UNIVERSITEIT
GENT

FACULTEIT ECONOMIE
EN BEDRIJFSKUNDE

TWEEKERKENSTRAAT 2
B-9000 GENT
Tel. : 32 - (0)9 – 264.34.61
Fax. : 32 - (0)9 – 264.35.92

WORKING PAPER

How Well Does Sticky Information Explain the Dynamics of Inflation, Output, and Real Wages?

Julio A. Carrillo

June 2011

2011/724

D/2011/7012/29

How Well Does Sticky Information Explain the Dynamics of Inflation, Output, and Real Wages?

Julio A. Carrillo[*]
Ghent University

June 7, 2011

Abstract

This paper finds that a model with *pervasive* information frictions is less successful than a standard model featuring nominal rigidities, inflation indexation, and habit persistence in generating the dynamics triggered by technology shocks, as estimated by a vector autoregression using key U.S. macroeconomic time series. The real wage responses after a permanent increase in productivity tilt the balance clearly in favor of the standard model. The sticky information model overestimates the speed of adjustment in the real wage and is hence particularly unsuccessful in replicating its inertial response, whereas the standard model relies on inflation indexation in wage-setting to achieve a better fit. The two models are, however, statistically equivalent in mimicking the responses of output, inflation, the real wage and the federal funds rate after a shock in monetary policy.

Keywords: Sticky prices, sticky information, inflation indexation, monetary and technology shocks

JEL Class.: E31, E52, C15

---

[*] Ghent University, Department of Financial Economics, W.Wilsonplein 5D, 9000 Ghent, Belgium. Tel. +32 (0)9264 7892, fax: +32 (0)9264 8995. Email: julio.carrillo@ugent.be. For helpful advices and discussions, I thank Paul Klein, two anonymous referees, Sanvi Avouyi-Dovi, Bertrand Candelon, Fabrice Collard, Martial Dupaigne, Patrick Fève, Punnoose Jacob, Vivien Lewis, Lenard Lieb, Joan Muysken, Gert Peersman, Céline Poilly, Ine van Robays, Arnaud Stevens, Raf Wouters, conference participants at the 2008 North American Summer Meeting of the Econometric Society, the 2008 Latin American Meetings of the Econometric Society. This piece of work has been benefited by past collaborations with Julien Mathéron, Patrick Fève, and Lenard Lieb; thanks for your help. All remaining errors are my own. A previous version of this paper was distributed under the title "How well does sticky information explains output and inflation inertia?".

1 Introduction

Inflation and output take time to adjust to different macroeconomic developments. Empirical evidence on monetary policy shocks, for instance, finds that output and inflation respond to a variation in the nominal interest rate in a sluggish manner, with peak responses occurring several quarters after the initial change in the monetary policy instrument; further, inflation responses lag behind those of output.[1] Fuhrer and Moore (1995), Chari, Kehoe, and McGrattan (2000), and Fuhrer (2006) have documented the inability of the standard sticky price model to replicate these patterns. Real rigidities, such as those that increase the degree of strategic complementarities among price-setters, are unable to reproduce the observed hump-shaped responses of inflation and output after a shock in monetary policy.[2]

Christiano, Eichenbaum, and Evans (2005), among many others, include indexation to past inflation in price-setting, habit formation in consumption, and adjustment costs in investment to generate hump-shaped responses in inflation and output. This approach, which we can call "backward-looking behavior," has been successful in empirical work.[3] An alternative is to assume environments where information is incomplete, as do Sims (2003), Woodford (2003a), and Mankiw and Reis (2002, 2006). The "sticky information" approach proposed by Mankiw and Reis assumes that information flows slowly throughout the population. In recent years, this approach has become one of the most studied incomplete information environments to generate hump-shaped inflation responses. Further, the sticky information hypothesis can be extended to consumers and workers to generate hump-shaped responses in output and nominal wage inflation as well.

Given the popularity of the backward-looking behavior approach and the sticky information approach, it is natural to ask which one better explains the sluggish macroeconomic dynamics that have repeatedly been characterized in the data. The strategy taken in this paper to answer this question is the following. A model containing real rigidities serves as a common structure to build two model variants: a *backward-looking behavior* variant and a *sticky information* variant. Household preferences and market structures are similar in the two variants, changing only the way in which nominal and information rigidities enter the models. In par-

---

[1] See Christiano *et al.* (1999) for the U.S.; Mojon and Peersman (2003) for Europe; and Wang and Wen (2007) for several OECD countries.

[2] Most real rigidities assumed in the literature diminish the contemporaneous response of prices to fluctuations in the marginal cost. In empirical work, these assumptions help to estimate a "plausible" degree of price stickiness in macro models, closing the gap between macro and micro evidence about the frequency of price changes (see Eichenbaum and Fisher, 2007). Modeling devices include firm-specific labor and capital (Woodford, 2003b; Altig et al., 2009), a countercyclical markup (Kimball, 1995; Rotemberg and Woodford, 1999), raw material inputs (Rotemberg and Woodford, 1995), among others. These devices, however, cannot generate the hump-shaped response of inflation that has been documented after a shock in monetary policy.

[3] See Christiano *et al.* (2005) and Smets and Wouters (2007), among others.

ticular, the backward-looking behavior variant adds price and wage rigidities *à la* Calvo, habits in consumption, and inflation indexation in price- and wage- setting. The sticky information variant assumes a stochastic process of updating information that applies to consumers, firms, and workers. The two variants are then compared in terms of their predicted dynamics after a shock in monetary policy and a permanent increase in labor productivity.

Other studies tackle a similar question, reporting a wide array of both answers and methodologies. Andrés, López-Salido and Nelson (2005) and Trabandt (2007) find that a sticky information model performs as well as a sticky price model with lagged inflation indexation. Kiley (2007), Korenok and Swanson (2007), and Coibion (2010) find, in contrast, that the data seem to favor a New Keynesian Phillips curve (i.e., derived from sticky prices and added, sometimes, with indexation) over a sticky information Phillips curve. Coibion and Gordonichenko (2010), Dupor, Kitamura, and Tsuruga (2010), and Knotek (2010) argue that a model containing both sticky prices and sticky information, i.e., a "dual stickiness" model, better explains the dynamics of inflation. Remarkably, all of these papers consider only the case of information frictions in firms, assuming that workers and consumers have full information. Thus, the models are most often compared in terms of certain moments of inflation and, sometimes, output.

Mankiw and Reis (2006) argue, in contrast, that a *pervasive* slow diffusion of information (in other words, that all agents are subject to information frictions) is a necessary feature of the sticky information approach to fit different moments of the data.[4] To the best of my knowledge, only Mankiw and Reis (2006, 2007), Reis (2009), and Gomes (2010) consider information frictions in firms, workers, and consumers all together. Nevertheless, these authors do not compare the performance of the pervasive sticky information model to that of the standard model with backward-looking behavior.

The contribution of this paper is threefold. First, it compares a full-fledged general equilibrium model with pervasive information frictions with a standard sticky price model with backward-looking behavior. Second, it extends the model comparison to more variables in addition to inflation and output, including the real wage, wage inflation, and the nominal interest rate. Third, the paper compares the models using the evidence from the type of structural vector autorregresions (SVARs) that motivated the departure from the pure sticky price model in the first place.

Using the minimum distance estimation proposed by Rotemberg and Woodford (1997), the pa-

---

[4] For instance: *1)* Inflation tend to rise jointly with output during booms; *2)* Real wages are smoother than output; and *3)* Real variables respond gradually to macroeconomic shocks.

rameters that generate persistence and hump-shaped responses in each of the model variants are estimated (such as the sticky price and sticky information probabilities, the degrees of inflation indexation, habits, and the monetary rule coefficients). The minimum-distance approach consists of choosing these parameters such that the distance between the model-based impulse responses and the SVAR responses is minimized given a certain weighting matrix. The empirical responses correspond to a shock in monetary policy and a permanent shock in labor productivity, as previously mentioned. The estimation procedure involves a bootstrapping method that helps to screen problems of parameter identification and computes the prediction accuracy of each model variant with respect to the empirical impulse responses of different variables.

The results are as follows. The two model variants are statistically equivalent after a shock in monetary policy. However, after a permanent shock in productivity, there is a clear and statistically significant difference favoring the backward-looking behavior model in terms of the responses of the real wage, the nominal wage, and output. Further, this result is confirmed in the course of different robustness exercises, where the backward-looking behavior variant is regularly better at predicting the responses either of the real wage or of wage inflation and inflation in general. The exercises include different identification strategies for the technology shock, sub-sample estimation, and model extensions, including a version with capital, and an alternative version of the sticky information model featuring “dual stickiness.”

Inflation indexation in nominal wages is the crucial device that allows the backward-looking behavior variant to fit closely the SVAR’s real wage responses to a permanent increase in productivity. Wage indexation can effectively explain why nominal wages have a positive or null effect at impact and afterwards decrease moderately in the periods that follow the technology shock. This behavior cannot be replicated by the sticky information model, which predicts an increase in nominal wages that lasts for several quarters and implies a quicker than observed rise in real wages.

The remainder of the paper is organized as follows. Section 2 presents the SVAR impulse responses that are used in the minimum-distance estimation. Section 3 describes the baseline model and presents the two variants. Section 4 details the econometric approach. Section 5 discusses the estimation results and presents a robustness analysis. Section 6 explains the estimation results in terms of the endogenous propagation mechanism of each model. Section 7 concludes.

2 Two structural VAR models

This section describes the two structural SVAR models used to identify a monetary policy shock and a technology shock, respectively. Each structural VAR is of the form:

$$A_0^\zeta Z_t^\zeta = A_1^\zeta Z_{t-1}^\zeta + \cdots + A_\ell^\zeta Z_{t-\ell}^\zeta + \eta_t^\zeta, \text{ where } \zeta \in \{\text{Monetary } (\mathcal{M}), \text{ Technology } (\mathcal{T})\} \quad (1)$$

The canonical innovations η_t^ζ are related to the structural shocks ν_t^ζ by a set of linear relationships summarized by the matrix S^ζ. Thus, $\eta_t^\zeta = S^\zeta \nu_t^\zeta$. Each structural VAR is focused on retrieving either the monetary policy shock or the technology shock, where the remaining shocks are partially identified. This strategy aims to minimize the controversies about the way a particular shock is identified and allows for a easy comparison with other papers that identify similar shocks. The data used for the two SVAR models are quaterly, belong to the U.S. Non-Farm Business sector and span 1954(3)-2007(4).[5]

2.1 Effects of a monetary policy shock

The monetary SVAR includes the short-term nominal interest rate (i_t), inflation (π_t), wage inflation (π_t^w), growth rate of real wages $(\Delta \ln w_t)$, and the output gap $\left(\ln \frac{y_t}{y_t^f}\right)$. The latter is measured by the linearly detrended logarithm of GDP per capita.[6] The nominal interest rate is given by the quarterly average of the overnight federal funds rate. Inflation and wage inflation are specified by the quarterly growth rates of the GDP's implicit price deflator, and the BLS index of nominal hourly compensation, respectively. Finally, the real wage is given by the BLS index of real compensation per hour. Following a standard practice in the literature, a measure for commodity price inflation (π_t^c) is included in the SVAR to mitigate the so-called price puzzle.[7] The ordering of the variables is the following: $Z_t^{\mathcal{M}} = \left[\ln \frac{y_t}{y_t^f}, \pi_t^c, \Delta \ln w_t, \pi_t, \pi_t^w, i_t\right]'$. The monetary policy shock $\nu_t^{\mathcal{M}}$, which is exemplified by an unexpected variation in the nominal interest rate, is identified using short-run restrictions. It is assumed that all variables placed before the federal funds rate respond to a shock in monetary policy with a one-period lag.[8] The lag length, ℓ, is set to 4.

The impulse responses of the output gap, inflation, wage inflation, the real wage (in levels), and the federal funds rate to a contractionary shock in monetary policy are reported in Figure 1,

---

[5] The data were extracted from the Bureau of Labor Statistics, the FREDII database, and the CRB.

[6] Results are qualitatively unaffected when other specifications for the output gap are considered, such as the CBO output gap.

[7] See Sims (1992), Christiano *et al.* (1996, 1999). Here, π_t^c is a mix of different indices including the quarterly growth rate of the Commodity Research Bureau (CRB) price index of sensitive commodities, the BLS's "all commodities" producer price index, and the BLS's "fuel and related products, and power" producer price index.

[8] See Christiano *et al.* (1996, 1999, 2005), Rotemberg and Woodford (1997, 1999), or Sims and Zha (2006) for more examples of identification strategies.

row 1. The line with circles contains the SVAR's point estimates, while the dotted lines indicate the 80-percent confidence interval computed using a simple bootstrap with 10,000 iterations. Output exhibits a considerable persistence and a hump-shaped response, peaking after six quarters. The response of inflation shows a hump-shaped profile, lagging behind output and peaking during the third year after the shock. The response of wage inflation is qualitatively similar to inflation. The federal funds rate increases immediately and then gradually declines to the point where it eventually crosses the x-axis. The real wage response is rather ambiguous because it is characterized by a wide confidence interval.

The evidence provided herein strongly resembles that described by Christiano *et al.* (1999, 2005) in the sense that, first, output and inflation take some time to respond to a variation in the interest rate and, second, the response of inflation lags behind that of output.

2.2 Effects of a permanent technology shock

The technology shock is pinned down using long-run restrictions, in line with Blanchard and Quah (1989) and Galí (1999). In this case, the SVAR contains the growth rate of labor productivity $\left(\Delta \ln \frac{y_t}{n_t}\right)$, growth in *total* hours per capita ($\Delta \ln n_t$), growth in the real wage, inflation, wage inflation, the short-term nominal interest rate, and a measure of commodity price inflation. Labor productivity is measured as the ratio of real GDP per capita to total hours per capita. $Z_t^{\mathcal{T}}$ is thus equal to $\left[\Delta \ln \frac{y_t}{n_t}, \Delta \ln n_t, \Delta \ln w_t, \pi_t^c, \pi_t, \pi_t^w, i_t\right]'$. A technology shock is identified by assuming that this is the only shock that has a permanent impact on the level of labor productivity. Notice that the responses of output are derived from the responses of hours and productivity. The lag length ℓ is set to 4.

The line with circles in figure 1, row 2, display the responses of output (in levels), inflation, wage inflation, the real wage (in levels), and the federal funds rate. A positive technology shock has a permanent effect on output and the real wage, which increase at a slow pace until they reach their new steady-state level.[9] These results are in line with Dedola and Neri (2007), who use an identification strategy based on sign restrictions, and Liu and Phaneuf (2007). Inflation falls at impact and slowly returns to its initial position, whereas the short-term nominal interest rate reaches its minimum level relatively quickly, after approximately three quarters. Galí (1999) finds similar evidence for inflation. For wage inflation, the amplitude of the confidence interval does not exclude the possibility of a null or positive response at impact. However, a few periods later, wage inflation is more likely to decrease before returning to its initial level. This behavior indicates that the permanent increase in the real wage is due to a larger decrease in inflation

---

[9] Notice that the variables in $Z_t^{\mathcal{T}}$ have been detrended, which implies that the steady-state growth rates of output, productivity, and the real wage are normalized to zero.

than in wage inflation. Liu and Phaneuf (2007) find comparable evidence and interpret the results similarly.

3 Model variants

In this section, I embed two variants that can generate sluggish macroeconomic dynamics, similar to those described in the previous section, in a New Keynesian model. First, I describe the common environment shared by each model variant, and then I specify their particularities.

3.1 Common environment

3.1.1 Final good sector

A perfectly competitive firm produces a homogenous good, d_t, that can be either consumed, y_t, or used as a production input in the intermediate-good sector, q_t. Aggregate demand for the homogenous good is thus given by $d_t = y_t + q_t$. The firm produces d_t by combining a continuum of intermediate goods, indexed by $\varsigma \in [0, 1]$, using the technology suggested by Kimball (1995):

$$\int_0^1 G\left(\frac{d_t(\varsigma)}{d_t}\right) \mathrm{d}\varsigma = 1, \tag{2}$$

where $G(\cdot)$ is an increasing and strictly concave function that satisfies the normalization $G(1) = 1$ and $d_t(\varsigma)$ is the input of intermediate good ς. The standard Dixit-Stiglitz specification is contained in Kimball's technology by setting $G(z) = z^{(\theta_p - 1)/\theta_p}$, with $z = d(\varsigma)/d$ and $\theta_p > 1$ as the elasticity of substitution between input goods. The general form used by Kimball offers some advantages, such as having a variable θ_p, that constitutes a source of strategic complementarities among intermediate-good producers. In this context, $\theta_p(z) \equiv -\frac{zG'(z)}{G''(z)}$.

The aggregate good firm chooses d_t and $d_t(\varsigma)$ to maximize its profits:

$$P_t d_t - \int_0^1 P_t(\varsigma) d_t(\varsigma)$$

subject to (2), where P_t and $P_t(\varsigma)$ are the nominal prices of the aggregate good and the intermediate input ς, respectively. The demand for input ς is given by:

$$d_t(\varsigma) = d_t G'^{-1}\left(\frac{P_t(\varsigma)}{P_t} \lambda_t\right), \tag{3}$$

where $\lambda_t = \int_0^1 G(d_t(u)/d_t) \cdot (d_t(u)/d_t) \mathrm{d}u$, and G'^{-1} is the inverse function of G'.

3.1.2 Intermediate good sector

Each intermediate good $d_t(\varsigma)$ is produced by a single monopolistic firm. Similar to Rotemberg and Woodford (1995), the gross-output production function takes the form:

$$d_t(\varsigma) = \min\left\{\frac{A_t F(n_t(\varsigma))}{1 - s_q}, \frac{q_t(\varsigma)}{s_q}\right\}, \tag{4}$$

where $F(\cdot)$ is an increasing and concave function, $n_t(\varsigma)$ is a composite labor input (to be defined later), $q_t(\varsigma)$ are raw materials employed by firm ς, $s_q \in [0,1]$ determines the coefficients of input requirements, and A_t reflects the level of current technology, which follows the process:

$$A_t = \exp\left(\nu_t^{\mathcal{T}}\right) A_{t-1}, \text{ with } \nu_t^{\mathcal{T}} \sim \text{iid}\left(0, \sigma_{\mathcal{T}}^2\right).$$

The latter implies that the steady-state balanced growth rate is normalized to zero because, in the absence of technology shocks, $\nu_t^{\mathcal{T}}$, none of the real variables of this economy grow in equilibrium. The real cost function is thus denoted by $S(d_t(\varsigma)) = w_t F^{-1}(A_t d_t(\varsigma)(1-s_q)) + s_q d_t(\varsigma)$, where $w_t \equiv W_t/P_t$ is the aggregate real wage.

Without loss of generality, I assume that in each period a monopolistic firm re-optimizes its price with a fixed probability $1-\alpha_p$, with $\alpha_p \in [0,1)$. In the backward-looking behavior variant, α_p is strictly positive, while in the (baseline) sticky information variant α_p is equal to zero. If firm ς is unable to re-optimize in period T, then its price is updated according to a rule-of-thumb of the form $P_T(\varsigma) = (1+\delta_{t,T}^p)P_t(\varsigma)$, where $t < T$ denotes the period of last reoptimization. The shape of the term $(1+\delta_{t,T}^p)$ is conditional on the assumed inertia-generating environment and is thus defined later.

Let $P_t^\star(\varsigma)$ denote the price of firm ς if it is allowed to reoptimize in period t, and $d_{t,T}^\star(\varsigma)$ the time T output of this firm. $P_t^\star(\varsigma)$ is chosen to maximize the present discounted sum of profit streams, based on firm ς's available information, i.e.:

$$\max_{P_t(\varsigma)} \mathrm{E}_{\Gamma_t(\varsigma)} \sum_{T=t}^{\infty} (\beta\alpha_p)^{T-t} \varphi_T \left[\left(\frac{(1+\delta_{t,T}^p)P_t(\varsigma)}{P_T} \right) d_{t,T}^\star(\varsigma) - S\left(d_{t,T}^\star(\varsigma)\right) \right]$$

$$\text{subject to } \; d_{t,T}^\star(\varsigma) = d_t G'^{-1}\left(\frac{(1+\delta_{t,T}^p)P_t(\varsigma)}{P_T} \lambda_T \right)$$

where $\beta^{T-t}\varphi_T$ is a stochastic discount factor and $\mathrm{E}_{\Gamma_t(\varsigma)}$ is the expectations operator conditional on the specific information available to firm ς, which is contained in the set $\Gamma_t(\varsigma)$.

3.1.3 Households

Households are composed of two agents: a consumer and a worker. The former chooses consumption and bond holdings, while the latter uses his monopolistic power to set his wage, as it is assumed that every worker has a unique labor type. As a result, labor is traded in specific labor markets. Also, we allow consumers and workers to differ in the information they possess and on which they make their decisions. This assumption is a model device that gives greater flexibility to match the dynamics of wages and output.[10] Households derive utility from consumption and leisure, where the instantaneous utility function is given by

$$U\left(\mathcal{H}(c_t(\upsilon), c_{t-1}(\upsilon)\right) - V(h_t(\varpi)).$$

Consumer and worker types are indexed by υ and ϖ, respectively, in the $[0,1]$ interval; $c_t(\upsilon)$ and $h_t(\varpi)$ denote consumption and labor, respectively; U is increasing and concave; V is increasing and convex; and, finally, $\mathcal{H}$ is a function that may allow for the existence of habit formation in consumption. The time t household budget constraint, in real terms, is given by:

$$c_t(\upsilon) + \frac{b_t(\upsilon)}{1+i_t} + \tau_t(\upsilon) \leq \frac{W_t(\varpi)}{P_t} h_t(\varpi) + \frac{b_{t-1}(\upsilon)}{1+\pi_t} + \mathrm{div}_t, \tag{5}$$

where $b_t(\upsilon)$ denotes the value, in real terms, of nominal bonds acquired in period t and maturing in period $t+1$; i_t is the nominal interest rate; π_t is the inflation rate of period t; $\tau_t(\upsilon)$ denotes real lump-sum government transfers and state-contingent securities that ensure that all households begin with the same wealth at time t; $W_t(\varpi)$ is the nominal wage rate earned by type-ϖ labor; and div_t represents real profits redistributed by monopolistic firms. Consumers choose a plan for current and future consumption and bond holdings to maximize:

$$\mathrm{E}_{\Upsilon_t(\upsilon)} \sum_{T=t}^{\infty} \beta^{T-t} U\left(\mathcal{H}(c_T(\upsilon), c_{T-1}(\upsilon))\right)$$

subject to (5) and no Ponzi schemes. $\beta \in (0,1)$ is the subjective discount factor and $\mathrm{E}_{\Upsilon_t(\upsilon)}$ represents the expectations operator conditional on the information set $\Upsilon_t(\upsilon)$.

Workers sell their labor input to a perfect competitive labor intermediary. The latter produces a single labor input using a Dixit-Stiglitz aggregator. Similar to the case of intermediate-good producers, it is assumed that in each and every period wages are re-optimized with a fixed probability $1-\alpha_w$, with $\alpha_w \in [0,1)$. Again, in the backward-looking behavior variant, α_w is strictly positive, while in the (baseline) sticky information variant α_w equals zero. If worker ϖ is unable to re-optimize in period T, then its wage is updated according to a rule-of-thumb of the form $W_T(\varpi) = (1+\delta^w_{t,T})W_t(\varpi)$, where $t < T$ denotes the period of the last re-optimization; $(1+\delta^w_{t,T})$ is defined later. Let $W^\star_t(\varpi)$ denote the wage of worker ϖ if he is allowed to re-optimize in period t, and let $h^\star_{t,T}(\varpi)$ denote his time T labor input. Therefore, $W^\star_t(\varpi)$ is chosen to maximize:

$$\mathrm{E}_{\Omega_t(\varpi)} \sum_{T=t}^{\infty} \beta^{T-t} \left[\Lambda_T(\upsilon) \frac{\left(1+\delta^w_{t,T}\right) W^\star_t(\varpi)}{W_T} h^\star_{t,T}(\varpi) - V(h^\star_{t,T}(\varpi)) \right]$$

---

[10] See Mankiw and Reis (2006, 2007). In addition, it can be argued that the information needed for wage setting is strongly influenced by specific structures, such as unions, whereas consumers are not influenced by the same factors.

$$\text{subject to } h^{\star}_{t,T}(\varpi) = \left(\frac{\left(1+\delta^{w}_{t,T}\right) W^{\star}_{t}(\varsigma)}{W_T}\right)^{-\theta_w} h_T,$$

where the last expression is the demand for labor input ϖ, h_t is the aggregate labor input, $\theta_w > 1$ is the elasticity of substitution between labor types, $\Lambda_t(\upsilon)$ is the type-υ's marginal utility of wealth, and $\mathrm{E}_{\Omega_t(\varpi)}$ is the expectations operator conditional to the information set $\Omega_t(\varpi)$.

3.1.4 Government and Equilibrium

The government budget constraint is balanced, and the central bank follows a Taylor-type rule of the form

$$i_t = i_* \left(\frac{1+\pi_t}{1+\pi}\right)^{a_\pi} \left(\frac{y_t}{y^f_t}\right)^{a_y} \exp\left(e_t\right), \text{ where} \tag{6}$$

$$e_t = \rho e_{t-1} + \nu^{\mathcal{M}}_t, \text{ with } \nu^{\mathcal{M}}_t \sim \text{iid}\left(0, \sigma^2_{\mathcal{M}}\right).$$

π is steady-state inflation; y^f_t is the level of output that would prevail if prices and wages were perfectly flexible and there were no information frictions; i_* is the level of the long-run nominal interest rate consistent with inflation and output gaps equal to zero; and $\nu^{\mathcal{M}}_t$ is the monetary policy shock that presents persistence as long as ρ is positive and lower than one.

The equilibrium of this economy is characterized by a set of prices $\{P_t, P_t(\varsigma), W_t, W_t(\varpi), i_t\}$ and a set of quantities $\{d_t, q_t, y_t, c_t(\upsilon), b_t(\upsilon), n_t(\varsigma), h_t, h_t(\varpi)\}$, for all ς, υ, ϖ, such that all markets clear at all times, and agents act consistently according to the maximization of their utility and profits. Notice that in equilibrium $y_t = \int_0^1 c_t(\upsilon)\mathrm{d}\upsilon$, $h_t = \int_0^1 n_t(\varsigma)\mathrm{d}\varsigma$, $\int_0^1 b_t(\upsilon)\mathrm{d}\upsilon = 0$, and $d_t = y_t + \int_0^1 q_t(\varsigma)\mathrm{d}\varsigma$.[11]

3.2 Backward-looking behavior variant: Inflation indexation and habits

In this variant, α_p and α_w are strictly positive, so prices and wages are not re-optimized every period. In case a firm (worker) is not drawn to choose a new price (wage) in period T, the latter is updated according to a rule-of-thumb of the form $X_T(\varrho) = (1+\delta^x_{t,T})X_t(\varrho)$, for $X \in \{P, W\}$ and $\varrho \in \{\varsigma, \varpi\}$, where $t < T$ denotes the period of the last re-optimization, and

$$1+\delta^x_{t,T} = \begin{cases} \prod_{j=t}^{T-1}(1+\pi)^{1-\gamma^b_x}(1+\pi_j)^{\gamma^b_x}, & \text{if } T > t; \\ 1, & \text{otherwise.} \end{cases}$$

---

[11] Notice that in equilibrium, the percentage deviations of aggregate consumption, aggregate raw materials, and aggregate demand are equal. That is, $\hat{y}_t = \hat{d}_t = \hat{q}_t$.

where $\gamma_x^b \in [0,1]$ for $x \in \{p, w\}$ measures the degree of indexation to past inflation values.[12] Households, in turn, display habits in their consumption patterns, and so $\mathcal{H}$ takes the form

$$\mathcal{H}\left(c_t(\upsilon), c_{t-1}(\upsilon)\right) = c_t(\upsilon) - \gamma_h^b c_{t-1}(\upsilon)$$

where $\gamma_h^b \in [0,1)$. Some assumptions regarding the information structure of the economy close the description of this environment. The model should be consistent with the restrictions used in the monetary SVAR. It is thus assumed that consumption, prices, and wages do not react contemporaneously to innovations in the interest rate. In contrast, the demand for bonds changes as a result of policy innovations. We can justify this structure by assuming that the goods and labor markets open before the central bank makes a decision, whereas the financial market opens just after. As a result, $\Gamma_t(\varsigma) = \Upsilon_t(\upsilon) = \Omega_t(\varpi) = I_{t-1}$ for all ς, υ, ϖ at the time consumption, prices and wages are decided, where I_{t-1} reflect all available information concerning shocks and innovations up to time $t-1$. In contrast, $\Upsilon_t(\upsilon) = I_t$ when the demand for bonds is chosen. For the technology shock, specific information constraints are not needed, and thus we assume that the population observes the realization of these shocks. Because all types of agents share the same preferences and production technologies, all agents re-optimizing in period t will choose the same values for their decision variables. We can thus drop type indexes and simply state that $P_t^\star(\upsilon) = P_t^\star$, $W_t^\star(\upsilon) = W_t^\star$, $\Lambda_t(\upsilon) = \Lambda_t$, and $c_t(\upsilon) = c_t = y_t$.

Denote by $x_{*,t}$ the time t steady-state level of variable x at which $\nu_t^{\mathcal{T}}$ is equal to zero. Thus, define $\hat{x}_t$ as the percent deviation of x_t with respect to $x_{*,t}$, i.e., the steady state that would prevail in the absence of a time t technology innovation. This simple notation allows us to express the model dynamics in terms of the transition path from the old to the new steady state after a technology shock.[13] The dynamics of the model economy can be thus stated as follows:

$$\begin{aligned}
\hat{\imath}_t &= a_\pi \hat{\pi}_t + a_y \left(\hat{y}_t - \hat{y}_t^f\right) + e_t && (7)\\
\hat{y}_t &= \phi^{-1}\hat{n}_t + \hat{a}_t && (8)\\
\mathrm{E}_{\Upsilon_t}\hat{\Lambda}_t &= \frac{\tilde{\sigma}}{1-\beta\gamma_h^b}\mathrm{E}_{\Upsilon_t}\left\{\beta\gamma_h^b\hat{y}_{t+1} - [1+\beta(\gamma_h^b)^2]\hat{y}_t + \gamma_h^b\hat{y}_{t-1}\right\} && (9)\\
\hat{\Lambda}_t &= \mathrm{E}_t\hat{\Lambda}_{t+1} + (\hat{\imath}_t - E_t\hat{\pi}_{t+1}) && (10)\\
\hat{p}_t^\star &= \mathrm{E}_{\Gamma_t}\left\{(1-\beta\alpha_p)\xi_p\hat{m}_{p,t} + \beta\alpha_p(\hat{p}_{t+1}^\star + \hat{\pi}_{t+1} - \gamma_p^b\hat{\pi}_t)\right\} && (11)\\
\hat{w}_t^\star &= \mathrm{E}_{\Omega_t}\{(1-\beta\alpha_w)\xi_w\hat{m}_{w,t} + \beta\alpha_w(\hat{w}_{t+1}^\star + \hat{\pi}_{t+1}^w - \gamma_w^b\hat{\pi}_t)\} && (12)\\
\hat{P}_t &= (1-\alpha_p)\hat{P}_t^\star + \alpha_p\hat{P}_{t-1} + \alpha_p\gamma_p^b\hat{\pi}_{t-1} && (13)\\
\hat{W}_t &= (1-\alpha_w)\hat{W}_t^\star + \alpha_p\hat{W}_{t-1} + \alpha_w\gamma_w^b\hat{\pi}_{t-1} && (14)
\end{aligned}$$

---

[12] When $\gamma_p^b = 1$, firms index their prices to reflect the last period's inflation, and thus $P_T(\varsigma) = (1+\pi_{t-1})P_{T-1}(\varsigma)$. The same logic applies to workers.

[13] Notice that the steady state is invariant to the monetary shock $\nu_t^{\mathcal{M}}$.

Eq. (7) and (8) denote the monetary policy rule and the intermediate-sector production technology, where $\phi^{-1} \equiv \frac{F'(n)n}{F(n)}$ is the elasticity of intermediate goods with respect to labor. Eq. (9) and (10) are the F.O.C. of consumption and bond holdings, in which $\tilde{\sigma} = \frac{\sigma}{(1-\gamma_h^b)}$, with $\sigma \equiv -\frac{U''(c)c}{U'(c)}$ as the inverse of the elasticity of intertemporal substitution. The optimal price- and wage- setting equations are given by (11) and (12), where $\hat{p}_t^\star = \hat{P}_t^\star - \hat{P}_t$; $\hat{w}_t^\star = \hat{W}_t^\star - \hat{W}_t$; $\hat{m}_{p,t} = \hat{w}_t + \hat{l}_t - \hat{y}_t$ is the percent deviation of the marginal cost; $\hat{m}_{w,t} = \omega_w \hat{l}_t - \hat{\Lambda}_t - \hat{w}_t$ is the percent deviation of the labor-income marginal rate of substitution, with $\omega_w^{-1} \equiv \frac{V'(h)}{V''(h)h}$ as the Frisch elasticity of labor supply; the steady-state percent deviations of inflation and wage inflation are denoted by $\hat{\pi}_t = \hat{P}_t - \hat{P}_{t-1}$ and $\hat{\pi}_t^w = \hat{W}_t - \hat{W}_{t-1}$; finally, ξ_p and ξ_w include parameters governing the sources of real rigidities and strategic complementarities between price- and wage-setters. In particular,

$$\xi_p = \frac{1}{\theta_p(1)\omega_p + (1+\theta_p(1)\epsilon_\mu)/(1-\mu_p(1)s_q)}, \quad \text{and} \quad \xi_w = \frac{1}{\theta_w \omega_w + 1}.$$

The terms $\theta_p(1)\omega_p$ and $\theta_w\omega_w$ are a consequence of assuming specific factor markets, where $\theta_p(z)$ is evaluated at its steady state level. The parameter $\epsilon_\mu \equiv \mu_p'(1)/\mu_p(1)$ indicates the elasticity of the desired intermediate producer markup, $\mu_p(z)$, evaluated at the steady state. When $\epsilon_\mu > 0$, the elasticity of demand is increasing in a firm's price. In this case, when the marginal cost increases, a monopolistic firm will moderate its price fluctuations because compensation results from a countercyclical markup (see Kimball, 1995). The term $\mu_p(1)s_q$ is due to the input-output structure of the economy described by the gross-output production function.[14] The percent deviations of the general price and the nominal wage indexes, obtained from the zero-profit condition of the final-good producer and the labor intermediary, are given by eq. (9) and (10), respectively. To conclude, the two stochastic drivers of the economy, namely the monetary and the technology shocks, are given, in logarithmic terms, by:

$$\begin{aligned} e_t &= \rho e_{t-1} + \nu_t^{\mathcal{M}}, \text{ and} \qquad (15) \\ \hat{a}_t &= \hat{a}_{t-1} + \nu_t^{\mathcal{T}}. \qquad (16) \end{aligned}$$

3.3 Sticky information variant: Pervasive information frictions

An alternative to include inertia in the model consists of adding sticky information in households, firms, and workers. It is possible to build a model in which sticky prices and sticky wages coexist with information frictions in price- and wage-setting, yielding a model characterized by "dual stickiness" along the lines of Knotek (2010) or Dupor *et al.* (2010). For the sake of generality, the

---

[14] Rotemberg and Woodford (1995) argue that adding a share of primary factor inputs represents a closer approximation of real production technologies, especially when prices do not co-move perfectly with marginal costs. Notably, a positive material goods share lowers the reaction of intermediate prices to movements in sales by decreasing the value of ξ_p. For further insights about these sources of strategic complementarities, see Woodford (2003b).

model description that follows allows for dual stickiness, although, for reasons that will become clear in the robustness analysis, the baseline results of the paper rely on the assumption that α_p and α_w are equal to zero, or that only information frictions are present in price- and wage-setting.

In this economy, the rule-of-thumb that workers and firms use to update wages and prices in period T takes the simple form $X_T(\varrho) = (1+\pi)X_t(\varrho)$, for $X \in \{P, W\}$ and $\varrho \in \{\varsigma, \varpi\}$ where $t < T$ denotes the period of the last re-optimization. That is, agents update their prices and wages using steady-state inflation. Also, habit formation is not longer allowed for consumers, implying that $\mathcal{H}(c_t(\upsilon), c_{t-1}(\upsilon)) = c_t(\upsilon)$. Consequently, the former statements assume that γ_w^b, γ_p^b, and γ_h^b are equal to zero.

In contrast, the information structure is much more complex in this environment. In line with Mankiw and Reis (2006), it is assumed that at each and every period, every agent in the economy has a probability $1 - \gamma_x^{si}$ of collecting the newest information available for $x \in \{p, w, h\}$ denoting prices, wages, and consumption, respectively. As in the backward-looking behavior variant, consumption, prices, and wages are decided prior to the decision of the central bank, whereas financial markets open afterward. Therefore, a proportion $1 - \gamma_h^{si}$ of consumers decide their consumption bundle with the information contained in set I_{t-1}; $(1-\gamma_h^{si})\gamma_h^{si}$ use the information of set I_{t-2}; $(1-\gamma_h^{si})(\gamma_h^{si})^2$ use the information contained in I_{t-3}; and so on. A similar structure applies for workers and firms using their relevant updating information probabilities.

One complication that arises in sticky-information environments is that solving for the equilibrium dynamics requires taking into account the sequence of delayed expectations of endogenous variables, which in this case is infinite. Some authors, such as Trabandt (2007), solve the problem by truncating the number of lags present in expectations. Notice, however, that the structure of the model economy allows us to restrict our attention to the particular decisions of the most-informed agents. The reason is that all agents re-optimizing in period t and sharing the same information will choose similar values for their decision variables because all agents have similar preferences, production technologies, and access to financial markets.

Formally, if $X_t^k(\varrho)$ for $X \in \{c, P^\star, W^\star\}$ and $\varrho \in \{\upsilon, \varsigma, \varpi\}$ represent the optimal consumption, price or wage chosen by an agent with information set I_{t-k}, for $k \geq 1$, then, as a consequence of similar preferences and technologies, we can drop type indexes and simply state that $X_t^k = E_{t-k}X_t$, for all $k > 1$, where, by convention, we set $X_t \equiv X_t^1$ for $X \in \{c, P^\star, W^\star\}$. Therefore, the dynamics of this model economy, as stated in terms of the most-informed agents, and as percent deviations from the time t steady state in which $\nu_t^{\mathcal{T}}$ is equal to zero (see section 3.2), are described by the monetary policy rule (eq. 7) , the intermediate sector production function (eq. 8), and the F.O.C. of consumption and bond holdings of the most attentive consumer,

$$0 = -\sigma \mathrm{E}_{\Upsilon_t} \hat{c}_t - \mathrm{E}_{\Upsilon_t} \hat{\Lambda}_t \tag{17}$$

$$\hat{\Lambda}_t = \mathrm{E}_t \hat{\Lambda}_{t+1} + (\hat{\imath}_t - E_t \hat{\pi}_{t+1}); \tag{18}$$

plus the optimal price- and wage-setting decision rules of the most attentive firm and worker,

$$\hat{p}_t^\star = \mathrm{E}_{\Gamma_t} \left\{ (1 - \beta\alpha_p)\xi_p \hat{m}_{p,t} + \beta\alpha_p(\hat{p}_{t+1}^\star + \hat{\pi}_{t+1}) \right\} \tag{19}$$

$$\hat{w}_t^\star = \mathrm{E}_{\Omega_t} \{ (1 - \beta\alpha_w)\xi_w \hat{m}_{w,t} + \beta\alpha_w(\hat{w}_{t+1}^\star + \hat{\pi}_{t+1}^w) \}, \tag{20}$$

where $\hat{p}_t^\star = \hat{P}_t^\star - \hat{P}_t$ and $\hat{w}_t^\star = \hat{W}_t^\star - \hat{W}_t$; plus the aggregate behavior of all consumers and price- and wage-setters,

$$\hat{y}_t = (1 - \gamma_h^{si}) \sum_{k=0}^{\infty} (\gamma_h^{si})^k \mathrm{E}_{\Upsilon_{t-k}} \hat{c}_t \tag{21}$$

$$\hat{P}_t = (1 - \alpha_p)(1 - \gamma_p^{si}) \sum_{k=0}^{\infty} (\gamma_p^{si})^k \mathrm{E}_{\Gamma_{t-k}} \hat{P}_t^\star + \alpha_p \hat{P}_{t-1} \tag{22}$$

$$\hat{W}_t = (1 - \alpha_w)(1 - \gamma_w^{si}) \sum_{k=0}^{\infty} (\gamma_w^{si})^k \mathrm{E}_{\Omega_{t-k}} \hat{W}_t^\star + \alpha_p \hat{W}_{t-1}. \tag{23}$$

The last three expressions add intrinsic inertia to the model. Also note that sticky prices and sticky information coexist as long as α_p and γ_p^{si} are greater than zero. The equilibrium dynamics are solved using the algorithm employed by Lieb (2009), which is a refinement of the principles provided by Meyer-Ghode (2010) and Uhlig's toolkit.

4 Econometric methodology

4.1 Minimum distance estimation

The model parameters are divided into two groups, ψ_1^m and ψ_2^m, where $m \in \{b, si\}$ refers to the model variant. For the backward-looking behavior variant, ψ_1^b is composed of parameters governing preferences, technology, and sources of strategic complementarity, i.e., $\psi_1^b \equiv \{\beta, \sigma, \theta_p, \theta_w, \omega_p, \omega_w, \epsilon_\mu, \phi, s_q\}$. For the sticky-information variant, ψ_1^{si} includes all parameters of ψ_1^b plus the degree of nominal rigidities, i.e., $\psi_1^{si} \equiv \left\{\psi_1^b, \alpha_p, \alpha_w\right\}$. β is set equal to 0.99, implying a steady-state annualized real interest rate of 4 percent. We set $\sigma = \omega_w = 1$, implying a logarithmic utility for consumption and a unitary Frisch labor supply elasticity, as considered by Christiano *et al.* (2005). ϕ equals 1.33, denoting a steady-state share of labor income of 62.5 percent after correcting for the markup. If the intermediate firm production function is a Cobb-Douglas, then ω_p equals $\phi - 1$. The share of material goods in gross output, s_q, is set to 50 percent because this may be a good approximation for the U.S. economy, as suggested by Rotemberg and Woodford (1995). We set $\theta_p = 6$ and $\theta_w = 21$ following Rotemberg and

Woodford (1997) and Christiano *et al.* (2005), which imply a price markup of 20 percent and a wage markup of 5 percent. The markup elasticity to relative demand, ϵ_μ, is set to 1, as in Woodford (2003b). Finally, for the sticky information variant only, α_p and α_w are both set to zero.

The second group of parameters includes the sources of price- and wage-setting of either the backward-looking behavior variant or the sticky-information variant, shock parameters, and the coefficients of the Taylor rule. For the sticky-information variant, $\psi_2^{si} \equiv \left\{\gamma_p, \gamma_w, \gamma_h, a_\pi, a_y, \rho, \sigma_{\mathcal{M}}, \sigma_{\mathcal{T}}\right\}$, whereas for the backward-looking behavior variant $\psi_2^b \equiv \left\{\psi_2^{si}, \alpha_p, \alpha_w\right\}$. Calibrated and estimated parameters are partitioned for two reasons: first, certain parameters can be inferred from observed aggregate quantities, such as β, ϕ, or s_q; second, it has proven difficult to identify some parameters simultaneously. For instance, estimating ϵ_μ, θ_p, and α_p together (or, equivalently, θ_w and α_w) raises issues in their identification because these parameters appear in a single reduced-form coefficient in the Phillips curve equation. In terms of Canova and Sala (2009), the lack of reduced-form parameters raises the problem of *partial identification.* The latter has been noticed in practice by Rotemberg and Woodford (1997), Amato and Laubach (2003), and Eichenbaum and Fisher (2007).[15] For the sticky information model, estimating α_p and γ_p^{si} (or α_w and γ_w^{si}) simultaneously raises serious suspicions of partial identification as well, as shown in section 5.2.1. It is for this reason that α_p and α_w are calibrated in the sticky information variant.

ψ_2 is estimated by minimizing a measure of the distance between the empirical impulse responses of key aggregate variables and their model counterparts.[16] Two sets of estimated parameters are obtained, each corresponding to one of the shocks described in section 2. This strategy allow us to analyze the performance of each model variant in response to the particular shock considered and delivers an overview of the stability of the estimated parameters across model variants and shocks.

The minimum distance estimation is performed using the responses of output, inflation, the real wage, and the federal funds rate. Define $h^\zeta(\psi_2)$ as the mapping from ψ_2 to the model-based impulse response functions to a monetary shock ($\zeta = \mathcal{M}$) or a technology shock ($\zeta = \mathcal{T}$). Next, let θ_k^ζ denote the vector of empirical responses to the shock ζ at horizon $k \geq 0$, as implied by the corresponding SVAR. The object to match is $\theta^\zeta = \text{vec}([\theta_0^\zeta, \theta_1^\zeta, \ldots, \theta_K^\zeta])'$, where K is the selected horizon. The vector of estimated parameters $\hat{\psi}_2^\zeta$ is obtained by solving

$$\hat{\psi}_2^\zeta = \arg\min_{\psi_2 \in \Psi} \mathcal{J}_T^\zeta,$$

---

[15] It is worth noting that no significant changes in the results were detected when using a different calibration.

[16] See Rotemberg and Woodford (1997), Amato and Laubach (2003), Christiano *et al.* (2005), Boivin and Giannoni (2006), or Altig et al. (2010).

where

$$\mathcal{J}_T^{\zeta} = (h^{\zeta}(\psi_2) - \hat{\theta}_T^{\zeta}) V_T^{\zeta} (h^{\zeta}(\psi_2) - \hat{\theta}_T^{\zeta})',$$

Ψ contains the admissible values for the parameters in ψ_2, $\hat{\theta}_T^{\zeta}$ is an estimate of θ^{ζ}, T is the sample size, and V_T^{ζ} is a diagonal matrix with the sample variances of θ^{ζ} along the diagonal. This particular weighting matrix has some specific advantages. As Christiano *et al.* (2005) note, it ensures that the model's impulse responses lie within the confidence interval of the SVAR impulse responses to the greatest possible extent. However, because V_T^{ζ} is not the optimal weighting matrix, it is likely that the asymptotic distribution of $\mathcal{J}_T^{\zeta}$ will not behave as a χ^2 distribution with dim(θ)-dim(ψ_2) degrees of freedom under the null hypothesis that $\mathcal{J}_T^{\zeta}$ equals zero. Fève *et al.* (2009) solve this problem using a bootstrapping method that computes the empirical distribution of $\mathcal{J}_T^{\zeta}$, and enables the null of $\mathcal{J}_T^{\zeta} = 0$ to be tested. Along the lines of Hall and Horowitz (1996), Fève *et al.*'s method proposes the generation of N bootstrap samples of the SVAR and impulse responses. For each iteration of impulse responses, represented by $\theta^{\zeta,i}$, ψ_2 is re-estimated by solving:

$$\hat{\psi}_2^{\zeta,i} = \arg \min_{\psi_2 \in \Psi} \mathcal{J}^{\zeta,i}, \tag{24}$$

where

$$\mathcal{J}^{\zeta,i} = (h^{\zeta}(\psi_2) - \theta_T^{\zeta,i} - \hat{\mu}_T^{\zeta}) V_T^{\zeta} (h^{\zeta}(\psi_2) - \theta_T^{\zeta,i} - \hat{\mu}_T^{\zeta})',$$

and $\hat{\mu}_T \equiv h^{\zeta}(\hat{\psi}_2) - \hat{\theta}_T^{\zeta}$ is used to re-center the bootstrapped analog of the moment condition. Hall and Horowitz point out that, without recentering, the bootstrap could implement a moment condition that does not hold in the bootstrapped sample. For instance, in the case of minimum distance estimation, not re-centering may increase the probability of accepting the null hypothesis of $\mathcal{J}_T^{\zeta} = 0$ when it should actually be rejected. In the present analysis, N is set to 1000.

The minimum distance estimation, like many others, can be subject to parameter identification problems, which, for this procedure, have recently been highlighted by Canova and Sala (2009). Even though the choice of the calibrated parameters tackles a well-identified problem of partial identification, we cannot rule out the possibility that some of the estimating parameters might encounter a problem of *weak identification*. One way to assess whether identification problems are important is by analyzing the bootstrap distribution of the estimating parameters, $\hat{\psi}_2^i$, computed in equation (24). A distribution that is informative about the value of a parameter can be interpreted as a signal that identification problems concerning this parameter are restrained.

4.2 Goodness of fit

To compare the prediction accuracy of each model variant, I compute the *root mean squared error* (*RMSE*) between the model-based responses and the SVAR responses. The *RMSE* statistic is computed for each of the variables considered in the estimation step (output, inflation, the real wage, and the federal funds), plus an additional out-of-sample variable, *wage inflation*, for which each model variant is subject to a prediction test. I use the bootstrap samples employed in the estimation step to infer the associated distribution of $RMSE$ statistics. A significant difference between the $RMSE$-statistic distributions of each model will indicate a model's advantage of better explaining the empirical dynamics of a certain variable.

5 Results

5.1 Baseline estimations

The baseline estimations for the backward-looking behavior (hereafter, BK) and the sticky-information (hereafter, SI) variants are presented in the first and second columns of tables 1 and 2. The sample period is 1954(3)-2007(4), and the horizon considered is 45 periods.[17] At the bottom of each table, the *p-values* associated with the $\mathcal{J}$-statistics show that we cannot reject the null hypothesis that $\mathcal{J}_T = 0$ for each model variant and shock considered. Tables 1 and 2 provide the standard deviations in parentheses and the 90 percent confidence intervals for the point estimates in brackets. If a fat tail makes the 90-percent interval uninformative, a band covering 80 percent of the estimated distribution, starting at one of the extremes of the parameter space, is shown instead (these cases are marked with a †). Fat tails are a consequence of restricting the parameter space to certain values. For instance, the Calvo pricing parameters can take values on the interval $[0, 0.99]$; or, to ensure determinacy and save on estimating time, the inflation coefficient in the Taylor rule can be constrained in the interval $[1.01, 5]$. If the 80-percent band is still large or uninformative about the value of a coefficient, we can suspect a problem of weak identification.

The model-based impulse responses for output, inflation, the real wage, the federal funds rate, and wage inflation are depicted in figure 1. For the monetary policy shock, both model variants are very similar in terms of their predicted dynamics. The most notable differences are present in the technology shock estimation, where the SI variant appears to overestimate the speed of adjustment of real wages and underestimate considerably the reaction of output. The mismatch in the real wage dynamics of the SI model is a feature that appears regularly in the robustness analysis.

---

[17] The rationale for a relatively long horizon is that the estimation method is fed with more information about the behavior of the aggregate dynamics. The results for different horizons, available upon request, shows that for small horizons (5 to 20), the estimating parameters are somehow unstable and the model fit is low; whereas for larger horizons (from 30 to 60), the estimating parameters and model fit do not really vary.

5.1.1 Monetary policy shock

The estimated parameters of the two model variants are very similar to previous empirical studies. For the BK model, for instance, the degrees of habit formation, price and wage stickiness, and inflation indexation lie well within the ranges of results of Christiano *et al.* (2005), and Smets and Wouters (2007). Accordingly, the BK model predicts that prices and wages are reoptimized on average every 6 quarters. In addition, full inflation indexation in prices and wages and habits in consumption drive the hump-shaped responses in inflation, wage inflation, and output.

For the SI model, the degree of information frictions for firms, workers, and consumers imply that these agents update their information on average every 4, 5, and 7 quarters, respectively. Similarly to the BK variant, information frictions in firms, workers, and consumers are responsible for the sluggish adjustment of prices, wages, and output, respectively. The estimated rate of updating information for firms, by far the most studied friction of the SI environment, lie well within the range of previous studies.[18] In the same vein, the degree of information frictions in wage-setting resembles the estimates of Mankiw and Reis (2007), who use a Bayesian estimation over a very similar sample period. Although the range of estimations for information frictions in consumers is wider (see Mankiw and Reis, 2006 and 2007; and Reis, 2009), it appears that a certain regularity exists across estimation methods and samples in which firms and workers tend to be more attentive than consumers are.

The two model variants are practically identical in terms of their estimates for the Taylor rule parameters. The point estimates for the inflation coefficient are close to 1.5, a level similar to the estimate of Smets and Wouters (2007) for an analogous sample period (1957(1)–2004(4)).[19] The point estimate for the output gap coefficient is virtually 0 in both model variants, which is again in line with the evidence of Smets and Wouters (2007) or Boivin and Giannoni (2006) for the two sub-samples they consider. The size of the monetary policy shock ($\sigma_{\mathcal{M}}$) matches the impact effect of its SVAR counterpart quite well (note the federal funds rate impact response in figure 1). Further, the shock is quite persistent ($\rho > 0.9$), which implies that the interest rate reflects an important degree of smoothing when there is a monetary policy shock.

---

[18] Andrés *et al.* (2005), Khan and Zu (2006), Mankiw and Reis (2006, 2007), Kiley (2007), Korenok (2008), Reis (2009), Dupor *et al.* (2010), and Knotek (2010) find periods of around 1.4 to 7 quarters between a firm's last information update and a new information update. Coibion and Gorodnichenko (2010) consider a model with heterogeneous firms, including sticky-price firms and sticky-information firms. The average time spanned between information updates, weighted by the kind of firms in their economy, is 5 quarters.

[19] In the post-1979 estimations considered in the robustness analysis, it is shown that the inflation coefficient increases substantially in most of the estimations, reflecting the well-known aggressive behavior of the Fed towards inflation stabilization after October, 1979.

To compare the size of uncertainty implied by each variant *vis-à-vis* the SVAR implied uncertainty, figure 2, row 1, shows the 80-percent confidence intervals of the model-based responses and the SVAR responses for a set of variables. It can be seen that both model variants account well for the sample uncertainty of output, inflation, wage inflation, and the federal funds rate. On the other hand, the models cannot replicate the sizable confidence interval of the real wage after a monetary policy shock. Both model variants predict that the real wage is more likely to decrease after a shock in monetary policy, whereas the SVAR evidence is not conclusive.

Because the implied model uncertainty of each variant is almost identical, we should expect to find no differences in the distributions of the *RMSE* statistics for the variables considered in the figure. This is precisely the case described in the second row of figure 2. The two models are statistically equivalent in terms of their prediction accuracy concerning the aggregate dynamics triggered by a shock in monetary policy.[20]

5.1.2 Technology shock

The baseline estimation of the BK variant as given by a technology shock is presented in the second column of table 1. The estimated degree of price stickiness is similar to the monetary shock estimation, whereas nominal wage rigidities and habit persistence increase. The point estimate of the degree of inflation indexation in prices is reduced by more than a half, whereas wage indexation remains very high. Similar findings have been documented by Edge, Laubach, and Williams (2003) and Avouyi-Dovi and Matheron (2007) and are in line with the intuitions provided by Liu and Phaneuf (2007) about the importance of nominal rigidities and habits for explaining the aggregate dynamics triggered by a technology shock.[21] Table 2, column 2, shows the technology shock estimation of the SI variant. The point estimates of the degree of information frictions imply that firms, workers, and consumers update their information on average every 2.5, 3, and 10 quarters, respectively. Similar to the analysis of Liu and Phaneuf, section 6 shows why information frictions need to be *pervasive* to produce a slow adjustment in real wages and output after a permanent increase in productivity. Both model variants are again similar with respect to their Taylor rule parameter estimates. Although the output gap

---

[20] Following the recommendation of one referee, I have checked the ability of each model to fit the responses of the real interest rate (defined as the nominal interest rate minus the realized-one-period-ahead inflation). The results of this comparison do not show significant differences between the two models in either the monetary policy shock or the technology shock estimation.

[21] These results contrast with the findings of Dupor, Han, and Tsai (2009) and Altig *et al.* (2010), who find that prices tend to be quite flexible after a shock in technology. With respect to Dupor *et al.* (2009), who also perform a minimum distance estimation, the differences can be explained by the fact that their SVAR predicts that inflation returns to its pre-shock level relatively quickly after falling during the impact period. On the other hand, Altig *et al.* (2010) assume a full inflation-indexation environment that might be compensated in their estimations by a very low price stickiness.

coefficient remains very close to zero, the inflation coefficient is now lower than in the monetary shock case. This result may indicate that the Federal Reserve tends to accommodate inflation when there is a permanent shock in productivity.

Figure 2, row 3, shows the implied model-based and SVAR uncertainties as given by the 80-percent confidence intervals of the impulse responses. The difference in the predictions of the real wage dynamics is evident. Whereas the BK variant captures the SVAR implied uncertainty of this variable well, the SI variant recurrently predicts a higher speed of adjustment of real wages. This difference can be explained as follows: the SI model systematically predicts a rise in nominal wages that lasts for several quarters after a permanent increase in labor productivity, a behavior not captured by the SVAR (see the wage inflation responses in figure 2). Consequently, real wages rise faster in the SI model than in the SVAR and the BK model. In contrast, the BK model predicts a null or positive response of wage inflation at impact, followed by a moderate decrease afterwards. This prediction is in line with the SVAR evidence. Section 6 shows that the BK variant relies on nominal wage indexation to mimic the behavior of wage inflation, a device that is missing in the SI model. The two models also differ with respect to their output predictions, which is explained by the lower point estimate (and smaller confidence interval) of $\sigma_{\mathcal{T}}$ in the SI variant with respect to the BK variant.

The different predictions in the responses of the real wage, nominal wage, and output are statistically significant. The latter is shown by the differences in the distributions of the *RMSE* statistics for these variables, shown in the last row of figure 2. The *RMSE* distributions of the BK model are closer to zero than those of the SI model for the variables listed above. In fact, the probability that the BK model's *RMSE* statistic for the real wage is higher than the mean value of the corresponding SI model's *RMSE* statistic is 1.6 percent.[22] For output, the corresponding probability is 1.8 percent, whereas for nominal wages it is 3.8 percent. In sum, after a technology shock, the backward-looking behavior model has more desired properties than the sticky information model in terms of prediction accuracy. The next section argues that these properties prevail in a set of robustness exercises.

5.2 Robustness analysis

5.2.1 Dual stickiness model *vs.* pure sticky information

Recent studies such as Coibion and Gorodnichenko (2010), Dupor *et al.* (2010), and Knotek (2010) find that a model displaying both sticky information and sticky prices, or a "dual stickiness" model, captures certain moments of inflation better than a pure sticky information model

---

[22] It is, Prob$\left[RMSE^{BK}(w)^{\mathcal{T},i} \geq \frac{1}{N}\sum_{i=1}^{N} RMSE^{SI}(w)^{\mathcal{T},i}\right]$

without nominal rigidities. To test this hypothesis, I allow α_p and α_w in the SI model presented in section 3.3 to be different from zero and be set for estimation. Figure 3 compares the distributions of the *RMSE* statistics from the (baseline) pure sticky information model and the dual stickiness model for the same set of variables as in the baseline case. The two models are statistically equivalent after a shock in monetary policy. In contrast, after a shock in productivity, the dual stickiness model presents a better fit than the pure sticky price model for inflation and wage inflation, thus providing evidence in favor of Coibion and Gorodnichenko, Dupor *et al.*, and Knotek. There are, however, some indications of a problem of partial identification in the dual stickiness model, at least when the latter is estimated using a minimum distance estimation to fit impulse responses.

Table 2, rows 3 and 4, displays the estimated parameters of the dual stickiness model. Interestingly, for the monetary shock estimation, the point estimates of α_p and α_w are equal to zero. The latter result implies that, from the perspective of the aggregated dynamics triggered by a monetary shock, the dual stickiness model effectively boils down to a simple pure sticky information model. On the other hand, in the technology shock estimation, the dual stickiness model displays positive estimates for the degrees of nominal and information frictions in price-setting, whereas it finds that workers have fully flexible wages and no information frictions! These contrasting parameter estimates, however, find no support in their 80-percent confidence bands, which are too wide to establish a conclusion. The lack of stability between the estimates of the monetary shock and the technology shock and the uninformative character of the 80-percent confidence bands suggest that there is a problem of *partial identification* between the parameters governing the degrees of nominal rigidities and information frictions.

Figure 3 also compares the prediction accuracy of the dual stickiness model with the backward-looking behavior model. The two models are still equivalent after a shock in monetary policy. For the technology shock comparison, the BK variant is, again, better than the dual stickiness model at predicting the responses of real wages and output. Accordingly, the probability that the BK variant would present a worse fit to the real wage impulse response than the average fit of the dual stickiness model[23] is only approximately 2 percent. For output, the corresponding probability is 3.4 percent.

5.2.2 Variants with investment and capital

To verify that the baseline results are not contingent on the particular common model specification proposed in section 3, this robustness exercise introduces investment and capital dynamics into the baseline BK and SI variants. Now, households can buy capital stock, choose the rate of

---

[23] See footnote 22.

capital utilization, and rent capital services to intermediate-good producers. Investment is introduced equally in both model variants. For simplicity, it is assumed that every household has a new member, namely the *investor*, who is confronted with adjustment costs and is mostly aware of macro innovations. Thus, an investor is not subject to information frictions as the consumer and the worker in the sticky information household. This conservative modeling choice aims to add a common framework across model variants, allowing them to vary in the same dimensions as the baseline case considered earlier.[24] Finally, to respect the identification strategy of the monetary SVAR, it is assumed that the investor chooses its capital purchases and the rate of capital utilization before the realization of the monetary policy shock.

The law of capital accumulation is given by $k_{t+1} = [1 - \delta(u_t)] k_t + \left[1 - S\left(\frac{x_t}{x_{t-1}}\right)\right] x_t$, where k_t is the stock of capital, u_t is the rate of capital utilization, and x_t is investment; $\delta(u_t) \in (0,1)$ is an increasing and convex depreciation function in the neighborhood of the steady state, with $\delta(0) = 0$, $\delta(\infty) = 1$, and $\delta(1) = \delta$ (similar to Greenwood *et al.,* 1988); function S satisfies $S(1) = S'(1) = 0$, and $\kappa \equiv S''(1)$, following Christiano *et al.* (2005). The production function of the intermediate firm now integrates capital services, and for simplicity and without loss of generality, eliminates raw input goods. Thus, $d_t(\varsigma) = [u_t k_t(\varsigma)]^{1-\psi} [A_t n_t(\varsigma)]^{\psi}$. Finally, given the particular form of the production technology, the real cost function becomes $S(d_t(\varsigma)) = \frac{w_t^{\psi} z_t^{1-\psi}}{A_t^{\psi} \psi^{\psi} (1-\psi)^{1-\psi}} d_t(\varsigma)$. The rest of the environment for each variant is left unchanged. The steady-state depreciation rate, δ, is set to 0.03, corresponding to an annual depreciation rate of 12 percent; ψ is simply equal to ϕ^{-1}; κ is set such that a permanent 1-percent change in Tobin's q would induce a change in investment of approximately 6.7 percent.[25] Finally, the curvature of the depreciation function, as denoted by $\frac{\delta''(1)}{\delta'(1)}$, is set to 0.01, which implies a large elasticity of the rate of capital utilization with respect to the rental rate of capital, similar to Christiano *et al.* (2005). The calibrated parameters for δ and ψ imply that the steady-state investment-to-output ratio is approximately 16 percent.

The SVARs and the minimum distance estimations now include consumption and investment. These variables are measured by the log of real per capita personal consumption expenditures (excluding durable goods), and the log of real per capita private non-residential investment, respectively, both obtained from the NIPA tables of the Bureau of Economic Analysis. For the

---

[24] This alternative also simplifies a potential problem of aggregation in capital markets because investment decisions and the supply of capital services across households depend only on aggregate variables.

[25] The elasticity of investment to a permanent change in Tobin's q is computed as follows $1/(\kappa(1-\beta))$ (see Christiano *et al.,* 2005, for further details). There is not a consensus about the value of κ in the literature. For instance, Christiano *et al.* (2005) assume a value of κ that implies that a permanent 1-percent increase in q induces a 55 percent change in investment. For Smets and Wouters (2007), the same elasticity is approximately17 percent. This contrasts greatly with the finance literature, which normally finds very small elasticities (see Erickson and Whited, 2000).

monetary SVAR, consumption and investment are placed before the federal funds rate, so they respond to variation in the nominal interest rate with a one-period lag.

The point estimates for the BK variant are shown in columns 3 and 4 of table 1, and those for the SI variant are presented in columns 5 and 6 of table 2. The parameter estimates of the two models show a similar configuration to the baseline estimates. The major differences in both models are a positive output gap coefficient in the Taylor rule and fewer rigidities in price- and wage-setting after a technology shock. Notice that because large capital adjustment costs are necessary to approximate the SVAR responses of investment, habits and information frictions in consumers are necessary to generate the hump-shaped response of output after a monetary shock and the slow adjustment of this variable after a technology shock. Effectively, large investment adjustment costs imply small investment fluctuations that represent only a minor part of the total output fluctuations, which are mainly explained by consumption.

The model-based and SVAR implied uncertainty are shown in figure 4, rows 1 and 3. The prediction accuracy of each variant is presented in the same figure, rows 2 and 4. For the monetary shock estimation, both models again show similar performance, in terms of both uncertainty and accuracy. For the technology shock, there are some differences with respect to the baseline results. The SI variant still predicts a higher speed of adjustment of real wages than the BK variant does, but the difference is no longer significant in terms of the distributions of the real wage *RMSE* statistic. In contrast, significant differences now appear in the components of the real wage, i.e., in nominal wages and prices. The SI variant predicts a smaller inflation variability than the SVAR does, along with a short lived increase in wage inflation that is also not observed in the SVAR. The BK variant, in contrast, captures better the empirical uncertainty of these variables. As a result, the *RMSE* distributions for inflation and wage inflation are closer to zero for the BK variant than for the SI variant. Accordingly, the probability that the BK variant presents a worse fit for inflation than the average fit of the SI variant for this variable is 8.7 percent. The corresponding probability for wage inflation is 7.7 percent.

5.2.3 Alternative specification of hours in the technology-shock SVAR

The debate about the empirical effect of a permanent increase in productivity on hours is ongoing. The evidence based on SVARs is not conclusive, because the response of hours depends on whether this variable enters the SVAR in log-levels or in log-differences. Although the *qualitative* responses of inflation, wage inflation, and real wages are not sensitive to the way one introduces hours in the SVAR (see Liu and Phaneuf, 2007), one may ask whether the latter alters their *quantitative* responses in such a way that the difference between model variants, in terms of prediction accuracy, is compromised. To test this hypothesis, I perform an additional technology-shock estimation using the baseline model variants and a technology-shock SVAR that includes hours in log-levels instead of log-differences.[26]

Figure 5, row 1, shows the 80-percent confidence intervals of the hours-in-levels technology SVAR for the same variables as baseline case. The responses of these variables are qualitatively similar to the hours-in-differences SVAR, although they have narrower confidence intervals. The figure also shows the model-based uncertainty and the distribution of the *RMSE* statistics. Both models predict a lower variability for inflation and wage inflation than the SVAR does. This is explained by a high degree of nominal rigidities and information frictions estimated in each model. For the BK variant, α_p and α_w were contained in the interval $[.75, .99]$ approximately 80 percent of the time; for the SI variant, γ_p^{si} and γ_w^{si} were inside the interval $[.85, .99]$ a similar percentage of the time.[27] Notice that the SI variant does not predict a fall in wage inflation, which is again at odds with the evidence of the SVAR. As a result, the SI variant again predicts a higher speed of adjustment in real wages than what is empirically observed. The BK variant is again better at fitting the SVAR impulse responses of the real wage, wage inflation, and inflation. Consequently, the respective probabilities that the BK variant presents a worse fit than the average fit of the SI variant for the real wage, inflation, and wage inflation are 2, 9, and 10 percent.

5.2.4 Post-1979 data

In October 1979, former Fed chairman Paul Volcker started an aggressive policy to control inflation. Clarida, Galí, and Gertler (2000) find that a Taylor rule fitted to post-1979 data presents an inflation coefficient that is significantly larger than a Taylor rule fitted to pre-1979 data, in line with the perception of an inflation-stabilizing regime after 1979. One may argue that other features that affect decision making, such as the degree of nominal rigidities or information frictions, might have changed as well in the post-Volcker regime. In the last robustness exercise, I re-estimate the BK and SI variants using the empirical impulse responses of a monetary- and a technology-shock SVAR using the sample period 1979(4)-2007(4).[28]

---

[26] Similar to Galí and Rabanal (2004) and Avouyi-Dovi and Matheron (2007), I extract a polynomial trend from hours. Hours in log-levels without detrending present a unit root in post-World War II U.S. data. The minimum degree of a polynomial trend for which a Phillips Perron test rejects the null of a unit root in detrended hours is 4, which is the polynomial trend assumed in this section. Galí and Rabanal and Avouyi-Dovi and Matheron use a quadratic trend. The results herein are invariant to the use of a quadratic trend.

[27] The rest of the parameter estimates show similar patterns to the baseline estimations. They are available upon request.

[28] In the post-1979 technology-shock SVAR, hours per capita enter in log-levels. The SVAR with hours-in-differences presents some anomalies, such as an apparent strong decrease in hours that pushes output downwards after a technology shock. Reducing the sample period to 1986-2007 solves the problem, but the confidence intervals are too wide to render the bootstrapping minimum distance estimation informative. Following Boivin and Giannoni (2006), I made a calibration adjustment concerning the elasticity of inter-temporal substitution in the utility function. These authors find that output reacts strongly to movements in the real interest rate in the post-1979 sample. In this robustness exercise, I set σ to $\frac{1}{4}$.

The parameter estimates for the BK variant are shown in table 1, columns 5 and 6. As expected, the most noticeable change with respect to the baseline estimations is in the inflation coefficient of the Taylor rule. The point estimate of this coefficient is much larger than it is in the baseline case for both the monetary-shock estimation and the technology-shock estimation. The output gap coefficient, in turn, is still equal to zero in both shock estimations. In contrast, the parameter estimates for the SI variant, as shown by table 2, columns 7 and 8, do not present an increase of the inflation coefficient in the Taylor rule for the post-Volcker period. Also, the estimate of the output gap coefficient is now positive. Also interesting is that the size of the shocks, as measured by $\sigma_{\mathcal{M}}$ and $\sigma_{\mathcal{T}}$, is significantly reduced for both model variants, in line with the perception that macroeconomic volatility decreased during the period known as the *Great Moderation*. The rest of the estimating parameters are more or less in line with previous estimations, although there are some differences in terms of household and firm related frictions (including habits) in the monetary shock estimations.

The model-based and SVAR confidence intervals and prediction accuracy of each variant are shown in figure 6 for output, inflation, and the real wage. Remarkably, similar results to all previous series of estimations emerge. Namely, the SI variant predicts a faster speed of adjustment in the real wage for the technology-shock estimation, and no significant differences in the monetary-shock estimation. The difference between the BK and the SI variants in terms of their real wage prediction fit after a technology shock is less appealing than in previous cases but remains relevant. Accordingly, the probability that the BK variant presents a worse fit for the real wage compared to the average fit of the SI variant is 14.6 percent.

6 Transmission mechanism after a permanent technology shock

The estimations presented above are quite consistent in the higher prediction accuracy of the BK model concerning the responses of wage inflation and real wages after a technology shock. This section explains the intuitions behind the differences between the two model variants with respect to these variables. It thus proves convenient to analyze the role played by each particular friction present in the two variants in propagating the effects of a permanent productivity shock. For this exercise, the models are calibrated similarly in terms of preferences, production technologies, the parameters of the Taylor rule, and the size of the productivity shock.[29]

A permanent increase in labor productivity produces a new steady state, equal in both models,

---

[29] Preferences and production parameters are calibrated similarly to the estimation step. $\sigma_{\mathcal{T}}$ equals 0.78, and the Taylor rule parameters are set as $a_\pi = 1.5$ and $a_y = 0$. The results of this exercise are robust to different calibrations of the Taylor rule parameters.

in which output and the real wage are higher and total hours in the economy do not change with respect to the old steady state. In the absence of capital accumulation, habits, nominal rigidities, and information frictions, the increases in output and the real wage are achieved immediately after the shock. For the adjustment in real wages, it suffices that nominal wages rise proportionally with labor productivity. The adjustment path of a model with neither capital accumulation nor habits or frictions of any kind is presented in the first row of figure 7. Notice that hours are unchanged in the transition path because after the shock, labor demand increases in exactly the same proportion as labor supply decreases; the former rises due to higher average productivity, whereas the latter falls due to a permanent income effect.[30] Prices will not be affected as long as the aggregate demand and aggregate supply increase in equal proportions. If this is the case, as in the model with no capital and no frictions, sticky prices in the BK variant, or sticky information in firms in the SI variant, would play no role in the adjustment process of the economy.

On the other hand, frictions in wage-setting alter the adjustment path of the economy. The second row in figure 7 presents the responses of the two variants displaying rigidities in nominal wages, assuming that prices are flexible and there are no frictions in consumption (including habits). The degrees of sticky wages in the BK variant and of sticky information on workers in the SI variant are set similarly as $\alpha_w = \gamma_w^{si} = 0.75$, indicating that nominal wages change (or react to new information) on average once per year. In this case, the long-term increase in the real wage takes a few periods to be completed, and it is achieved mainly through a decrease in prices. In addition, hours and output have interesting short-term dynamics in this case. Frictions in wage-setting stop workers from decreasing their labor supply as quickly as they should to reflect the long-term impact of a permanent income effect. Thus, labor demand varies by more than labor supply, causing the slow increase in the real wage and a short-run increase in hours. Output, consequently, overshoots its new steady-state level. Given an equal calibration, the similarity of the two variants is remarkable.

The models' dynamics start showing differences when frictions in both wage- and price-setting are present. Figure 7, row 2, shows this case, still assuming that consumers are free of frictions or habits. Sticky prices in the BK variant and sticky information in firms are calibrated similarly as it is assumed that prices change (or react to new information) on average twice per year, $\alpha_p = \gamma_p^b = 0.5$. Wage-setting frictions are calibrated as in the previous case. Now, real wages take more time to adjust because prices and wages cannot change instantaneously. The short-run increase in hours and overshoot in output still occur, but they are of smaller proportions. Notice

---

[30] In the real business cycle model, hours increase in the short-run due to the slow adjustment of capital towards its new steady-state level. A substitution effect between capital and labor then pushes firms to increase their demand for the latter. This is the classic RBC prediction about the response of hours after a permanent increase in productivity. When there is no capital and no frictions, variations in hours are simply not generated.

that the responses of inflation and wage inflation in the SI variant are hump-shaped. Accordingly, inflation achieves its trough level in the BK variant faster than it does in the SI variant. The protracted decline in prices in the SI variant induces a faster adjustment in the real wage than is observed in the BK variant after period 5. Both models, however, predict a long-lasting increase in wage inflation. As a reminder, the latter is not observed in the SVAR responses of section 2.2.

Frictions in consumer decisions are responsible for the slow adjustment of output and a short-run decline in hours after a technology shock. The fourth row of figure 7 shows the dynamics of each model variant featuring all three frictions in prices, wages, and consumption. The latter are again calibrated similarly across variants, as it is assumed that $\gamma_h^{si} = \gamma_h^b = 0.8$. Price and wage frictions take the values of the previous case. The reason behind the short-run decline of hours and the slow adjustment of output is straightforward: the income effect that results from an increase in productivity is reinforced when there are habits or sticky information in consumption. From the consumer point of view, there are too many goods available after the productivity shock that cannot be *optimally* absorbed in the short run. Consequently, consumers spend the extra income in leisure. A similar explanation can be found in Francis and Ramey (2005). Still, both models predict the empirically unobserved rise in wage inflation.

Inflation indexation in nominal wages is the determining factor that explains the success of the BK variant in the empirical estimations. The last row of figure 7 considers all three frictions in decision making described in the previous case, and adds wage indexation in the BK model (with a half indexation index $\gamma_w^b = 0.5$). The BK variant can now replicate the response of wage inflation as implied by the SVAR. Namely, wage inflation tends to increase at impact and afterwards decrease moderately towards negative values in the periods that follow. The SI variant, in contrast, cannot replicate this behavior because it predicts the downward adjustment in wage inflation too late (only after quarter 7, according to the assumed calibration). More importantly, wage indexation sufficiently enlarges the gap between the real wage responses of each model to allow for empirical testing.

Concluding remarks

This paper considers two alternative model variants that aim to explain the sluggish behavior of aggregate data that has been documented empirically. A baseline model containing a certain number of real rigidities is added with two specifications that create intrinsic persistence in macro variables. The *backward-looking behavior* variant adds nominal rigidities *à la* Calvo and inflation indexation to price- and wage-setting, and habits to consumption decisions. The second variant adds *sticky information* to households, firms, and workers, thus assuming that there is a pervasive slow diffusion of information that applies throughout the population. Both models are estimated to fit the empirical impulse responses of a set of aggregate variables to a shock in monetary policy and a permanent increase in productivity.

The findings are as follows. The backward-looking behavior model is consistently better than the sticky information model at predicting the dynamics of the real wage and wage inflation after a technology shock. The success of the backward-looking behavior model relies on wage indexation. This device, absent in the sticky information model, can effectively explain why wage inflation has a null or positive response at impact after a shock in productivity and afterwards decreases moderately in the periods that follow, thus accompanying the decrease in inflation that is also observed in the SVAR. The sticky information model, in contrast, predicts an increase in wage inflation lasting for several periods, thus overestimating the speed of adjustment of real wages. However, the two models are statistically equivalent in terms of their predicted responses after a shock in monetary policy.

References

[1] Andrés, J., López-Salido, J.D., and Nelson, E., 2005. Sticky price models and the natural rate of hypothesis. Journal of Monetary Economics, 52, 1025–1053.

[2] Altig, D., Christiano, L.J., Eichenbaum, M., Linde, J., 2010. Firm-specific capital, nominal rigidities, and the business cycle. Board of Governors of the Federal Reserve System, International Finance Discussion Papers 990.

[3] Amato, J.D., Laubach, T., 2003. Estimation and control of an optimization-based model with sticky prices and wages. Journal of Economic Dynamics and Control, 27, 1181-1215.

[4] Avouyi-Dovi, S., Matheron, J., 2007. Technology shocks and monetary policy: Revisiting the Fed's performance. Journal of Money, Credit and Banking, 39, 471-507.

[5] Blanchard, O.J., Quah, D., 1989. The dynamic effects of aggregate demand and supply disturbances. American Economic Review, 79, 655-73.

[6] Boivin, J., Giannoni, M.P., 2006. Has monetary policy become more effective? Review of Economics and Statistics, 88, 430-450.

[7] Canova, F. and Sala, L., 2009. Back to square one: identification issues in DSGE models. Journal of Monetary Economics, 56, 431-49.

[8] Chari, V.V., Kehoe, P.J., McGrattan, E.R., 2000. Sticky price models of the business cycle: Can the contract multiplier solve the persistence problem? Econometrica, 68, 1151-79.

[9] Christiano, L.J., Eichenbaum, M., Evans, C.L., 1996. The effects of monetary policy shocks: Evidence form the flow of funds. Review of Economics and Statistics, 78, 16-34.

[10] Christiano, L.J., Eichenbaum, M., Evans, C.L., 1999. Monetary policy shocks: What have we learned and to what end? In: Taylor, J.B., Woodford, M. (Eds.), Handbook of Macroeconomics, Vol. 1A. Elsevier, Amsterdam, 65-148.

[11] Christiano, L.J., Eichenbaum, M., Evans, C.L., 2005. Nominal rigidities and the dynamic effects of a shock to monetary policy. Journal of Political Economy, 113, 1-45.

[12] Christiano, L.J., Eichenbaum, M., Vigfusson, R., 2006. In: Acemoglu, D., Rogoff, K., Woodford, M. (Eds), Assessing structural VARs. NBER Macroeconomics Annual 2006.

[13] Clarida, R., Galí, J., Gertler, M., 2000. Monetary policy rules and macroeconomic stability: Evidence and some theory. Quarterly Journal of Economics, 115, 147-180.

[14] Coibion, O., 2010. Testing the sticky information Phillips curve. Review of Economics and Statistics, 92, 87-101.

[15] Coibion, O., Gorodnichenko, Y., 2010. Strategic interaction among heterogeneous price-setters in an estimated DSGE model. College of William and Mary, Working Paper 93.

[16] Dedola, L., Neri, S., 2007. What does a technology shock do? A VAR analysis with model-based sign restrictions. Journal of Monetary Economics, 54, 512-549.

[17] Dupor, B., Han, J., Tsai, Y.C., 2009. What do technology shocks tell us about the New Keynesian paradigm? Journal of Monetary Economics, 56, 560-569.

[18] Dupor, B., Kitamura, T., Tsuruga, T., 2010. Integrating sticky prices and sticky information. Review of Economics and Statistics, 92, 657-669.

[19] Eichenbaum, M., Fisher, J.D.M., 2007. Estimating the frequency of price re-optimization in Calvo-style models. Journal of Monetary Economics, 54, 2032-2047.

[20] Edge, R.M., Laubach, T., Williams, J.C., 2003. The responses of wages and prices to technology shocks. Finance and Economics Discussion Series 2003-65, Board of Governors of the Federal Reserve System.

[21] Erickson, T., Whited, T.M., 2000. Measurement error and the relationship between investment and q. Journal of Political Economy, 108, 1027-1057.

[22] Francis, N., Ramey, V.A., 2005. Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. Journal of Monetary Economics, 52, 1379-1399.

[23] Fève, P., Matheron, J., Sahuc, J.G., 2009. Minimum distance estimation and testing of DSGE models from structural VARs. Oxford Bulletin of Economics and Statistics, 71, 883-894.

[24] Fuhrer, J., 2006. Intrinsic and inherited inflation persistence. International Journal of Central Banking, 2, 49-86.

[25] Fuhrer, J., Moore, G., 1995. Inflation Persistence. Quarterly Journal of Economics, 110, 127-160.

[26] Galí, J., 1999. Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? American Economic Review, 89, 249-271.

[27] Galí, J., Rabanal, P., 2004. Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. data? In NBER Macroeconomics Annual, edited by Mark Gertler and Kenneth Rogoff, 225û319. Cambridge, MA. MIT Press.

[28] Gomes, O., 2010. Transitional dynamics in sticky-information general equilibrium models. Computational Economics, *forthcoming.*

[29] Greenwood, J., Hercowitz, Z., Huffman, G.W., 1988. Investment, capacity utilization, and the Real Business Cycle. American Economic Review, 78, 402-417.

[30] Hall, P., Horowitz, J., 1996. Bootstrap critical values for tests based on generalized-method-of-moments estimators. Econometrica, 64, 891û916.

[31] Kahn, H., Zhu, Z., 2006. Estimates of the sticky information Phillips Curve for the United States. Journal of Money, Credit and Banking, 38, 195-208.

[32] Kiley, M., 2007. Quantitative comparison of sticky-price and sticky information models of price setting. Journal of Money, Credit and Banking, 39, 101-125.

[33] Kimball, M.S., 1995. The quantitative analytics of the basic neomonetarist model. Journal of Money, Credit and Banking, 27, 1241-1277.

[34] Knotek, E.S.II., 2010. A tale of two rigidities: sticky prices in a sticky-information environment. Journal of Money, Credit, and Banking, 42, 1543-1564.

[35] Korenok, O., 2008. Empirical comparison of sticky price and sticky information models. Journal of Macroeconomics, 30, 906-927

[36] Korenok, O., Swanson, N.R., 2007. How sticky is sticky enough? A distributional and impulse response analysis of New Keynesian DSGE models. Journal of Money, Credit and Banking, 39, 1481-1508.

[37] Lieb, L., 2009. Taking real rigidities seriously: Implications for optimal policy design in a currency union. Research Memoranda 032, Maastricht Research School of Economics of Technology and Organization.

[38] Liu, Z., Phaneuf, L., 2007. Technology shocks and labor market dynamics: Some evidence and theory. Journal of Monetary Economics, 54, 2534-2553.

[39] Mankiw, G., Reis, R., 2002. Sticky information versus sticky prices: A proposal to replace the New Keynesian Phillips curve. Quarterly Journal of Economics, 117, 1295-1328.

[40] Mankiw, G., Reis, R., 2006. Pervasive stickiness. American Economic Review, 96, 164-169.

[41] Mankiw, G., Reis, R., 2007. Sticky information in general equilibrium. Journal of the European Economic Association, 5, 603-613.

[42] Meyer-Gohde, A. 2010. Linear rational expectations models with lagged expectations: A synthetic method. Journal of Economic Dynamics and Control, 34, 984-1002.

[43] Mojon, B., Peersman, G., 2003. A VAR description of the effects of monetary policy in the individual countries of the Euro Area. In: Angeloni, I., Kashyat, A., Mojon, B. (Eds.), Monetary policy transmission in the Euro Area, Cambridge University Press.

[44] Reis, R., 2009. Optimal monetary policy rules in an estimated sticky-information model. American Economic Journal: Macroeconomics, 1, 1-28.

[45] Rotemberg, J.J., Woodford, M., 1995. Dynamic general equilibrium models with imperfectly competitive product markets. In: Cooley, T.F. (Ed.), Frontiers of Business Cycle Research. Princeton University Press.

[46] Rotemberg, J.J., Woodford, M., 1997. An optimization-based econometric framework for the evaluation of monetary policy. In: Bernanke, B.S., Rotemberg, J.J. (Eds.). NBER Macroeconomics Annual. MIT Press.

[47] Rotemberg, J.J., Woodford, M., 1999. The cyclical behavior of prices and costs. In: Taylor J.B., Woodford, M. (Eds.), Handbook of Macroeconomics. Elsevier.

[48] Sims, C.A., 1992. Interpreting the macroeconomic time series facts: the effects of monetary policy. European Economic Review, 36, 975-1000.

[49] Sims, C.A., 2003. Implications of rational inattention. Journal of Monetary Economics, 50, 665û90.

[50] Sims, C.A., Zha, T., 2006. Does monetary policy generate recessions? Macroeconomic Dynamics, 10, 231-272.

[51] Smets, F., Wouters, R., 2007. Shocks and frictions in U.S. business cycles: A Bayesian DSGE approach. American Economic Review, 97, 586-606.

[52] Trabandt, M., 2007. Sticky information vs. sticky prices: A horse race in a DSGE framework. Sveriges Riksbank Working Paper Series 209.

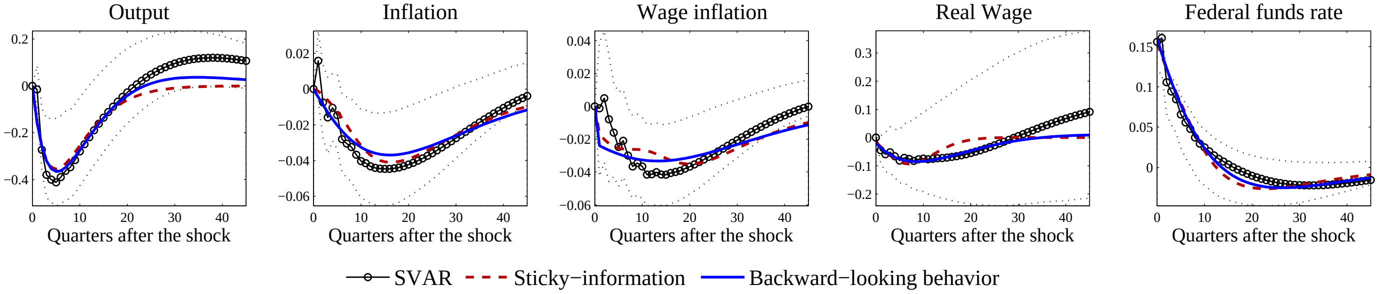
[53] Wang, P., Wen, Y., 2007. Inflation dynamics: A cross-country investigation. Journal of Monetary Economics, 54, 2004-31.

[54] Woodford, M., 2003a. Imperfect common knowledge and the effects of monetary policy. In: Aghion, P, Frydman, R., Stiglitz, J., Woodford, M. (Eds.), Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps. Princeton University Press.

[55] Woodford, M., 2003b. Interest and prices: Foundation of a theory of monetary policy. Princeton University Press.

Figure 1: Two structural VARs and model predictions

Monetary policy shock



Techonology shock

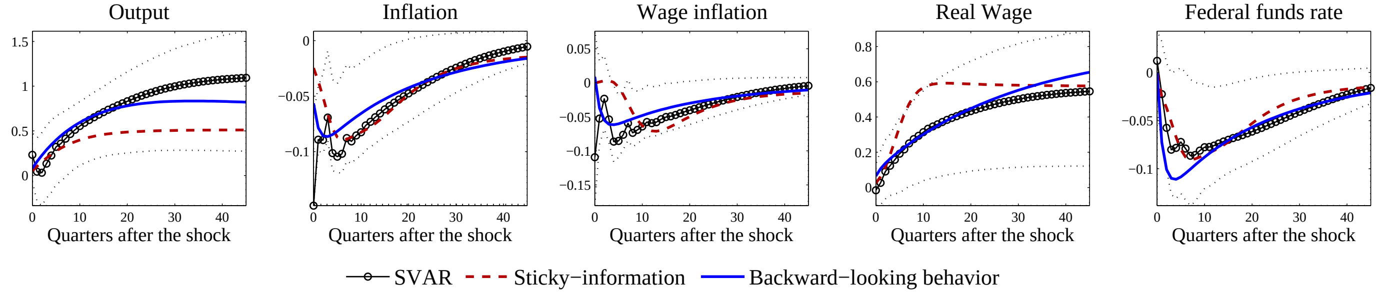
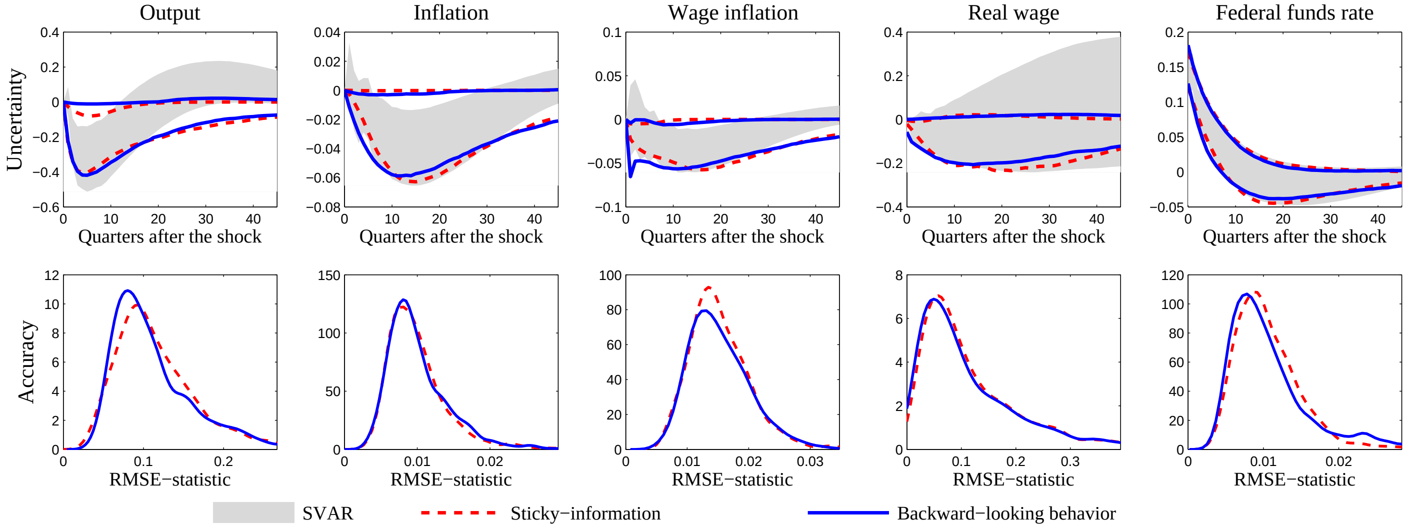


Figure 2: Baseline: Model-based uncertainty and prediction accuracy

Monetary policy shock



Technology shock

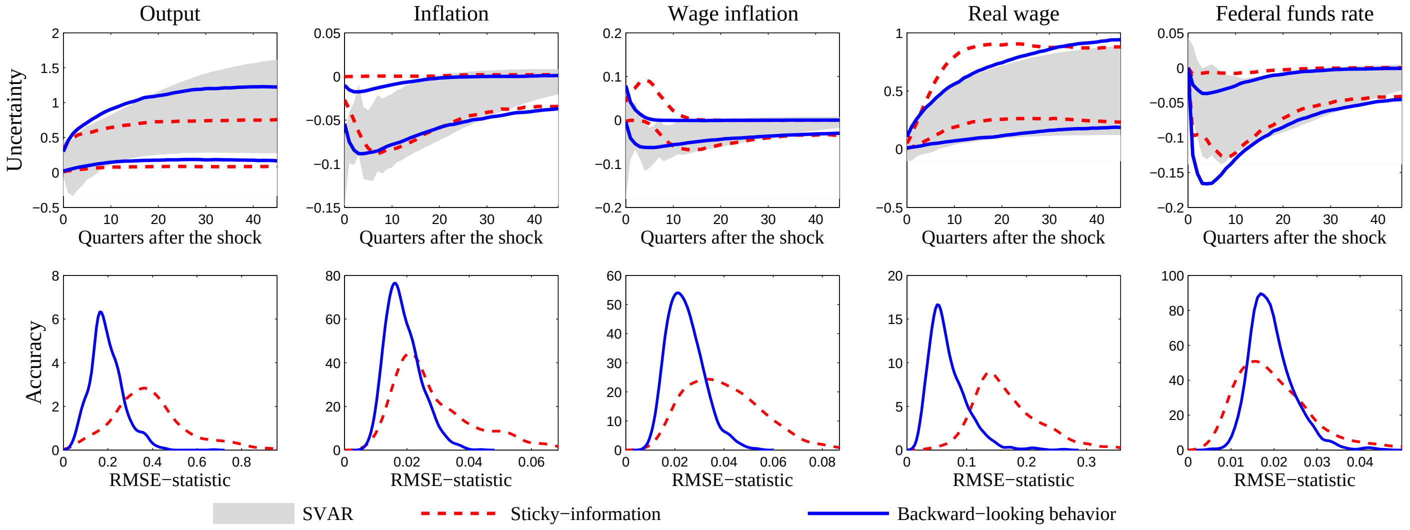


Figure 3: Performance of "dual stickiness" model

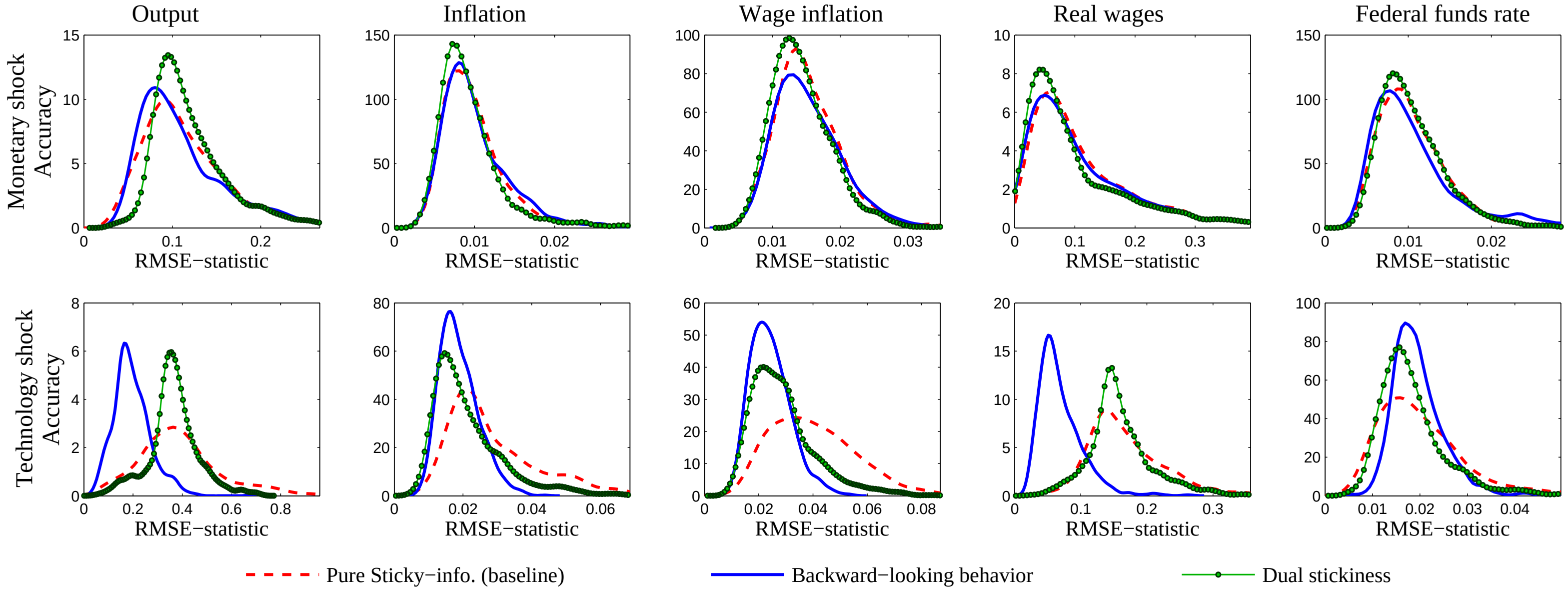
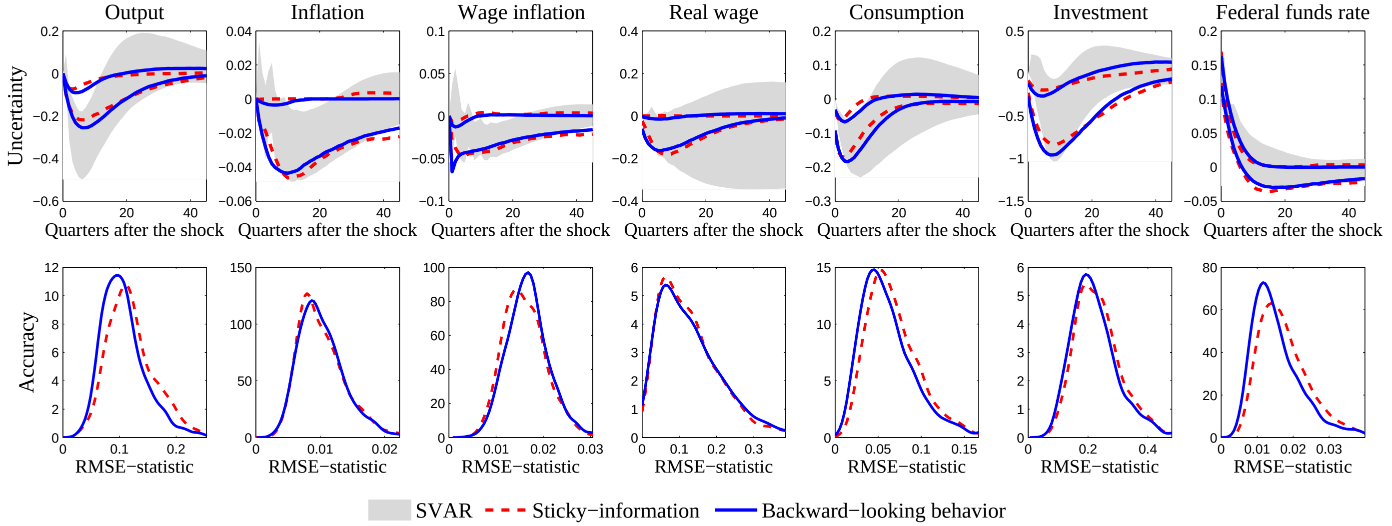


Figure 4: Variants with capital: Model-based uncertainty and prediction accuracy

Monetary policy shock



Technology shock

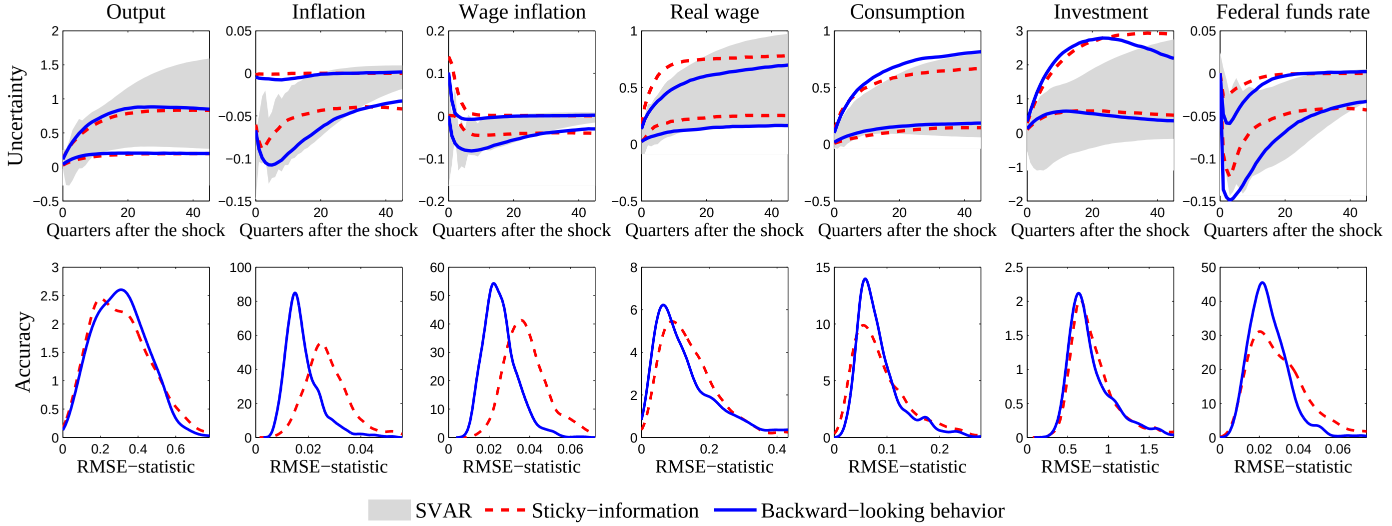


Figure 5: Hours in levels: Model-based uncertainty and prediction accuracy

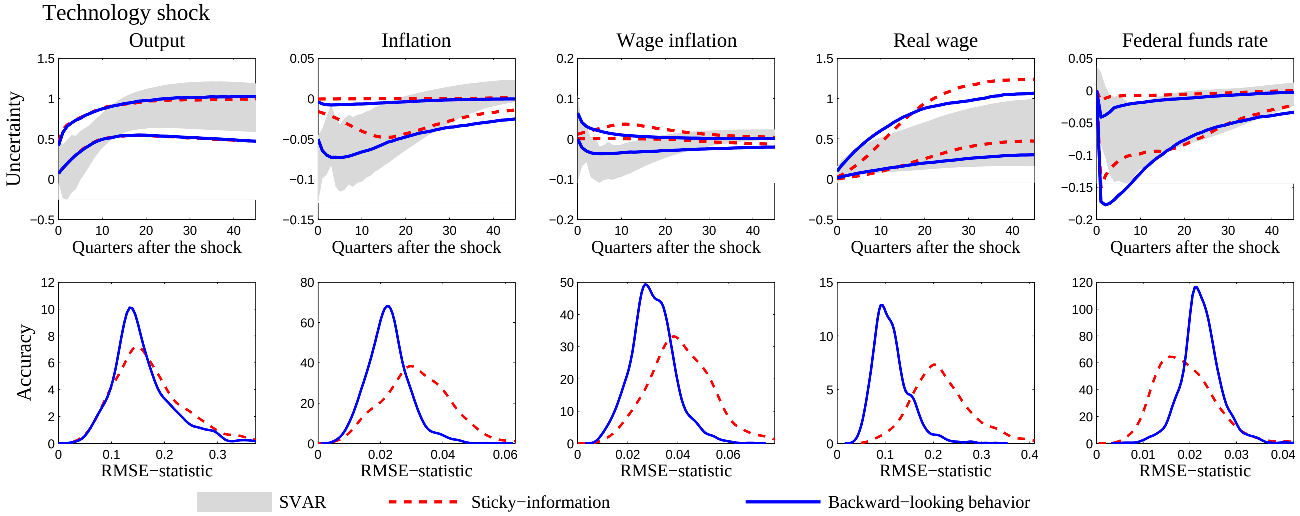


Figure 6: Post-79 data: Model-based uncertainty and prediction accuracy

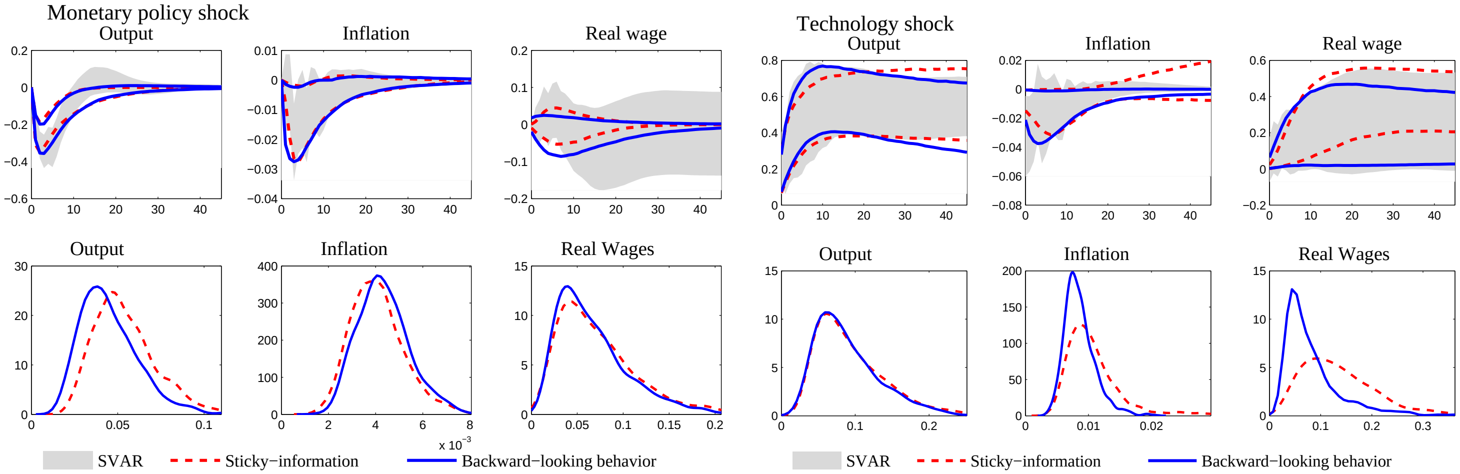


Figure 7: Permanent increase in productivity: Endogenous transmission mechanisms

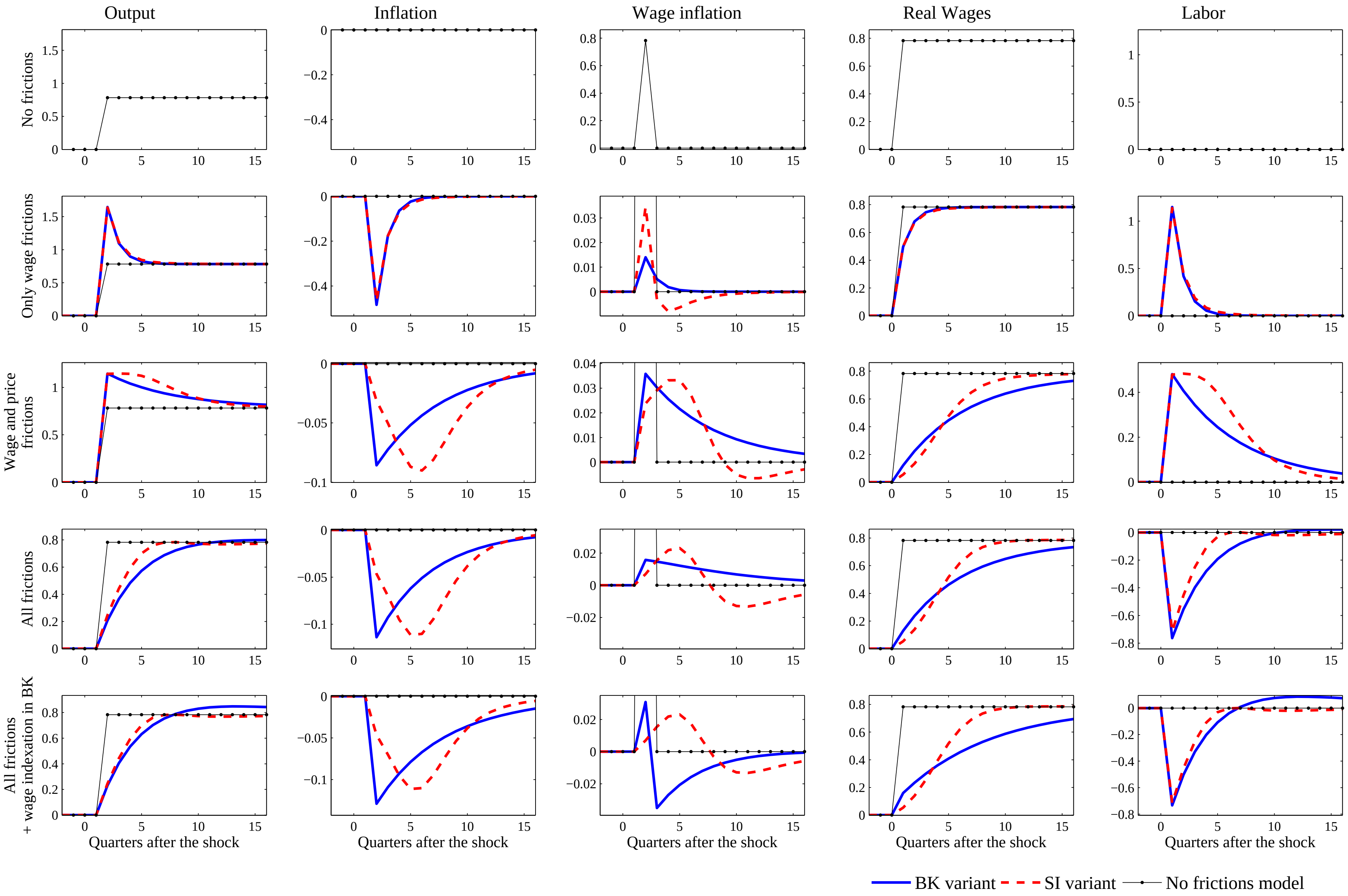


Table 1. Estimated results for the **backward-looking behavior** variant.

	Baseline estimation		Model with capital		Post-1979	
	Monetary sh.	Technology sh.	Monetary sh.	Technology sh.	Monetary sh.	Technology sh.
γ_h	0.78 (0.14) [0.57, 0.99]	0.93 (0.19) [0.45, 0.99]	0.83 (0.08) [0.69, 0.90]	0.93 (0.08) [0.82, 0.97]	0.58 (0.12) [0.38, 0.77]	0.90 (0.16) [0.49, 0.96]
γ_p	0.99 (0.28) [0.86, 0.99]†	0.44 (0.28) [0.32, 0.99]†	0.97 (0.27) [0.98, 0.99]†	0.40 (0.35) [0.24, 0.99]†	0.27 (0.38) [0.01, 0.99]	0.69 (0.31) [0.52, 0.99]†
γ_w	0.99 (0.29) [0.69, 0.99]†	0.81 (0.32) [0.43, 0.99]†	0.99 (0.26) [0.86, 0.99]†	0.99 (0.24) [0.65, 0.99]†	0.99 (0.32) [0.77, 0.99]†	0.99 (0.43) [0.01, 0.99]†
α_p	0.83 (0.17) [0.50, 0.98]	0.78 (0.14) [0.52, 0.97]	0.89 (0.09) [0.65, 0.99]	0.69 (0.27) [0.33, 0.99]†	0.58 (0.19) [0.44, 0.99]†	0.76 (0.16) [0.49, 0.99]
α_w	0.81 (0.24) [0.71, 0.99]†	0.93 (0.22) [0.71, 0.99]†	0.67 (0.15) [0.39, 0.89]	0.79 (0.26) [0.64, 0.99]†	0.83 (0.13) [0.57, 0.99]	0.77 (0.26) [0.55, 0.99]†
a_π	1.53 (1.34) [1, 2.89]†	1.28 (1.03) [1, 2.37]†	2.00 (0.96) [1, 2.51]†	1.10 (0.72) [1, 1.61]†	2.58 (1.31) [1, 2.92]†	2.83 (1.33) [1, 4.57]†
a_y	0 (0.32) [0, 0.11]†	0 (0.11) [0, 0.08]†	0.11 (0.18) [0, 0.20]†	0.05 (0.26) [0, 0.29]†	0 (0.07) [0, 0.09]†	0 (0.05) [0, 0.03]†
ρ	0.93 (0.07) [0.75, 0.98]	0 –	0.92 (0.06) [0.80, 0.97]	0 –	0.84 (0.06) [0.72, 0.92]	0 –
$\sigma_{\mathcal{M}}$	0.16 (0.02) [0.12, 0.19]	0 –	0.15 (0.02) [0.11, 0.17]	0 –	0.09 (0.01) [0.08, 0.10]	0 –
$\sigma_{\mathcal{T}}$	0 –	0.78 (0.94) [0, 1.42]†	0 –	0.60 (0.39) [0.17, 0.93]	0 –	0.38 (0.18) [0.16, 0.70]
$\mathcal{J}_T$	31.91 [0.75]	29.77 [0.35]	122.90 [0.54]	84.55 [0.32]	29.87 [0.74]	8.98 [0.96]

Note : The standard deviation of a parameter estimate is shown in parenthesis, and its confidence interval is in brackets. † indicates an interval starting at one of the extremes of the parameter space and covers a 80 percent mass of the estimate distribution. Confidence intervals without † start at the 5th percentile and end at the 95th percentile. For the $\mathcal{J}_T$ statistic, the p-value of the null $\mathcal{J}_T = 0$ is shown in brackets.

Table 2. Estimated results for the **sticky information** variant.

	Baseline estimation		Dual stickiness		Model with capital		Post-1979	
	Monetary sh.	Technology sh.	Monetary sh.	Technology sh.	Monetary sh.	Technology sh.	Monetary sh.	Technology sh.
γ_h	0.85 (0.13) [0.58, 0.99]	0.90 (0.32) [0.50, 0.99]†	0.85 (0.12) [0.60, 0.99]	0.95 (0.25) [0.78, 0.99]†	0.87 (0.10) [0.65, 0.94]	0.92 (0.11) [0.72, 0.99]	0.65 (0.13) [0.43, 0.88]	0.92 (0.18) [0.45, 0.99]
γ_p	0.75 (0.16) [0.54, 0.99]	0.60 (0.17) [0.51, 0.99]	0.75 (0.20) [0.65, 0.99]†	0.32 (0.24) [0, 0.64]†	0.79 (0.13) [0.54, 0.99]	0.40 (0.24) [0.18, 0.68]†	0.51 (0.18) [0.33, 0.92]	0.77 (0.11) [0.64, 0.99]
γ_w	0.80 (0.09) [0.67, 0.99]	0.68 (0.29) [0.48, 0.99]†	0.80 (0.25) [0.66, 0.99]†	0 (0.44) [0, 0.99]†	0.67 (0.12) [0.45, 0.87]	0.49 (0.28) [0, 0.73]†	0.76 (0.10) [0.61, 0.98]	0.77 (0.21) [0.67, 0.99]†
α_p	0 –	0 –	0 (0.34) [0, 0.66]†	0.69 (0.25) [0.43, 0.99]†	0 –	0 –	0 –	0 –
α_w	0 –	0 –	0 (0.37) [0, 0.79]†	0 (0.36) [0.28, 0.99]†	0 –	0 –	0 –	0 –
a_π	1.56 (1.36) [1, 2.16]†	1.01 (0.98) [1, 1.89]†	1.56 (1.62) [1, 3.70]†	1.01 (0.91) [1, 2.10]†	1.71 (1.01) [1, 2.79]†	1.10 (0.89) [1, 1.94]†	1.09 (1.32) [1, 2.38]†	1.01 (1.15) [1, 1.81]†
a_y	0.02 (0.19) [0, 0.10]†	0 (0.28) [0, 0.16]†	0.02 (0.18) [0, 0.10]†	0 (0.17) [0, 0.05]†	0.32 (0.25) [0.03, 0.56]†	0.02 (0.13) [0, 0.06]†	0.07 (0.07) [0, 0.11]†	0.13 (0.13) [0, 0.22]†
ρ	0.93 (0.05) [0.82, 0.99]	0 –	0.93 (0.06) [0.83, 0.99]	0 –	0.93 (0.07) [0.74, 0.98]	0 –	0.81 (0.06) [0.72, 0.93]	0 –
$\sigma_{\mathcal{M}}$	0.15 (0.02) [0.11, 0.18]	0 –	0.15 (0.02) [0.11, 0.18]	0 –	0.16 (0.02) [0.12, 0.18]	0 –	0.09 (0.01) [0.07, 0.10]	0 –
$\sigma_{\mathcal{T}}$	0 –	0.57 (1.04) [0, 0.95]†	0 –	0.81 (1.15) [0.29, 4.67]	0 –	0.59 (0.43) [0.22, 1.01]	0 –	0.42 (0.16) [0.27, 0.75]
$\mathcal{J}_T$	52.79 [0.63]	88.70 [0.33]	52.79 [0.53]	61.52 [0.25]	155.32 [0.41]	126.44 [0.25]	41.59 [0.60]	19.01 [0.76]

Note : The standard deviation of a parameter estimate is shown in parenthesis, and its confidence interval is in brackets. † indicates an interval starting at one of the extremes of the parameter space and covers a 80 percent mass of the estimate distribution. Confidence intervals without † start at the 5th percentile and end at the 95th percentile. For the $\mathcal{J}_T$ statistic, the p-value of the null $\mathcal{J}_T = 0$ is shown in brackets.