ISSN 1988-088X

Departamento de Fundamentos del Análisis Económico II

Department of Foundations of Economic Analysis II
University of the Basque Country
Avda. Lehendakari Aguirre 83
48015 Bilbao (SPAIN)
http://www.dfaeii.ehu.es

DFAE-II WP Series

2012-06

Miguel Casares & Jesús Vázquez.

Data Revisions in the Estimation of DSGE Models

Data Revisions in the Estimation of DSGE models*

Miguel Casares[†] and Jesús Vázquez[‡]

(First version: November, 2010. This version: February, 2012)

Abstract

Revisions of US macroeconomic data are not white-noise. They are persistent, correlated with real-time data, and with high variability (around 80% of volatility observed in US real-time data). Their business cycle effects are examined in an estimated DSGE model extended with both real-time and final data. After implementing a Bayesian estimation approach, the role of both habit formation and price indexation fall significantly in the extended model. The results show how revision shocks of both output and inflation are expansionary because they occur when real-time published data are too low and the Fed reacts by cutting interest rates. Consumption revisions, by contrast, are countercyclical as consumption habits mirror the observed reduction in real-time consumption. In turn, revisions of the three variables explain 9.3% of changes of output in its long-run variance decomposition.

Keywords: Data revisions, DSGE models, business cycles.

JEL codes: C32, E30.

*We are grateful for helpful comments from Steve Cassou, Antonio Moreno and Hugo Rodríguez-Mendizábal. The authors would like to acknowledge financial support from the Spanish government (research projects ECO2011-24304 and ECO2010-16970 from Ministerio de Ciencia e Innovación, respectively).

[†]Departamento de Economía, Universidad Pública de Navarra. E-mail: mcasares@unavarra.es

[‡]Department FAE II, Universidad del País Vasco. E-mail: jesus.vazquez@ehu.es

1 Introduction

Three important facts explain the increasing popularity of economic analysis based on real-time data and data revisions: the collection of a "Real-Time Data Set for Macroeconomists" by Dean Croushore and Tom Stark (2001), the regularly updated on-line publication of US real-time data available at the Philadelphia Fed website, and the evidence provided in many papers that data revisions matter in business cycles.[1]

One of the first studies to investigate the properties of revision processes is Diebold and Rudebusch (1991).[2] They show that the US index of leading indicators does a poor job in predicting future movements of output in real time because it was built to explain the past. Orphanides (2001, 2003) argues that US monetary policy was too loose due to misperceptions in the real-time output gap. Croushore and Stark (2001) discuss the implications of data revisions on the estimation of macroeconomic models as they can incorporate co-movements with either real-time data or final data.

Empirical evidence seems to support the lack of orthogonality between initial announcements and data revisions. As two examples, Faust, Rogers and Wright (2005) find that revisions of GDP in Japan and the UK are forecastable in real time, while Aruoba (2008) provides evidence indicating that the initial announcements of US aggregate variables are not rational forecasts of revised data. Thus, final revisions of output growth and inflation are persistent and correlated with real-time data initially released by statistical agencies. Moreover, the volatility of data revisions is high: the standard deviations of inflation and for the growth rate of output are of similar magnitude to the corresponding standard deviations of real-time data.

[1] Croushore (2011) provides an excellent survey of the literature on real-time data analysis.

[2] It is fair to refer to Mankiw, Runkle, and Shapiro (1984) as one earlier paper that introduces a theoretical framework for real-time data analysis.

This paper contributes to the real-time data literature by estimating a Dynamic Stochastic General Equilibrium (DSGE) model that considers both revised and real-time data. Should revisions of real-time data be rational forecast errors, then the arrival of revised data would not be relevant for private agents (households and firms) and policy makers, and the parameter estimates would be rather similar using revised, real-time data or both together. If data revisions were not rational forecast errors, DSGE models estimated with only revised data would be misleading for two main reasons. From a theoretical perspective, model dynamics could be different when agents take into account initial announcements that are not rational forecast of revised data. From an empirical perspective, parameter estimates could be biased.

As representative of DSGE models, we have extended the model of Smets and Wouters (2007) to incorporate data revisions of output, inflation and consumption.[3] In the model variant presented here, economic agents make decisions taking into account real-time data available, and these decisions might have some impact on revised data. The extended model is estimated using both revised and real-time US data whereas the Smets and Wouters (2007) model is also re-estimated using only revised US data.[4] The aim of this exercise is twofold. First, to assess the importance of data revisions in the estimation of DSGE models. Second, to examine the implications of revisions

[3]Many earlier New Keynesian models such as Rotemberg and Woodford (1997), or Christiano, Eichenbaum, and Evans (2005), could be mentioned as predecessors of Smets and Wouters (2007).

[4]In a similar vein, Vázquez, María-Dolores and Londoño (2010) study the importance of real-time data in a canonical New Keynesian model. A crucial difference between the two papers is that household and firm choices are not affected by real-time data issues in their canonical model. Aruoba (2004) and Priutt (2007) are two other unpublished papers closed in spirit to the idea explored in this paper that data revisions (and, more generally, data uncertainty) affect agents' decisions, but the DSGE model and the empirical approaches considered in these two papers differ substantially from the ones followed here.

variability on US business cycle fluctuations.[5]

Regarding the estimation results, the comparison across models indicates that most parameter estimates are fairly robust to whether taking or not taking into account real-time data. Nevertheless, there are some noticeable differences. The most significant ones are lower estimates of both the consumption habit formation and the price indexation coefficient of lagged inflation in the extended model. As for the role of data revisions in cyclical variability, we find that innovations in data revisions explain 9.3% of output variability in the extended model. This result suggests that DSGE models that ignore data revisions may overestimate the role of other sources of cyclical fluctuations.

In the business cycle analysis, the estimated extended model provides a good matching to the second-moment statistics of US data revisions, with similar volatilities to those observed in fluctuations of actual revisions. The revisions of output and consumption are positively related to their corresponding real-time variables, whereas inflation revisions are negatively anticipated by real-time inflation data. The statistical dependence of data revisions on real-time data implies that revisions reduce economic noise as opposed to revisions that can be sources of additional news. Finally, the revisions of both output and inflation are procyclical, while the revisions of consumption are countercyclical.

The rest of the paper is organized as follows. Section 2 introduces the extension of Smets and Wouters (2007) model to consider both revised and real-time data. Section 3 describes the US data set and the Bayesian estimation procedure. Section 4 discusses the estimation results and conducts the business cycle analysis. Finally, Section 5 summarizes the findings of the paper in the conclusions.

[5] Other recent papers explore the out-of-sample forecasting performance of DSGE models by using real-time data instead of final revised data (Edge, Kiley and Laforte, 2010; Herbst and Schorfheide, 2011).

2 A DSGE model with real-time data

This section builds on the popular DSGE model described in Smets and Wouters (2007), SW henceforth, to accommodate the fact that economic decisions of the central bank, households and firms might be based on real-time data of aggregate output, consumption and inflation. At first sight, this approach may be considered quite restrictive since many other aggregate variables such as hours, wages and investment are also revised series.[6] The approach followed in this paper to allow for the interaction between data uncertainty and economic decisions is to impose that certain model features depend precisely on real-time values of aggregate variables, as a result of either limited information or institutional arrangements. The SW model provides three appropriate channels for this interaction. First, price and wage indexation rules are implemented with real-time data on inflation, available at the time of application. Second, consumption is affected by real-time consumption data as external habit formation depends on the first announcement of aggregate consumption data. Finally, the systematic monetary policy is conducted using real-time data of inflation and output available at the central bank.

The complete loglinearized model is presented in the Appendix together with a table describing parameter notation. Here, the attention is only focused on the equations of the SW model that are modified as a result of incorporating real-time data on inflation, output and consumption: the New-Keynesian Phillips curve, the real wage dynamic equation, the monetary policy rule, the consumption (IS-type) curve, the wage mark-up equation and the exogenous shocks. Prior to that, revision processes are defined to relate the initial announcements of output, inflation and consumption to their respective final revised values.

[6] However, standard DSGE models rely on representative agent frameworks in which household and firm decisions determine the final (revised) values of macroeconomic variables, so revised values belong to the representative agent information set.

2.1 Revision processes

Taking US data as our reference, the initial announcements of quarterly real GDP, the GDP deflator and real consumption are typically made by statistical agencies with one quarter of delay.[7] Final revisions may take much longer time to be released. Depending upon circumstances, final data on macroeconomic variables may need between 2 and 12 quarters to be released.[8] In order to simplify the analysis, the number of periods after which there are no more revisions, other than benchmark revisions, is assumed to be constant and denoted by S. Subsequently, let us consider the following identities relating revised data on the cyclical component of output, y_t, inflation, π_t, and consumption, c_t, with both the initial announcements and the final revisions:

$$y_t \equiv y^r_{t,t+1} + rev^y_{t,t+S}, \tag{1}$$

$$\pi_t \equiv \pi^r_{t,t+1} + rev^\pi_{t,t+S}, \tag{2}$$

$$c_t \equiv c^r_{t,t+1} + rev^c_{t,t+S}, \tag{3}$$

where $y^r_{t,t+1}$ denotes real-time output at time t (released in quarter $t+1$), and $rev^y_{t,t+S}$ denotes the final revision of output that will be announced in quarter $t+S$. Analogous notation is used for the revisions of both inflation and consumption.

[7] The Bureau of Economic Analysis (BEA) publishes statistical releases of quarterly GDP on a monthly basis. Thus, at the end of January the BEA releases the first estimate of the fourth quarter from last year. By the end of February, the second estimate comes out, at the end of March (end of the first quarter), the agency delivers the third estimate and so on.

[8] In particular, as pointed out by Croushore (2011), GDP data are revised twice one and two months after the initial release, then at the end of July of each of the following three years, and again every five years after that due to benchmark revisions. These benchmark revisions take place every five years and involve changing methodologies or statistical changes such as base years. Arguably, they do not add much valuable information about the true values and their presence should not affect agents decisions.

Aruoba (2008) argues that US data revisions of many aggregate time series -such as output growth, consumption growth and inflation- are not rational forecast errors and might be related to their initial (real-time) announcements.[9] We follow this line of argument to assume that revisions of output, inflation and consumption are determined by the following processes

$$rev^{y}_{t,t+S} = b_{yy} y^{r}_{t,t+1} + \varepsilon^{y}_{t,t+S}, \tag{4}$$

$$rev^{\pi}_{t,t+S} = b_{\pi\pi} \pi^{r}_{t,t+1} + \varepsilon^{\pi}_{t,t+S}, \tag{5}$$

$$rev^{c}_{t,t+S} = b_{cc} c^{r}_{t,t+1} + \varepsilon^{c}_{t,t+S}. \tag{6}$$

These three revision processes are not intended to provide a structural characterization of statistical agencies, but to provide a simple framework to assess whether departures from the hypothesis of well-behaved revision processes (i.e., white-noise draws) might affect the estimates of behavioral and policy parameters.[10] More precisely, these processes allow for (i) the existence of non-zero correlations between output, inflation and consumption revisions and their initial announcements; and (ii) the presence of persistent revision processes. In particular, the revision process shocks $\varepsilon^{y}_{t,t+S}$, $\varepsilon^{\pi}_{t,t+S}$ and $\varepsilon^{c}_{t,t+S}$ are assumed to follow AR(1) processes with persistence parameters denoted by ρ_{yr}, $\rho_{\pi r}$ and ρ_{cr}, respectively.

2.2 New Keynesian Phillips curve

The separation between real-time data and final data may have an impact on pricing decisions that use indexation rules. SW (2007), and many other papers, consider that all firms that cannot

[9] See also Faust, Rogers and Wright (2005) for an analysis of GDP revisions in the G7 countries.

[10] In order to simplify the analysis, we assume that revisions process are linear since we end up estimating a linearized version of a medium-scale model as is standard in the literature. Nevertheless, it is worthwhile to notice that Corradi, Fernandez and Swanson (2009) have found evidence of nonlinear dependence between data revisions and variables entering in the information set at time the initial announcements were released.

price optimally follow an indexation rule on lagged inflation to adjust their prices. Here, we use real-time inflation for price adjustment. For example, some ω firm would apply the indexation rule $P_t(\omega) = (1 + \pi^r_{t-1,t})P_{t-1}(\omega)$ with the extended data set described above, whereas it was charging $P_t(\omega) = (1 + \pi_{t-1})P_{t-1}(\omega)$ in SW (2007). As we adopt such real-time price indexation scheme, the loglinearized equation for the optimal price set by firms capable of reoptimizing their prices becomes:[11]

$$p^*_t(i) = \left(1 - \overline{\beta}\xi_p\right) E_t \sum_{j=0}^{\infty} \overline{\beta}^j \xi_p^j \left(A \left(mc_{t+j}(i) + \lambda^p_{t+j} \right) + p_{t+j} - \iota_p \sum_{k=1}^{j} \pi^r_{t+k-1,t+k} \right),$$

where $p^*_t(i)$ is the log of the optimal price set by firm i, E_t is the rational expectation operator conditional to the absence of optimal pricing in the future, $\overline{\beta} = \beta\gamma^{(1-\sigma_c)}$ is a discount factor that incorporates long-run balanced growth at the γ rate and consumption elasticity in the utility function at σ_c, the parameter ξ_p denotes the Calvo probability of price rigidity, and $A > 0$ is a constant parameter that depends on both the Kimball (1995) goods market aggregator and the steady-state price mark-up.[12] The log of the optimal price depends on the expectation of three factors: the log of the real marginal costs, $mc_{t+j}(i)$, exogenous price mark-up variations, λ^p_{t+j}, and the log of the aggregate price level adjusted by the indexation rule, $p_{t+j} - \iota_p \sum_{k=1}^{j} \pi^r_{t+k-1,t+k}$ which, in contrast to the SW model, considers that the indexation rule takes into account initial announcements of inflation, $\pi^r_{t+k-1,t+k}$, instead of revised inflation, π_{t+k-1}. Using $p_{t+j} = p_t + \sum_{k=1}^{j} \pi_{t+k}$, the optimal relative price ($\widetilde{P}^*_t(i) = p^*_t(i) - p_t$) can be written as follows:

$$\widetilde{P}^*_t(i) = A\left(1 - \overline{\beta}\xi_p\right) E_t \sum_{j=0}^{\infty} \overline{\beta}^j \xi_p^j \left(mc_{t+j}(i) + \lambda^p_{t+j} \right) + E_t \sum_{j=1}^{\infty} \overline{\beta}^j \xi_p^j \left(\pi_{t+j} - \iota_p \pi^r_{t+j-1,t+j} \right).$$

[11] The technical appendix of SW (2007), available at http://www.aeaweb.org/aer/data/june07/2041254_app.pdf, shows how the loglinearized pricing equation is derived.

[12] Concretely, $A = \left(\left(\phi_p - 1 \right) \varepsilon_p + 1 \right)^{-1}$ where ε_p is the curvature of the Kimball aggregator and ϕ_p is the steady-state price mark-up.

Since all firms choosing the optimal price face the same optimizing program, the symmetric pricing behavior implies the following optimal relative price

$$\widetilde{P}_t^* = A\left(1-\overline{\beta}\xi_p\right)E_t\sum_{j=0}^{\infty}\overline{\beta}^j\xi_p^j\left(mc_{t+j}+\lambda_{t+j}^p\right)+E_t\sum_{j=1}^{\infty}\overline{\beta}^j\xi_p^j\left(\pi_{t+j}-\iota_p\pi_{t+j-1,t+j}^r\right). \tag{7}$$

Loglinearizing the aggregate price level with Calvo pricing and the indexation rule lead to the semi-loglinear relationship

$$\widetilde{P}_t^* = \tfrac{\xi_p}{1-\xi_p}\left(\pi_t-\iota_p\pi_{t-1,t}^r\right),$$

which can be substituted in (7) to obtain[13]

$$\pi_t = \iota_p\pi_{t-1,t}^r-\overline{\beta}\iota_pE_t\pi_{t,t+1}^r+\overline{\beta}E_t\pi_{t+1}-A\left[\tfrac{\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\xi_p}\right]\mu_t^p+(1+\overline{\beta}\iota_p)\varepsilon_t^p, \tag{8}$$

where the mark-up shock has been re-scaled at $\varepsilon_t^p = A\left[\tfrac{\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\xi_p}\right]\lambda_t^p$ and -following the SW convention- we have denoted μ_t^p as the log deviation of the price mark-up ($\mu_t^p=-mc_t$). It should be noticed that when initial announcements and revised data coincide ($\pi_{t-1,t}^r=\pi_{t-1}$, $\pi_{t,t+1}^r=\pi_t$) the New Keynesian Phillips curve (8) is identical to equation (10) in SW (2007) reproduced here as follows

$$\pi_t = \tfrac{\iota_p}{1+\overline{\beta}\iota_p}\pi_{t-1}+\tfrac{\overline{\beta}}{1+\overline{\beta}\iota_p}E_t\pi_{t+1}-\tfrac{A}{1+\overline{\beta}\iota_p}\left[\tfrac{\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\xi_p}\right]\mu_t^p+\varepsilon_t^p. \tag{9}$$

Using equations (2) and (5), we obtain after some algebra

$$E_t\pi_{t,t+1}^r = B\left[\pi_t-\rho_{\pi r}^S\varepsilon_{t-S,t}^{\pi}\right], \tag{10}$$

where $B=\frac{1}{(1+b_{\pi\pi})}>1$ whenever $b_{\pi\pi}<0$. Substituting equation (10) into (8) yields

$$\pi_t = \tfrac{\iota_p}{1+\overline{\beta}\iota_pB}\pi_{t-1,t}^r+\tfrac{\overline{\beta}}{1+\overline{\beta}\iota_pB}E_t\pi_{t+1}-\left[\tfrac{A\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\left(1+\overline{\beta}\iota_pB\right)\xi_p}\right]\mu_t^p+\tfrac{1+\overline{\beta}\iota_p}{1+\overline{\beta}\iota_pB}\varepsilon_t^p+\tfrac{\overline{\beta}\iota_pB}{1+\overline{\beta}\iota_pB}\rho_{\pi}^S\varepsilon_{t-S,t}^{\pi}. \tag{11}$$

Comparing equations (9) and (11), we observe that introducing indexation based on real-time data has three type of effects on the NKPC specification. First, lagged inflation, π_{t-1}, is replaced by

[13] For the algebra, it should be noticed that equation (7) is equivalent to $\widetilde{P}_t^*-\overline{\beta}\xi_pE_t\widetilde{P}_{t+1}^* = A\left(1-\overline{\beta}\xi_p\right)(mc_t+\lambda_t^p)+\overline{\beta}\xi_pE_t\left(\pi_{t+1}-\iota_p\pi_{t,t+1}^r\right)$.

lagged real-time inflation, $\pi^r_{t-1,t}$. Second, current inflation is also affected by the innovations of data revisions: there is a positive impact from the inflation-revision shock, $\varepsilon^\pi_{t-S,t}$. Finally, the slope of the NKPC with data revisions is flatter (i.e. $\left[\frac{A\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\left(1+\overline{\beta}\iota_p B\right)\xi_p}\right] < \left[\frac{A\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\left(1+\overline{\beta}\iota_p\right)\xi_p}\right]$) whenever $B > 1$.

2.3 Real wage dynamics

SW (2007) borrow the labor market structure with wage-setting households and sticky wages from Erceg *et al.* (2000). They use the standard Calvo (1983)-type rigidity for wage adjustments. For non-optimal wage adjustments households follow an indexation rule on lagged inflation, analogous to the one described above for non-optimal price adjustments. In our extension to SW (2007), we are replacing lagged inflation for its real-time observation. In turn, relative optimal wages, $\widetilde{W}^*_t$, become

$$\widetilde{W}^*_t = \tfrac{\xi_w}{1-\xi_w}\left(\pi^w_t - \iota_w \pi^r_{t-1,t}\right),$$

where ξ_w is the Calvo probability of not being able to set the optimal wage. In turn, the real wage dynamic equation only departs from the one considered in the SW model in those terms related to the indexation factor (i.e. those terms containing the indexation parameter, ι_w)

$$w_t = w_1 w_{t-1} + (1-w_1)\left(E_t w_{t+1} + E_t \pi_{t+1}\right) - w_1 \pi_t - w_1 \overline{\beta}\iota_w E_t \pi^r_{t,t+1} + w_2 \pi^r_{t-1,t} - w_3 \mu^w_t + \varepsilon^w_t, \quad (12)$$

where $w_1 = \frac{1}{1+\overline{\beta}}$, $w_2 = \frac{\iota_w}{1+\overline{\beta}}$, and $w_3 = \frac{1}{1+\overline{\beta}}\left[\frac{\left(1-\overline{\beta}\xi_w\right)\left(1-\xi_w\right)}{\xi_w\left(\left(\phi_w-1\right)\varepsilon_w+1\right)}\right]$. As expected, if $\pi_t = \pi^r_{t,t+1}$ then equation (12) is identical to the corresponding equation in SW (2007). Noticing that $E_t\pi^r_{t,t+1} = B\left[\pi_t - \rho^S_\pi \varepsilon^\pi_{t-S,t}\right]$, (12) yields (after grouping terms)

$$\begin{aligned} w_t &= w_1 w_{t-1} + (1-w_1)\left(E_t w_{t+1} + E_t \pi_{t+1}\right) - w_1\left(1+\overline{\beta}\iota_w B\right)\pi_t + w_2 \pi^r_{t-1,t} - w_3 \mu^w_t \\ &\quad + w_1 \overline{\beta}\iota_w B \rho^S_\pi \varepsilon^\pi_{t-S,t} + \varepsilon^w_t. \end{aligned}$$

The implications of introducing real-time data on real wage dynamics are the presence of real-time lagged inflation instead of lagged inflation ($\pi^r_{t-1,t}$ replaces π_{t-1}), and the inclusion of inflation revision innovations, $\varepsilon^{\pi}_{t-S,t}$.

2.4 Monetary policy rule

Adapting the SW (2007) specification, the Taylor (1993)-type rule of the extended model is

$$\begin{aligned} R_t &= \rho R_{t-1} + (1-\rho)[r_\pi E_t \pi_{t-1} + r_y \left(E_t y_{t-1} - y^p_{t-1}\right)] + \\ & r_{\Delta y}\left[\left(E_t y_{t-1} - y^p_{t-1}\right) - \left(E_t y_{t-2} - y^p_{t-2}\right)\right] + \varepsilon^R_t, \end{aligned}$$

where the p superscripts denote potential (natural-rate) variables and ε^R_t is a monetary policy shock. Hence, the monetary policy rule of the extended model includes lagged values of inflation and output, whose fully-revised observations will be released with a delay of $t-1+S$ periods. It explains why the rational expectation operator, E_t, is written in front of the lagged variables. Using identities (1) and (2) that relate final revised data to real-time data transforms the previous expression into

$$\begin{aligned} R_t &= \rho R_{t-1} + (1-\rho)[r_\pi(\pi^r_{t-1,t} + E_t rev^{\pi}_{t-1,t-1+S}) + r_y(y^r_{t-1,t} + E_t rev^y_{t-1,t-1+S} - y^p_{t-1})] + \\ & r_{\Delta y}\left[\left(y^r_{t-1,t} + E_t rev^y_{t-1,t-1+S} - y^p_{t-1}\right) - \left(y^r_{t-2,t-1} + E_t rev^y_{t-2,t-2+S} - y^p_{t-2}\right)\right] + \varepsilon^R_t, \end{aligned}$$

where the revision processes (4) and (5) can be inserted to yield[14]

$$\begin{aligned} R_t &= \rho R_{t-1} + (1-\rho)[r_\pi((1+b_{\pi\pi})\,\pi^r_{t-1,t} + \rho^{S-1}_{\pi r}\varepsilon^{\pi}_{t-S,t})) + r_y((1+b_{yy})\,y^r_{t-1,t} + \rho^{S-1}_{yr}\varepsilon^y_{t-S,t} - y^p_{t-1})] + \\ & r_{\Delta y}\left[((1+b_{yy})\,y^r_{t-1,t} + \rho^{S-1}_{yr}\varepsilon^y_{t-S,t} - y^p_{t-1}) - ((1+b_{yy})\,y^r_{t-2,t-1} + \rho^{S-2}_{yr}\varepsilon^y_{t-S,t} - y^p_{t-2})\right] + \varepsilon^R_t. \quad (13) \end{aligned}$$

Both real-time data and data revisions enter the reaction function of the central bank (13). It is then useful for comparing its properties with those obtained from the estimation of reduced-

[14] The AR(1) processes characterizing output and inflation revision shocks were also used to incorporate the autocorrelation coefficients ρ_{yr} and $\rho_{\pi r}$.

form monetary rules based only on either (final) revised or real-time data. For example, SW (2007) estimate their model with the whole sample of revised data. Our approach should also be distinguished from Orphanides and Van Norden (2002), where output gap estimates are obtained in real time (i.e. the output gap estimate for a particular period takes only into account the real-time data really available at the time).[15]

2.5 Consumption equation

Unlike SW (2007), the consumption habit of the household is built upon the real-time observation of lagged aggregate consumption, $C_t(i) - hC^r_{t-1,t}$, where h is the habit parameter. Recalling the optimizing program of the i representative household of SW (2007), the first order conditions of consumption and purchases of bonds are[16]

$$\left(C_t(i) - hC^r_{t-1,t}\right)^{-\sigma_c} \exp\left(\frac{\sigma_c - 1}{1+\sigma_l}\left(L_t(i)\right)^{1+\sigma_l}\right) - \Xi_t = 0, \tag{14}$$

$$-\Xi_t E_t \frac{(1+\pi_{t+1})}{e^{\varepsilon^b_t}(1+R_t)} + \beta E_t \Xi_{t+1} = 0, \tag{15}$$

where $L_t(i)$ is the amount of labor in period t, σ_l is the labor elasticity parameter in the utility function, Ξ_t is the Lagrange multiplier of the budget constraint in period t, and ε^b_t is the risk-premium shock. Loglinearizing both (14) and (15) yields

$$\log \Xi_t = -\frac{\sigma_c}{1-h/\gamma} c_t(i) + \frac{(h/\gamma)\,\sigma_c}{1-(h/\gamma)} c^r_{t-1,t} + (\sigma_c - 1)\, L^{1+\sigma_l} l_t(i), \tag{16}$$

$$\log \Xi_t = E_t \log \Xi_{t+1} + (R_t - E_t \pi_{t+1} + \varepsilon^b_t). \tag{17}$$

[15] It is assumed that potential output belongs to the information set of the central bank. In order to analyze the importance of this assumption, we have also estimated the extended model removing potential output from the policy rule. The estimation results are robust to this alternative specification because the output coefficients, r_y and $r_{\Delta y}$, are always close to zero. These results are available from the authors upon request.

[16] The utility function of the households in SW (2007) is not separable between consumption and labor.

Using both (16) and the corresponding expression of (16) for period $t+1$ in equation (17), we obtain, after aggregating across all households, the consumption equation

$$c_t = (h/\gamma)\, c^r_{t-1,t} - (h/\gamma)\, E_t c^r_{t,t+1} + E_t c_{t+1} + \tfrac{(1-h/\gamma)(\sigma_c-1)L^{1+\sigma_l}}{\sigma_c}\left(l_t - E_t l_{t+1}\right) - \tfrac{1-h/\gamma}{\sigma_c}(R_t - E_t\pi_{t+1} + \varepsilon^b_t). \tag{18}$$

Since the value of $c^r_{t,t+1}$ has not been released yet in period t, its rational expectation is taken using the generating processes (3) and (6) one period ahead

$$E_t c^r_{t,t+1} = (1+b_{cc})^{-1}\left[c_t - \rho^S_{cr}\varepsilon^c_{t-S,t}\right]. \tag{19}$$

Inserting (19) in (18), and applying the steady-state relationship $w = \phi_w(1-h/\gamma)CL^{\sigma_l}$ leads to the IS-style consumption equation

$$c_t = c_1 c^r_{t-1,t} + (1-c_1)E_t c_{t+1} + c_2\left(l_t - E_t l_{t+1}\right) - c_3(R_t - E_t\pi_{t+1} + \varepsilon^b_t) + c_4\varepsilon^c_{t-S,t}, \tag{20}$$

where $c_1 = \frac{h/\gamma}{1+(h/\gamma)(1+b_{cc})^{-1}}$, $c_2 = \frac{(\sigma_c-1)wL/(\phi_w C)}{\sigma_c(1+(h/\gamma)(1+b_{cc})^{-1})}$, $c_3 = \frac{1-h/\gamma}{\sigma_c(1+(h/\gamma)(1+b_{cc})^{-1})}$ and $c_4 = \frac{(h/\gamma)\rho^S_{cr}}{(1+b_{cc})(1+(h/\gamma)(1+b_{cc})^{-1})}$.

2.6 Wage mark-up equation

The log fluctuation of the household-specific wage mark-up is defined as the log difference between the real wage and the marginal rate of substitution of work hours and consumption. It gives

$$\mu^w_t(i) = w_t(i) - mrs_t(i) = w_t(i) - \left(\sigma_l l_t(i) + \tfrac{1}{1-h/\gamma}\left(c_t(i) - (h/\gamma)\, c^r_{t-1,t}\right)\right),$$

which, after aggregation across households, implies

$$\mu^w_t = w_t - mrs_t = w_t - \left(\sigma_l l_t + \tfrac{1}{1-h/\gamma}\left(c_t - (h/\gamma)\, c^r_{t-1,t}\right)\right).$$

2.7 Shocks

The complete model includes ten shock processes. The AR(1) technology shock $\varepsilon^a_t = \rho_a\varepsilon^a_{t-1} + \eta^a_t$, the AR(1) risk premium disturbance that shifts the demand for purchases of consumption and investment goods $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$, the exogenous spending shock driven by an AR(1) process with an extra term capturing the potential influence of technology innovations on exogenous spending $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a$, the AR(1) investment shock $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \eta_t^i$, the AR(1) monetary policy shock $\varepsilon_t^R = \rho_R \varepsilon_{t-1}^R + \eta_t^R$, the ARMA(1,1) price mark-up shock $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p$, the ARMA(1,1) wage shock $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w - \mu_w \eta_{t-1}^w$, the AR(1) inflation revision shock $\varepsilon_{t,t+S}^\pi = \rho_{\pi r} \varepsilon_{t-1,t-1+S}^\pi + \eta_{t,t+S}^\pi$, the AR(1) output revision shock $\varepsilon_{t,t+S}^y = \rho_{yr} \varepsilon_{t-1,t-1+S}^y + \eta_{t,t+S}^y$ and the AR(1) consumption revision shock $\varepsilon_{t,t+S}^c = \rho_{cr} \varepsilon_{t-1,t-1+S}^c + \eta_{t,t+S}^c$. The latter three shocks are introduced in our extended SW-type DSGE model to study the business cycle implications of data revisions. Notice that model's solutions depends on $E_t \varepsilon_{t,t+S}^\pi$, $E_t \varepsilon_{t,t+S}^y$ and $E_t \varepsilon_{t,t+S}^c$ and these three expected values depend on the number of periods, S, after which there are no more revisions for each variable other that benchmark revisions. Unfortunately, looking at US data shows that S is not constant neither over time nor across variables (Croushore, 2011). As a conservative setting, it is assumed that final revisions are reached after six quarters (i.e. $S = 6$) when solving the model.[17]

3 Data and estimation procedure

Both the SW model and the extended model are estimated with US data from the first quarter of 1983 to the first quarter of 2008. Following SW (2007), all the variables displaying a long-run trend enter the estimation procedure in log differences to extract their stationary business cycle component, and to avoid the well-known measurement error implied by standard filtering treatments. More recent data are not considered to minimize the chance of taking observations

[17] We have also estimated the model assuming two other alternative values: $S = 3$ and $S = 12$. The latter value for S is considered by Aruoba (2008) as the maximum number of quarters after which there are no more revisions for each variable, except for benchmark revisions. The estimation results are not sensitive to these alternative values of S. These estimation results are also available upon direct request to the authors.

with final revisions that can still be released in the future.[18] The list of observable variables contains quarterly series of the inflation rate, the Federal funds rate, the log of hours worked, and the log differences of real Gross Domestic Product (GDP), real consumption, real investment, and the real wage. The rate of inflation is obtained as the first difference of (the log of) the implicit GDP deflator, whereas the real wage is computed as the ratio between nominal compensation per hour and the GDP price deflator. All data series were retrieved from the Federal Reserve Bank of St. Louis (FRED2) database. This group of observables is the same as the one used by SW (2007), but considering now a more recent sample. For the estimation of the extended model, we include, in the set of observables, the real-time data series of output growth, inflation, and consumption growth reported by the Federal Reserve Bank of Philadelphia.[19] The three times series of US data revisions taken for the estimation are shown in the bottom row of Figure 1.

Variability of US data revisions of output growth, inflation and consumption growth is really high. Comparing the plots in the top row with those in the bottom row of Figure 1, we can observe similar volatilities between series of real-time data, revised data and revisions. Table 3 reports standard deviation of data revisions around 80% as high as standard deviations of real-time data and of very similar magnitude to standard deviations of revised data. As one remarkable example, revisions of US consumption growth report a standard deviation of 0.61% over the period 1983-2008, while the standard deviation of the corresponding revised data is just 0.53%. Such a high variability of US data revisions can give us one indication of the significance of these data

[18] Except for some of the last quarters of the sample, corresponding to the 2007-08 financial crisis, this period is characterized by mild fluctuations (the so-called Great Moderation) of aggregate variables (Stock and Watson, 2002, among others).

[19] We have eliminated the jumps that result from benchmark (scale) revisions by replacing the updated value of the corresponding variable with the average of the two observations released before and after the jump. As in the case of revised data, real-time data is measured in per-capita terms (if applicable).

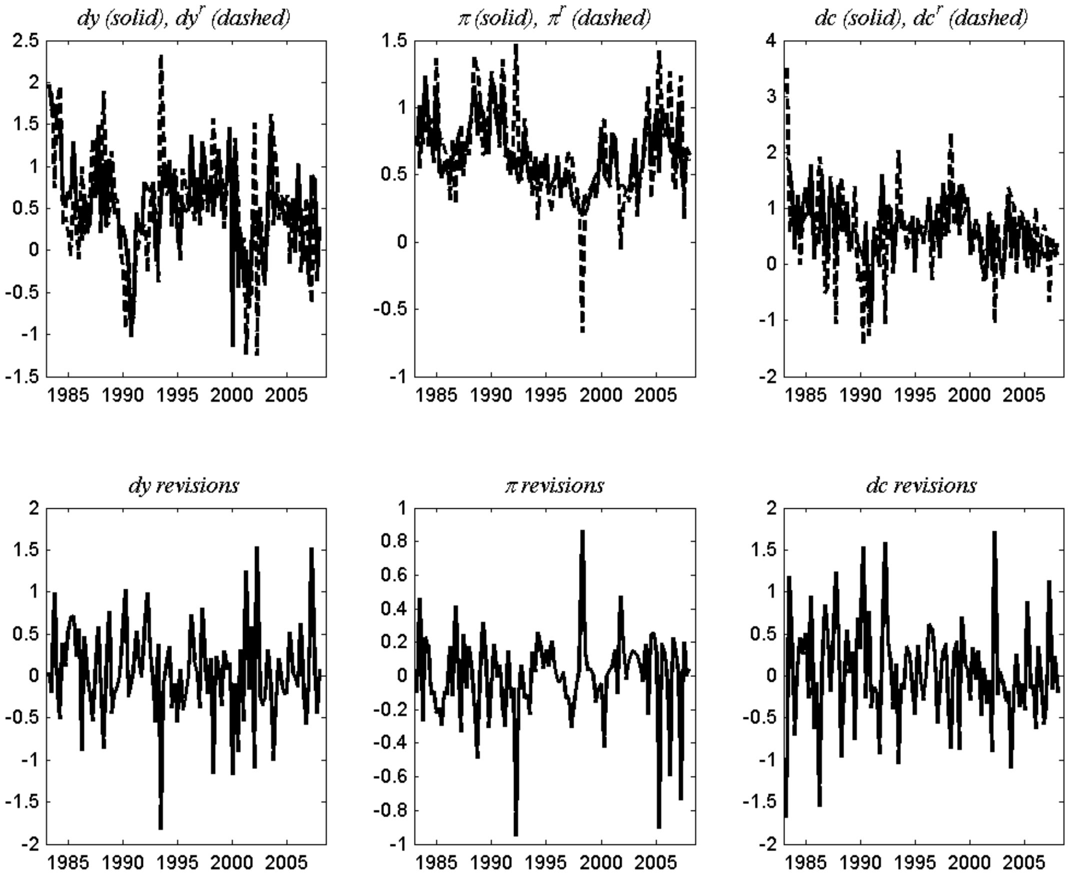

Figure 1: Revised data, real-time data, and revisions of output growth (dy), inflation (π), and consumption growth (dc) in the US, 1983:1-2008:1.

corrections for the US business cycle analysis.

The estimation procedure also follows SW (2007). Thus, we run a two-step Bayesian econometric estimation in Dynare. In the first step, the log posterior function is maximized in a way that combines the prior information of the parameters with the empirical likelihood of the data. In a second step, we perform the Metropolis-Hastings algorithm to compute the posterior distribution of the parameter set.[20] In regards to priors, we select the same prior distributions as in SW (2007) for those parameters appearing in the two models (see the first three columns in Tables 1A and 1B). We have also borrowed their notation for the structural parameters in order to facilitate comparison.[21] For the parameters associated with the three revision processes, we consider rather loose prior distributions as shown in the first three columns of Table 1C.[22]

4 Estimation results

Tables 1A, 1B and 1C show the posterior distribution for the parameters of the two models. The confidence band for each structural parameter -displayed in Table 1A- overlaps to a great extent with the corresponding confidence interval reported in SW (2007). A similar conclusion regarding the

[20] All estimation exercises are performed with DYNARE free routine software, which can be downloaded from http://www.dynare.org. A sample of 250,000 draws was used (ignoring the first 20% of draws). A step size of 0.3 resulted in an average acceptation rate of roughly 26% across the two Metropolis-Hastings blocks used.

[21] See also Tables A.1 and A.2 in the Appendix for a description of model parameters.

[22] Preliminary attempts to estimate the extended model with real-time data result in high estimates of the steady-state growth rate parameter, γ, which also lead to sample instability as shown by the Brooks and Gelman (1998) diagnostic tests implemented by Dynare. One possible reason for this sample instability is that γ is not well identified when estimating a relatively short-sample period featuring higher-than-average growth over the postwar period. For these reasons, we decided to fix $\gamma = 0.0040$ prior to estimation; that is, the mean of the prior normal distribution used in the estimation of the SW model. Remarkably, the estimated values of the structural parameters do not change significantly when compared with those obtained by leaving γ free in the estimation procedure.

estimated parameters of the shock processes -displayed in Table 1B- is reached with four exceptions. The standard deviation of risk premium, government spending and policy rule shocks are slightly, but significantly, smaller in our sample whereas our persistence estimate of the risk premium shock is larger than the one reported in SW (2007).

[Insert Table 1A, Table 1B and Table 1C here]

The parameter estimates associated with the revision processes are shown in Table 1C. The output revision process coefficient, b_{yy}, is significantly positive, which implies that a high initial announcement of output anticipates a positive revision of this initially observed value. The consumption revision coefficient b_{cc} is also significantly positive. However, the inflation revision coefficient $b_{\pi\pi}$ is significantly negative, which implies that a high real-time inflation predicts a negative revision. In addition, the slope of the New Keynesian Phillips curve is flatter in the extended model (11) than in the SW model (9).

The persistence parameters associated with the shock revision processes are high for output and consumption revisions ($\rho_{yr} = 0.89$ and $\rho_{cr} = 0.80$), whereas the one associated with inflation revisions is quite low ($\rho_{\pi r} = 0.09$). Moreover, the standard deviation of the output and consumption revision innovations (σ_{yr} and σ_{cr}, respectively) are roughly three times greater than the one of the inflation revision innovation ($\sigma_{\pi r}$). These estimation results suggest that i) revisions of output, consumption and inflation are not white-noise errors, and ii) the revision process of inflation features much lower inertia and volatility than the revision processes of either output or consumption. These conclusions based on a structural model are somewhat in line with the empirical evidence reported by Aruoba (2008), who used regression analysis.

Comparing the set of estimates obtained from the two models, it can be said that most structural parameters do not change significantly by considering real-time data in addition to revised data.

Indeed, the only important exceptions are the habit formation parameter, h, which is much lower in the extended model (0.13) than in the SW model (0.57), and the price-indexation parameter, ι_p, which is lower in the extended model (0.09) than in the SW model (0.33). This result indicates that the structural equations of consumption (20) and inflation (11) are more forward-looking in the estimated extended model than in the SW model. Meanwhile, the estimated monetary policy rule parameters are rather similar across models. In particular, the policy rule inflation coefficient, r_π, is slightly lower in the extended model, but it is still clearly higher than 1.0, as prescribed by Taylor principle.

On the evaluation of the goodness of the estimation, Dynare package supplies, as a by-product, several tests such as graphical convergence diagnostic tests suggested by Brooks and Gelman (1998). According to these graphical tests, the overall performance is good. Another way to analyze the quality of estimation results is by comparing the prior and posterior distributions for each parameter, which shows that the data are quite informative about the posterior distribution of the model parameters. Finally, the smoothed estimates of the shock innovation paths show that these innovation estimates look clearly stationary.[23]

The remaining of the section compares the performance of the two models across four dimensions: second-moment statistics characterizing business cycle fluctuations, variance decomposition, impulse-response analysis, and an assessment on the relative importance of alternative frictions; towards a deeper understanding of the role of data revisions. But before doing that, we examine the relative importance of the two sources of deviation from well-behaved revision process by estimating the extended model under three alternative null-hypothesis:

(i) Revisions unrelated to initial announcements ($b_{yy} = b_{\pi\pi} = b_{cc} = 0$),

[23] The graphical convergence diagnostic test results are available upon request from the corresponding author. The other two diagnostic test results are available in the "Supplementary material" file.

(ii) Revisions depend on initial announcements, but revision shocks are white noise ($\rho_{yr} = \rho_{\pi r} = \rho_{cr} = 0$),

(iii) Revisions are white noise ($\rho_{yr} = \rho_{\pi r} = \rho_{cr} = b_{yy} = b_{\pi\pi} = b_{cc} = 0$),

and compare the marginal data densities of the model under these three alternative hypothesis with the one obtained in the baseline case. Hence, Table 2 shows the estimates of the structural parameters and the marginal likelihood for the baseline and for the three alternative hypothesis about revisions.[24] This table also gives an idea of the robustness of structural parameters and the overall performance of the model with respect to the alternative sources of non-rational data revisions. We observe that the restrictions imposed by any of the three hypothesis lead to an important deterioration of the marginal likelihood. This deterioration is larger when revisions shocks are assumed to be white noise (i.e. $\rho_{yr} = \rho_{\pi r} = \rho_{cr} = 0$) than when revisions are unrelated to initial announcements (i.e. $b_{yy} = b_{\pi\pi} = b_{cc} = 0$). Moreover, by comparing the model under the white noise revision hypothesis with the other cases, it is found that persistent revision shocks are required for good model fit. Furthermore, Table 2 shows that the estimated parameters are relatively robust to the alternative specifications of revision process. One noticeable difference is that the standard deviations associated with estimated parameters related to nominal frictions, such as Calvo probability parameters (ξ_p and ξ_w) and indexations parameters (ι_p and ι_w), are much higher when the set of restrictions $b_{yy} = b_{\pi\pi} = b_{cc} = 0$ is imposed.

4.1 Second-moment statistics

Figure 1 plots series of real-time data, revised data and revisions to show the importance of revisions. The relevance of revisions in actual data is further confirmed when the standard deviation of revisions are compared with the standard deviation of both revised and real-time data shown in

[24] The estimates of the remaining parameters are not shown to save space, but again they are available upon request.

Table 3, Panel A. Thus, the volatility of data revisions is really significant for the three revised variables, with standard deviations around 80% as high as those of the corresponding real-time variables and similar to those of the revised variables.

Apart from standard deviations of time series, Table 3, Panel A, shows other second-moment statistics obtained from actual US data and in the estimated extended model. The numbers provided by the model replicate to some extent the volatility, correlation with output and autocorrelation of US real-time data and revisions. Perhaps, it could be said that the extended model gives higher volatility on real-time data.

Table 3, Panel B, shows second-moment statistics obtained from US revised data and in the two estimated models. A comparison of the ability of the two models to reproduce the second-moment statistics of revised data shows some important differences. First, the estimated models give higher standard deviations for most variables than the ones obtained from actual data, while business cycle volatility of changes in output, consumption and investment in the extended model is clearly greater than in the SW model. The introduction of three additional shocks on data revision can explain this increase of variability. Second, the extended model reproduces the degree of inertia much better than the SW model in terms of closer autocorrelation coefficients. Finally, no clear conclusion emerges when comparing the ability of the two models for reproducing the correlation with quarterly output growth. Thus, the extended model fits better the correlation of inflation with output growth, whereas the opposite is true for the correlation between quarterly changes in consumption and output.

[Insert Table 3]

4.2 Variance decomposition

Table 4 shows the variance decomposition analysis. A significant fraction of fluctuations of output growth are driven by demand-side perturbations: risk-premium shocks (27.3% in the extended model and 20.2% in the SW model) and exogenous spending (10.3% in the extended model and 19.9% in the SW model). Wage mark-up shocks also play a significant role with 16.7% and 18% of output growth variability, respectively, in the variance decomposition of both models. Finally, monetary policy shocks explain around 10% of output changes in both models.

Wage mark-up shocks are the major source of variability of the real wage, labor, the nominal interest rate and inflation. This result is found in the estimated variance decomposition of both models and confirms the importance of wage mark-up shocks in the variance decomposition of DSGE models highlighted by SW (2007).

As for the role of data revision shocks on business cycle fluctuations, Table 4 indicates that innovations on inflation revisions explain 4.3% of output growth fluctuations, innovations on consumption revisions 4.0% of changes in output and, innovations on output revisions just 1% of output growth variability. So, the exogenous variability of data revisions would jointly explain 9.3% of output growth fluctuations. This important result implies that models ignoring data revisions, such as the SW model, are leaving nearly one tenth of total variability of output driven by data revision shocks that would be overestimating the role of other sources of cyclical fluctuations (in particular, technology shocks and exogenous spending shocks).

[Insert Table 4]

4.3 Impulse response analysis

The business cycle implications of data revisions can be examined by looking into the impulse-response functions obtained in the estimated extended model with revision shocks. Figure 2 plots the results for the three revised variables: output, inflation and consumption. The revision shock is absorbed between the real-time variable and the revised variable. In fact, the reaction of real-time data goes strongly in the opposite direction to the revision shock in the three types of revisions. For example, Figure 2 shows how a +0.55% output revision shock corresponds to a +0.10% increase in revised output and a -0.45% decline in real-time output. Hence, a positive-side revision is indicative of a too low real-time announcement that will be corrected over time.

The observation that shocks on data revisions have much larger effects on real-time data than on revised data supports the view of revisions as reducing noise rather than adding news. The impulse-response analysis is consistent with both the higher volatility of real-time data than revised data (noticeable in Figure 1 and in the second-moment statistics reported in Table 2) and the estimation results showing the presence of non-rational revision processes (the estimates of b_{yy}, $b_{\pi\pi}$, b_{cc}, ρ_{yr}, $\rho_{\pi r}$, and ρ_{cr} are all significantly different from zero in Table 1C). The alternative view of revisions adding only news would have brought data revisions with no impact on real-time data because revision shocks and real-time data would then be orthogonal.

Let us examine the transmission from revision shocks to final variables in order to understand the effects of data revisions on business cycle fluctuations. Figure 2 shows that both output and inflation revisions are procyclical. The mistake in data announcement revisions of either output or inflation bring some monetary expansion because the central bank lowers the interest-rate in response to the decline in real-time data (see equation 13). The reduction of interest rates stimulate the endogenous components of demand (consumption and investment), labor demand, and output. Figure 2 informs that the estimated output revision shock increases output, investment, consumption and labor by

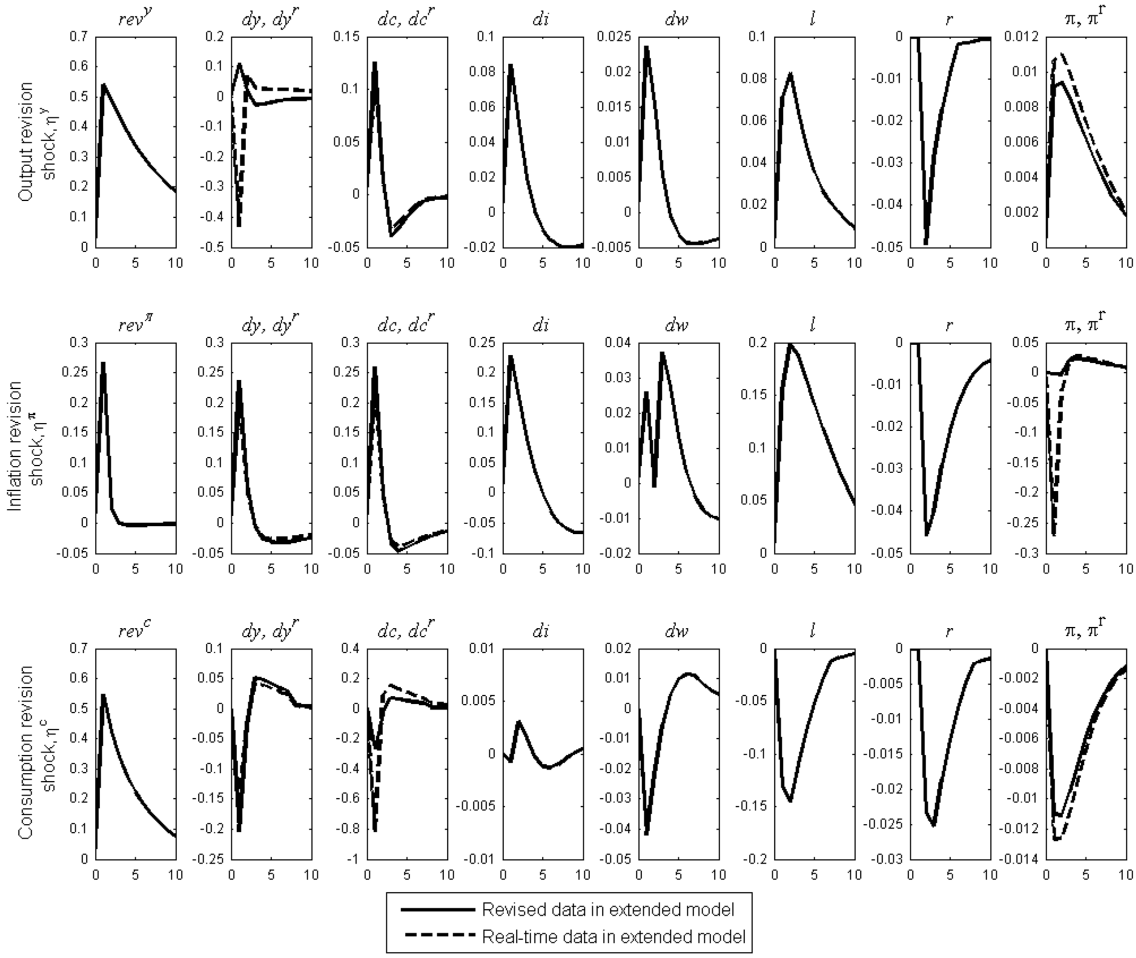

Figure 2: Responses to data revision shocks.

around 0.1%, while these expansions are roughly by 0.2% when there is an estimated inflation revision shock.

By contrast, the consumption revision describes a countercyclical pattern. A positive data revision of consumption corresponds to a low real-time consumption announcement that is going to reduce current consumption in equation (20) as the household identifies consumption habit with the real-time data release. Investment barely changes after the consumption revision shock and the contractionary response of consumption collects most of the change in output. The responses are quantitatively significant; the estimated consumption revision shock produces declines of -0.2% in output, -0.25% in consumption, and -0.15% in labor. The significance of these quantitative results is consistent with the variance decomposition discussed above.

A comparison between the responses in the extended model and those in the SW model is carried out in Figure 3. Due to space constraints, we report only the responses of output growth, consumption growth and inflation as the three variables that include data revisions. In overall terms, both models provide similar responses. Let us just comment on the noticeable differences. The reaction of inflation is somewhat stronger in the model with data revisions after either technology innovations or risk premium shocks. Meanwhile, cost-push shocks and monetary policy shocks bring deeper responses of output and consumption growth in the extended model compared to the SW model. Therefore, it could be said that data revisions induce higher variability in some of the responses to shocks.

In the comparison of real-time data with revised data (that belong to the extended model), we find significant co-movements between both variables. The reactions of revised output growth and consumption growth go slightly further than those observed in real time, which indicates revisions of positive sign. By contrast, real-time inflation responds somewhat more aggressively than revised inflation as a result of inflation revisions of negative sign. Such different revision signs are consistent with the estimated coefficients of the revision-generating processes reported in Table 1C ($b_{yy} > 0$, $b_{cc} > 0$, and $b_{\pi\pi} < 0$).

4.4 An assessment on the relative importance of alternative frictions

Mirroring SW (2007), this subsection studies the partial contribution of each friction to the marginal likelihood of the extended model with data revisions. Thus, Table 5 shows the estimates of the mode of the structural parameters and the marginal likelihood when each friction is either cancelled

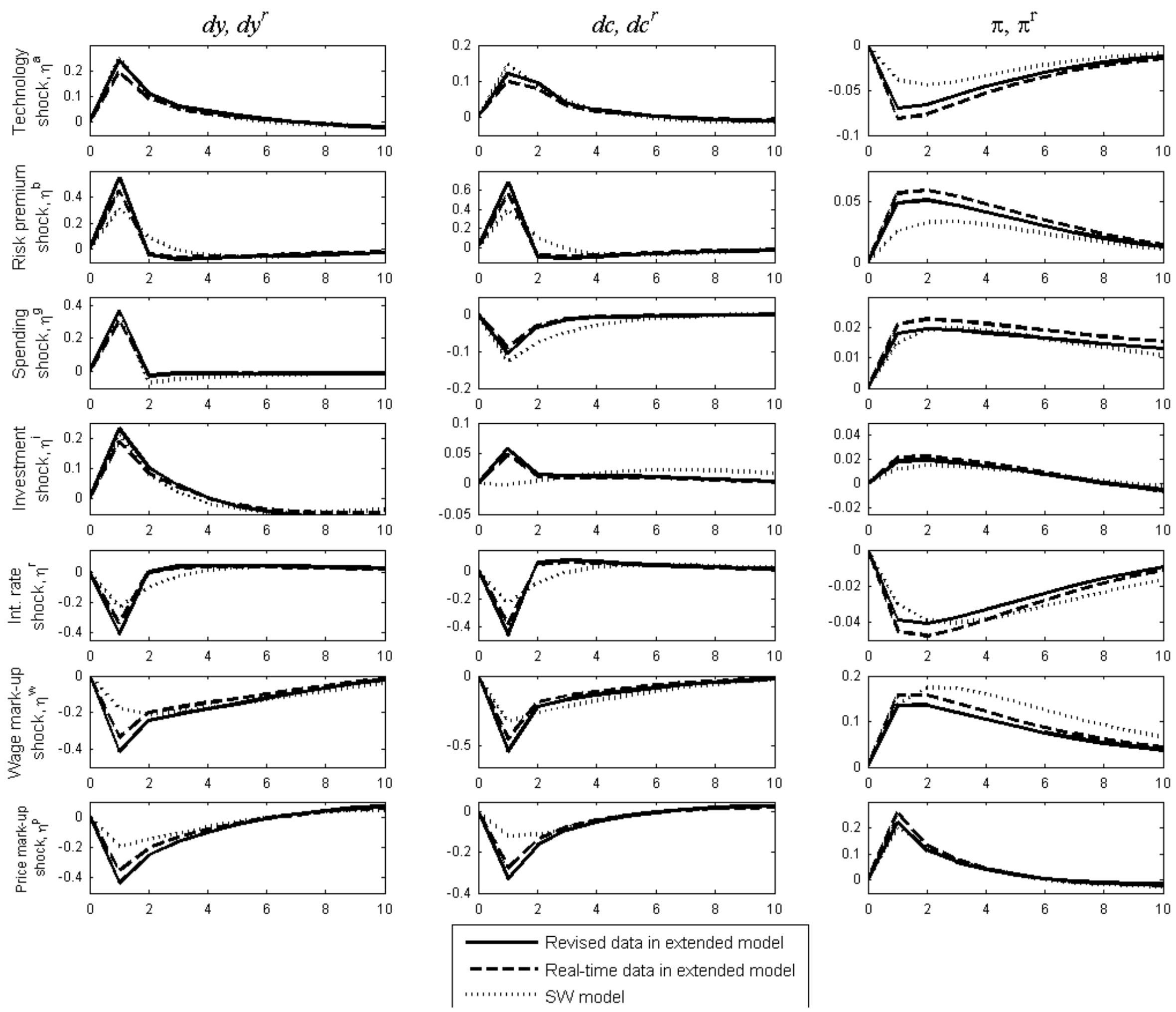

Figure 3: Responses of revised and real-time data in the estimated extended model, and in the estimated SW model.

or substantially reduced. The cases with quasi-flexible nominal wages ($\xi_w = 0.1$) and low elasticity of adjustment costs on investment ($\varphi = 0.1$) bring a substantial deterioration of the model fit to the data, with a reduction in marginal likelihood by more than 35% of its value. In all the other cases ($\xi_p = 0.1, \iota_p = 0.0, \iota_w = 0.0, h = 0.0, \psi = 0.99, \Phi = 1.1$), the goodness of fit does not vary substantially in comparison with the baseline model.

The model estimation under quasi-flexible prices ($\xi_p = 0.1$) increases the role of both price indexation and wage indexation, while the prevalence of wage stickiness is reduced. The parameter estimates are robust to shutting down price indexation ($\iota_p = 0.1$), wage indexation ($\iota_w = 0.1$), and habit formation ($h = 0.0$), which reflect the relative unimportance of these three elements once real-time data and data revisions are taken into account.

Regarding the parameters of data revisions (at the continuation of Table 5), the negative dependence of inflation revisions on the initial announcements ($b_{\pi\pi} < 0$) only turns positive if price indexation is ignored remaining negative in all the other cases. The consumption revision becomes negatively influenced by real-time consumption data ($b_{cc} < 0$) when $\xi_w = 0.1$. All the other parameters that shape revision processes are not quite sensitive to imposing restrictions in the structural parameters. In particular, the estimates of autocorrelation and volatility of data revisions are very similar across all cases, indicating robustness to changes in model assumptions.

5 Conclusions

The significance of data revisions for US business cycles has been examined in an extended version of the DSGE model of Smets and Wouters (2007). The separation between real-time and revised data must be considered in the estimation of a structural model because: i) the initial announcements are not a rational forecast of revised data, and ii) economic decisions such as pricing, wage setting, consuming or setting the interest rates depend upon real-time data.

The empirical analysis shows that revisions of inflation, output and consumption have two main effects in the estimation of the extended model. First, the estimates of both consumption habit and price indexation fall significantly. Second, data revisions explain 9.3% of output variability in the long-run variance decomposition, that is ignored in standard DSGE models such as Smets and Wouters (2007).

In addition, the extended model is able to replicate, among other second-moment statistics, the high variability featured by US data revisions. Moreover, the estimation of the extended model provides information about US data revision dynamics. Thus, the revisions of both output and consumption are positively correlated to their real-time observations and present high persistence. Meanwhile, inflation revisions are negatively related to real-time inflation and have very little inertia. The results also show that a revision shock is mostly transmitted into real-time data rather than on revised data. In other words, data revisions mainly reduce noise instead of adding news.

The extended model remains stylized and should be further extended to investigate additional ways in which real-time data might play an important role. In particular, investment decisions are not directly affected by real-time data in our extended model. However, investment, as consumption, is likely to be largely determined by real-time measures of aggregate economic activity. The study of these potentially useful extensions is left for future research.

References

Aruoba, Borogan S. 2008. “Data Revisions Are Not Well-Behaved”, *Journal of Money, Credit and Banking* 40, 319-340.

Bernanke, Ben S., and Jean Boivin. 2003. “Monetary Policy in a Data-Rich Environment”, *Journal of Monetary Economics* 50, 525-546.

Brooks, Stephen P., and Andrew Gelman. 1998. “General Methods for Monitoring Converge of Iterative Simulations.” *Journal of Computational and Graphical Statistics* 7, 434-455.

Calvo, G. A. 1983. "Staggered Pricing in a Utility-Maximizing Framework." *Journal of Monetary Economics* 12, 383-396.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. “Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy.” *Journal of Political Economy* 113, 1-45.

Corradi, Valentina, Andres Fernandez, and Norman R. Swanson. 2009. “Information in the Revision Process of Real-Time Datasets.” *Journal of Business and Economic Statistics* 27, 455–67.

Croushore, Dean, and Tom Stark. 2001. “A Real-Time Data Set for Macroeconomists”, *Journal of Econometrics* 105,111-130.

Croushore, Dean, and Charles L. Evans. 2006. “Data Revisions and the Identification of Monetary Policy Shocks”, *Journal of Monetary Economics* 53, 1135-1160.

Croushore, Dean. 2011.“Frontiers of Real-Time Data Analysis.” *Journal of Economic Literature* 49, 72-100.

Diebold, Francis X., and Glenn D. Rudebusch. 1991. “Forecasting Output With the Composite Leading Index: A Real-Time Analysis.” *Journal of the American Statistical Association* 86, 603-610.

Edge, Rochelle M., Michael T. Kiley, and Jean-Philippe Laforte. 2010. “A comparison of forecast performance between Federal Reserve Staff forecast, simple reduced-form models, and a

DSGE model." *Journal of Applied Econometrics* 25, 720-754.

Erceg, Christopher J., Dale W. Henderson, and Andrew T. Levin. 2000. "Optimal monetary policy with staggered wage and price contracts." *Journal of Monetary Economics* 46, 281-313.

Faust, Jon, John H. Rogers, and Jonathan H. Wright. 2005. "News and Noise in G-7 GDP Announcements." *Journal of Money, Credit, and Banking* 37, 403-419.

Herbst, Edward, and Frank Schorfheide. 2011. "Evaluating DSGE model forecasts of comovements." Federal Reserve Bank of Philadelphia, Research Department Working Paper No. 11-5.

Kimball, Miles S. 1995. "The Quantitative Analytics of the Basic Neomonetarist Model." *Journal of Money, Credit, and Banking* 27, 1241-1277.

Mankiw, N. Gregory, David E. Runkle, and Matthew D. Shapiro. 1984. "Are Preliminary Announcements of the Money Stock Rational Forecasts?". *Journal of Monetary Economics* 14, 15-27.

Orphanides, Athanasios. 2001. "Monetary Policy Rules Based on Real-Time Data," *American Economic Review* 91, 964-985.

Orphanides, Athanasios. 2003. "Monetary Policy Evaluation with Noisy Information," *Journal of Monetary Economics* 50, 605-631.

Orphanides, Athanasios, and Simon van Norden. 2002. "The Unreliability of Output-Gap Estimates in Real Time," *The Review of Economics and Statistics* 84, 569-583.

Rotemberg, Julio J., and Michael Woodford. 1997. "An Optimizing-Based Econometric Framework for the Evaluation of Monetary Policy." In *NBER Macroeconomics Annual 1997*, eds. Ben S .Bernanke and Julio J. Rotemberg, 297-346. Cambridge: MIT Press.

Smets, Frank R., and Rafael Wouters. 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach." *American Economic Review* 97, 586-606.

Stock, James H., and Mark W. Watson. 2002. "Has the Business Cycle Changed and Why?" In *NBER Macroeconomics Annual 2002*, eds. Mark Gertler and Kenneth Rogoff, 159-218. Cambridge: MIT Press.

Taylor, John B. 1993. "Discretion versus policy rules in practice." *Carnegie-Rochester Conference Series on Public Policy* 39, 195-214.

Vázquez, Jesús, Ramón María-Dolores, Juan M. Londoño. 2010 "Data Revisions and the Monetary Policy Rule: An analysis based on an extension of the basic New Keynesian model." The University of the Basque Country, *Mimeo.*

Woodford, Michael 2003. *Interest and Prices: Foundations of a Theory of Monetary Policy.* Princeton: Princeton University Press.

Table 1A. Priors and estimated posteriors of the structural parameters

	Priors			Posteriors					
				Extended model			SW model		
	Distr	Mean	Std D.	Mean	5%	95%	Mean	5%	95%
φ	Normal	4.00	1.50	5.26	3.46	7.09	5.93	4.06	7.85
h	Beta	0.70	0.10	0.13	0.10	0.16	0.57	0.45	0.67
σ_c	Normal	1.50	0.37	1.34	1.08	1.62	1.07	0.76	1.35
σ_l	Normal	2.00	0.75	1.79	0.81	2.79	1.95	0.99	2.85
ξ_p	Beta	0.50	0.10	0.66	0.58	0.75	0.72	0.63	0.81
ξ_w	Beta	0.50	0.10	0.51	0.38	0.65	0.59	0.45	0.72
ι_w	Beta	0.50	0.15	0.35	0.15	0.55	0.48	0.24	0.72
ι_p	Beta	0.50	0.15	0.09	0.03	0.15	0.33	0.14	0.51
ψ	Beta	0.50	0.15	0.77	0.63	0.90	0.72	0.57	0.88
Φ	Normal	1.25	0.12	1.44	1.31	1.57	1.48	1.34	1.61
r_π	Normal	1.50	0.25	1.86	1.56	2.13	2.09	1.78	2.42
ρ	Beta	0.75	0.10	0.84	0.81	0.87	0.83	0.80	0.87
r_y	Normal	0.12	0.05	-0.01	-0.03	0.01	0.04	0.01	0.08
$r_{\Delta y}$	Normal	0.12	0.05	0.10	0.07	0.12	0.18	0.13	0.22
π	Gamma	0.62	0.10	0.67	0.54	0.81	0.70	0.57	0.85
$100(\beta^{-1}-1)$	Gamma	0.25	0.10	0.17	0.07	0.28	0.20	0.10	0.31
l	Normal	0.00	2.00	-1.48	-3.79	0.79	0.18	-1.77	2.30
$100(\gamma-1)$	Normal	0.40	0.10	–	–	–	0.39	0.35	0.43
α	Normal	0.30	0.05	0.17	0.13	0.20	0.17	0.14	0.21

Table 1B. Priors and estimated posteriors of the shock processes

	Priors			Posteriors					
				Extended model			SW model		
	Distr	Mean	Std D.	Mean	5%	95%	Mean	5%	95%
σ_a	Invgamma	0.10	2.00	0.39	0.35	0.44	0.38	0.34	0.43
σ_b	Invgamma	0.10	2.00	0.12	0.08	0.16	0.09	0.05	0.13
σ_g	Invgamma	0.10	2.00	0.39	0.35	0.44	0.40	0.35	0.45
σ_i	Invgamma	0.10	2.00	0.29	0.22	0.36	0.35	0.25	0.43
σ_R	Invgamma	0.10	2.00	0.13	0.11	0.15	0.13	0.11	0.14
σ_p	Invgamma	0.10	2.00	0.13	0.09	0.16	0.11	0.09	0.14
σ_w	Invgamma	0.10	2.00	0.33	0.25	0.40	0.30	0.23	0.36
ρ_a	Beta	0.50	0.20	0.91	0.87	0.96	0.92	0.87	0.97
ρ_b	Beta	0.50	0.20	0.84	0.77	0.91	0.74	0.55	0.93
ρ_g	Beta	0.50	0.20	0.98	0.97	0.996	0.97	0.96	0.99
ρ_i	Beta	0.50	0.20	0.82	0.70	0.94	0.70	0.57	0.84
ρ_R	Beta	0.50	0.20	0.09	0.02	0.16	0.27	0.13	0.40
ρ_p	Beta	0.50	0.20	0.88	0.78	0.98	0.81	0.68	0.95
ρ_w	Beta	0.50	0.20	0.97	0.94	0.996	0.96	0.93	0.99
μ_p	Beta	0.50	0.20	0.57	0.35	0.78	0.60	0.38	0.82
μ_w	Beta	0.50	0.20	0.63	0.43	0.84	0.66	0.46	0.86
ρ_{ga}	Beta	0.50	0.20	0.40	0.25	0.57	0.40	0.24	0.56

Table 1C. Priors and estimated posteriors of revision processes parameters

	Priors			Posteriors					
				Extended model			SW model		
	Distr	Mean	Std D.	Mean	5%	95%	Mean	5%	95%
b_{yy}	Normal	0.00	2.00	0.23	0.05	0.40	–	–	–
$b_{\pi\pi}$	Normal	0.00	2.00	-0.14	-0.25	-0.02	–	–	–
b_{cc}	Normal	0.00	2.00	0.20	0.11	0.29	–	–	–
σ_{yr}	Invgamma	0.10	2.00	0.64	0.53	0.76	–	–	–
$\sigma_{\pi r}$	Invgamma	0.10	2.00	0.23	0.19	0.26	–	–	–
σ_{cr}	Invgamma	0.10	2.00	0.71	0.61	0.81	–	–	–
ρ_{yr}	Beta	0.50	0.20	0.89	0.83	0.96	–	–	–
$\rho_{\pi r}$	Beta	0.50	0.20	0.09	0.02	0.17	–	–	–
ρ_{cr}	Beta	0.50	0.20	0.80	0.74	0.87	–	–	–

Table 2. Importance of the two sources of non-rational revision processes

	Base		$b_{yy}= b_{\pi\pi}= b_{cc}= 0$		$\rho_{yr}= \rho_{\pi r}= \rho_{cr}= 0$		White noise revisions	
Marginal likelihood (based on Laplace aproximation):								
	-756		-865		-900		-901	
	Mode	SD	Mode	SD	Mode	SD	Mode	SD
φ	5.04	1.11	4.01	3.78	4.72	1.14	6.03	1.12
h	0.11	0.02	0.10	0.00	0.19	0.04	0.42	0.08
σ_c	1.39	0.16	1.36	0.20	1.32	0.17	1.09	0.18
σ_l	1.68	0.63	2.02	0.68	1.55	0.63	1.70	0.62
ξ_p	0.67	0.05	0.61	0.29	0.68	0.05	0.69	0.05
ξ_w	0.53	0.09	0.70	0.33	0.53	0.09	0.56	0.09
ι_w	0.31	0.12	0.46	0.39	0.31	0.13	0.33	0.13
ι_p	0.07	0.03	0.15	0.18	0.07	0.03	0.09	0.04
ψ	0.79	0.09	0.71	0.09	0.80	0.09	0.67	0.12
Φ	1.43	0.08	1.45	0.09	1.46	0.08	1.46	0.08
r_π	1.80	0.18	1.60	0.20	1.64	0.08	1.75	0.20
ρ	0.84	0.02	0.84	0.03	0.84	0.02	0.86	0.02
r_y	-0.01	0.01	0.01	0.04	-0.03	0.01	0.01	0.01
$r_{\Delta y}$	0.10	0.01	0.11	0.01	0.10	0.01	0.10	0.01
π	0.66	0.08	0.59	0.11	0.64	0.08	0.68	0.07
$100(\beta^{-1}-1)$	0.14	0.06	0.15	0.06	0.17	0.07	0.17	0.07
l	-1.81	1.48	0.02	1.33	-2.01	1.46	-0.32	1.49
α	0.16	0.02	0.20	0.07	0.17	0.02	0.14	0.02

Table 3. Second-moment statistics

Panel A	Δy^r	π^r	Δc^r	$rev^{\Delta y}$	rev^{π}	$rev^{\Delta c}$
US data:						
Stand. deviation (%)	0.68	0.34	0.74	0.55	0.26	0.61
Correlation with Δy	0.63	-0.01	0.37	0.27	-0.11	0.09
Autocorrelation	0.25	0.42	0.06	-0.14	0.00	-0.14
Extended model:						
Stand. deviation (%)	0.95	0.58	1.21	0.59	0.28	0.61
	(0.81,1.05)	(0.45,0.67)	(1.07,1.33)	(0.52,0.66)	(0.23,0.31)	(0.53,0.68)
Correlation with Δy	0.82	-0.26	0.69	0.39	0.23	0.04
	(0.77,0.88)	(-0.34,-0.18)	(0.62,0.74)	(0.25,0.60)	(0.19,0.28)	(-0.07,0.16)
Autocorrelation	0.17	0.65	0.05	-0.01	0.15	-0.10
	(0.10,0.23)	(0.53,0.74)	(0.02,0.09)	(-0.06,0.04)	(0.03,0.24)	(-0.14,-0.06)

Table 3. (Continued)

Panel B	Δy	Δc	Δi	Δw	l	R	π
US data:							
Stand. deviation (%)	0.58	0.53	1.74	0.65	2.19	0.61	0.24
Correlation with Δy	1.0	0.62	0.63	−0.13	−0.16	0.20	−0.14
Autocorrelation	0.29	0.17	0.56	0.18	0.97	0.98	0.51
Extended:							
Stand. deviation (%)	1.0	1.06	2.56	0.76	4.35	0.62	0.45
	(0.91,1.09)	(0.95,1.15)	(2.13,2.92)	(0.66,0.85)	(2.50,5.39)	(0.41,0.79)	(0.34,0.53)
Correlation with Δy	1.0	0.81	0.62	0.23	0.14	−0.10	−0.19
		(0.76,0.86)	(0.54,0.69)	(0.07,0.35)	(0.10,0.18)	(-0.17,-0.04)	(-0.28,-0.09)
Autocorrelation	0.25	0.12	0.74	0.33	0.98	0.94	0.80
	(0.19,0.33)	(0.06,0.17)	(0.65,0.80)	(0.21,0.47)	(0.97,0.99)	(0.91,0.98)	(0.72,0.86)
SW model:							
Stand. deviation (%)	0.78	0.68	2.08	0.75	3.62	0.45	0.47
	(0.68,0.85)	(0.60,0.75)	(1.79,2.35)	(0.64,0.83)	(2.46,4.44)	(0.35,0.52)	(0.34,0.55)
Correlation with Δy	1.0	0.68	0.65	0.19	0.11	−0.17	−0.34
		(0.60,0.77)	(0.57,0.71)	(0.07,0.30)	(0.07,0.14)	(-0.23,-0.10)	(-0.46,-0.23)
Autocorrelation	0.41	0.52	0.65	0.33	0.98	0.95	0.83
	(0.35,0.49)	(0.44,0.62)	(0.57,0.75)	(0.21,0.50)	(0.98,0.99)	(0.93,0.97)	(0.78,0.89)

Note: 95% posterior confidence intervals for second-moment statistics obtained from the models are reported in parentheses.

Table 4. Variance decomposition (percent)

Extended model

Innovations	Δy	Δy^r	Δc	Δc^r	Δi	Δw	l	R	π	π^r
Technology, η^a	7.6	5.7	1.5	0.8	3.6	1.2	1.2	4.9	5.3	4.2
Risk premium, η^b	27.3	20.7	41.0	21.8	3.9	7.5	3.2	14.9	14.1	11.3
Fiscal/Net exports, η^g	10.3	7.8	1.7	0.9	0.6	0.2	5.8	7.5	4.4	3.5
Investment adj. costs, η^i	7.6	5.8	1.1	0.6	59.8	2.4	5.2	15.5	10.9	8.7
Interest-rate, η^R	12.7	9.7	19.0	10.1	2.0	3.7	1.6	8.1	7.0	5.6
Wage-push, η^w	16.7	12.6	15.0	7.9	18.9	56.4	74.2	42.2	33.5	26.9
Price-push, η^p	8.5	6.5	5.7	3.0	9.8	26.0	7.5	3.6	22.1	17.5
Output revision, η^y	1.0	25.1	1.5	0.8	0.1	0.3	0.1	1.1	0.4	0.3
Inflation revision, η^π	4.3	3.2	5.7	3.0	1.2	1.2	0.9	1.6	2.0	21.7
Consumption revision, η^c	4.0	3.0	7.8	51.1	0.1	1.1	0.4	0.6	0.5	0.4

SW model

Innovations	Δy	Δy^r	Δc	Δc^r	Δi	Δw	l	R	π	π^r
Technology, η^a	12.6	–	5.2	–	3.0	1.1	1.3	7.1	2.3	–
Risk premium, η^b	20.2	–	37.4	–	3.8	5.0	3.3	30.5	7.0	–
Fiscal/Net exports, η^g	19.9	–	4.1	–	0.2	0.1	5.6	2.1	0.5	–
Investment adj. costs, η^i	12.3	–	1.9	–	74.4	1.9	4.2	13.1	3.0	–
Interest-rate, η^R	9.2	–	15.0	–	2.6	3.3	2.3	7.2	6.1	–
Wage-push, η^w	18.0	–	29.5	–	9.9	70.0	78.6	34.1	53.4	–
Price-push, η^p	7.6	–	6.9	–	6.1	18.7	4.7	5.9	27.8	–

Table 5. Marginal likelihood and mode of parameters under some restrictions

	Base	$\xi_p = 0.1$	$\xi_w = 0.1$	$\iota_p = 0.0$	$\iota_w = 0.0$	$\varphi = 0.1$	$h = 0.0$	$\psi = 0.99$	$\Phi = 1.1$
Marginal likelihood (based on Laplace aproximation):									
	-756	-794	-1042	-747	-754	-1047	-736	-752	-766
Mode of the structural parameters:									
φ	5.05	3.55	4.16	5.08	5.05	0.1	5.02	5.03	4.81
h	0.11	0.12	0.10	0.12	0.11	0.10	0.0	0.11	0.12
σ_c	1.39	1.38	1.41	1.38	1.40	1.06	1.61	1.41	1.29
σ_l	1.68	2.06	-0.36	1.64	1.72	2.34	2.01	1.72	1.97
ξ_p	0.67	0.1	0.59	0.69	0.67	0.41	0.69	0.66	0.74
ξ_w	0.53	0.32	0.1	0.54	0.55	0.28	0.58	0.52	0.50
ι_w	0.31	0.50	0.41	0.31	0.0	0.41	0.28	0.31	0.31
ι_p	0.07	0.81	0.03	0.0	0.07	0.11	0.07	0.08	0.08
ψ	0.79	0.86	0.79	0.67	0.79	0.86	0.76	0.99	0.81
Φ	1.43	1.57	1.54	1.43	1.43	1.31	1.44	1.42	1.1
r_π	1.80	2.00	1.03	1.82	1.81	2.08	1.67	1.80	1.88
ρ	0.84	0.82	0.84	0.84	0.84	0.79	0.85	0.84	0.83
r_y	-0.01	-0.02	0.01	-0.01	-0.01	-0.02	0.02	-0.01	-0.01
$r_{\Delta y}$	0.10	0.08	0.05	0.10	0.10	0.10	0.09	0.10	0.09
α	0.17	0.20	0.18	0.16	0.17	0.24	0.17	0.16	0.15

Table 5. (*Continued*)

	Base	$\xi_p = 0.1$	$\xi_w = 0.1$	$\iota_p = 0.0$	$\iota_w = 0.0$	$\varphi = 0.1$	$h = 0.0$	$\psi = 0.99$	$\Phi = 1.1$
Mode of the revision process parameters:									
b_{yy}	0.21	0.23	0.27	0.20	0.20	0.19	0.13	0.21	0.23
$b_{\pi\pi}$	−0.15	−0.33	−0.04	0.18	−0.16	−0.30	−0.12	−0.16	−0.18
b_{cc}	0.21	0.21	−0.21	0.21	0.21	0.26	0.19	0.22	0.21
ρ_{yr}	0.90	0.90	0.92	0.90	0.90	0.89	0.87	0.89	0.90
$\rho_{\pi r}$	0.07	0.08	0.08	0.08	0.07	0.08	0.08	0.07	0.07
ρ_{cr}	0.81	0.81	0.98	0.81	0.81	0.79	0.88	0.81	0.81
σ_{yr}	0.62	0.63	0.64	0.62	0.62	0.61	0.59	0.62	0.63
$\sigma_{\pi r}$	0.22	0.19	0.24	0.21	0.22	0.19	0.23	0.22	0.21
σ_{cr}	0.70	0.71	0.47	0.71	0.70	0.75	0.68	0.71	0.70

Appendix

Set of log-linearized dynamic equations:

- Inflation identity:

$$\pi_t = \pi^r_{t,t+1} + rev^\pi_{t,t+S}. \tag{A1}$$

- Output identity:

$$y_t \equiv y^r_{t,t+1} + rev^y_{t,t+S}. \tag{A2}$$

- Consumption identity:

$$c_t \equiv c^r_{t,t+1} + rev^c_{t,t+S}. \tag{A3}$$

- Revision process of inflation:

$$rev^\pi_{t,t+S} = b_{\pi\pi}\pi^r_{t,t+1} + \varepsilon^\pi_{t,t+S}. \tag{A4}$$

- Revision process of output:

$$rev^y_{t,t+S} = b_{yy}y^r_{t,t+1} + \varepsilon^y_{t,t+S}. \tag{A5}$$

- Revision process of consumption:

$$rev^c_{t,t+S} = b_{cc}c^r_{t,t+1} + \varepsilon^c_{t,t+S}. \tag{21}$$

- Aggregate resource constraint:

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon^g_t, \tag{A7}$$

where $c_y = \frac{C}{Y} = 1 - g_y - i_y$, $i_y = \frac{I}{Y} = (\gamma - 1 + \delta)\frac{K}{Y}$, and $z_y = r^k\frac{K}{Y}$ are steady-state ratios. As in Smets and Wouters (2007), the depreciation rate and the exogenous spending-GDP ratio are fixed in the estimation procedure at $\delta = 0.025$ and $g_y = 0.18$.

- Consumption equation:

$$c_t = c_1 c^r_{t-1,t} + (1-c_1)E_t c_{t+1} + c_2\left(l_t - E_t l_{t+1}\right) - c_3(R_t - E_t\pi_{t+1}) + \varepsilon^b_t + c_4\varepsilon^c_{t-s,t} \tag{A8}$$

where $c_1 = \frac{h/\gamma}{1+(h/\gamma)(1+b_{cc})^{-1}}$, $c_2 = \frac{(\sigma_c-1)wL/(\phi_w C)}{\sigma_c(1+(h/\gamma)(1+b_{cc})^{-1})}$, $c_3 = \frac{1-h/\gamma}{\sigma_c(1+(h/\gamma)(1+b_{cc})^{-1})}$ and $c_4 = \frac{(h/\gamma)\rho^S_c}{(1+b_{cc})(1+(h/\gamma)(1+b_{cc})^{-1})}$.

- Investment equation:

$$i_t = i_1 i_{t-1} + (1-i_1)\, E_t i_{t+1} + i_2 q_t + \varepsilon^i_t, \tag{A9}$$

where $i_1 = \frac{1}{1+\overline{\beta}}$, and $i_2 = \frac{1}{\left(1+\overline{\beta}\right)\gamma^2\varphi}$ with $\overline{\beta} = \beta\gamma^{(1-\sigma_c)}$.

- Arbitrage condition (value of capital, q_t):

$$q_t = q_1 E_t q_{t+1} + (1-q_1)E_t r^k_{t+1} - (R_t - E_t\pi_{t+1}) + c_3^{-1}\varepsilon^b_t, \tag{A10}$$

where $q_1 = \overline{\beta}\gamma^{-1}(1-\delta) = \frac{(1-\delta)}{\left(r^k+1-\delta\right)}$.

- Log-linearized aggregate production function:

$$y_t = \phi_p\left(\alpha k^s_t + (1-\alpha)l_t + \varepsilon^a_t\right), \tag{A11}$$

where $\phi_p = 1 + \frac{\phi}{Y} = 1 + \frac{\text{Steady-state fixed cost}}{Y}$ and α is the capital-share in the production function.[25]

- Effective capital (with one period time-to-build):

$$k^s_t = k_{t-1} + z_t. \tag{A12}$$

- Capital utilization:

$$z_t = z_1 r^k_t, \tag{A13}$$

where $z_1 = \frac{1-\psi}{\psi}$.

[25] From the zero profit condition in steady-state, it should be noticed that ϕ_p also represents the value of the steady-state price mark-up.

- Capital accumulation equation:

$$k_t = k_1 k_{t-1} + (1 - k_1) i_t + k_2 \varepsilon_t^i, \tag{A14}$$

where $k_1 = \frac{1-\delta}{\gamma}$ and $k_2 = \left(1 - \frac{1-\delta}{\gamma}\right)\left(1 + \overline{\beta}\right)\gamma^2 \varphi$.

- Price mark-up (negative of the log of the real marginal cost):

$$\mu_t^p = mpl_t - w_t = \alpha\left(k_t^s - l_t\right) + \varepsilon_t^a - w_t. \tag{A15}$$

- New-Keynesian Phillips curve (price inflation dynamics):

$$\pi_t = \pi_1 \pi_{t-1,t}^r + \pi_2 E_t \pi_{t+1} - \pi_3 \mu_t^p + \pi_4 \varepsilon_t^p + \pi_5 \varepsilon_{t-s,t}^\pi. \tag{A16}$$

where $\pi_1 = \frac{\iota_p}{1+\overline{\beta}\iota_p B}$, $\pi_2 = \frac{\overline{\beta}}{1+\overline{\beta}\iota_p B}$, $\pi_3 = \frac{A}{1+\overline{\beta}\iota_p B}\left[\frac{\left(1-\overline{\beta}\xi_p\right)\left(1-\xi_p\right)}{\xi_p}\right]$, $\pi_4 = \frac{1+\overline{\beta}\iota_p}{1+\overline{\beta}\iota_p B}$ and $\pi_5 = \frac{\overline{\beta}\iota_p B \rho_\pi^S}{1+\overline{\beta}\iota_p B}$. The coefficient of the curvature of the Kimball goods market aggregator, included in the definition of A, is fixed in the estimation procedure at $\varepsilon_p = 10$ as in Smets and Wouters (2007).

- Optimal demand for capital by firms:

$$-\left(k_t^s - l_t\right) + w_t = r_t^k. \tag{A17}$$

- Wage markup equation:

$$\mu_t^w = w_t - mrs_t = w_t - \left(\sigma_l l_t + \frac{1}{1-h/\gamma}\left(c_t - \left(h/\gamma\right) c_{t-1,t}^r\right)\right). \tag{A18}$$

- Real wage dynamic equation:

$$w_t = w_1 w_{t-1} + (1 - w_1)\left(E_t w_{t+1} + E_t \pi_{t+1}\right) - w_2 \pi_t + w_3 \pi_{t-1,t}^r - w_4 \mu_t^w + w_5 \varepsilon_{t-s,t}^\pi + \varepsilon_t^w. \tag{A19}$$

where $w_1 = \frac{1}{1+\overline{\beta}}$, $w_2 = \frac{1+\overline{\beta}\iota_w B}{1+\overline{\beta}}$, $w_3 = \frac{\iota_w}{1+\overline{\beta}}$, $w_4 = \frac{1}{1+\overline{\beta}}\left[\frac{\left(1-\overline{\beta}\xi_w\right)\left(1-\xi_w\right)}{\xi_w\left(\left(\phi_w-1\right)\varepsilon_w+1\right)}\right]$ and $w_5 = w_1 \overline{\beta}\iota_w B \rho_\pi^S$ with the curvature of the Kimball labor aggregator fixed at $\varepsilon_w = 10.0$ and a steady-state wage mark-up fixed at $\phi_w = 1.5$ as in Smets and Wouters (2007).

- Monetary policy rule, a Taylor-type rule for nominal interest rate management:

$$\begin{aligned} R_t &= \rho R_{t-1} + (1-\rho)[r_\pi E_t \pi_{t-1} + r_y (E_t y_{t-1} - y^p_{t-1})] + \\ & \quad r_{\Delta y}\left[(E_t y_{t-1} - y^p_{t-1}) - (E_t y_{t-2} - y^p_{t-2})\right] + \varepsilon^R_t \end{aligned} \tag{A20}$$

where $E_t\pi_{t-1} = \pi^r_{t-1,t} + b_{\pi\pi}\pi^r_{t-1,t} + \rho_\pi^{S-1}\varepsilon^\pi_{t-S,t}$, $E_t y_{t-1} = y^r_{t-1,t} + b_{yy}y^r_{t-1,t} + \rho_y^{S-1}\varepsilon^y_{t-S,t}$ and $E_t y_{t-2} = y^r_{t-2,t-1} + b_{yy}y^r_{t-2,t-1} + \rho_y^{S-2}\varepsilon^y_{t-S,t}$.

Potential (natural-rate) variables, assuming flexible prices, flexible wages and shutting down price mark-up and wage indexation shocks as well as revision shocks:

- Flexible-price condition (no price mark-up fluctuations, $\mu^p_t = mpl_t - w_t = 0$):

$$\alpha\,(k^{s,p}_t - l^p_t) + \varepsilon^a_t = w^p_t. \tag{A21}$$

- Flexible-wage condition (no wage mark-up fluctuations, $\mu^w_t = w_t - mrs_t = 0$):

$$w^p_t = \sigma_l l^p_t + \tfrac{1}{1-\lambda/\gamma}\left(c^p_t - \lambda/\gamma c^p_{t-1}\right). \tag{A22}$$

- Potential aggregate resources constraint:

$$y^p_t = c_y c^p_t + i_y i^p_t + z_y z^p_t + \varepsilon^g_t. \tag{A23}$$

- Potential consumption equation:

$$c^p_t = c_1 c^p_{t-1} + (1-c_1)\,E_t c^p_{t+1} + c_2\left(l^p_t - E_t l^p_{t+1}\right) - c_3\left(R^p_t - E_t\pi^p_{t+1}\right) + \varepsilon^b_t. \tag{A24}$$

- Potential investment equation:

$$i^p_t = i_1 i^p_{t-1} + (1-i_1)\,E_t i^p_{t+1} + i_2 q^p_t + \varepsilon^i_t. \tag{A25}$$

- Arbitrage condition (value of potential capital, q^p_t):

$$q^p_t = q_1 E_t q^p_{t+1} + (1-q_1)E_t r^{k,p}_{t+1} - \left(R^p_t - E_t\pi^p_{t+1}\right) + c_3^{-1}\varepsilon^b_t. \tag{A26}$$

- Log-linearized potential aggregate production function:

$$y_t^p = \phi_p \left(\alpha k_t^{s,p} + (1-\alpha) l_t^p + \varepsilon_t^a\right). \tag{A27}$$

- Potential capital (with one period time-to-build):

$$k_t^{s,p} = k_{t-1}^p + z_t^p. \tag{A28}$$

- Potential capital utilization:

$$z_t^p = z_1 r_t^{k,p}. \tag{A29}$$

- Potential capital accumulation equation:

$$k_t^p = k_1 k_{t-1}^p + (1-k_1) i_t^p + k_2 \varepsilon_t^i. \tag{A30}$$

- Potential demand for capital by firms ($r_t^{k,p}$ is the potential log of the rental rate of capital):

$$-\left(k_t^{s,p} - l_t^p\right) + w_t^p = r_t^{k,p}. \tag{A31}$$

- Monetary policy rule (under flexible prices and flexible wages):

$$R_t^p = \rho R_{t-1}^p + (1-\rho)\left[r_\pi \pi_t^p\right] + \varepsilon_t^R. \tag{A32}$$

Equations-and-variables summary

- Set of equations:

Equations (A1)-(A32) determine solution paths for 32 endogenous variables.

- Set of variables:

Endogenous variables (32): y_t, c_t, i_t, z_t, l_t, R_t, π_t, q_t, r_t^k, k_t^s, k_t, μ_t^w, μ_t^p, w_t, y_t^r, π_t^r, c_t^r, r_t^y, r_t^π, r_t^c, y_t^p, c_t^p, i_t^p, z_t^p, l_t^p, R_t^p, π_t^p, q_t^p, $r_t^{k,p}$, $k_t^{s,p}$, k_t^p, and w_t^p.

Predetermined variables (17): c_{t-1}, i_{t-1}, k_{t-1}, π_{t-1}, w_{t-1}, R_{t-1}, y_{t-1}, y_{t-1}^r, π_{t-1}^r, c_{t-1}^r, r_{t-1}^y, r_{t-1}^π, r_{t-1}^c, c_{t-1}^p, i_{t-1}^p, k_{t-1}^p, and r_{t-1}^p.

Exogenous variables (10): AR(1) technology shock $\varepsilon_t^a = \rho_a \varepsilon_{t-1}^a + \eta_t^a$, AR(1) risk premium shock $\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b$, AR(1) exogenous spending shock cross-correlated to technology innovations $\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a$, AR(1) investment shock $\varepsilon_t^i = \rho_i \varepsilon_{t-1}^i + \eta_t^i$, AR(1) monetary policy shock $\varepsilon_t^R = \rho_R \varepsilon_{t-1}^R + \eta_t^R$, ARMA(1,1) price mark-up shock $\varepsilon_t^p = \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p$, ARMA(1,1) wage mark-up shock $\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w - \mu_w \eta_{t-1}^w$, AR(1) output revision shock $\varepsilon_{t,t+S}^y = \rho_{yr} \varepsilon_{t-1,t-1+S}^y + \eta_{t+S}^y$, AR(1) inflation revision shock $\varepsilon_{t,t+S}^\pi = \rho_{\pi r} \varepsilon_{t-1,t-1+S}^\pi + \eta_{t+S}^\pi$ and AR(1) consumption revision shock $\varepsilon_{t,t+S}^c = \rho_{cr} \varepsilon_{t-1,t-1+S}^c + \eta_{t+S}^c$.

Table A. Model parameter description

φ	Elasticity of the cost of adjusting capital
h	External habit formation
σ_c	Inverse of the elasticity of intertemporal substitution in utility function
σ_l	Inverse of the elasticity of labor supply with respect to the real wage
ξ_p	Calvo probability that measures the degree of price stickiness
ξ_w	Calvo probability that measures the degree of wage stickiness
ι_w	Degree of wage indexation to past wage inflation
ι_p	Degree of price indexation to past price inflation
ψ	Elasticity of capital utilization adjustment cost
Φ	One plus steady-state fixed cost to total cost ratio (price mark-up)
r_π	Inflation coefficient in monetary policy rule
ρ	Smoothing coefficient in monetary policy rule
r_Y	Output gap coefficient in monetary policy rule
π	Steady-state rate of inflation
$100(\beta^{-1}-1)$	Steady-state rate of discount
l	Steady-state labor
$100(\gamma-1)$	One plus steady-state rate of output growth
α	Capital share in production function
b_{yy}	Output coefficient in output revision process
$b_{\pi\pi}$	Inflation coefficient in inflation revision process
b_{cc}	Consumption coefficient in consumption revision process

Table A. (*Continued*)

σ_a	Standard deviation of productivity innovation
σ_b	Standard deviation of risk premium innovation
σ_g	Standard deviation of exogenous spending innovation
σ_i	Standard deviation of investment-specific innovation
σ_R	Standard deviation of monetary policy rule innovation
σ_p	Standard deviation of price mark-up innovation
σ_w	Standard deviation of wage mark-up innovation
σ_y^r	Standard deviation of output revision innovation
σ_π^r	Standard deviation of inflation revision innovation
σ_c^r	Standard deviation of consumption revision innovation
ρ_a	Autoregressive coefficient of productivity shock
ρ_b	Autoregressive coefficient of risk premium shock
ρ_g	Autoregressive coefficient of exogenous spending shock
ρ_i	Autoregressive coefficient of investment-specific shock
ρ_R	Autoregressive coefficient of policy rule shock
ρ_p	Autoregressive coefficient of price mark-up shock
ρ_w	Autoregressive coefficient of wage mark-up shock
μ_p	Moving-average coefficient of price mark-up shock
μ_w	Moving-average coefficient of wage mark-up shock
ρ_{ga}	Correlation coefficient between productivity and exogenous spending shocks
ρ_{yr}	Autoregressive coefficient of output revision shock
$\rho_{\pi r}$	Autoregressive coefficient of inflation revision shock
ρ_{cr}	Autoregressive coefficient of consumption revision shock