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Extending the New Keynesian Monetary Model with Information Revision Processes: Real-time and Revised Data

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Extending the New Keynesian Monetary Model with Information Revision Processes: Real-Time and Revised Data⋆

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Abstract. This paper proposes an extended version of the New Keynesian Monetary (NKM) model which contemplates revision processes of output and inflation data in order to assess the influence of data revisions on the estimated monetary policy rule parameters. In line with the evidence provided by Aruoba (2008), by using the indirect inference principle, we observe that real-time data are not rational forecasts of revised data. This result along with the differences observed when estimating a model restricted to white noise revision processes provide evidence that policymakers decisions could be determined by the availability of data at the time of policy implementation.

Key words: NKM model, monetary policy rule, indirect inference, real-time data, rational forecast errors
JEL classification numbers: C32, E30, E52

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1 INTRODUCTION

Nowadays, the importance of timing and availability of the data used in the empirical evaluation of policy rules has converted in something crucial. There were some preliminary studies about real-time data such as Maravall and Pierce (1986), Trivellato and Rettore (1986) and Ghyssels, Swanson and Callan (2002) which examined revision process errors. Maravall and Pierce (1986) analyze how preliminary and incomplete data affect monetary policy and demonstrate that even though revisions to measures of money supply are large, monetary policy would not have been much different if more accurate data had been known. By contrast, Ghyssels, Swanson and Callan (2002) find that Taylor-type rule would have improved significantly if policymakers waited for data to be revised rather than reacting to newly released data.[3]

From a statistical point of view, Aruoba (2008) documents the empirical properties of revisions to major macroeconomic variables in the U.S. and points out that they are not well behaved. That is, they do not satisfy simple desirable properties such as zero mean, which indicates that the revisions of initial announcements made by statistical agencies are biased, and that they might be predictable using the information set available at the time of the initial announcement.

Two of the most well-known studies that compare results based on real-time data with those obtained with revised data were Diebold and Rudebusch (1991) and Orphanides (2001). The first one, shows that the index of leading indicators does a much worse job in predicting future movements of output in real time than it does after data are revised. The second one, uses data over a period of more than 20 years and examines parameter as well as model specification uncertainty in the Taylor-rule and demonstrates that Taylor principle does not prevail using real-time data. This result is in sharp contrast with the empirical evidence found by Clarida, Galí and Gertler (2000). With regard to the Taylor-rule, Rudebusch (2002) indicates

[3] Mankiw, Runkle and Shapiro (1984) developed a theoretical framework of analyzing initial announcements of economic data and applied that framework to the money stock.

that data uncertainty potentially plays an important role in reducing the coefficients in the rule such as policy inertia and persistency of shocks.[4] The main advantage of using real-time data in estimating policy rules is to reduce the effects of parameter uncertainty in actual policy setting since the researcher can estimate policy rules with data which were truly available at any given point in time. This is particularly important with seasonally adjusted data as such data are subject to revisions based on two-sided filters.[5]

This paper extends the NKM model to include revision processes of output and inflation data, and thus to analyze revised and real-time data together. This extension allows for (i) a joint estimation procedure of both monetary policy rule and revision process parameters, (ii) an assessment of the interaction between these two sets of parameters and (iii) a test of the null hypothesis establishing that real-time data are rational forecast of revised data.

The use of real-time data in the estimation of structural DSGE models may look tricky because private agents' (households and firms) decisions determine the true (revised) values of macroeconomic variables, such as output and inflation, and they are not observable without error by policymakers in real time.

We follow a classical approach based on the indirect inference principle suggested by Smith (1993, 2008) to estimate our extended version of the NKM model. In particular, we follow Smith (1993) by using an unrestricted VAR as the auxiliary model. More precisely, the distance function is built upon the coefficients estimated from a five-variable VAR that considers U.S. quarterly data of revised output growth, revised inflation, real-time output growth, real-time inflation and the Fed funds rate.

[4] By using reduced-form estimation approaches, some empirical studies, such as English, Nelson and Sack (2003) and Gerlach-Kirsten (2004) showed that persistent shocks and policy inertia enter the U.S. estimated monetary policy rule. María-Dolores and Vazquez (2006, 2008) obtained similar results for the U.S. and Eurozone using a structural approach.

[5] Kavajecz and Collins (1995) conclude, using Monte Carlo simulations, that irrationality in seasonality adjusted data arise from the specific seasonal adjustment procedure used by the Federal Reserve.

The estimation results show that some policy rule parameter estimates depend on whether or not the revision processes of output and inflation are well behaved (i.e. they are allowed to be correlated with the initial announcements of these variables). In particular, the policy inertia parameter is larger whereas monetary shock persistence decreases substantially by allowing for the possibility of non-rational revision processes. Moreover, the estimates of the revision process parameters show that the initial announcements of output and inflation are not rational forecasts. For instance, a 1% increase in the initial announcement of inflation leads to a downward revision in output of 2.99%. These differences provide evidence that policy-makers decisions could be determined by the availability of data at the time of policy implementation. This evidence is also in line with the empirical evidence provided by Aruoba (2008) who finds that data revisions are not well behaved (i.e. they are not white noise).

The rest of the paper is organized as follows. Section 2 introduces the log-linearized approximation of an augmented version of the NKM model that includes the revision processes for output and inflation. Section 3 describes the structural estimation method used in this paper. Section 4 describes the data and the empirical evidence found following an indirect inference econometric strategy. Finally, section 5 concludes.

2 A NEW KEYNESIAN MONETARY MODEL INCLUDING DATA REVISION PROCESSES

The model analyzed in this paper is an augmented version of the NKM which includes data revision processes. It is given by the following set of equations:

$$x_t = E_t x_{t+1} - \tau(i_t - E_t \pi_{t+1}) - \phi(1-\rho_\chi)\chi_t \tag{1}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + z_t, \tag{2}$$

$$i_t = \rho i_{t-1} + (1-\rho)[\psi_1 \pi^r_{t-1} + \psi_2 x^r_{t-1}] + v_t. \tag{3}$$

$$x_t \equiv x_t^r + r_t^x, \tag{4}$$

$$\pi_t \equiv \pi_t^r + r_t^\pi, \tag{5}$$

$$r_t^x = b_{xx} x_t^r + b_{x\pi} \pi_t^r + \epsilon_{xt}^r, \tag{6}$$

$$r_t^\pi = b_{\pi x} x_t^r + b_{\pi\pi} \pi_t^r + \epsilon_{\pi t}^r, \tag{7}$$

where x denotes revised output gap (that is, the log-deviation of output with respect to the level of output under flexible prices) and π and i denote the deviations from the steady states of revised inflation and nominal interest rate, respectively. π_t^r and x_t^r are real-time data for inflation and output gap, respectively. E_t denotes the conditional expectation based on the agents' information set at time t. χ, z and v denote aggregate productivity, inflation and monetary policy shocks, respectively. Each of these shocks is further assumed to follow a first-order autoregressive process:

$$\chi_t = \rho_\chi \chi_{t-1} + \epsilon_{\chi t}, \tag{8}$$

$$z_t = \rho_z z_{t-1} + \epsilon_{zt}, \tag{9}$$

$$v_t = \rho_v v_{t-1} + \epsilon_{vt}, \tag{10}$$

where $\epsilon_{\chi t}$, ϵ_{zt} and ϵ_{vt} denote i.i.d. random innovations associated with these shocks.

Equation (1) is the log-linearized consumption first-order condition obtained from the representative agent optimization plan. The parameter $\tau > 0$ represents the intertemporal elasticity of substitution obtained when assuming a standard constant relative risk aversion utility function.

Equation (2) is the New Phillips curve that is obtained in a sticky price à la Calvo (1983) model where monopolistically competitive firms produce (a continuum of) differentiated goods and each firm faces a downward sloping demand curve for its produced good. The parameter $\beta \in (0,1)$ is the agent discount factor, and κ measures the slope of the New Phillips curve that is related to other structural parameters as follows

$$\kappa = \frac{[(1/\tau) + \eta](1-\omega)(1-\omega\beta)}{\omega}.$$

In particular, κ is a decreasing function of ω. The parameter ω is a measure of the degree of nominal rigidity; a larger ω implies that fewer firms adjust prices each period and that the expected time between price changes is longer.[6] The IS and Phillips curve equations are described in terms of the revised output and inflation data since they are indeed determined by the optimal choices of private agents (households and firms).

Equation (3) describes the monetary policy rule based on real-time data of output and inflation truly available at the time of implementing monetary policy and where the nominal interest rate exhibits smoothing behavior. The initial announcement of quarterly (monthly) macroeconomic variables corresponding to a particular quarter (month) appears in the vintage of the next quarter (month), roughly 45 (at least 15) days after the end of quarter (month). Then, a backward-looking Taylor rule that includes lagged values of real-time data on output and inflation would more accurately approximate the information set available to the Fed at the time of implementing the policy.

The model is also extended to incorporate the revision processes of output and inflation data, respectively. Equation (4) and (5) are identities showing how revised data of output and inflation are related to real-time output and inflation, respectively. Then, r_t^x (r_t^π) denotes the revision of output (inflation).[7] Equations (6) and (7) describe the revision processes associated with output and inflation, respectively. These processes allow for the existence of contemporaneous correlation between the revision of output and inflation and the initial announcements of these variables.[8]

Finally, the model is completed by the following identities:

$$x_t = E_{t-1}x_t + (x_t - E_{t-1}x_t),$$

[6] See, for instance, Walsh (2003, chapter 5.4) for detailed analytical derivations of the New Phillips curve.

[7] By adding the log of potential output on both sides of (4), we have that r_t^x also denotes the revision of the log of output.

[8] The two revision processes assumed do not intend to provide a structural characterization of the revision processes indeed follow by statistical agencies, but to provide a simple framework to assess whether the nature of the revision process might affect the estimated monetary policy rule.

$$\pi_t = E_{t-1}\pi_t + (\pi_t - E_{t-1}\pi_t).$$

The system of equations (1)-(10) (together with the latter two identities involving forecast errors) can be written in matrix form as follows.

$$\mathit{\Gamma}_0 Y_t = \mathit{\Gamma}_1 Y_{t-1} + \mathit{\Psi}\epsilon_t + \mathit{\Pi}\eta_t \tag{11}$$

$$Y_t = (x_t, \pi_t, i_t, E_t x_{t+1}, E_t\pi_{t+1}, \chi_t, z_t, v_t, x_t^r, \pi_t^r, r_t^x, r_t^\pi)',$$

$$\epsilon_t = (\epsilon_{\chi t}, \epsilon_{zt}, \epsilon_{vt}, \epsilon_{xt}^r, \epsilon_{\pi t}^r)'.$$

$$\eta_t = (x_t - E_{t-1}x_t, \pi_t - E_{t-1}\pi_t)'.$$

Equation (11) represents a linear rational expectations (LRE) system. It is well known that LRE systems deliver multiple stable equilibrium solutions for certain parameter values. Lubik and Schorfheide (2003) characterize the complete set of LRE models with indeterminacies and provide a numerical method for computing them. In this paper, we deal only with sets of parameter values that imply determinacy (uniqueness) of the rational expectations equilibrium.

The model's solution yields the output gap, x_t. This measure is not observable. In order to estimate the model by simulation, we have to transform the output gap into a measure that has an observable counterpart. This is a quite straightforward exercise since the log-deviation of output from its steady state can be defined as the output gap plus the (log of the) flexible-price equilibrium level of output, y_t^f, and the latter can be expressed as a linear function of the productivity shock:

$$y_t^f = \phi\chi_t.$$

The log-deviation of output from its steady state is also unobservable. However, the growth rate of output is observable and its model counterpart is obtained from the first-difference of the log-deviation of output from its steady state.

Similarly, the solution of the model yields the deviations of inflation and the interest rate from their respective steady states. In order to obtain the levels of inflation and nominal interest rate, we first calibrate the steady-state value of inflation as the sample mean of the inflation rate. Second, using the calibrated value of steady-state inflation and the definition of the steady-state value of real interest rate, we can easily compute the steady-state value of the nominal interest rate. Third, the level of the nominal interest rate is obtained by adding the deviation (from its steady-state value) of the nominal rate to its steady-state value computed in the previous step. Finally, since a period is identified with a quarter and the nominal interest rate is measured in quarterlized values, the quarterlized interest rate is transformed in an annualized value as in actual data.

3 ESTIMATION PROCEDURE

In order to carry out a joint estimation of the NKM model with the revision processes using both revised and real-time data, we follow a classical approach based on the indirect inference principle suggested by Smith (1993, 2008). In particular, we follow Smith (1993) by using an unrestricted VAR as the auxiliary model. More precisely, the distance function is built upon the coefficients estimated from a five-variable VAR that considers U.S. quarterly data of revised output growth, revised inflation, real-time output growth, real-time inflation and the Fed funds rate. In this context, we believe it is useful to consider an unrestricted VAR (which imposes mild restrictions) as the auxiliary model, letting the data speak more freely than other estimation approaches such as maximum-likelihood.[9]

This estimation procedure starts by constructing a $p \times 1$ vector with the coefficients of the VAR representation obtained from actual data, denoted by $H_T(\theta_0)$ where p in this application is 120. We have 105 coefficients from a four-lag, five-variable system and 15 extra coefficients from the non-redundant elements of the variance-covariance matrix of the VAR residuals. T denotes the length of the time series data, and θ is a $k \times 1$ vector whose components are the model parameters. The true parameter values are denoted by

[9] For a detailed description of this estimation procedure see María-Dolores and Vázquez (2006, 2008).

θ_0. Since our main goal is to estimate policy rule parameters, prior to estimation we split the model parameters into two groups. The first group is formed by the pre-assigned structural parameters β, τ, η, ω. We set $\beta = 0.995$, $\tau = 0.5$, $\gamma = 3.0$ and $\omega = 0.75$, corresponding to standard values assumed in the relevant literature for the discount factor, consumption intertemporal elasticity, the Frisch elasticity and Calvo's probability, respectively. The second group, formed by policy and shock parameters, is the one being estimated. In the NKM augmented model, the estimated parameters are $\theta = (\rho, \psi_1, \psi_2, \rho_\chi, \rho_z, \rho_v, b_{xx}, b_{x\pi}, b_{\pi x}, b_{\pi\pi}, \sigma_\chi, \sigma_z, \sigma_v, \sigma_\pi^r, \sigma_x^r)$ and then $k = 15$.

As pointed out by Lee and Ingram (1991), the randomness in the estimator is derived from two sources: the randomness in the actual data and the simulation. The importance of the randomness in the simulation to the covariance matrix of the estimator is decreased by simulating the model a large number of times. For each simulation a $p \times 1$ vector of VAR coefficients, denoted by $H_{N,i}(\theta)$, is obtained from the simulated time series of output growth, inflation and FED funds interest rate generated from the NKM model, where $N = nT$ is the length of the simulated data. By averaging the m realizations of the simulated coefficients, i.e., $H_N(\theta) = \frac{1}{m}\sum_{i=1}^{m} H_{Ni}(\theta)$, we obtain a measure of the expected value of these coefficients, $E(H_{Ni}(\theta))$. The choice of values for n and m deserves some attention. Gouriéroux, Renault and Touzi (2000) suggest that is important for the sample size of synthetic data to be identical to T (that is, $n = 1$) to get an identical size of finite sample bias in estimators of the auxiliary parameters computed from actual and synthetic data. We make $n = 1$ and $m = 500$ in this application. To generate simulated values of the output growth, inflation and interest rate time series we need the starting values of these variables. For the SME to be consistent, the initial values must have been drawn from a stationary distribution. In practice, to avoid the influence of starting values we generate a realization from the stochastic processes of the five variables of length $200 + T$, discard the first 200 simulated observations, and use only the remaining T observations to carry out the estimation. After two hundred observations have been simulated, the influence of the initial conditions must have disappeared.

The SME of θ_0 is obtained from the minimization of a distance function of VAR coefficients from actual and synthetic data. Formally,

$$\min_{\theta} \ J_T = [H_T(\theta_0) - H_N(\theta)]' W [H_T(\theta_0) - H_N(\theta)],$$

where W^{-1} is the covariance matrix of $H_T(\theta_0)$.

Denoting the solution of the minimization problem by $\hat{\theta}$, Lee and Ingram (1991) and Duffie and Singleton (1993) prove the following results:

$$\sqrt{T}(\hat{\theta} - \theta_0) \rightarrow \mathrm{N}\left[0, \left(1 + \frac{1}{m}\right)(B'WB)^{-1}\right],$$

$$\left(1 + \frac{1}{m}\right) T J_T \rightarrow \chi^2(p - k), \tag{12}$$

where B is a full rank matrix given by $B = E(\frac{\partial H_{Ni}(\theta)}{\partial \theta})$.

The objective function J_T is minimized using the optimization package OPTMUM programmed in GAUSS language. We apply the Broyden-Fletcher-Glodfard-Shanno algorithm. To compute the covariance matrix we need to obtain B. Computation of B requires two steps: first, obtaining the numerical first derivatives of the coefficients of the VAR representation with respect to the estimates of the structural parameters θ for each of the m simulations; second, averaging the m-numerical first derivatives to get B.

4 DATA AND ESTIMATION RESULTS

We consider quarterly U.S. data for the growth rate of output, the inflation rate obtained for the implicit GDP deflator and the Fed funds rate during the post-Volcker period (1983:1-2008:1). We focus on this sample period for two main reasons. First, the Taylor rule seems to fit better in this period than in the pre-Volcker era. Second, considering the pre-Volcker era opens the door to many issues studied in the literature, including the presence of macroeconomic switching regimes and the existence of switches in monetary policy (see, for instance, Sims and Zha, 2006). In addition, we have also considered real-time data on output and inflation as reported by the Federal

Reserve Bank of Philadelphia.[10] Figure 1 shows the five time series considered in the paper.

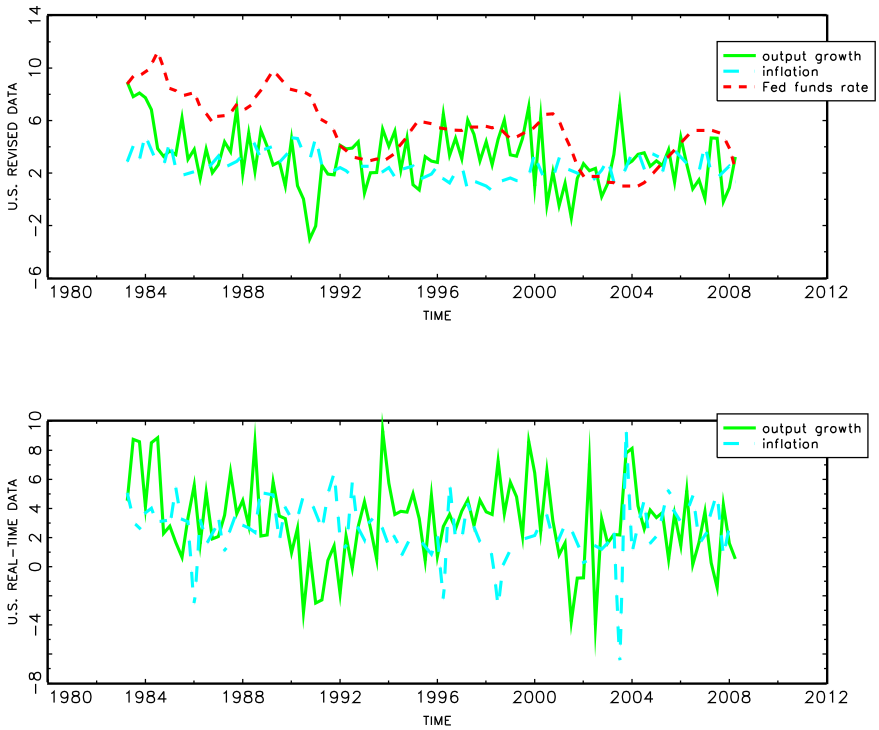

Fig. 1. U.S. Time Series

We start by motivating the inclusion of real-time data. As a preliminary step we analyze whether real-time data are rational forecast of revised data. Following Aruoba (2008), Table 1 shows a set of summary statistics and tests that allow us to analyze whether revision processes for output growth and inflation are "well-behaved". For both revision processes we cannot reject the null hypothesis that the unconditional mean is null. However, on the one hand, the standard

[10] See Croushore and Stark (2001) for the details of the real-time data set.

deviation for the two revision processes is quite large, especially when compared to revised data standard deviations (i.e. noise/signal parameter). On the other hand, the revision processes are likely to show a first order autocorrelation pattern. The evidence that revisions are not rational forecast errors is further supported by the statistics displayed in panel B. For both, output growth and inflation, revision processes are not orthogonal to their respective initial announcements and the conditional mean is not null. This evidence is in line with the empirical evidence provided by Aruoba (2008) who finds that data revisions for these variables are not white noise. The characteristics of the revision processes and the differences in estimated parameters when real-time and revised data are used suggest preliminary evidence that policymaker's decisions could be determined by the availability of data at the time of policy implementation. The next step is to estimate the extended version of the NKM model.

Table 2 shows the estimation results obtained using both revised and real-time data. The inflation parameter is extremely close to one and the output gap coefficient is significant. Moreover, the policy shock persistence parameter is smaller than in previous studies mentioned above, but is still significant ($\rho_v = 0.46$). With respect to the estimates of the remaining shocks, they all display large persistence. The estimation results also show that many revision process parameters are significant, suggesting that real-time data are not rational forecasts in line with the evidence provided by Aruoba (2008) and that shown in Table 1 (Panel B). In particular, the coefficient of inflation in the output revision equation is large and significant ($b_{x\pi} = -2.996$). Finally, we also observe that the innovations associated with output revision are much higher than the inflation revision process innovations.

Under the null hypothesis, $H_0 : b_{xx} = b_{x\pi} = b_{\pi x} = b_{\pi\pi} = 0$, r_t^x and r_t^x can be viewed as rational forecast errors. This hypothesis implies that the two revision processes are characterized by two white noise processes ϵ_{xt}^r and $\epsilon_{\pi t}^r$, where both have zero mean and variance σ_x^r and σ_π^r, respectively.

To observe if the characteristics of revision processes for both actual and simulated data have an effect on estimated policy rule

Table 1. Revision process analysis. Actual data.

Panel A: Summary Statistics

	r_t^y	r_t^π
Mean	0.074	-0.046
Median	-0.176	0.033
Min	-7.053	-7.273
Max	6.343	8.940
St.dev	2.968	2.039
Noise/Signal	1.350	2.076
corr.with initial	0.319	0.238
AC(1)	-0.229^{**}	-0.316^{***}
$E(r_t)=0$ t-stat	0.301	-0.302

Panel B: Conditional Mean

	r_t^y		r_t^π	
	Coef.	t-stat	Coef	t-stat
const	2.614	5.235^{***}	2.094	9.421^{***}
$(y_t^r - y_{t-1}^r) * 400$	-0.757	-7.399^{***}	0.040	0.999
$(\pi_t^r) * 400$	-0.072	-0.546	-0.879	-14.619^{***}
$F_{3,90}$		33.904^{***}		33.904^{***}

Note: revisions are calculated over annual GDP growth and inflation respectively. Since revisions are likely to have a first-order autocorrelation pattern, t-statistics for testing whether unconditional means are null are calculated based on Newey-West corrected standard deviations. Noise/signal is calculated as the standard deviation of the revision over the standard deviation of the revised data. The null hypothesis for the F-test in Panel B or conditional mean hypothesis is that all coefficients for real-time information are null.

Table 2. Joint estimation of the NKM model and the revision processes using both revised and real-time data.

$J_T(\theta)$	8.6653				
Policy parameter	Estimate	Shock parameter	Estimate	Revision parameter	Estimate
ρ	0.9682 (0.0137)	ρ_χ	0.9652 (0.0235)	b_{xx}	0.1733 (0.0786)
ψ_1	1.0000 (0.4150)	ρ_z	0.9476 (0.0132)	$b_{x\pi}$	-2.9620 (0.4214)
ψ_2	0.8430 (0.3878)	σ_χ	$9.4e-05$ ($3.9e-05$)	$b_{\pi x}$	0.0229 (0.0094)
ρ_v	0.4639 (0.0403)	σ_z	$4.7e-04$ ($6.3e-05$)	$b_{\pi\pi}$	0.0845 (0.0583)
σ_v	$5.3e-05$ ($1.1e-05$)	σ_π^r	$1.7e-04$ ($4.3e-05$)	σ_x^r	0.0014 ($2.7e-04$)

results we estimate the system under the null hypothesis that r_t^x and r_t^x are rational forecast errors. Table 3 shows the estimation results imposing H_0. It is well known that the null hypothesis H_0 can be tested using the following Wald statistic

$$F_1 = \left(1 + \frac{1}{m}\right) T \left[J_T(\theta) - J_T(\theta')\right] \rightarrow \chi^2(4).$$

F_1-statistic takes the value 432.2. Therefore, we can reject the joint hypothesis that the revision processes of output and inflation are both white noise at any standard significance level. Moreover, comparing the estimation results of Tables 2 and 3 it is interesting to observe that the autoregressive coefficient for monetary policy shocks increases when imposing the restriction that the two revision processes are well behaved. Furthermore, the estimate of policy shock persistence, ρ_v, is much larger when H_0 is imposed, which is consistent with the estimate of this parameter obtained in previous papers using only revised data.

So, we have noticed that imposing H_0 leads to some poor estimates of the standard deviation of revision processes (i.e. σ_x^r and σ_π^r).

Thus, the estimate of the standard deviation of inflation revision is fifteen times larger than the one associated with output revision. These estimation results are in sharp contrast with those displayed in Table 2, but also with the actual statistics reported by Aruoba (2008, Table 1), which shows that actual output revision volatility is twice larger than inflation revision volatility.

Finally, Tables 4 and 5 show a set of summary statistics for the simulated revision processes of output and inflation, respectively. The simulated series are computed using the estimates shown in Table 2. By comparing the properties of estimated revision processes obtained from simulated data with those obtained from actual revisions data shown in Table 1, we can assess the ability of the extended NKM model to capture the main regularities observed in actual revision processes of output growth and inflation. For output growth, the model underestimates the standard deviation of the revision process. With such a low standard deviation, only for 40% of the simulated series, we could not reject the hypothesis that the unconditional mean is null. That is, output growth revision is not well behaved. We also find evidence of an autocorrelation pattern, and the conditional mean is zero. Using simulated data, all real-time variables seem to play a role in explaining the revision process, which confirms the hypothesis that the revision process is not a rational forecast error. For inflation, we again underestimate the standard deviation of the revision process. This result is driven by the low estimate for the standard deviation of the innovation associated with the inflation revision process. Consistent with actual data, the conditional mean of the inflation revision process is also different from zero using simulated data.

5 CONCLUSIONS

This paper suggests an augmented version of the New Keynesian Monetary (NKM) model, which contemplates revision processes of output and inflation data in order to (i) test whether initial announcements are rational forecast of revised data and (ii) assess the influence of deviations of real time data from being rational forecast of revised data on the estimated monetary policy rule parameters.

Table 3. Joint estimation of the NKM model assuming that the revision processes are well-behaved.

$J_T(\theta)$	13.1120				
Policy parameter	Estimate	Shock parameter	Estimate	Revision parameter	Estimate
ρ	0.9172 (0.0100)	ρ_χ	0.9815 (0.0380)	σ^r_π	0.0032 ($3.8e-04$)
ψ_1	1.0002 (0.1113)	ρ_z	0.8865 (0.0126)	σ^r_x	$2.1e-04$ ($3.8e-05$)
ψ_2	0.6618 (0.0973)	σ_χ	$1.6e-04$ ($8.9e-05$)	σ_v	$6.0e-05$ ($1.2e-05$)
ρ_v	0.8414 (0.0215)	σ_z	$2.5e-04$ ($4.0e-05$)		

Table 4. Output growth revision process analysis. Simulated series.

Panel A: Summary Statistics								
		percentile						
	Av.Coef	1	5	10	50	90	95	99
Mean	0.000	−0.061	−0.041	−0.031	0.001	0.032	0.040	0.050
Median	−0.001	−0.245	−0.176	−0.144	−0.004	0.142	0.179	0.227
Min	−3.515	−5.323	−4.633	−4.325	−3.428	−2.801	−2.696	−2.341
Max	3.511	2.410	2.674	2.861	3.440	4.279	4.655	5.094
St.dev	1.403	1.156	1.241	1.276	1.400	1.540	1.572	1.666
Noise/Signal	5.583	4.451	4.793	4.929	5.565	6.250	6.495	6.735
corr.with initial	0.462	0.319	0.362	0.382	0.467	0.531	0.553	0.593
AC(1)	−0.248	0.478	0.956	1.362	2.403	3.222	3.396	3.618***
$E(r_t)=0$ t-stat		0.003	0.020	0.031	0.190	0.445	0.506	0.641
Panel B: Conditional Mean								
	percentile T-stats							
	Av.Coef	1	5	10	50	90	95	99
const	0.562	3.578	4.296	4.745	6.719	9.524	10.487	12.129***
$(y^r_t - y^r_{t-1}) * 400$	−0.895	49.167	56.405	60.062	75.245	93.617	100.849	117.126***
$(\pi^r_t) * 400$	−0.219	3.379	4.398	4.842	7.035	9.728	10.852	12.726***
$F_{3,90}$		1163.8	1355.1	1427.1	1873.7	2449.3	2693.5	2967.4***

Table 5. Inflation revision process analysis. Simulated series.

Panel A: Summary Statistics								
		percentile						
	Av.Coef	1	5	10	50	90	95	99
Mean	−0.047	−0.101	−0.080	−0.073	−0.046	−0.023	−0.017	0.001
Median	−0.046	−0.100	−0.081	−0.075	−0.046	−0.020	−0.012	0.004
Min	−0.305	−0.429	−0.380	−0.364	−0.301	−0.247	−0.235	−0.209
Max	0.208	0.117	0.135	0.155	0.204	0.271	0.297	0.344
St.dev	0.102	0.084	0.089	0.092	0.102	0.113	0.118	0.123
Noise/Signal	0.151	0.123	0.130	0.135	0.151	0.165	0.169	0.175
corr.with initial	0.994	0.991	0.992	0.993	0.995	0.996	0.996	0.997
AC(1)	0.350	0.940	1.719	2.089	3.178	4.012	4.264	4.525***
$E(r_t)=0$ t-stat		0.361	1.157	1.564	3.286	5.553	6.219	7.383
Panel B: Conditional Mean								
	percentile	T-stats						
	Av.Coef	1	5	10	50	90	95	99
const	−0.353	6.205	7.766	8.510	11.335	15.948	17.125	19.365***
$(y_t^r - y_{t-1}^r) * 400$	0.004	0.034	0.087	0.224	1.043	2.356	2.828	3.682
$(\pi_t^r) * 400$	0.119	5.485	6.768	7.573	10.071	13.648	14.961	17.867***
$F_{3,90}$		16.987	22.059	24.481	37.363	54.693	59.024	68.454***

The estimation results show that policy inertia becomes even larger whereas policy shock persistence substantially decreases by allowing for the possibility that the initial announcements are not rational forecast of revised data. The estimation results indeed show that many revision process parameters are significant, suggesting that real-time data are not rational forecasts. In particular, the coefficient of inflation in the output revision equation is large and significant. Furthermore, the estimation results show that the innovations associated with output revision are much higher than the inflation revision process innovations. We observe that real-time data are not rational forecasts of revised data by estimating this model. In line with the empirical evidence provided by Aruoba (2008) that focus on the properties of revision process based on reduced form analysis, this result provide evidence that policymakers' decisions could be determined by the availability of data at the time of policy implementation based on structural estimation of the augmented NKM model.

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APPENDIX

$$\mathit{\Gamma}_0 = \begin{pmatrix} 1 & 0 & \tau & -1 & -\tau & \phi(1-\rho_\chi) & 0 & 0 & 0 & 0 & 0 & 0 \\ -\kappa & 1 & 0 & 0 & -\beta & 0 & -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -b_{xx} & -b_{x\pi} & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -b_{\pi x} & -b_{\pi\pi} & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix},$$

$$\mathit{\Gamma}_1 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho & 0 & 0 & 0 & 0 & 0 & \mathit{\Gamma}_1^{3,9} & \mathit{\Gamma}_1^{3,10} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \rho_\chi & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho_z & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_v & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix},$$

where

$$\mathit{\Gamma}_0^{3,9} = (1-\rho)\psi_2, \mathit{\Gamma}_0^{3,10} = (1-\rho)\psi_1$$

$$\Psi = \begin{pmatrix} 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,1\,0 \\ 0\,0\,0\,0\,1 \\ 1\,0\,0\,0\,0 \\ 0\,1\,0\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0 \end{pmatrix}, \Pi = \begin{pmatrix} 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 0\,0 \\ 1\,0 \\ 0\,1 \end{pmatrix}$$

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