_i}\left(1-\xi\right)\eta\sigma}
\end{aligned}$$

and that (2.43) can be expressed as

$$\rho_{ia}^{*} \leq 1 : 2^{\kappa_i}\tfrac{\xi}{1-\xi} \geq \tfrac{1}{\eta\sigma} \geq 2^{-\kappa_i}\tfrac{1-\xi}{\xi} \quad if\ \eta\sigma > 1$$

$$\rho_{ir}^{*} \leq 1 : 2^{\kappa_i}\tfrac{\xi}{1-\xi} \geq \eta\sigma \geq 2^{-\kappa_i}\tfrac{1-\xi}{\xi} \quad if\ \eta\sigma < 1$$

$$\begin{aligned}
\rho_{ia}^{*} &\leq 1 : 2^{\kappa_i}\frac{\xi}{1-\xi} \geq \frac{1}{\eta\sigma} \geq 2^{-\kappa_i}\frac{1-\xi}{\xi}, \\
\rho_{ir}^{*} &\leq 1 : 2^{\kappa_i}\frac{\xi}{1-\xi} \geq \eta\sigma \geq 2^{-\kappa_i}\frac{1-\xi}{\xi},
\end{aligned}$$

Therefore if I fefine $\varphi = 2^{\kappa_i}\frac{\xi}{1-\xi}$, the condition for an interior solution is that

$$\frac{1}{\varphi} \leq \eta\sigma \leq \varphi.$$

5.2.5. E Proof of Proposition 3

It follows from above that the level of ξ below which there is a corner solution, $\bar{\xi}$, is given by

$$\bar{\xi} = \begin{bmatrix} \frac{\eta\sigma}{\eta\sigma+2^{\kappa_i}} & \text{if } \eta\sigma > 1 \\ \frac{\frac{1}{\eta\sigma}}{\frac{1}{\eta\sigma}+2^{\kappa_i}} & \text{if } \eta\sigma < 1 \end{bmatrix}$$

At these values it follows that either $\eta\sigma > \varphi$ or that $\eta\sigma < \frac{1}{\varphi}$, and from results in Appendix D it follows that there is a corner solution.

5.2.6. F Proof of Proposition 4

At an interior solution, and if κ is finite, the function $F(\cdot)$ in (2.57) is strictly decreasing in ints argument:

$$F'(\cdot) = \frac{-2^{-\kappa}}{\xi^2 - 2^{-2\kappa}(1-\xi)^2} < 0.$$

Therefore $F(\cdot)$ is decreasing in both σ and η. From the definition of γ in (2.64), it follows directly that γ is increasing in σ and η :

$$\begin{aligned} \frac{\partial\gamma}{\partial\sigma} &= \frac{\eta^2}{F(\sigma\eta)}\left(F'\left(\frac{1}{\sigma\eta}\right) - F'(\sigma\eta)\right) < 0 \\ \frac{\partial\gamma}{\partial\eta} &= \frac{\sigma\eta}{F(\sigma\eta)}\left(F'\left(\frac{1}{\sigma\eta}\right) - F'(\sigma\eta)\right) + \gamma < 0 \end{aligned}$$

The derivative of γ with respect to the degree of strategic complementarity in price setting is given by

$$\frac{\partial \gamma}{\partial \xi} = \frac{\eta}{F(\sigma\eta)} \left(\frac{\partial F\left(\frac{1}{\sigma\eta}\right)}{\partial \xi} - \frac{\partial F(\sigma\eta)}{\partial \xi} \right)$$

where

$$\frac{\partial F\left(\frac{1}{\sigma\eta}\right)}{\partial \xi} - \frac{\partial F(\sigma\eta)}{\partial \xi} = \frac{2^{-\kappa+1}\left(\xi + 2^{-2\kappa}(1-\xi)\right)}{\left(\xi^2 - 2^{-2\kappa}(1-\xi)^2\right)^2} \left(\frac{1}{\sigma\eta} - \sigma\eta \right)$$

Therefore it follows that

$$\begin{aligned} &\tfrac{\partial \gamma}{\partial \xi} < 0 \quad \text{if } \sigma\eta > 1 \\ &\tfrac{\partial \gamma}{\partial \xi} > 0 \quad \text{if } \sigma\eta < 1 \end{aligned}$$

5.2.7. G Proof of Propositions 5 and 6

The coefficients γ_a and γ_r are derived exactly as shown in Appendix D, with the only difference that the coefficients ω_a and ω_r under the Taylor rule are given by

$$\begin{aligned} \omega_a &= (1 - \phi\xi)\,\gamma_a - \xi, \\ \omega_r &= (1 - \phi\xi)\,\gamma_r - \xi. \end{aligned}$$

Then the same proof of Propositions 2 and 4 applies respectively to Propositions 5 and 6.

5.3. Appendix to Chapter 3

5.3.1. A Macroeconomic Data

Mnemon	Series	Entering Order in Y	Small	Large	d-Log
GDPQ/LBMNU	Labor prod.	X	v	v	v
LBMNU	Index total hours worked	X	v	v	v
FYFF	:FEDERAL FUNDS	S	v	v	
PFDIGDP	GDP price deflator	X	v	v	v
FSPCOM	S&Poor's stock price index	F	v	v	v
CES002	Number of employees	X		v	v
A0M051	Personal income	X		v	v
JQCR	Real Personal Consumption	X		v	v
IFNRER	Real non-residential investments	X		v	v
JQIFRESR	Real residential investments	X		v	v
IPS10	Industrial production	X		v	v
UTL11	Capacity utilization	X		v	
LHUR	Unemployment rate	X		v	
HSFR	Housing starts (NONFARM)	X		v	
PSM99Q	Index of sensitive material prices	X		v	v
PWFSA	Producer price index	X		v	v
GDMC	PCE deflator	X		v	v

PUNEW	Consumer price index	X	v	v
CES275	Average hourly earnings	X	v	v
FM1	M1 monetary stock	Z	v	v
FM2	M2 monetary stock	Z	v	v
FMRRA	Non-borrowed reserves	Z	v	v
FMRNBA	Total reserves	Z	v	v
FTFP	Fernald (2007)'s TFP growth estimate	X	v	v

Most data is available at a monthly frequency. Output, GDP deflator, residential and non-residential investments are not. When monthly frequency is needed I use Sims and Zha (2007) interpolated monthly series for those 4 time series. Also LBMNU is not available at the monthly frequency and in that case it is replaced with BLS index for average weekly hours worked. I interpolate the quarterly TFP series from Fernald (2007) with the Chow-Lin method.

5.3.2. B Microeconimic data

The source of this data is Boivin, Giannoni and Mihov (2007). The 154 series are entered in the model in log-differences. In the BVAR, I assume a white-noise prior for each series.

	Forecast Variance Decomposition (% of total)					
	H=2		H=6		H=16	
	NT	MP	NT	MP	NT	MP
PGDP						
	41.9	0.0	39.3	1.3	41.2	2.4
	(0.0)	(0.0)	(3.7)	(1.8)	(6.9)	(3.8)

Table 1: Small model. Average forecast-error variance decomposition. Standard deviations in parenthesis

	Forecast Variance Decomposition (% of total)					
	H=2		H=6		H=16	
	NT	MP	NT	MP	NT	MP
CPI						
	20.5	0.0	25.8	0.5	30.3	2.3
	(0.0)	(0.0)	(2.0)	(0.5)	(3.8)	(1.5)
PPI						
	16.0	0.0	19.5	0.3	22.0	2.1
	(0.0)	(0.0)	(1.4)	(0.3)	(2.6)	(1.4)
PCE						
	35.0	0.0	39.4	0.3	41.8	1.8
	(0.0)	(0.0)	(2.4)	(0.4)	(4.7)	(1.6)
PGDP						
	35.2	0.0	44.3	0.2	46.1	2.6
	(0.0)	(0.0)	(3.0)	(0.4)	(6.0)	(1.9)

Table 2: Large model. Average forecast-error variance decomposition. Standard deviations in parenthesis

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	6.11	-0.68	3.22	0.41	0.01	0.24
Median	9.00	-2.00	5.00	0.50	0.05	0.40
Max	16.00	16.00	16.00	1.00	1.00	1.00
Min	-10.00	-17.00	-17.00	-0.78	-1.00	-1.00
Std	5.54	5.92	6.62	0.27	0.39	0.38
Fraction >0	0.83	0.39	0.64	0.91	0.53	0.75

Table 3: Small model. Fraction of draws in R is 57%. Quarters.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
CPI						
Average	5.59	-2.07	5.20	0.46	-0.10	0.44
Median	6.00	-3.00	6.00	0.49	-0.13	0.49
Max	18.00	17.00	18.00	1.00	1.00	1.00
Min	-10.00	-14.00	-14.00	-0.90	-0.94	-0.94
Std	2.31	6.06	3.03	0.16	0.45	0.22
Fraction >0	0.98	0.34	0.95	0.98	0.36	0.95
PPI						
Average	4.77	-1.10	4.56	0.37	-0.04	0.36
Median	5.00	-2.00	5.00	0.39	-0.05	0.38
Max	14.00	18.00	18.00	1.00	1.00	1.00
Min	-12.00	-14.00	-14.00	-0.85	-0.88	-0.88
Std	2.29	5.69	0.00	0.17	0.37	0.20
Fraction >0	0.97	0.43	0.95	0.97	0.42	0.95
PCE						
Average	5.67	-2.02	5.20	0.44	-0.15	0.41
Median	6.00	-3.00	6.00	0.47	-0.22	0.46
Max	18.00	18.00	18.00	1.00	1.00	1.00
Min	-11.00	-13.00	-13.00	-0.83	-0.91	-0.91
Std	2.40	5.72	0.00	0.16	0.43	0.23
Fraction >0	0.98	0.31	0.94	0.98	0.32	0.94
PGDP						
Average	5.69	-1.98	5.28	0.43	-0.13	0.40
Median	6.00	-3.00	6.00	0.45	-0.18	0.44
Max	18.00	15.00	18.00	1.00	1.00	1.00
Min	-11.00	-15.00	-15.00	-0.86	-0.94	-0.94
Std	2.20	5.61	0.00	0.14	0.43	0.21
Fraction >0	0.98	0.34	0.95	0.99	0.35	0.95

Table 4: Large model. Fraction of draws in R is 94%. Quarters.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	5.76	-0.78	5.15	0.45	0.01	0.41
Median	6.00	-1.00	6.00	0.44	0.00	0.43
Max	15.00	14.00	15.00	1.00	1.00	1.00
Min	-7.00	-16.00	-16.00	-0.47	-1.00	-1.00
Std	2.23	5.77	0.00	0.18	0.39	0.24
Fraction >0	0.98	0.46	0.93	0.98	0.48	0.94

Table 5: Large model. FTFP-identification. Fraction of draws in R is 91%.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	5.43	0.47	4.72	0.38	0.01	0.33
Median	6.00	0.00	5.00	0.40	0.00	0.36
Max	19.00	19.00	19.00	1.00	1.00	1.00
Min	-15.00	-19.00	-19.00	-0.81	-1.00	-1.00
Std	4.82	7.18	5.50	0.33	0.46	0.38
Fraction >0	0.89	0.53	0.84	0.87	0.40	0.80

Table 6: Large model. Sign Restrictions-identification. Fraction of draws in R is 94%.

	Sign Restrictions	
	MP	NT
PGDP	2 (-)	20 (-)
M2	2 (-)	NAN
FYFF	2 (+)	NAN
I	2 (-)	10 (+)
C	2 (-)	5 (+)
GDPQ/H	NAN	20 (+)
H	2 (-)	NAN
GDPQ	2 (-)	10 (+)
W	NAN	20 (+)

Table 7: The second and third columns contain the sign restriction (in parenthesis) and the number of quarters it is assumed to hold at least. Sign restrictions are weak in the sense that the zero response is included. The restrictions on NT follow Dedola and Neri (2006). I have also tried the case where restrictions on TFP are imposed on the first 10 quarters for all variables and obtain very similar results in terms of price responsiveness and more general for all the other impulse responses.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	20.10	-3.23	17.30	0.53	-0.07	0.46
Median	21.00	-4.00	20.00	0.56	-0.03	0.54
Max	49.00	35.00	49.00	1.00	0.84	1.00
Min	-21.00	-33.00	-33.00	-0.36	-0.70	-0.70
Std	7.86	14.75	0.00	0.18	0.38	0.29
Fraction >0	0.99	0.45	0.92	0.99	0.42	0.92

Table 8: Large model. Monthly Frequency. Fraction of draws in R is 90%.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	4.86	-0.88	4.44	0.35	-0.14	0.32
Median	5.00	-2.00	5.00	0.34	-0.26	0.33
Max	16.00	16.00	16.00	1.00	1.00	1.00
Min	-15.00	-14.00	-15.00	-0.50	-1.00	-1.00
Std	2.73	4.65	0.00	0.19	0.36	0.25
Fraction >0	0.97	0.37	0.92	0.96	0.27	0.91

Table 9: Large model. $\lambda = 0.05$. Fraction of draws in R is 91%.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	5.68	-1.98	5.38	0.41	-0.17	0.39
Median	6.00	-3.00	6.00	0.42	-0.31	0.41
Max	15.00	17.00	17.00	1.00	1.00	1.00
Min	-10.00	-16.00	-16.00	-0.77	-1.00	-1.00
Std	2.25	6.37	0.00	0.16	0.45	0.21
Fraction >0	0.98	0.34	0.96	0.98	0.29	0.96

Table 10: Large model. $\lambda = 0.07$. Fraction of draws in R is 96%.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	4.14	-2.68	3.51	0.30	-0.16	0.26
Median	5.00	-4.00	5.00	0.38	-0.14	0.37
Max	15.00	15.00	15.00	1.00	0.96	1.00
Min	-14.00	-12.00	-14.00	-0.98	-0.79	-0.98
Std	3.48	5.45	0.00	0.21	0.38	0.27
Fraction >0	0.89	0.31	0.83	0.90	0.35	0.85

Table 11: Large model. $\lambda = 0.5$. Fraction of draws in R is 91%.

	τ			ψ		
	Subset R	Subset W	All draws	Subset R	Subset W	All draws
PGDP						
Average	4.03	-2.26	3.22	0.27	-0.11	0.22
Median	5.00	-3.00	5.00	0.36	-0.08	0.35
Max	15.00	14.00	15.00	1.00	0.96	1.00
Min	-14.00	-13.00	-14.00	-0.89	-0.92	-0.92
Std	4.19	5.84	0.00	0.26	0.38	0.30
Fraction >0	0.86	0.36	0.79	0.88	0.41	0.82

Table 12: Large model. $\lambda = 5$. Fraction of draws in R is 87%.

	Standard deviation (in %)	Forecast Error Variance Decomposition (% of total)					
		H=6		H=18		H=48	
	Inflation	NT Inflation	MP Inflation	NT Inflation	MP Inflation	NT Inflation	MP Inflation
Aggregate Prices							
CPI	0.29	8.0	0.21	8.8	0.2	9.9	0.31
PCE	0.24	9.9	005	10.6	0.05	11.9	0.1
PGDP	0.22	10.4	004	11.0	0.07	12.1	0.1
PPI	0.47	6.0	0.06	6.3	0.02	6.5	0.13
Disaggregate PPI							
Average	1.36	1.04	0.04	1.24	0.05	1.4	0.08
Median	0.92	0.8	0.015	1.02	0.03	1.17	0.06
Max	7.75	5.42	0.18	5.5	0.2	6.32	0.26
Min	0.35	0.03	0.00	0.05	0.003	0.06	0.006
Std	1.16	0.96	0.03	1.04	0.03	1.13	0.06

Table 13: volatilities of price series and forecast errors variance decompositions. H is the horizon of the forecast.

	τ			ψ			dIRF6 (%)		
	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries
Average	12.6	-3.75	9.5	0.32	-0.19	0.22	0.3	0.2	0.25
Median	13	-14.5	11.5	0.32	-0.4	0.26	0.2	0.2	0.2
Max	37	59	59	1	1	1	1.4	0.6	1.4
Min	-29	-47	-47	-0.66	-1	-1	-0.2	-0.3	-0.3
Std	10.9	26.8	16.3	0.27	0.59	0.39	0.2	0.2	0.2
Fraction >0	0.92	0.29	0.8	0.84	0.29	0.73	0.95	0.85	0.93

Table 14: BVAR model. λ = 0.033. dIRF6 is the difference in price responses between the NT and MP shock 6 months after the shock.

Correlations	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	1.00	0.74	0.88	-0.31	-0.49	0.00	-0.47	-0.05	-0.03	-0.018
Σ^{NT}		1.00	0.65	0.04	-0.26	0.25	-0.38	-0.01	-0.01	-0.007
Σ^{MP}			1.00	-0.45	-0.38	0.14	-0.37	-0.04	0.02	-0.122
Σ^{NT}/Σ^{MP}				1.00	0.31	0.12	0.27	-0.06	-0.07	-0.001
ρ					1.00	0.32	0.51	0.10	0.11	-0.077
AR1						1.00	-0.07	0.11	0.11	-0.042
AR12							1.00	0.01	0.05	-0.089
τ								1.00	0.78	0.193
ψ									1.00	0.143
dIRF6										1.000

p-values	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	-	0.00	0.00	0.00	0.00	0.98	0.00	0.52	0.70	0.82
Σ^{NT}		-	0.00	0.59	0.00	0.00	0.00	0.94	0.95	0.93
Σ^{MP}			-	0.00	0.00	0.08	0.00	0.61	0.76	0.13
Σ^{NT}/Σ^{MP}				-	0.00	0.14	0.00	0.45	0.40	0.99
ρ					-	0.00	0.00	0.22	0.17	0.34
AR1						-	0.37	0.17	0.16	0.60
AR12							-	0.94	0.56	0.27
τ								-	0.00	0.02
ψ									-	0.08
dIRF6										-

Table 15 : Correlations and associated p-values. Σ is the standard deviation of the 6-digitis PPI series, Σ^{NT} and Σ^{MP} are the standard deviation of the 6-digitis PPI series due to the NT and MP shock respectively. ρ is the correlation between aggregate and disaggregate PPI. AR1 and AR12 are the 1st and 12th order autocorrelations. τ and ψ are defined in the test.

Correlations	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	1.00	0.77	0.91	-0.33	-0.49	0.07	-0.48	-0.24	-0.27	0.19
Σ^{NT}		1.00	0.70	0.01	-0.30	0.31	-0.40	-0.09	-0.26	0.59
Σ^{MP}			1.00	-0.44	-0.43	0.16	-0.40	-0.32	-0.30	0.09
Σ^{NT}/Σ^{MP}				1.00	0.35	0.11	0.31	0.23	0.07	0.23
ρ					1.00	0.27	0.52	0.36	0.35	-0.01
AR1						1.00	-0.11	-0.09	-0.25	0.36
AR12							1.00	0.23	0.30	-0.29
τ								1.00	0.71	0.21
ψ									1.00	-0.08
dIRF6										1.00

p-values	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	-	0.00	0.00	0.00	0.00	0.47	0.00	0.01	0.00	0.04
Σ^{NT}		-	0.00	0.88	0.00	0.00	0.00	0.34	0.00	0.00
Σ^{MP}			-	0.00	0.00	0.07	0.00	0.00	0.00	0.30
Σ^{NT}/Σ^{MP}				-	0.00	0.21	0.00	0.01	0.42	0.01
ρ					-	0.00	0.00	0.00	0.00	0.92
AR1						-	0.21	0.32	0.01	0.00
AR12							-	0.01	0.00	0.00
τ								-	0.00	0.02
ψ									-	0.37
dIRF6										-

Table 16: Correlations and associated p-values computed for the industries in the subset R (82% of total).

	τ (1)	ψ (2)	τ (3)	ψ (4)	τ (5)	ψ (6)	τ (7)	ψ (8)
c	56.9	1.09	49.9	1.24	-13.9	0.04	8.6	0.23
	(14.3)	(0.35)	(20.8)	(0.5)	(10.3)	(0.25)	(2.6)	(0.06)
log(hours)	-4.2	-0.08						
	(1.25)	(0.03)						
log(revenues)			-2.45	-0.06				
			(1.24)	(0.03)				
log(productivtiy)					5.12	0.04		
					(2.22)	(0.05)		
invc4							27.5	-0.12
							(76.3)	(1.9)
R^2	0.07	0.03	0.02	0.03	0.03	0.00	0.00	0.00

Table 17 : Other industry characteristics and price responsiveness. All industries.

	τ (1)	ψ (2)	τ (3)	ψ (4)	τ (5)	ψ (6)	τ (7)	ψ (8)
c	32.9	0.68	36.7	0.93	1.11	0.18	13.5	0.37
	(11.1)	(0.27)	(16.6)	(0.4)	(8.4)	(0.2)	(1.9)	(0.04)
log(hours)	-1.8	-0.03						
	(0.98)	(0.02)						
log(revenues)			-1.45	-0.04				
			(0.99)	(0.02)				
log(productivtiy)					2.5	0.03		
					(1.8)	(0.04)		
invc4							-34.6	-1.79
							(54.6)	(1.31)
R^2	0.03	0.01	0.02	0.02	0.01	0.01	0.01	0.01

Table 18 : Other industry characteristics and price responsiveness. Subset R.

Hours is the average from 2002 to 2006 over production worker hours at the 5-digits industry level. Hours (worked), Revenues, (labor) Productivity and unit-labor-costs are an average over from 2002 to 2006 at the 5-digits industry level. invc4 is the 1997 6-digits inverse of the C4 ratio.

Correlations	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	1.00	0.85	0.91	-0.18	-0.47	0.04	-0.45	-0.17	-0.02	0.04
Σ^{NT}		1.00	0.81	0.05	-0.48	0.11	-0.47	-0.06	0.03	0.22
Σ^{MP}			1.00	-0.33	-0.46	0.11	-0.41	-0.24	-0.09	-0.06
Σ^{NT}/Σ^{MP}				1.00	0.13	0.08	0.13	0.31	0.26	0.25
ρ					1.00	0.35	0.50	0.23	0.21	0.06
AR1						1.00	-0.07	-0.12	-0.20	0.15
AR12							1.00	0.01	0.03	-0.15
τ								1.00	0.82	0.40
ψ									1.00	0.35
dIRF6										1.00

p-values	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	-	0.00	0.00	0.03	0.00	0.66	0.00	0.04	0.78	0.60
Σ^{NT}		-	0.00	0.54	0.00	0.18	0.00	0.51	0.69	0.01
Σ^{MP}			-	0.00	0.00	0.21	0.00	0.00	0.31	0.51
Σ^{NT}/Σ^{MP}				-	0.11	0.37	0.13	0.00	0.00	0.00
ρ					-	0.00	0.00	0.01	0.01	0.51
AR1						-	0.38	0.14	0.02	0.07
AR12							-	0.90	0.76	0.07
τ								-	0.00	0.00
ψ									-	0.00
dIRF6										-

Table 19: Correlations and associated p-values computed for the industries in the subset R, which 92% of total industries. BVAR model. $\lambda = 0.1$.

	τ			ψ			dIRF6 (%)		
	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries
Average	4.04	-4.09	3.46	0.10	0.08	0.10	0.10	-0.03	0.09
Median	4.00	1.00	4.00	0.12	0.32	0.13	0.09	0.00	0.09
Max	42.00	30.00	42.00	1.00	1.00	1.00	0.56	0.06	0.56
Min	-31.00	-38.00	-38.00	-1.00	-1.00	-1.00	-0.44	-0.19	-0.44
Std	13.21	25.47	14.45	0.33	0.66	0.36	0.15	0.09	0.15
Fraction >0	0.69	0.55	0.68	0.64	0.55	0.63	0.83	0.55	0.81

Table 20: BVAR model. $\lambda = 0.1$.

Correlations	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	1.00	0.75	0.82	-0.28	-0.49	-0.03	-0.49	-0.16	-0.14	0.38
Σ^{NT}		1.00	0.68	0.01	-0.30	0.24	-0.41	-0.02	-0.17	0.77
Σ^{MP}			1.00	-0.51	-0.42	0.11	-0.40	-0.19	-0.14	0.35
Σ^{NT}/Σ^{MP}				1.00	0.20	0.04	0.24	0.11	0.03	0.14
ρ					1.00	0.27	0.48	0.31	0.37	-0.11
AR1						1.00	-0.17	0.05	-0.10	0.45
AR12							1.00	0.17	0.27	-0.33
τ								1.00	0.86	0.22
ψ									1.00	-0.07
dIRF6										1.00

p-values	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	ρ	AR1	AR12	τ	ψ	dIRF6
Σ	-	0.00	0.00	0.01	0.00	0.78	0.00	0.13	0.19	0.00
Σ^{NT}		-	0.00	0.92	0.01	0.03	0.00	0.86	0.13	0.00
Σ^{MP}			-	0.00	0.00	0.32	0.00	0.07	0.18	0.00
Σ^{NT}/Σ^{MP}				-	0.07	0.71	0.03	0.29	0.76	0.20
ρ					-	0.01	0.00	0.00	0.00	0.32
AR1						-	0.12	0.62	0.38	0.00
AR12							-	0.12	0.01	0.00
τ								-	0.00	0.04
ψ									-	0.52
dIRF6										1.00

Table 21: Correlations and associated p-values computed for the industries in the subset R, which are 56% of total industries. BVAR model. $\lambda = 0.02$.

	τ			ψ			dIRF6 (%)		
	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries
Average	13.27	-1.68	6.67	0.31	-0.07	0.14	0.35	0.19	0.28
Median	14.00	-4.00	10.00	0.30	-0.05	0.16	0.25	0.18	0.22
Max	37.00	50.00	50.00	1.00	1.00	1.00	1.51	0.80	1.51
Min	-33.00	-52.00	-52.00	-0.75	-1.00	-1.00	-0.26	-0.37	-0.37
Std	11.06	19.40	16.98	0.33	0.46	0.44	0.29	0.18	0.26
Fraction >0	0.92	0.38	0.68	0.74	0.40	0.59	0.94	0.93	0.94

Table 22: BVAR model. $\lambda = 0.02$.

	Forecast Variance Decomposition (% of total)					
	H=6		H=18		H=48	
	NT Inflation	MP Inflation	NT Inflation	MP Inflation	NT Inflation	MP Inflation
CPI	14.4	10.6	10.9	5.2	12.1	5.1
PCE	12.4	1.5	9.9	2.2	9.8	2.9
PGDP	19.3	7.8	14.0	4.5	14.5	5.1
PPI	25.1	8.2	17.0	4.7	16.3	5.2
Disaggregate Prices						
Average	4.64	1.39	3.9	1.5	3.69	1.59
Median	2.15	0.96	2.3	1.3	2.48	1.43
Max	34.42	9.60	24.4	5.4	19.02	5.47
Min	0.02	0.06	0.1	0.1	0.10	0.07
Std	5.88	1.32	4.1	1.1	3.40	1.08

Table 23: volatilities of price series and forecast errors variance decompositions

Correlations	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	S(e)	S(y)	ρ	AR1	AR12	τ
Σ	1.00	-0.32	-0.38	-0.25	0.12	-0.18	-0.49	0.02	-0.47	-0.31
Σ^{NT}		1.00	0.78	0.40	-0.56	0.54	0.58	0.19	0.66	0.35
Σ^{MP}			1.00	0.00	-0.73	0.72	0.67	0.37	0.50	0.21
Σ^{NT}/Σ^{MP}				1.00	-0.03	0.05	0.18	-0.13	0.40	0.46
S(e)					1.00	-0.97	-0.52	-0.50	-0.30	0.11
S(y)						1.00	0.60	0.50	0.34	-0.11
ρ							1.00	0.32	0.47	0.19
AR1								1.00	-0.13	-0.32
AR12									1.00	0.44
τ										1.00

p-values	Σ	Σ^{NT}	Σ^{MP}	Σ^{NT}/Σ^{MP}	S(e)	S(y)	ρ	AR1	AR12	τ
Σ	-	0.00	0.00	0.00	0.17	0.04	0.00	0.81	0.00	0.00
Σ^{NT}		-	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
Σ^{MP}			-	0.98	0.00	0.00	0.00	0.00	0.00	0.01
Σ^{NT}/Σ^{MP}				-	0.71	0.57	0.04	0.15	0.00	0.00
S(e)					-	0.00	0.00	0.00	0.00	0.19
S(y)						-	0.00	0.00	0.00	0.18
ρ							-	0.00	0.00	0.02
AR1								-	0.12	0.00
AR12									-	0.00
τ										-

Table 24: Correlations and associated p-values. Subset R of all industries. Contain 88% of total.

	τ			ψ			dIRF6 (%)		
	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries	Subset R	Subset W	All Industries
Average	3.61	-6.83	2.39	0.07	-0.16	0.05	1.10	-1.45	0.81
Median	4.00	-19.50	4.00	0.11	-0.32	0.10	1.22	0.18	1.20
Max	16.00	37.00	37.00	0.52	0.88	0.88	16.40	2.68	16.40
Min	-18.00	-42.00	-42.00	-0.28	-0.93	-0.93	-8.59	-8.61	-8.61
Std	6.70	28.80	11.96	0.14	0.64	0.26	2.70	3.54	2.91
Fraction >0	0.78	0.39	0.73	0.74	0.39	0.69	0.78	0.56	0.75

Table 25: FAVAR model. K = 3.

	Data	RI Model with attention allocation				Calvo Model			
		κ	ξ	λ^a	λ^m	α	ξ	λ^a	λ^m
ρ ; Σ	-	+	-	+/-	+/-	+	-	+/-	+/-
ρ ; Σ^a / Σ^m	+	-	+	+/-	-/+	0	0	+/-	-/+
ρ ; Δ	+	+	+	+/-	-/+	0	0	+/-	-/+
Σ ; Σ^a / Σ^m	-	-	-	+	-	0	0	+	-
Σ ; Δ	-	-	-	+	-	0	0	+	-
Δ ; Σ^a / Σ^m	+	+	+	+	+	0	0	+	+

Table 26: Signs of the correlations for the pairs of variables in the first column. The second column is the data. The 3rd –5th columns are the sign in the correlations in the rational inattention model implied by a cross-section change in κ, ξ and λ respectively. The 6th –8th columns are the sign in the correlations in the Calvo model implied by a cross-section change in α, ξ and λ respectively. Each column is computed assuming that it is the only source of heterogeneity.

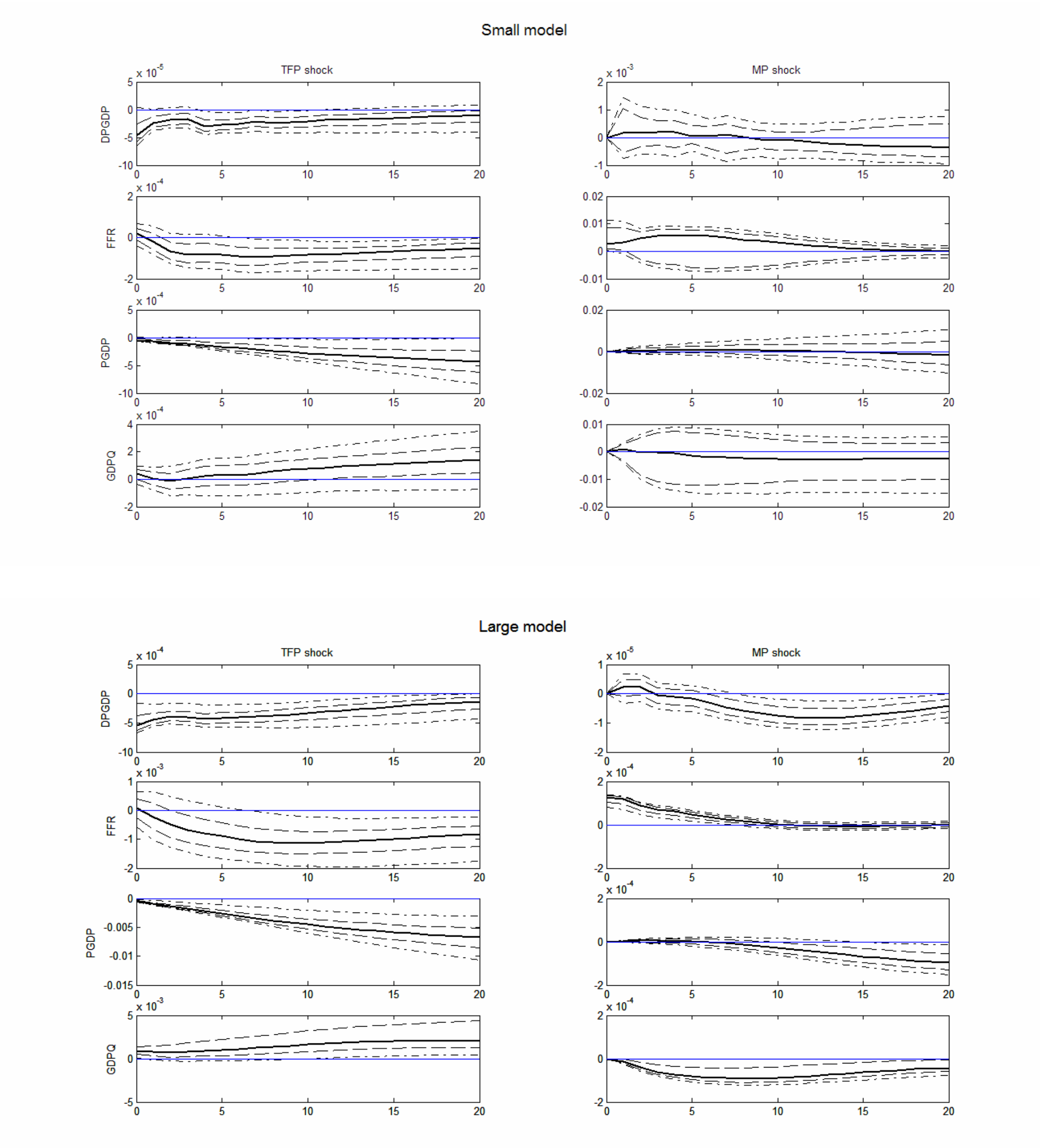

Figure 1 : Benchmark identification.

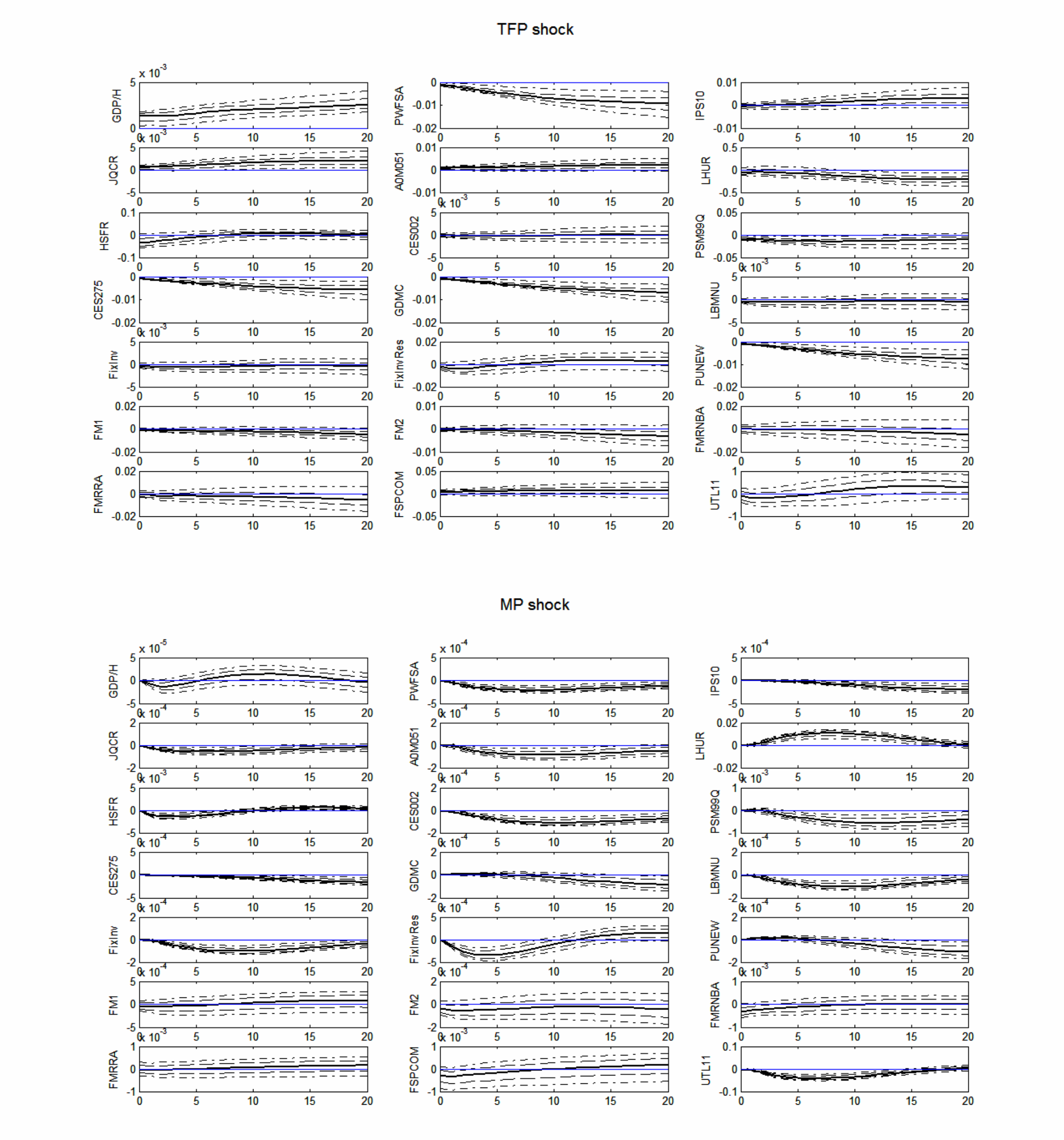

Figure 2 : Benchmark identification.

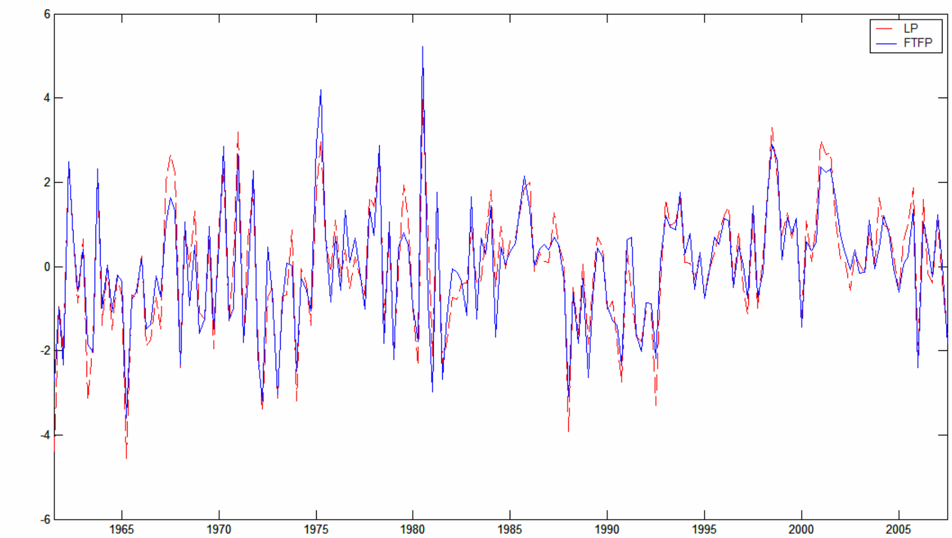

Figure 3: FTFP- and LP- identified TFP shocks.

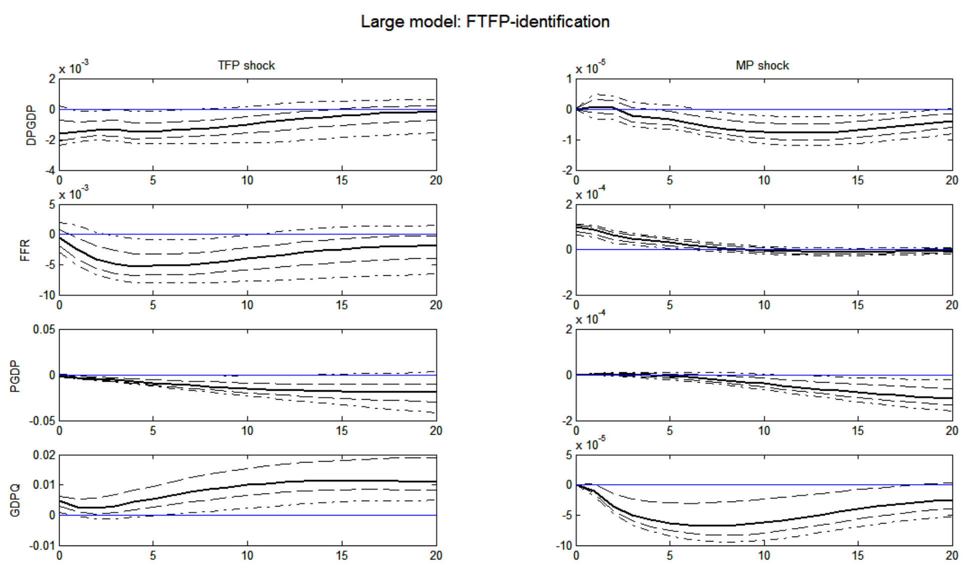

Figure 4: FTFP identification

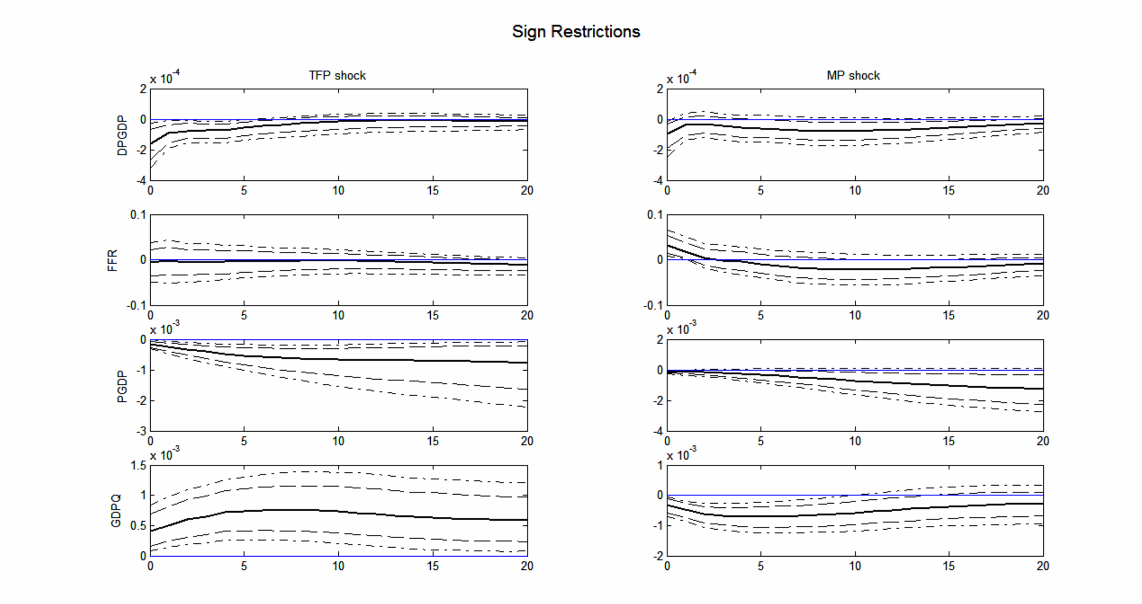

Figure 5: Sign - Restrictions identification

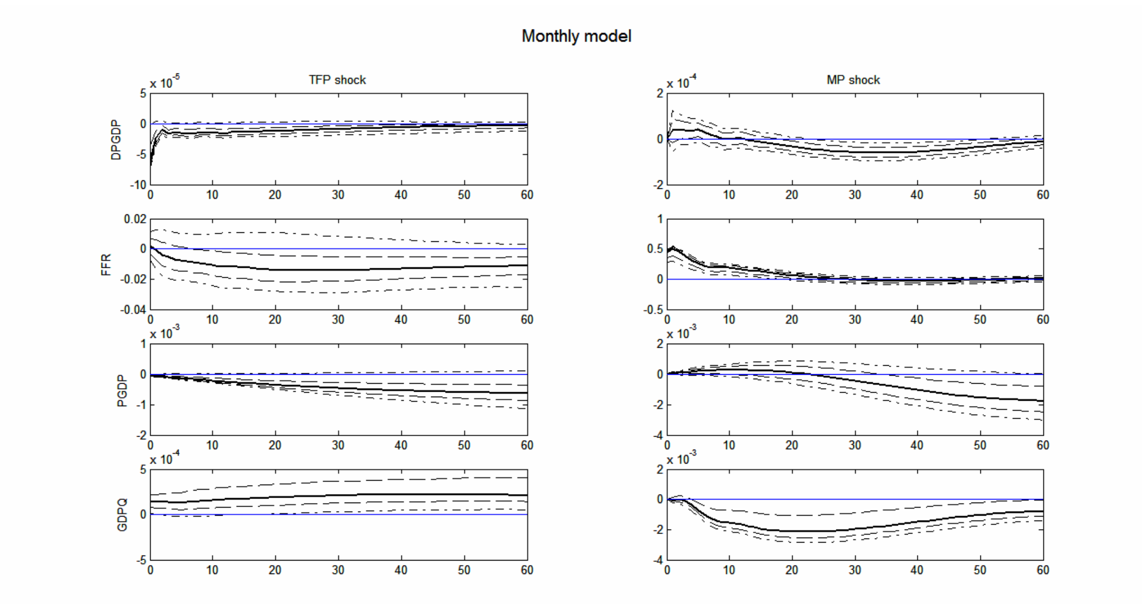

Figure 6: Monthly frequency.

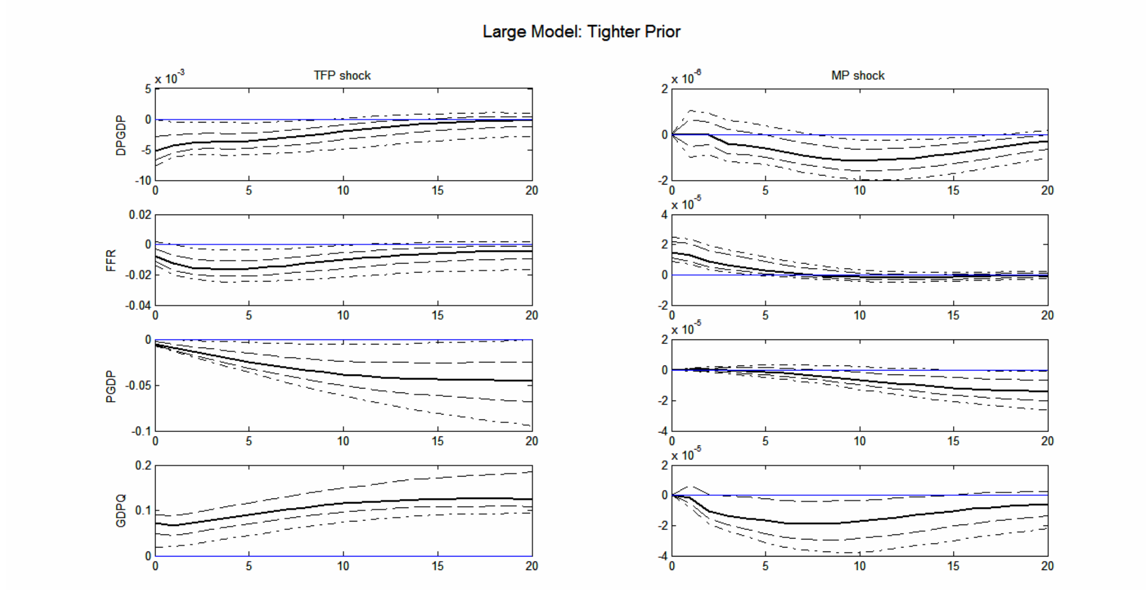

Figure 7: Tighter prior

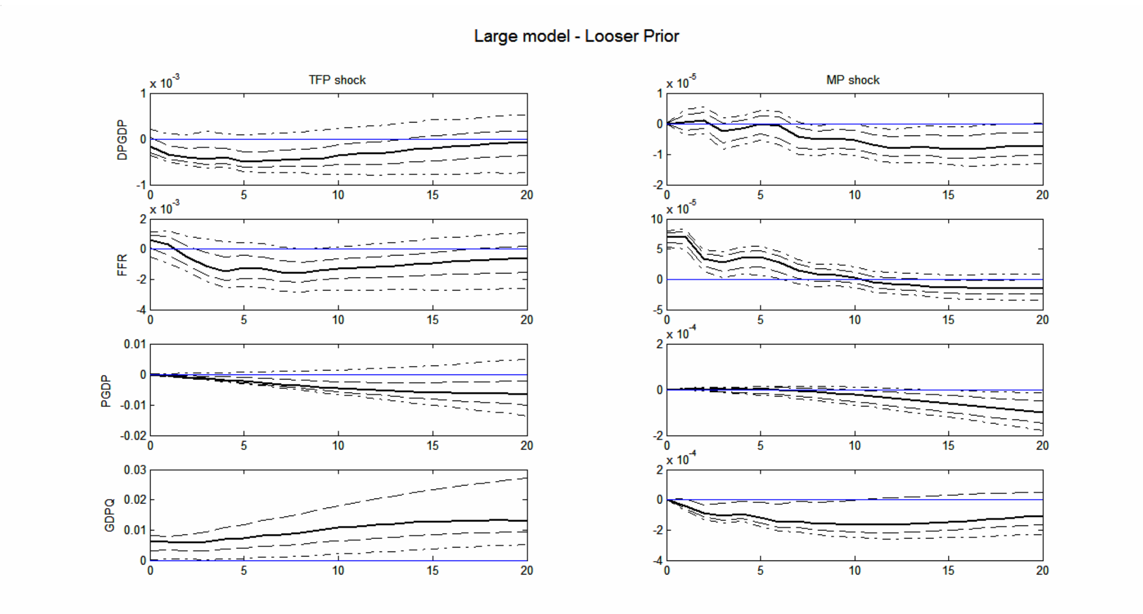

Figure 8: Looser prior

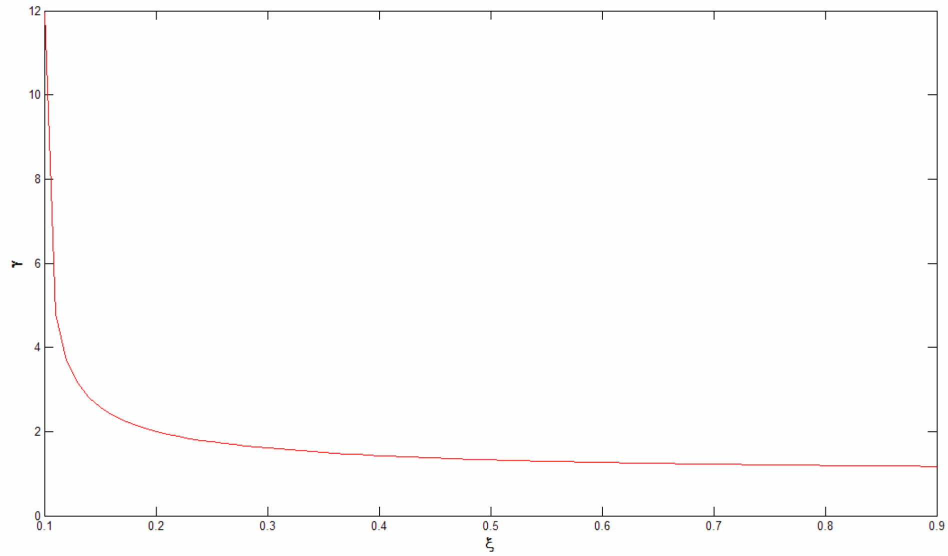

Figure 9: Model with endogenous signals. Relative price responsiveness (γ) as a function of the of strategic complementarity in price setting. Model calibration: κ=2, σ=2, ϕ_p =1.5, ϕ_c=0.5.

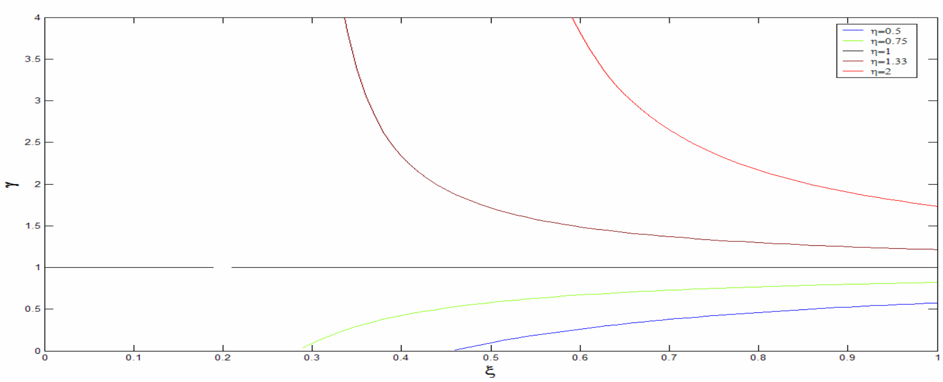

Figure 10: Model with input decision under rational inattention. Relative price responsiveness (γ) as a function of the degree of strategic complementarity in price- setting (ξ), for different values of η. Model calibration: κ=2, σ = 1.

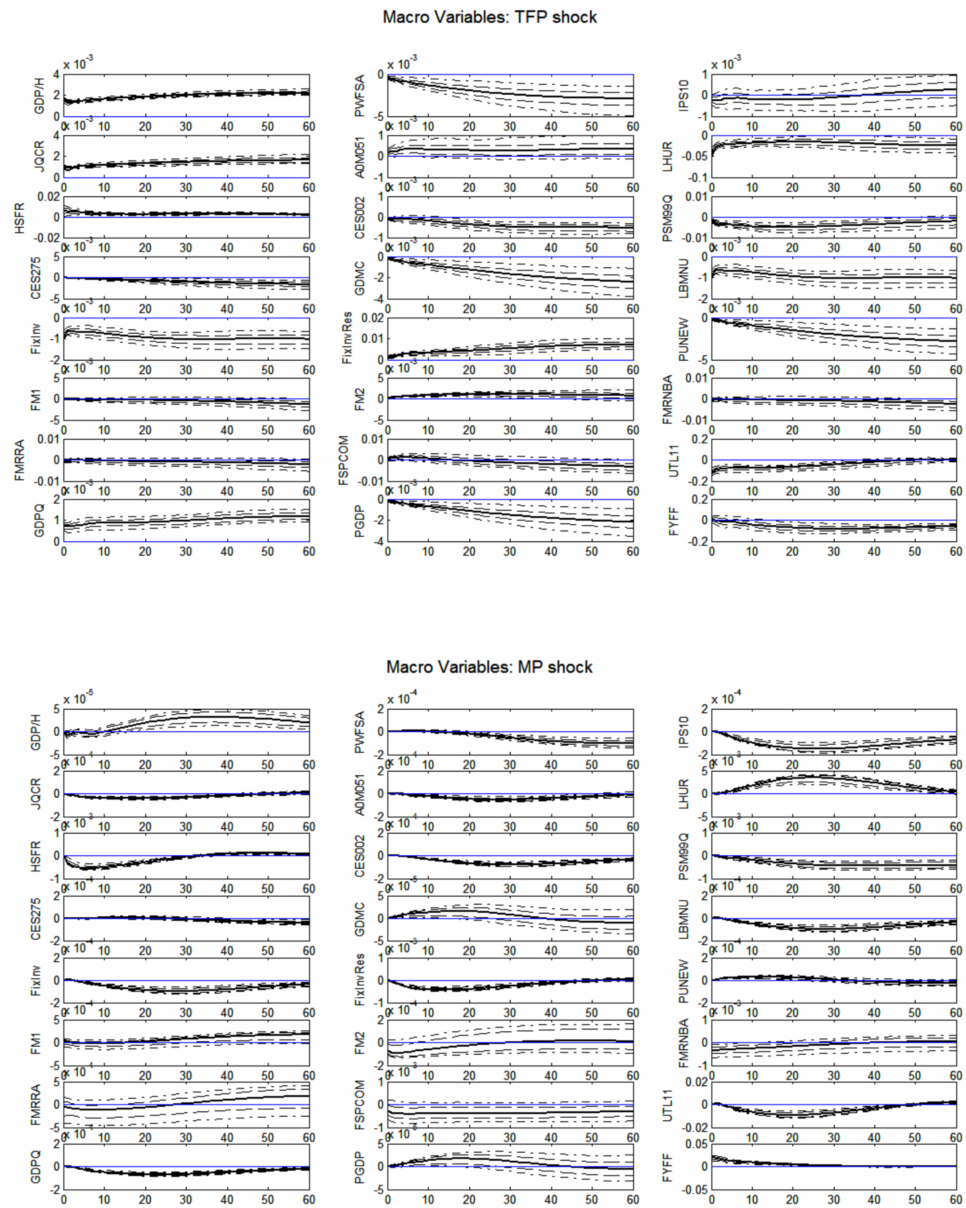

Figure 11: Aggregate variables impulse responses

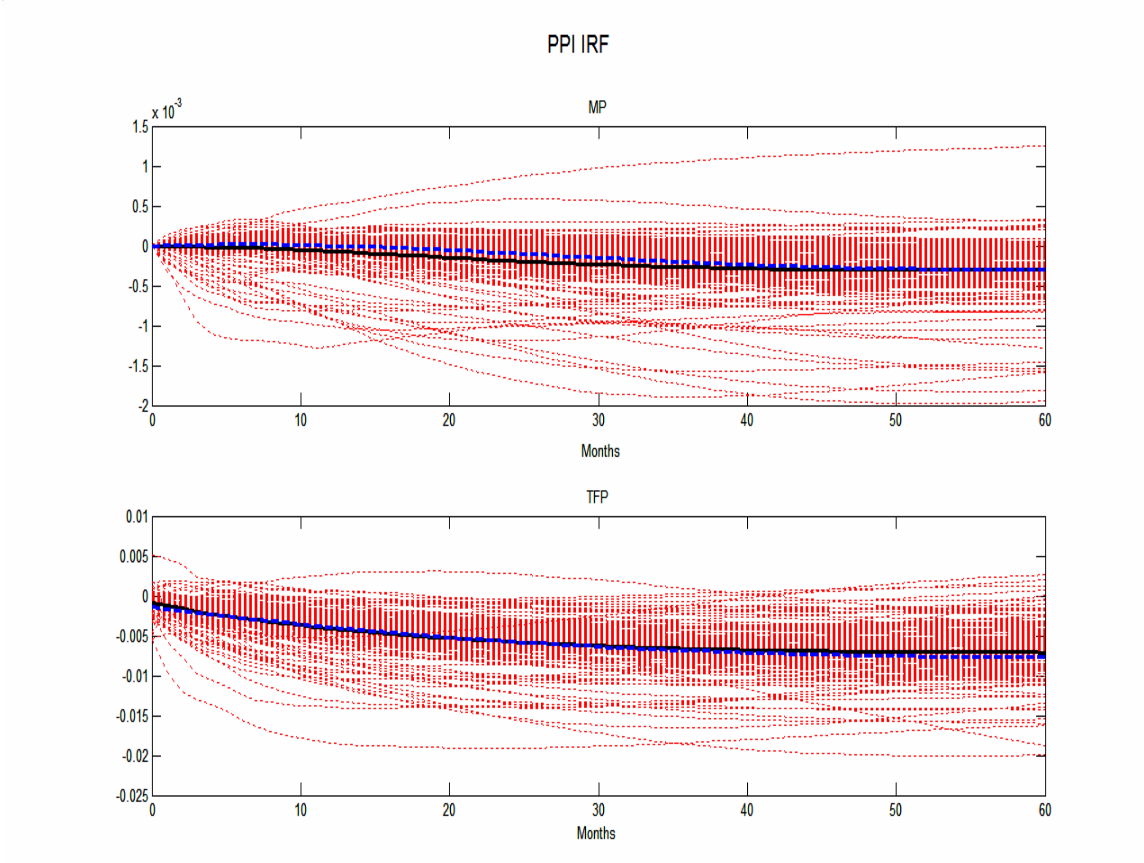

Figure 12: IRF of disaggregated PPI series. Red dots are the disaggregated series. The blue dotted-line is the aggregate PPI response. The black solid line is the average over the disaggregated responses.

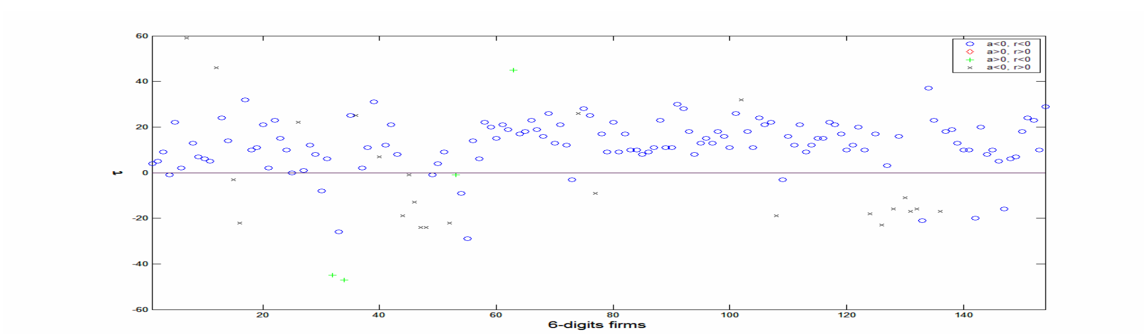

Figure 13: Difference in price responsiveness across industries according to τ_α for α set to 0.5. The legend specifies the sign of the long-run response to the two shocks and divides the firms in 4 subsets according to that; a and r label NT and MP shocks respectively.

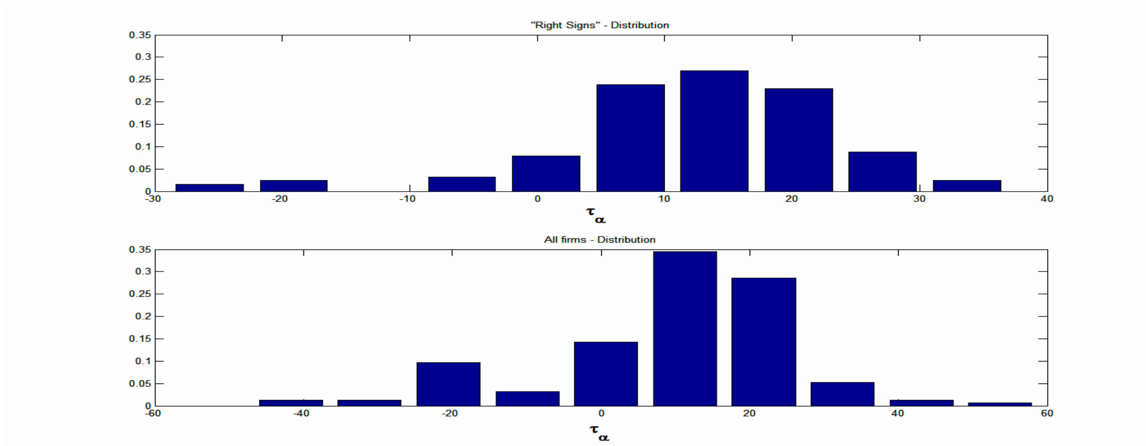

Figure 14: Histograms about τ_α for α set to 0.5. On the vertical axis the fraction of total firms in the subset. The right sign distribution refer to those firm for which prices drop in the long run to both NT and MP positive shock.

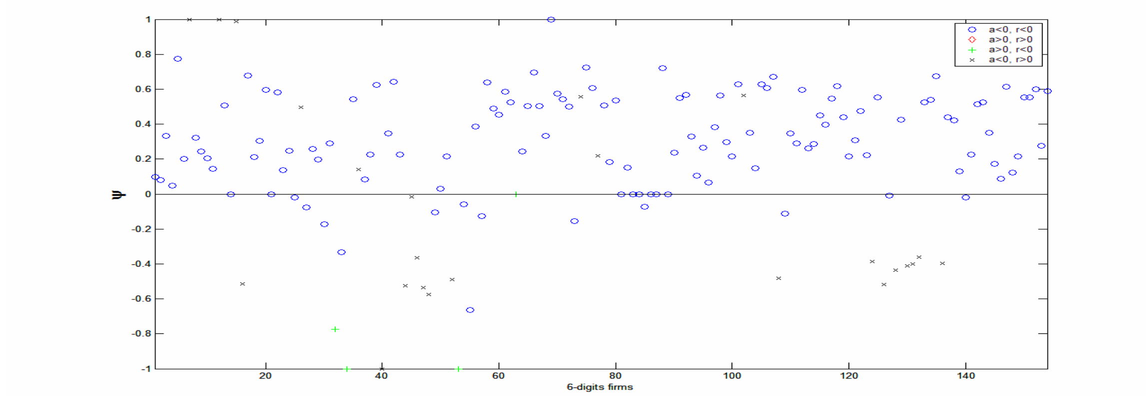

Figure 15: Difference in price responsiveness across firms according to ψ_j for j set to 24. The legend specifies the sign of the long-run response to the two shocks and divides the firms in 4 subsets according to that; a and r label NT and MP shocks respectively.

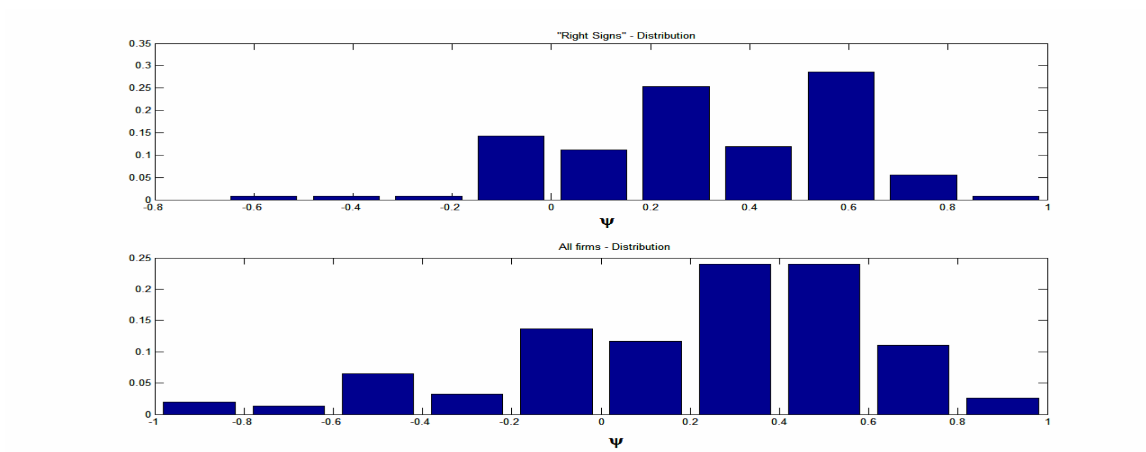

Figure 16: Histograms about ψ_j for j set to 24. On the vertical axis the fraction of total firms in the subset. The right sign distribution refer to those firm for which prices drop in the long run to both NT and MP positive shock.

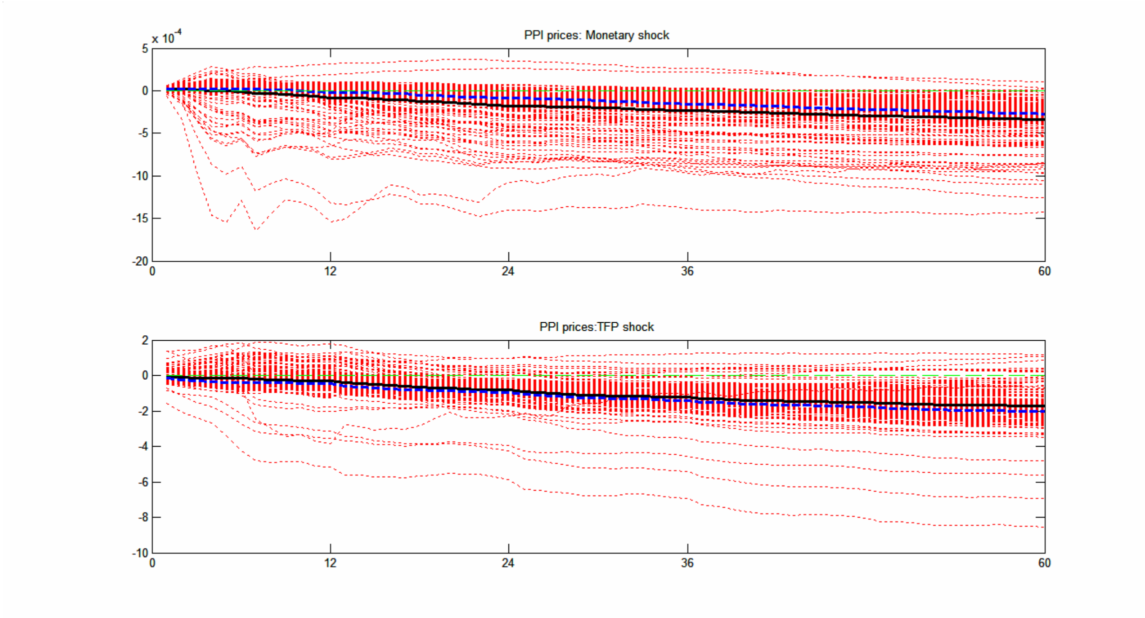

Figure 17: FAVAR, K=3.