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ARTICLES

DATA REVISIONS IN THE ESTIMATION OF DSGE MODELS

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Revisions of U.S. macroeconomic data are persistent, correlated with real-time data, and with high variability (around 80% of U.S. real-time data volatility). This paper adapts a DSGE-style model to accommodate both real-time and revised data from the U.S. economy. The results show a lesser role of both habit formation and price indexation than in the standard model. In the simulations, revision shocks to both output and inflation are expansionary because the Fed reacts by cutting interest rates. Consumption revisions, in contrast, are countercyclical, consumption mirrors the observed reduction in real-time consumption. In the variance decomposition, data revisions explain 9.3% of output changes.

Keywords: Data Revisions, DSGE Models, Business Cycles

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 U.S. real-time data available at the Philadelphia Fed Website, and the evidence provided in many papers that data revisions matter in business cycles. Croushore (2011) provides an excellent survey on the frontiers of real-time data analysis.

The aim of this paper is to analyze how structural modeling is affected by data revisions. If revisions of real-time data are rational forecast errors (i.e., revisions are orthogonal to each data release), revised data will not be relevant for either private agents or policy makers. In turn, the optimal decision rules and the parameter estimates of a DSGE model will be rather similar using revised or real-time data or both together. However, if data revisions were not rational forecast errors,

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DSGE models would be misleading for two main reasons. From a theoretical perspective, model dynamics could be different when agents took into account initial announcements that were not rational forecast of revised data. From an empirical perspective, parameter estimates could be biased.

Empirical evidence seems to support the lack of orthogonality between initial announcements and data revisions. As two examples, Faust et al. (2005) find that revisions of gross domestic product (GDP) in Japan and in the United Kingdom are forecastable in real time, whereas Aruoba (2008) provides evidence indicating that the initial announcements of U.S. aggregate variables are not rational forecasts of revised data. Thus, U.S. data revisions are found to be persistent and correlated with real-time data initially released by statistical agencies. Moreover, the volatility of U.S. data revisions is high: the standard deviation of revisions is of similar magnitude to the corresponding standard deviation of real-time data (as will be documented).

This paper contributes to the real-time data literature by extending the conventional DSGE model of Smets and Wouters (2007) to incorporate data revisions of output, inflation, and consumption.[1] In the model variant introduced here, it is assumed that economic agents make some normative decisions taking into account real-time data, and they also consider that real-time data may not be a rational forecast of revised data. Consequently, the generating processes of these revisions might have some impact on final revised data as well. More precisely, the introduction of real-time data leads to alternative specifications of the New Keynesian Phillips curve, the real wage equation, the IS curve, and the monetary policy rule. These alternative specifications would have been identical to the original ones, except for a white noise component, if revisions of real-time data were rational forecast errors.

In the econometric exercise, the extended model with data revisions is estimated using both revised and real-time U.S. data, whereas the Smets and Wouters (2007) model is reestimated using only revised U.S. data. The aim of the estimation exercise is twofold: first, to assess the importance of data revisions in the estimation of DSGE models; second, to examine the implications of revisions variability for U.S. business cycle fluctuations.

The results indicate that most parameter estimates are fairly robust to whether real-time data are taken into account or not. Nevertheless, there are some noticeable differences. The most significant are lower estimates of both consumption habit formation and the price indexation coefficient of lagged inflation in the extended model with data revisions. As for the role of data revisions in the variance decomposition, 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 match to the second-moment statistics of U.S. data revisions, with volatilities similar to those observed in fluctuations of actual revisions. The revisions of output

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and consumption are positively related to the 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 noise, as opposed to revisions that can be a source of additional news. Finally, the revisions of both output and inflation are procyclical, whereas the revisions of consumption are countercyclical.

The rest of the paper is organized as follows. Section 2 briefly summarizes the related literature. Section 3 extends the Smets and Wouters (2007) model to consider both revised and real-time data. Section 4 describes the U.S. data set and the Bayesian estimation procedure. Section 5 discusses the estimation results and conducts the business cycle analysis. Finally, Section 6 concludes.

2. RELATED LITERATURE

As pointed out, Croushore (2011) provides an up-to-date survey of the literature on real-time data analysis. Let us highlight here a few of these contributions. One of the first studies to investigate the properties of revision processes is Diebold and Rudebusch (1991).[2] They show that the U.S. index of leading indicators does a poor job in predicting future movements of output in real time because it is built to explain the past. More recently, Orphanides (2001, 2003) focuses on real-time aspects of monetary policy. He argues that U.S. monetary policy was too loose because of misperceptions in the real-time output gap. More closely connected to this paper, 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.

Our paper is in the same vein as Vázquez et al. (2012). They study the importance of real-time data in a canonical three-equation 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) is another unpublished paper close in spirit to the idea explored in this paper that data revisions (and, more generally, data uncertainty) affect economic decisions, but the DSGE model and the empirical approach considered in his paper differ substantially from the ones followed here.

More generally, our approach is also linked to a recent macroeconomic literature analyzing imperfect information issues in the context of small-scale models, where the assumption of perfect information for the private sector is somehow relaxed. This literature includes, among others, the rational inattention approach [Sims (2003); Adam (2007); Mackowiach and Wiederholt (2009)], the sticky information approach [Reis (2009)], and the imperfect information approach [Svensson and Woodford (2004); Coenen et al. (2005); Levine et al. (2012); Pruitt (2012); Berardi and Duffy (2015)]. In our model, expectations are fully rational, as is standard in (medium-scale) DSGE models, but some of the sluggishness mechanisms in place (consumption habits and indexation rules) are built upon real-time data. The reason for maintaining the rational expectations assumption in the private sector

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is that including data revisions in an otherwise standard medium-scale model à la Smets and Wouters (2007) seems like a first promising step to isolate the effect of data revisions from other imperfect information, learning issues, and alternative modeling strategies.

The use of a medium-scale model in this paper, as opposed to small-scale models used in the limited information literature summarized in the preceding, is well motivated in the literature, because medium-scale models incorporate price/wage indexation schemes, consumption habits, variable capital utilization, and adjustment costs for changes in investment, which help to improve the fitting of sticky-price models to regularities found in actual business cycle fluctuations [see Kimball (1995), King and Watson (1996), and Casares and McCallum (2006), among others]. However, some of these sluggishness mechanisms, such as variable capital utilization and adjustment costs for changes in investment, are missing in the small-scale models that belong to the imperfect information literature. Moreover, Ireland (2003) has shown that using data on both consumption and investment in addition to output, as opposed to only using output [as in Levine et al. (2012)], helps to estimate adjustment cost parameters for both capital and prices.

Finally, our paper is also related to other recent papers assessing DSGE models. Whereas our paper looks at the ability of these models to reproduce the business cycle features of data revisions, other papers, such as Edge et al. (2010) and Herbst and Schorfheide (2011), explore their out-of-sample forecasting performance by using real-time data instead of final revised data.

3. A DSGE MODEL WITH REAL-TIME DATA

This section extends the well-known DSGE model described in Smets and Wouters (2007), SW henceforth, with both real-time data and data revisions. The goal is to let data uncertainty and economic decisions interact, assuming that some decisions rely 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 on 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: 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 introduced.

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3.1. Revision Processes

Initial announcements of quarterly U.S. real GDP, the GDP deflator, and real private consumption are typically made by statistical agencies with a short delay. Thus, the first release of quarterly GDP is reported at the end of the month of the next quarter.[3] Final revisions may take much longer time to be published. Depending upon circumstances, final data on macroeconomic variables may need between 2 and 12 quarters to be released.[4]

In our model, the number of periods (quarters) of delay for data revisions is constant and denoted by S.[5] Subsequently, let us consider the following identities relating revised data on the cyclical components of output, y_t, inflation, π_t, and consumption, c_t, to both the initial announcements and the final revisions:

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

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

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

where $y^r_{t,t+1}$ denotes real-time output at time t, released at the beginning of quarter $t+1$, and $\text{rev}^y_{t,t+S}$ denotes the final revision of output that will be announced in quarter $t+S$. Analogous notation and timing conventions are used for the revisions of both inflation and consumption. Hence, we assume that real-time data for a given period (say t) are released at the beginning of the following period (say $t+1$), just before economic decisions for period $t+1$ are made. This assumption is consistent with the timing observed in the initial announcements of U.S. data.

Aruoba (2008) argues that U.S. 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.[6] We follow this line of argument to assume that revisions of output, inflation, and consumption are determined by the following processes:

$$\text{rev}^y_{t,t+S} = b_{yy} y^r_{t,t+1} + \varepsilon^y_{t,t+S}, \tag{4}$$

$$\text{rev}^\pi_{t,t+S} = b_{\pi\pi} \pi^r_{t,t+1} + \varepsilon^\pi_{t,t+S}, \tag{5}$$

$$\text{rev}^c_{t,t+S} = b_{cc} c^r_{t,t+1} + \varepsilon^c_{t,t+S}. \tag{6}$$

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.[7] More precisely, these processes allow for (i) the existence of nonzero correlations between output, inflation, and consumption revisions and their initial announcements; and (ii) the presence of persistent revision processes. In particular, the

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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.

3.2. New Keynesian Phillips Curve

The separation between real-time data and revised data may have an impact on pricing decisions that use indexation rules. SW (2007), and many other papers, consider that all firms that cannot 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 previously, whereas it was charging $P_t(\omega) = (1 + \pi_{t-1})P_{t-1}(\omega)$ in SW (2007). Notice that the timing convention assumed above in the preceding implies that $\pi^{r}_{t-1,t}$ is known at the beginning of period t when firms set their prices. As we adopt such a real-time price indexation scheme, the loglinearized equation for the optimal price set by firms capable of reoptimizing their prices becomes[8]

$$p^{*}_{t}(i) = \left(1 - \overline{\beta}\xi_p\right) E_t \sum_{j=0}^{\infty} \overline{\beta}^{j} \xi_p^{j} \left\{ A \left[\mathrm{mc}_{t+j}(i) + \lambda^{p}_{t+j} \right] + p_{t+j} - \iota_p \sum_{k=1}^{j} \pi^{r}_{t+k-1,t+k} \right\},$$

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 future optimal pricing, $\overline{\beta} = \beta\gamma^{(1-\sigma_c)}$ is a discount factor that incorporates γ as the long-run balanced rate of economic growth, σ_c is the consumption elasticity in the utility function, 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.[9] The optimal price depends on the expectations of three factors: the log of the real marginal cost, $\mathrm{mc}_{t+j}(i)$, 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, 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:

$$\widetilde{P}^{*}_{t}(i) = A\left(1 - \overline{\beta}\xi_p\right) E_t \sum_{j=0}^{\infty} \overline{\beta}^{j} \xi_p^{j} \left[\mathrm{mc}_{t+j}(i) + \lambda^{p}_{t+j}\right] + E_t \sum_{j=1}^{\infty} \overline{\beta}^{j} \xi_p^{j} \left(\pi_{t+j} - \iota_p \pi^{r}_{t+j-1,t+j}\right). \quad (7)$$

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Loglinearizing the aggregate price level with Calvo pricing and the indexation rule lead to the semi-loglinear relationship $\widetilde{P}_t^*(i) = \frac{\xi_p}{1-\xi_p}(\pi_t - \iota_p \pi_{t-1,t}^r)$, which can be substituted in (7) to obtain[10]

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

where, following the SW (2007) convention, the mark-up shock has been rescaled at $\varepsilon_t^p = A[\frac{(1-\overline{\beta}\xi_p)(1-\xi_p)}{\xi_p}]\lambda_t^p$ and we have denoted μ_t^p as the log deviation of the price mark-up ($\mu_t^p = -\mathrm{mc}_t$). It should be noticed that when real-time 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 the equation (10), on p. 590 of SW (2007), reproduced here as follows:

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

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

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

where $B = \frac{1}{(1+b_{\pi\pi})} > 1$ whenever $b_{\pi\pi} < 0$. Applying rational expectations to (8), we have $E_t\pi_t = \pi_t$. Substituting equation (10) into equation (8) yields

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

Comparing equations (9) and (11), we observe that introducing inflation inertia based on real-time data has three type of effect on the NKPC specification. First, lagged inflation, π_{t-1}, is replaced by lagged real-time inflation, $\pi_{t-1,t}^r$. Second, current inflation is also affected by data revisions: there is a positive impact from the inflation-revision shock, $\varepsilon_{t-S,t}^{\pi}$. Finally, the slope of the NKPC with data revisions is flatter (i.e., $[\frac{A(1-\overline{\beta}\xi_p)(1-\xi_p)}{(1+\overline{\beta}\iota_p B)\xi_p}] < [\frac{A(1-\overline{\beta}\xi_p)(1-\xi_p)}{(1+\overline{\beta}\iota_p)\xi_p}]$) whenever $B > 1$.

3.3. 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 and one indexation rule based on lagged inflation. The separation between real-time data and revised data motivates a wage

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indexation rule that uses real-time lagged inflation, $\pi^r_{t-1,t}$, instead of revised lagged inflation, π_{t-1}. In turn, the relative optimal wage, $\widetilde{W}^*_t$, in our extended model becomes

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

where ξ_w is the Calvo probability of not being able to set the optimal wage and ι_w is the wage indexation parameter. As a result, the real wage dynamic equation differs from the one considered in the SW model in those terms related to the indexation factor,

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

where $w_1 = \frac{1}{1+\overline{\beta}}$, $w_2 = \frac{\iota_w}{1+\overline{\beta}}$, and $w_3 = \frac{1}{1+\overline{\beta}}\left[\frac{(1-\overline{\beta}\xi_w)(1-\xi_w)}{\xi_w((\phi_w-1)\varepsilon_w+1)}\right]$. If $\pi_t = \pi^r_{t,t+1}$ then equation (12) becomes identical to the corresponding equation (13) on p. 591 of SW (2007). Noticing that $E_t \pi^r_{t,t+1} = B[\pi_t - \rho^S_{\pi r} \varepsilon^\pi_{t-S,t}]$, (12) yields (after grouping terms)

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

There are two implications of introducing real-time data: the presence of real-time lagged inflation, $\pi^r_{t-1,t}$, and the inclusion of inflation revision innovations, $\varepsilon^\pi_{t-S,t}$.

3.4. Monetary Policy Rule

Adapting equation (14) on p. 591 of SW (2007) to interest-rate setting in real time, 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 R_t is the nominal interest rate set at the beginning of period t, $0 < \rho < 1$ is the policy smoothing coefficient, 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 the output gap, 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

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variables. Using identities (1) and (2), the preceding expression gives

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

where the revision processes (4) and (5) can be inserted to yield[11]

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

Both real-time data and data revisions enter the reaction function of the central bank (13). This is different from reduced-form monetary rules based only on either 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 that of Orphanides and Van Norden (2002), where output gap estimates are obtained in real time.[12]

3.5. Consumption Equation

Unlike SW (2007), we assume that consumption habits are built upon the real-time observation of lagged aggregate consumption, $c^r_{t-1,t}$. Recalling the optimizing program of the i representative household in SW (2007), the log-linearized first-order conditions of consumption and purchases of bonds are[13]

$$\log \Xi_t = -\frac{\sigma_c}{1-h/\gamma}c_t + \frac{(h/\gamma)\,\sigma_c}{1-(h/\gamma)}c^r_{t-1,t} + (\sigma_c - 1)\,L^{1+\sigma_l}l_t, \tag{14}$$

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

where Ξ_t is the Lagrange multiplier of the budget constraint, $0 \le h \le 1$ is the habit parameter, l_t is the log deviation of hours worked from their steady-state value (L), σ_l is the labor elasticity parameter in the utility function, and ε^b_t is the risk-premium shock. Using (14) and the corresponding expression of (14) for

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period $t+1$ in equation (15), the following consumption equation is obtained:

$$c_t = (h/\gamma)\, c^r_{t-1,t} - (h/\gamma)\, E_t c^r_{t,t+1} + E_t c_{t+1} + \frac{(1-h/\gamma)\,(\sigma_c-1)\,L^{1+\sigma_l}}{\sigma_c}(l_t - E_t l_{t+1}) - \frac{1-h/\gamma}{\sigma_c}(R_t - E_t\pi_{t+1} + \varepsilon^b_t). \tag{16}$$

Because 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,

$$E_t c^r_{t,t+1} = (1+b_{cc})^{-1}\left[c_t - \rho^S_{cr}\varepsilon^c_{t-S,t}\right], \tag{17}$$

where $E_t c_t = c_t$ was used as implied by (16). Inserting (17) into (16) and applying the steady-state wage mark-up $w = \phi_w(1-h/\gamma)CL^{\sigma_l}$ leads to the IS-style consumption equation

$$c_t = c_1 c^r_{t-1,t} + (1-c_1)E_t c_{t+1} + c_2\,(l_t - E_t l_{t+1}) - c_3(R_t - E_t\pi_{t+1} + \varepsilon^b_t) + c_4\varepsilon^c_{t-S,t}, \tag{18}$$

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 $c_4 = \frac{(h/\gamma)\rho^S_{cr}}{(1+b_{cc})(1+(h/\gamma)(1+b_{cc})^{-1})}$, and real-time lagged consumption, $c^r_{t-1,t}$, brings the backward-looking pattern of consumption dynamics.

3.6. Wage Mark-Up Equation

The log fluctuation of the wage mark-up, μ^w_t, is defined as the log difference between the real wage and the marginal rate of substitution between hours worked and consumption, mrs_t. It gives

$$\mu^w_t = w_t - \text{mrs}_t = w_t - \left\{\sigma_l l_t + \frac{1}{1-h/\gamma}\left[c_t - (h/\gamma)\, c^r_{t-1,t}\right]\right\}, \tag{19}$$

which also incorporates real-time lagged consumption, $c^r_{t-1,t}$, in the extended model.

3.7. 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 $\varepsilon^b_t = \rho_b\varepsilon^b_{t-1} + \eta^b_t$, the exogenous spending shock driven by an AR(1) process with an extra term capturing the potential influence of technology innovations on exogenous spending $\varepsilon^g_t = \rho_g\varepsilon^g_{t-1} + \eta^g_t + \rho_{ga}\eta^a_t$, the AR(1) investment shock $\varepsilon^i_t = \rho_i\varepsilon^i_{t-1} + \eta^i_t$, the AR(1) monetary policy shock $\varepsilon^R_t = \rho_R\varepsilon^R_{t-1} + \eta^R_t$, the ARMA(1,1) price mark-up shock $\varepsilon^p_t = \rho_p\varepsilon^p_{t-1} + \eta^p_t - \mu_p\eta^p_{t-1}$, the ARMA(1,1) wage mark-up shock $\varepsilon^w_t = \rho_w\varepsilon^w_{t-1} + \eta^w_t - \mu_w\eta^w_{t-1}$, the AR(1) inflation revision shock $\varepsilon^\pi_{t,t+S} = \rho_{\pi r}\varepsilon^\pi_{t-1,t-1+S} + \eta^\pi_{t,t+S}$, the AR(1) output revision shock $\varepsilon^y_{t,t+S} = \rho_{yr}\varepsilon^y_{t-1,t-1+S} + \eta^y_{t,t+S}$, and the AR(1)

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consumption revision shock $\varepsilon^c_{t,t+S} = \rho_{cr}\varepsilon^c_{t-1,t-1+S} + \eta^c_{t,t+S}$. The last three shocks are introduced into our extended SW-type DSGE model to study the business cycle implications of data revisions.

4. DATA AND ESTIMATION PROCEDURE

Both the SW model and the extended model are estimated with U.S. 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 measurement errors of other filtering treatments. More recent data are not considered, to minimize the chance of taking observations with final revisions that can still be released in the future.[14] 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 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. As in the case of revised data, real-time data are measured in per capita units (if applicable).

The series of U.S. data revisions include all the changes made after the first release, with a smoothing pattern applied for scale adjustments.[15] The times series of U.S. revised data, real-time data, and data revisions are plotted in Figure 1.

Figure 1 shows that the variability of U.S. data revisions of output growth, inflation, and consumption growth is extremely high. Comparing the three plots in each column of Figure 1, we can observe similar volatilities between series of real-time data, revised data and revisions. Table 5 (in Section 5) reports that the standard deviations of data revisions are about 80% as high as the standard deviations of real-time data and of very similar magnitude to standard deviations of revised data (the scale of the Y-axis is identical across variables displayed in Figure 1, to illustrate this empirical finding). As one remarkable example, revisions of U.S. consumption growth report a standard deviation of 0.61% over the period 1983:2–2008:1, whereas the standard deviation of the corresponding revised data is just 0.53%. Such a high variability of U.S. data revisions can give us one indication of the significance of these data corrections for U.S. business cycle analysis.

The estimation procedure also follows SW (2007). 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

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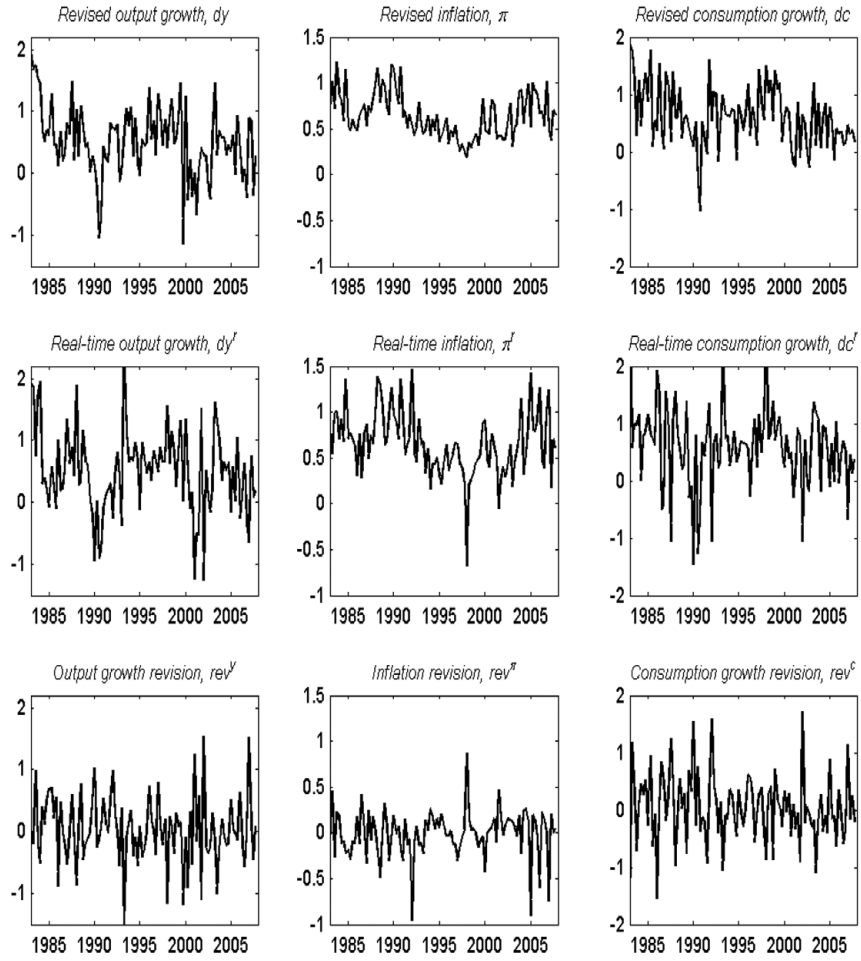


FIGURE 1. Revised data, real-time data, and revisions of output growth (left), inflation (center), and consumption growth (right) in the United States, 1983:1–2008:1.

the empirical likelihood of the data. In a second step, we apply the Metropolis–Hastings algorithm to compute the posterior distribution of the parameter set.[16] In regards to priors, we select the same prior distributions as in SW (2007) for the parameters appearing in the two models (see the first three columns in Tables 1 and 2 in Section 5). We have also borrowed their notation for the structural parameters in order to facilitate comparison.[17] For the parameters associated with the three revision processes, we consider rather loose prior distributions (as shown in the first three columns of Table 3 in Section 5).[18] Finally, the number of periods, S, after which there are no more revisions is fixed. Unfortunately, looking at US data shows that S is not constant, neither over time nor across variables [Croushore

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TABLE 1. 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	5.92	4.06	7.83
h	Beta	0.70	0.10	0.13	0.10	0.16	0.57	0.46	0.69
σ_c	Normal	1.50	0.37	1.34	1.08	1.62	1.06	0.75	1.39
σ_l	Normal	2.00	0.75	1.79	0.81	2.79	1.94	1.05	2.90
ξ_p	Beta	0.50	0.10	0.66	0.58	0.75	0.72	0.64	0.81
ξ_w	Beta	0.50	0.10	0.51	0.38	0.65	0.59	0.44	0.74
ι_w	Beta	0.50	0.15	0.35	0.15	0.55	0.48	0.23	0.72
ι_p	Beta	0.50	0.15	0.09	0.03	0.15	0.32	0.13	0.49
ψ	Beta	0.50	0.15	0.77	0.63	0.90	0.71	0.57	0.87
Φ	Normal	1.25	0.12	1.44	1.31	1.57	1.46	1.33	1.61
r_π	Normal	1.50	0.25	1.86	1.56	2.13	2.10	1.78	2.41
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	0.07
$r_{\Delta y}$	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	0.56	0.84
$100(\beta^{-1}-1)$	Gamma	0.25	0.10	0.17	0.07	0.28	0.20	0.09	0.31
l	Normal	0.00	2.00	−1.48	−3.79	0.79	0.22	−1.80	2.19
α	Normal	0.30	0.05	0.17	0.13	0.20	0.17	0.13	0.21

(2011)]. As a conservative setting, it is assumed that final revisions are reached after six quarters ($S = 6$) when the model is solved.[19]

5. ESTIMATION RESULTS

Tables 1, 2, and 3 show the posterior distribution for the parameters of the two models. The confidence bands for each structural parameter, displayed in Table 1, overlap to a great extent with the corresponding confidence interval of the estimated SW model. A similar conclusion is reached regarding the estimated parameters of the shock processes, displayed in Table 2.

The parameter estimates associated with the revision processes are shown in Table 3. 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 high real-time inflation predicts a negative revision. In addition, the slope of the New Keynesian Phillips curve is slightly flatter in the extended model (11) than in the SW model (9).

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TABLE 2. 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	0.14
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	0.34	0.26	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	0.91	0.87	0.96
ρ_b	Beta	0.50	0.20	0.84	0.77	0.91	0.75	0.49	0.94
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	0.26	0.12	0.39
ρ_p	Beta	0.50	0.20	0.88	0.78	0.98	0.81	0.67	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	0.39	0.82
μ_w	Beta	0.50	0.20	0.63	0.43	0.84	0.67	0.47	0.87
ρ_{ga}	Beta	0.50	0.20	0.40	0.25	0.57	0.40	0.23	0.56

TABLE 3. Priors and estimated posteriors of revision process 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	–	–	–

At first sight, a positive value of b_{yy} seems to contradict reduced-form evidence based on output growth observations. However, as pointed out by Vázquez et al. (2012), the results from a structural estimation approach are not directly comparable to those obtained from a reduced-form approach. On one hand, the log deviation of output from its steady state level is the explanatory variable in

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equation (4). On the other hand, reduced-form revision parameters are difficult to interpret because revision processes interact with other components of the DSGE model.

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 deviations of the output and consumption revision innovations (σ_{yr} and σ_{cr}, respectively) are roughly three times greater than that 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 process 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 sets of estimates obtained from the two models, it can be said that a few structural parameters change significantly when real-time data are considered in addition to revised data. Indeed, the habit formation parameter, h, is much lower in the extended model (0.13) than in the SW model (0.57), and the price-indexation parameter, ι_p, becomes lower in the extended model (0.09) than in the SW model (0.33). Our interpretation of these results is that the persistence of both the consumption and inflation revision shocks is, respectively, picking up some of the consumption habit and indexation inertia captured by the SW model to explain the serial correlation observed in macroeconomic series. Moreover, the estimation results indicate that the structural equations of consumption (18) and inflation (11) are more forward-looking in the estimated extended model than in the SW model.

A few minor differences are also reported in the monetary policy parameters. In particular, the policy rule inflation coefficient, r_π, is lower in the extended model (1.86) than in the SW model (2.10). The finding that monetary policy responses to real-time inflation are not much different from those obtained with revised inflation is not surprising at all, because inflation revisions do not deviate much from a white noise process (i.e., the estimates of $b_{\pi\pi}$ and $\rho_{\pi r}$ are small). Moreover, the robustness of policy rule parameter estimates across models is in line with the estimation results found by Levine et al. (2012), which considers another source of limited information.

On the evaluation of the goodness of the estimation, the Dynare package supplies, as a by-product, several tests such as the 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.[20]

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Next, we examine the relative importance of the two sources of deviation from well-behaved revision processes by estimating the extended model under three alternative null hypotheses:

(i) Revisions are unrelated to initial announcements ($b_{yy} = b_{\pi\pi} = b_{cc} = 0$),
(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 ($\rho_{yr} = \rho_{\pi r} = \rho_{cr} = b_{yy} = b_{\pi\pi} = b_{cc} = 0$).

We compare the marginal data densities of the model under these three alternative hypotheses with that obtained for the unrestricted model with data revisions. Table 4 shows the estimates of the structural parameters and the marginal likelihood for the unrestricted model and for the three alternative hypotheses about revisions.[21] 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. The restrictions imposed by any of the three hypotheses lead to a large deterioration of the marginal likelihood. This deterioration is higher when revision shocks are assumed to be white noise ($\rho_{yr} = \rho_{\pi r} = \rho_{cr} = 0$) than when revisions are unrelated to initial announcements ($b_{yy} = b_{\pi\pi} = b_{cc} = 0$). Moreover, the size of the Bayes factor between the benchmark model and the closest alternative model is gigantic (e^{109}). In contrast, the Bayes factor between the second and third best models is much lower (e^{35}). These results suggest that the two sources of deviation from well-behaved revision processes are important. If one of them is ignored, the omission of the other has a much smaller impact on the fit, as a sign of complementarity between the two sources. Furthermore, Table 4 shows that the parameter estimates are relatively robust to the alternative specifications of revision process. A similar conclusion is reached in the impulse response analysis in Section 5.3.[22] 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 indexation parameters (ι_p and ι_w), are much higher when the set of restrictions $b_{yy} = b_{\pi\pi} = b_{cc} = 0$ is imposed.

The remainder of this section compares the performance of the two models on four business-cycle dimensions: second-moment statistics, variance decomposition, impulse-response functions, and one assessment on the relative importance of alternative frictions.

5.1. Second-Moment Statistics

The relevance of revisions in actual U.S. data (already shown in Figure 1) is confirmed when the standard deviation of revisions is computed. A comparison with the standard deviations of revised and real-time data is shown in Table 5, Panel A. Clearly, the volatility of data revisions is highly 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 5, Panel A, shows other second-moment statistics obtained from actual U.S. data and from the estimated

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TABLE 4. Importance of the two sources of nonrational revision processes

	Base		$b_{yy}=b_{\pi\pi}=b_{cc}=0$		$\rho_{yr}=\rho_{\pi r}=\rho_{cr}=0$		White noise revisions	
Marg. lik.	−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

extended model. The numbers provided by the model replicate to some extent the volatility, correlation with output, and autocorrelation of U.S. real-time data and revisions. Perhaps it could be said that the extended model built to accommodate data revisions gives higher volatility on real-time data.

Table 5, Panel B, shows second-moment statistics obtained from U.S. 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, whereas the business cycle volatility of changes in output, consumption, and investment in the extended model is greater than in the SW model. The introduction of three additional shocks to data revision can explain this rise of variability. Second, the model with data revisions reproduces the degree of inertia much better than the SW model in terms of matching coefficients of autocorrelation. Finally, no clear conclusion emerges from comparing the ability of the two models to reproduce the cyclical correlation with output growth. As reported in Table 5, the model with data revisions fits better the correlation of inflation with output growth, whereas the opposite is true for the correlation between changes in consumption and output.

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TABLE 5. Second-moment statistics

	Panel A					
	Δy^r	π^r	Δc^r	$\text{rev}^{\Delta y}$	rev^{π}	$\text{rev}^{\Delta c}$
	U.S. data					
Std. 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					
Std. 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)

	Panel B						
	Δy	Δc	Δi	Δw	l	R	π
	U.S. data						
Std. 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						
Std. 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						
Std. deviation (%)	0.78	0.68	2.10	0.74	3.59	0.45	0.47
	(0.70,0.85)	(0.61,0.75)	(1.81,2.43)	(0.65,0.83)	(2.60,4.47)	(0.35,0.52)	(0.36,0.55)
Correlation with Δy	1.0	0.68	0.64	0.19	0.11	−0.16	−0.35
		(0.60,0.77)	(0.57,0.71)	(0.06,0.30)	(0.07,0.14)	(-0.24,-0.10)	(-0.44,-0.23)
Autocorrelation	0.42	0.53	0.66	0.33	0.98	0.95	0.83
	(0.34,0.48)	(0.45,0.59)	(0.58,0.75)	(0.20,0.46)	(0.98,0.99)	(0.93,0.97)	(0.77,0.89)

Note: The 90% posterior confidence intervals for second-moment statistics obtained from the models are reported in parentheses.

5.2. Variance Decomposition

Table 6 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 20.0% in the SW model). Wage mark-up shocks also play a significant role in both models, with 16.7% and 18.6% of

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TABLE 6. Variance decomposition (percent)

Innovation	Δy	Δy^r	Δc	Δc^r	Δi	Δw	l	R	π	π^r
				Extended model						
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						
Technology, η^a	12.8	–	5.3	–	2.9	1.1	1.2	6.5	2.1	–
Risk premium, η^b	20.1	–	36.2	–	4.1	5.5	3.5	34.7	8.4	–
Fiscal/net exports, η^g	20.0	–	4.4	–	0.2	0.1	5.8	1.9	0.5	–
Investment adj. costs, η^i	11.1	–	2.0	–	72.9	1.6	3.8	11.5	2.6	–
Interest rate, η^R	9.2	–	15.0	–	2.5	3.2	2.1	6.9	6.1	–
Wage push, η^w	18.6	–	29.9	–	10.6	68.8	78.2	32.6	52.3	–
Price push, η^p	8.2	–	7.2	–	6.8	19.7	5.4	5.9	28.0	–

output growth variability, respectively. 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 in business cycle fluctuations, Table 6 indicates that innovations in inflation revisions explain 4.3% of output growth fluctuations, innovations on consumption revisions 4.0% of changes in output, and innovations in 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 out nearly one-tenth of total variability of output driven by data revision shocks, which would overestimate the role of other sources of cyclical fluctuations (in particular, technology shocks and exogenous spending shocks).

5.3. 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 too low a real-time announcement, which will be corrected over time.

The observation that shocks to data revisions have stronger 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 the high volatility of real-time data relative to revised data (noticeable in Figure 1 and in the second-moment statistics reported in Table 5), and also with the estimation results showing the presence of nonrational 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 3). The alternative view of revisions adding only news would have brought about 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 channel 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. When real-time data on either output or inflation fall, the central bank lowers the interest-rate

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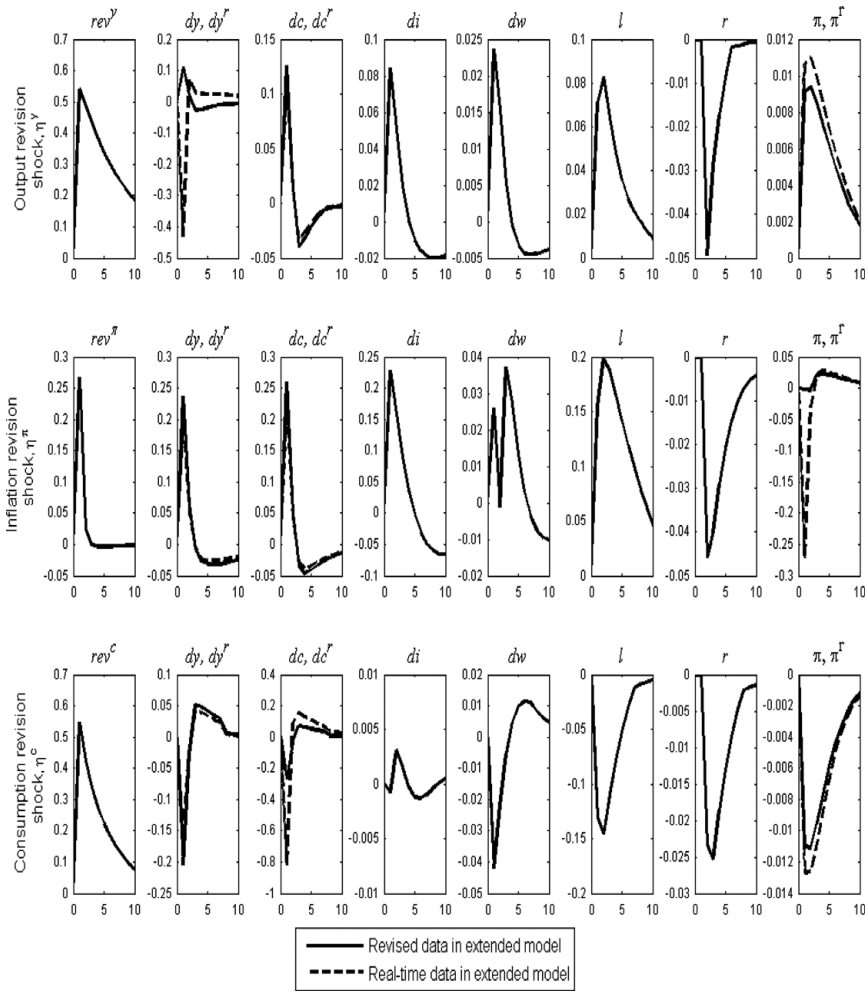


FIGURE 2. Responses to data revision shocks.

[see equation (13)]. For instance, a positive inflation revision comes from having real-time inflation below the true value (real-time deflation), and the central bank needs to cut interest rates to implement the desired monetary expansion that wipes away deflation. As displayed in Figure 2, the reduction of interest rates then stimulates the endogenous components of demand (consumption and investment), labor demand, and output. In numerical terms, the estimated output revision shock increases output, investment, consumption, and labor by around 0.1%, whereas these expansions are roughly by 0.2% when there is an estimated inflation revision shock.

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In contrast, the consumption revision describes a countercyclical pattern due to an adverse spending shift. A positive data revision of consumption corresponds to a low real-time consumption announcement that is going to reduce current consumption in equation (18) as the household identifies consumption habits 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. Inflation and the nominal interest rate fall as a consequence of the demand shrinking. 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 previously.

A comparison between the responses in the extended model and those in the SW model is carried out in Figure 3. Because of space constraints, there are only plots of output growth, consumption growth, and inflation as the three variables that include data revisions.[23] In overall terms, both models provide similar responses. Nevertheless, there are some impulse responses significantly different across models. Thus, the reaction of inflation is stronger in the model with data revisions after either technology innovations or risk premium shocks. Meanwhile, cost-push 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.

5.4. An Assessment of the Relative Importance of Alternative Frictions and Indexation Rules

Following SW (2007), this subsection studies the partial contribution of each friction to the marginal likelihood of the extended model with data revisions. The cases with quasi-flexible nominal wages ($\xi_w = 0.1$) and with low elasticity of adjustment costs on investment ($\varphi = 0.1$) bring about 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 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 extended model with data revisions.

Model estimation under quasi-flexible prices ($\xi_p = 0.1$) increases the role of both price indexation and wage indexation, whereas 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. These results confirm the intuition stated earlier that the persistence of consumption and inflation revision processes is able to capture inertia associated with habit formation and inflation indexation structures when data revisions are ignored, as in the SW model.

Regarding the parameters of data revisions (at the continuation of Table 7), the negative dependence of inflation revisions on the initial announcements ($b_{\pi\pi} < 0$)

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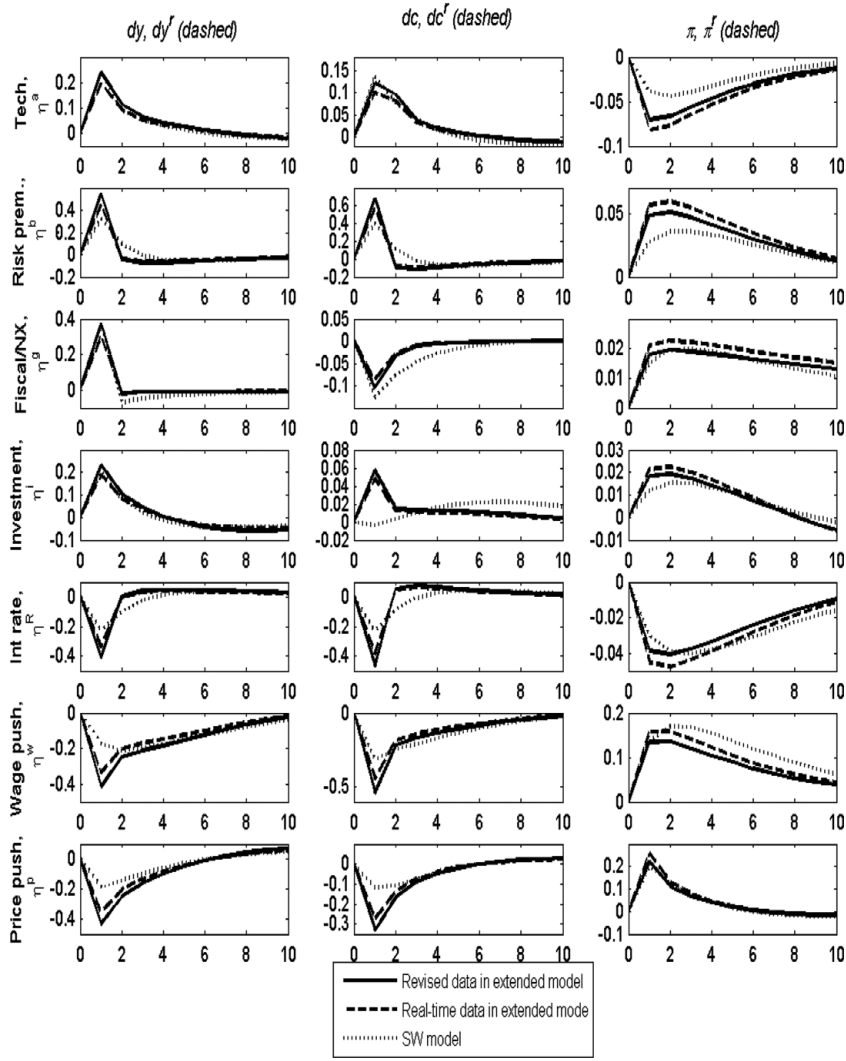


FIGURE 3. Responses of revised data (solid lines) and real-time data (dashed lines) in the estimated extended model and in the estimated SW model (dotted lines).

only turns positive if price indexation is ignored. The consumption revisions become 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.

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TABLE 7. Marginal likelihood and mode of parameters under some restrictions

	Base	$\xi_p = 0.1$	$\xi_w = 0.1$	$\iota_p = 0.0$	$\iota_w = 0.0$	$\varphi = 0.1$	$h = 0.0$	$\psi = 0.99$	$\Phi = 1.1$	4-lag ind
					Marginal likelihood (based on Laplace approximation)					
	−756	−794	−1042	−747	−754	−1047	−736	−752	−766	−729
					Mode of the structural parameters					
φ	5.05	3.55	4.16	5.08	5.05	0.1	5.02	5.03	4.81	4.97
h	0.11	0.12	0.10	0.12	0.11	0.10	0.0	0.11	0.12	0.11
σ_c	1.39	1.38	1.41	1.38	1.40	1.06	1.61	1.41	1.29	1.40
σ_l	1.68	2.06	−0.36	1.64	1.72	2.34	2.01	1.72	1.97	1.82
ξ_p	0.67	0.1	0.59	0.69	0.67	0.41	0.69	0.66	0.74	0.62
ξ_w	0.53	0.32	0.1	0.54	0.55	0.28	0.58	0.52	0.50	0.53
ι_w	0.31	0.50	0.41	0.31	0.0	0.41	0.28	0.31	0.31	0.54
ι_p	0.07	0.81	0.03	0.0	0.07	0.11	0.07	0.08	0.08	0.61
ψ	0.79	0.86	0.79	0.67	0.79	0.86	0.76	0.99	0.81	0.79
Φ	1.43	1.57	1.54	1.43	1.43	1.31	1.44	1.42	1.1	1.43
r_π	1.80	2.00	1.03	1.82	1.81	2.08	1.67	1.80	1.88	1.83
ρ	0.84	0.82	0.84	0.84	0.84	0.79	0.85	0.84	0.83	0.84
r_y	−0.01	−0.02	0.01	−0.01	−0.01	−0.02	0.02	−0.01	−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	0.09
α	0.17	0.20	0.18	0.16	0.17	0.24	0.17	0.16	0.15	0.17

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TABLE 7. Continued

	Base	$\xi_p = 0.1$	$\xi_w = 0.1$	$\iota_p = 0.0$	$\iota_w = 0.0$	$\varphi = 0.1$	$h = 0.0$	$\psi = 0.99$	$\Phi = 1.1$	4-lag ind
					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	0.19
$b_{\pi\pi}$	−0.15	−0.33	−0.04	0.18	−0.16	−0.30	−0.12	−0.16	−0.18	−0.25
b_{cc}	0.21	0.21	−0.21	0.21	0.21	0.26	0.19	0.22	0.21	0.21
ρ_{yr}	0.90	0.90	0.92	0.90	0.90	0.89	0.87	0.89	0.90	0.90
$\rho_{\pi r}$	0.07	0.08	0.08	0.08	0.07	0.08	0.08	0.07	0.07	0.08
ρ_{cr}	0.81	0.81	0.98	0.81	0.81	0.79	0.88	0.81	0.81	0.81
σ_{yr}	0.62	0.63	0.64	0.62	0.62	0.61	0.59	0.62	0.63	0.61
$\sigma_{\pi r}$	0.22	0.19	0.24	0.21	0.22	0.19	0.23	0.22	0.21	0.20
σ_{cr}	0.70	0.71	0.47	0.71	0.70	0.75	0.68	0.71	0.70	0.71

Note: "Base" refers to the baseline extended model and "4-lag ind" refers to the extended model with price/wage indexation rules that use the average of real-time inflation during the previous four quarters.

A similar conclusion is reached when alternative indexation rules are considered that take into account average real-time inflation over the previous four quarters, $0.25(\pi^r_{t-1,t}+\pi^r_{t-2,t}+\pi^r_{t-3,t}+\pi^r_{t-4,t})$, instead of lagged real-time inflation, $\pi^r_{t-1,t}$. This extension would reflect the fact that economic agents notice the volatile nature of quarterly inflation. The last column of Table 7 shows that most estimated parameters are not affected by alternative indexation rules. There are two exceptions: the two indexation parameters, ι_p and ι_w, which become higher under the alternative indexation rules. More importantly, data revision shocks still explain a sizable fraction of the total variability of output and consumption growth (7.6% and 13.1%, respectively) under the alternative indexation rules.[24]

6. CONCLUSIONS

The significance of data revisions for U.S. business cycles has been examined in an extended version of the DSGE model of Smets and Wouters (2007). In the extended model, indexation rules used for both price and wage setting are applied with real-time data on lagged inflation. Similarly, the consumption habit formation of the households is built upon real-time data available for lagged consumption. The separation between real-time and revised data must be considered in the analysis of a structural model because (i) the initial announcements may not be a rational forecast of revised data, and (ii) economic decisions such as pricing, wage setting, consuming, or setting the interest rates may 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 the influence of consumption habits 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 U.S. data revisions. Moreover, the estimation of the extended model shows that U.S. data revisions are not white noise processes. Thus, the revisions of both output and consumption are positively correlated with their real-time observations and show 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 revised data. In other words, data revisions mainly reduce noise instead of adding news.

The medium-scale DSGE model with data revisions remains stylized and should be further extended to investigate additional ways in which real-time data might play a role in business cycle fluctuations. In particular, investment decisions are not directly affected by real-time data in our extended model. However, investment spending, as well as consumption, is likely to be largely decided by looking at real-time measures of aggregate economic activity. Another promising extension

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is to consider an imperfect information set-up [such as the one recently suggested by Levine et al. (2012)], where agents have limited knowledge and use learning procedures to guess the state of the economy.

In spite of the importance of our results and those that could come from other useful extensions, the use of medium-scale DSGE models with data revisions should be understood as a step forward to assess the role of data revisions in both business cycle analysis and macroeconomic policy evaluation.

NOTES

1. Many earlier New Keynesian models such as Rotemberg and Woodford (1997) or Christiano et al. (2005) could be mentioned as predecessors of Smets and Wouters (2007). This generation of medium-scale DSGE models is currently used for policy evaluation in many central banks.

2. It is fair to refer to Mankiw et al. (1984) as one earlier paper that introduces a theoretical framework for real-time data analysis.

3. 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 the previous 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.

4. 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 because of 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.

5. A fixed value of S is needed to solve the extended model because it is an element of the New Keynesian Phillips curve, the real wage dynamic equation, the IS curve, and the monetary policy rule derived subsequently.

6. See also Faust et al. (2005) for an analysis of GDP revisions in the G7 countries.

7. To simplify the analysis, we assume that revisions process are linear, because 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 et al. (2009) have found evidence of nonlinear dependence between data revisions and variables entering into the information set at the time the initial announcements were released.

8. The technical appendix of Smets and Wouters (2007), available at http://www.aeaweb.org/aer/data/june07/2041254_app.pdf, shows how the loglinearized pricing equation is derived.

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

10. For the algebra, it should be noticed that equation (7) is equivalent to $\widetilde{P}_t^* - \overline{\beta}\xi_p E_t \widetilde{P}_{t+1}^* = A(1 - \overline{\beta}\xi_p)(\mathrm{mc}_t + \lambda_t^p) + \overline{\beta}\xi_p E_t(\pi_{t+1} - \iota_p \pi_{t,t+1}^r)$.

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

12. It is assumed that potential output belongs to the information set of the central bank. 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.

13. The utility function of the households in Smets and Wouters (2007) is not separable between consumption and labor.

14. With the exception of the quarters of the 2007–2008 financial crisis, this period is characterized by mild fluctuations (the so-called Great Moderation) of aggregate variables [Stock and Watson (2002), among others].

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15. 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. Alternatively, one can replace those observations by using the Kalman filter to estimate the missing observations. The conclusions of the paper are not affected by the treatment of missing observations, because they represent only 5% of total observations.

16. 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.

17. See also Table A.1 in the Appendix for a description of model parameters.

18. 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 Brooks and Gelman (1998). One possible reason for this sample instability is that γ is not well identified when a relatively short sample period was estimated. For these reasons, we decided to fix $\gamma = 1.0040$ prior to estimation, which corresponds to the mean of the prior normal distribution used in Smets and Wouters (2007). Remarkably, the estimated values of the structural parameters do not change significantly when γ is left free in the estimation procedure. To make things more comparable, we also fix $\gamma = 1.0040$ in our estimation of the SW model.

19. 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. We found that estimation results are not sensitive to alternative values of S. Estimation results from this robustness analysis are also available upon direct request to the authors.

20. The graphical convergence diagnostic test results are available from the corresponding author upon request. The other two diagnostic test results are available in the Supplementary Material file.

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

22. This result, together with the large deterioration of the likelihood function when white noise revisions are assumed, suggests that the inclusion of nonrational revisions, on one hand, has only a limited effect on the characterization of model dynamics, but on the other hand, helps a lot in improving revision process characterization.

23. The confidence bands have not been displayed in Figure 3 to keep the whole figure visible, because it already contains many graphs and plots. The whole set of impulse response plots, including their confidence bands, are available from the authors upon request, as a by-product of the estimation procedure.

24. Although the alternative indexation rules are (arguably) more realistic than the ones considered in the model, they bring about very high inflation persistence, which is at odds with actual data. A full set of estimation results and business cycle properties of the model under the alternative indexation rules is available from the authors upon request.

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APPENDIX

Set of log-linearized dynamic equations (see Table A.1 for model parameter descriptions):

- Inflation identity:

$$\pi_t = \pi^r_{t,t+1} + \text{rev}^{\pi}_{t,t+S}. \tag{A.1}$$

- Output identity:

$$y_t \equiv y^r_{t,t+1} + \text{rev}^{y}_{t,t+S}. \tag{A.2}$$

- Consumption identity:

$$c_t \equiv c^r_{t,t+1} + \text{rev}^{c}_{t,t+S}. \tag{A.3}$$

- Revision process of inflation:

$$\text{rev}^{\pi}_{t,t+S} = b_{\pi\pi}\pi^r_{t,t+1} + \varepsilon^{\pi}_{t,t+S}. \tag{A.4}$$

- Revision process of output:

$$\text{rev}^{y}_{t,t+S} = b_{yy}y^r_{t,t+1} + \varepsilon^{y}_{t,t+S}. \tag{A.5}$$

- Revision process of consumption:

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

- Aggregate resource constraint:

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon^g_t, \tag{A.7}$$

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:

$$c_t = c_1 c^r_{t-1,t} + (1-c_1)E_t c_{t+1} + c_2\,(l_t - E_t l_{t+1}) - c_3(R_t - E_t\pi_{t+1}) + \varepsilon^b_t + c_4\varepsilon^c_{t-s,t}, \tag{A.8}$$

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 $c_4 = \frac{(h/\gamma)\rho^S_c}{(1+b_{cc})[1+(h/\gamma)(1+b_{cc})^{-1}]}$.

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TABLE A.1. 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 the 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 price 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
γ	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
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

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- Investment equation:

$$i_t = i_1 i_{t-1} + (1 - i_1)\, E_t i_{t+1} + i_2 q_t + \varepsilon_t^i, \tag{A.9}$$

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

- Arbitrage condition (value of capital, q_t):

$$q_t = q_1 E_t q_{t+1} + (1 - q_1) E_t r_{t+1}^k - (R_t - E_t\pi_{t+1}) + c_3^{-1}\varepsilon_t^b, \tag{A.10}$$

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

- Log-linearized aggregate production function:

$$y_t = \phi_p \left(\alpha k_t^s + (1-\alpha) l_t + \varepsilon_t^a\right), \tag{A.11}$$

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

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

$$k_t^s = k_{t-1} + z_t. \tag{A.12}$$

- Capital utilization:

$$z_t = z_1 r_t^k, \tag{A.13}$$

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

- Capital accumulation equation:

$$k_t = k_1 k_{t-1} + (1 - k_1) i_t + k_2 \varepsilon_t^i, \tag{A.14}$$

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

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

$$\mu_t^p = mpl_t - w_t = \alpha\left(k_t^s - l_t\right) + \varepsilon_t^a - w_t. \tag{A.15}$$

- New Keynesian Phillips curve (price inflation dynamics):

$$\pi_t = \pi_1 \pi_{t-1,t}^r + \pi_2 E_t \pi_{t+1} - \pi_3 \mu_t^p + \pi_4 \varepsilon_t^p + \pi_5 \varepsilon_{t-s,t}^{\pi}, \tag{A.16}$$

where $\pi_1 = \frac{\iota_p}{1+\overline{\beta}\iota_p B}$, $\pi_2 = \frac{\overline{\beta}}{1+\overline{\beta}\iota_p B}$, $\pi_3 = \frac{A}{1+\overline{\beta}\iota_p B}[\frac{(1-\overline{\beta}\xi_p)(1-\xi_p)}{\xi_p}]$, $\pi_4 = \frac{1+\overline{\beta}\iota_p}{1+\overline{\beta}\iota_p B}$, 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:

$$-\left(k_t^s - l_t\right) + w_t = r_t^k. \tag{A.17}$$

- Wage markup equation:

$$\mu_t^w = w_t - \text{mrs}_t = w_t - \left\{\sigma_l l_t + \frac{1}{1-h/\gamma}\left[c_t - (h/\gamma)\, c_{t-1,t}^r\right]\right\}. \tag{A.18}$$

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- Real wage dynamic equation:

$$w_t = w_1 w_{t-1} + (1-w_1)\,(E_t w_{t+1} + E_t \pi_{t+1}) - w_2 \pi_t + w_3 \pi^r_{t-1,t} - w_4 \mu^w_t + w_5 \varepsilon^{\pi}_{t-s,t} + \varepsilon^w_t, \tag{A.19}$$

where $w_1 = \frac{1}{1+\overline{\beta}}$, $w_2 = \frac{1+\overline{\beta}\iota_w B}{1+\overline{\beta}}$, $w_3 = \frac{\iota_w}{1+\overline{\beta}}$, $w_4 = \frac{1}{1+\overline{\beta}}\{\frac{(1-\overline{\beta}\xi_w)(1-\xi_w)}{\xi_w[(\phi_w-1)\varepsilon_w+1]}\}$, and $w_5 = w_1\overline{\beta}\iota_w B\rho^S_\pi$ 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:

$$\begin{aligned} R_t &= \rho R_{t-1} + (1-\rho)[r_\pi E_t \pi_{t-1} + r_y (E_t y_{t-1} - y^p_{t-1})] \\ &\quad + r_{\Delta y}\left[(E_t y_{t-1} - y^p_{t-1}) - (E_t y_{t-2} - y^p_{t-2})\right] + \varepsilon^R_t, \end{aligned} \tag{A.20}$$

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

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, $\mu^p_t = mpl_t - w_t = 0$):

$$\alpha\left(k^{s,p}_t - l^p_t\right) + \varepsilon^a_t = w^p_t. \tag{A.21}$$

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

$$w^p_t = \sigma_l l^p_t + \frac{1}{1-\lambda/\gamma}\left(c^p_t - \lambda/\gamma c^p_{t-1}\right). \tag{A.22}$$

- Potential aggregate resources constraint:

$$y^p_t = c_y c^p_t + i_y i^p_t + z_y z^p_t + \varepsilon^g_t. \tag{A.23}$$

- Potential consumption equation:

$$c^p_t = c_1 c^p_{t-1} + (1-c_1)\,E_t c^p_{t+1} + c_2\left(l^p_t - E_t l^p_{t+1}\right) - c_3\left(R^p_t - E_t \pi^p_{t+1}\right) + \varepsilon^b_t. \tag{A.24}$$

- Potential investment equation:

$$i^p_t = i_1 i^p_{t-1} + (1-i_1)\,E_t i^p_{t+1} + i_2 q^p_t + \varepsilon^i_t. \tag{A.25}$$

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

$$q^p_t = q_1 E_t q^p_{t+1} + (1-q_1) E_t r^{k,p}_{t+1} - \left(R^p_t - E_t \pi^p_{t+1}\right) + c^{-1}_3 \varepsilon^b_t. \tag{A.26}$$

- Log-linearized potential aggregate production function:

$$y^p_t = \phi_p\left[\alpha k^{s,p}_t + (1-\alpha) l^p_t + \varepsilon^a_t\right]. \tag{A.27}$$

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

$$k^{s,p}_t = k^p_{t-1} + z^p_t. \tag{A.28}$$

- Potential capital utilization:

$$z^p_t = z_1 r^{k,p}_t. \tag{A.29}$$

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- Potential capital accumulation equation:

$$k_t^p = k_1 k_{t-1}^p + (1-k_1) i_t^p + k_2 \varepsilon_t^i. \tag{A.30}$$

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

$$-\left(k_t^{s,p} - l_t^p\right) + w_t^p = r_t^{k,p}. \tag{A.31}$$

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

$$R_t^p = \rho R_{t-1}^p + (1-\rho)\left[r_\pi \pi_t^p\right] + \varepsilon_t^R. \tag{A.32}$$

A.1. EQUATIONS-AND-VARIABLES SUMMARY

Set of equations:

Equations (A.1)–(A.32) 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 $\varepsilon_{t,t+S}^c = \rho_{cr} \varepsilon_{t-1,t-1+S}^c + \eta_{t+S}^c$.

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