Optimal monetary policy revisited: Does considering real-time data change things?

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- Our models identifies several **new** potential **sources of inflation bias due to data revisions**
- Our empirical results suggest that the **Fed** mainly focuses on targeting revised data, but it **does weigh real-time data too**
- Thus, the **inflation bias induced by real-time data increases by 12.6 basis points** on average, but this figure becomes roughly twice as large at the start of recessions

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- These inconsistencies may be important due to the fact that **policy makers** really want to influence the performance of the actual economy, but because of long lags associated with the revised data that more accurately measures this performance, they are **forced to take action** based on the most readily available data which arrives **in real-time**
- As noted by Croushore (2011), if data revisions are small and random, then this distinction would not be an issue. However, this is not the case, **revisions are predictable**, and this predictability may induce policy makers to undertake policies that are stronger or weaker than might be optimal

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- We find weaker evidence on bias induced by output revisions

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- Finally, we present estimates of the full theoretical model

Short-run supply curve

- We consider Lucas (1977) short run supply curve

$$Y_t = Y_t^p + \alpha(\pi_t - \pi_t^e) + \eta_t, \tag{1}$$

where Y_t is output produced at time t, Y_t^p is permanent or potential output at time t, π_t is inflation at time t, π_t^e is expected inflation at time t based on information at time $t-1$, η_t is a supply disturbance and α reflects the sensitivity of firm output to unexpected inflation

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- This equation is not impacted by the data lag issue, one need only recall the foundations for it

Permanent output

- We assume that permanent output fluctuates over time in response to a real shock ζ_t according to the AR process

$$\widehat{Y}_t^p - \widehat{Y}_{t-1}^p = \psi - (1-\delta)\widehat{Y}_{t-1}^p + \theta(\widehat{Y}_{t-1}^p - \widehat{Y}_{t-2}^p) + \zeta_t, \quad (2)$$

where $\widehat{Y}_t^p = Y_t^p - (1-\delta)t$ is detrended potential output, $-1 < \theta < 1$, $0 < \delta \leq 1$ and ζ_t is serially uncorrelated and normally distributed with mean zero and standard deviation σ_ζ

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- δ captures different types of trend possibilities. To see this, rewrite (2) as
$$Y_t^p - Y_{t-1}^p = \psi' + (1-\delta)^2 t - (1-\delta) Y_{t-1}^p + \theta(Y_{t-1}^p - Y_{t-2}^p) + \zeta_t, \quad (3)$$
where $\psi' = \psi + (1-\delta)\left[1 - \theta - (1-\delta)\right]$. This formulation shows that when $\delta = 1$, the model has no deterministic trend, $\psi' = \psi$ and there is a unit root. When $\delta < 1$, there is a deterministic trend and no stochastic trend

The relationship between real-time inflation and policy choice

We extend the policy structure in Ruge-Murcia (2003a, 2004) in formulating the connection between the interest rate chosen by the monetary authority in the preceding period, denoted by i_t, a control error, denoted by ε_t, and the weighted average of the revised (actual) inflation data, denoted by π_t, and the real-time inflation data, denoted by $\pi^r_{t,t+1}$

$$\lambda_1 \pi_t + (1 - \lambda_1)\pi^r_{t,t+1} = i_t + \varepsilon_t. \tag{4}$$

Here the notation $\pi^r_{t,t+1}$ indicates that time t inflation is first observed in real-time immediately after the period ends, which is date $t+1$ One can interpret $(1 - \lambda_1)$ as a measure of the short-term pressure the central bank gets from the government and economic agents to react to real-time inflation data. Similarly for output

$$\lambda_2 Y_t + (1 - \lambda_2) Y^r_{t,t+1}, \tag{5}$$

Revised and Real-time relationships

We model the relationship between the real-time data and the revised data by two simple identities,

$$Y_t = Y^r_{t,t+1} + r^Y_{t,t+s}, \tag{6}$$
$$\pi_t = \pi^r_{t,t+1} + r^\pi_{t,t+s}, \tag{7}$$

where $r^Y_{t,t+s}$ ($r^\pi_{t,t+s}$) denotes the final revision of the initial output (inflation) data, which is released s periods later (i.e. date $t+s$). We assume the data revision processes are given by

$$r^Y_{t,t+s} - \mu = \beta_Y (r^Y_{t-1,t-1+s} - \mu) + \varepsilon^Y_{t,t+s}, \tag{8}$$
$$r^\pi_{t,t+s} = \alpha_\pi + \beta_\pi \pi^r_{t,t+1} + \varepsilon^\pi_{t,t+s}, \tag{9}$$

where $\varepsilon^Y_{t,t+s}$ and $\varepsilon^\pi_{t,t+s}$ are white noise for all t

The error structure

ξ_t is a vector that contains the model's random elements. The vector includes the structural shocks at time t and all the (white noise) output revision innovations up to time $t+s$. We assume that

$$\xi_t | I_{t-1} = \begin{bmatrix} \eta_t \\ \zeta_t \\ \nu_t \\ \left(\bar{\varepsilon}^Y_{t,s}\right)' \end{bmatrix} | I_{t-1} \tilde{} N(0, \Omega_t), \tag{10}$$

where

$$\left(\bar{\varepsilon}^Y_{t,s}\right)' = \left[\varepsilon^Y_{t,t+s}, \varepsilon^Y_{t-1,t+s-1}, \varepsilon^Y_{t-2,t+s-2}, \ldots, \varepsilon^Y_{t-s,t}\right]'.$$

Under this formulation, ξ_t has normal distribution with mean zero and variance–covariance matrix Ω_t. So ξ_t could be conditionally heteroskedastic.

Policy maker objective

The policy maker selects i_t to minimize a loss function that penalizes the variations of the averages of revised and real-time inflation and output around target values according to

$$\min_{i_t} E_{t-1} \left\{ \begin{array}{c} \left(\frac{1}{2}\right) \left[\lambda_1 \pi_t + (1-\lambda_1)\pi^r_{t,t+1} - \pi^*_t\right]^2 \\ + \left(\frac{\phi}{\gamma^2}\right) \left(\begin{array}{c} \exp\left(\gamma(Y^*_t - \lambda_2 Y_t - (1-\lambda_2) Y^r_{t,t+1})\right) \\ -\gamma\left(Y^*_t - \lambda_2 Y_t - (1-\lambda_2) Y^r_{t,t+1}\right) - 1 \end{array} \right) \end{array} \right\},$$

where $\gamma \neq 0$ and $\phi > 0$ are preference parameters and π^*_t and Y^*_t are desired rates of inflation and output, respectively.
We assume π^*_t is constant and denote it by π^*. The desired output level is proportional to the expected permanent value according to

$$Y^*_t = kE_{t-1} Y^p_t \quad \text{for} \quad k \geq 1. \tag{11}$$

When $k = 1$, the authority targets permanent output, while for $k > 1$ the authority targets output beyond the permanent level inducing Barro-Gordon type of bias

Policy maker objective (continued)

After some algebra, standard optimization yields the following key first order condition

$$\begin{aligned} & E_{t-1}\left[\lambda_1 \pi_t + (1-\lambda_1)\pi^r_{t,t+1}\right] - \pi^* \\ & -\left(\frac{\phi\alpha}{\gamma}\right) E_{t-1}\{\exp[\gamma(kE_{t-1}Y^p_t - Y_t + (1-\lambda_2)r^Y_{t,t+s})] - 1\} = 0. \end{aligned} \tag{12}$$

It can be shown that the assumption that the structural disturbances are normal implies that, conditional on the information set,

$$\lambda_2 Y_t + (1-\lambda_2)Y^r_{t,t+1} (= Y_t - (1-\lambda_2)r^Y_{t,t+s} = Y^r_{t,t+1} + \lambda_2 r^Y_{t,t+s})$$

is also normally distributed. This implies that

$$\exp(\gamma(kE_{t-1}Y^p_t - Y_t + (1-\lambda_2)r^Y_{t,t+s}))$$

is distributed log normal

Reduced form inflation equation

Thus, the optimality condition (12) can be written, after some small algebra, as follows

$$\begin{aligned} \pi_t &= a + bE_{t-1}Y_t + c_1\sigma^2_{Y_t} + c_2\sigma_{Y_t, r^Y_{t,t+s}} + c_3\sigma^2_{r^Y_{t,t+s}} \\ &\quad + dr^Y_{t-s-1,t-1} + (1-\lambda_1)r^\pi_{t,t+s} + e_t, \end{aligned} \tag{13}$$

where $a = \pi^* - \left(\frac{\phi\alpha}{\gamma}\right) + \phi\alpha(1-\lambda_2)\mu\left[1-(\beta_Y)^{s+1}\right]$, $b = \phi\alpha(k-1) \geq 0$, $c_1 = \frac{\phi\alpha\gamma}{2} \gtrless 0$, $c_2 = -\phi\alpha\gamma(1-\lambda_2) \gtrless 0$, $c_3 = \frac{\phi\alpha\gamma(1-\lambda_2)^2}{2} \gtrless 0$, $d = \phi\alpha(1-\lambda_2)(\beta_Y)^{s+1} \geq 0$, and e_t is a reduced form disturbance. In our empirical calculations we reduce the number of estimated parameters by imposing $c_2 = -2c_1(1-\lambda_2)$ and $c_3 = c_1(1-\lambda_2)^2$. Notice that, in the case where $\gamma > 0$, c_1 is positive, and thus c_2 is non-positive and c_3 is non-negative

Testing theoretical hypothesis

It is not possible to identify all structural parameters of the model from the reduced-form estimates. In particular, the policy maker preference parameter γ is not identified. However, the sign of parameter c is informative about central banker preferences. As in the Ruge-Murcia model, as $\gamma \rightarrow 0$ (with $k > 1$) one obtains an inflation-output version of the Barro and Gordon model. So a test of that model is, $H_0 : c = 0$. Also, when $k = 1$ the policy preferences are such that the monetary authority targets expected permanent output, so a test of this is, $H_0 : b = 0$.

Alternative empirical equation for inflation

An alternative empirical model can be found by first noting that (6) implies $Y_t - (1-\lambda_2) r^Y_{t,t+s} = Y^r_{t,t+1} + \lambda_2 r^Y_{t,t+s}$ so following the same steps as above, one can get

$$\begin{aligned} \pi_t \quad = \quad & a + bE_{t-1} Y_t + c_1 \sigma^2_{Y^r_{t,t+1}} + c_2' \sigma_{Y^r_{t,t+1}, r^Y_{t,t+s}} + c_3' \sigma^2_{r^Y_{t,t+s}} \quad (14) \\ & + d r^Y_{t-s-1,t-1} + (1-\lambda_1) r^\pi_{t,t+s} + e_t', \end{aligned}$$

where a, b, c_1 and d were defined above and $c_2' = \phi\alpha\gamma\lambda_2 \gtrless 0$ and $c_3' = \frac{\phi\alpha\gamma\lambda_2^2}{2} \gtrless 0$. In our empirical calculations for this formulation we again reduce the number of estimated parameters by imposing $c_2' = 2c_1'\lambda_2$ and $c_3' = c_1'\lambda_2^2$. Again notice that when $\gamma > 0$, whereas c_2' and c_3' are both non-negative. This alternative empirical equation for inflation is expressed in terms of the conditional volatility of real-time output, $\sigma^2_{Y^r_{t,t+1}}$, and the conditional covariance between real-time output and output revisions, $\sigma_{Y^r_{t,t+1}, r^Y_{t,t+s}}$.

Reduced form output equation

Each of the two empirical inflation models when combined with the reduced form for the output process represent a different bivariate output-inflation model. A reduced form for the output process is constructed by using (9), (4), (7), (1), and (3) we get

$$\begin{aligned} Y_t &= Y^p_{t-1} + \psi' + (1-\delta)^2 t - (1-\delta) Y^p_{t-1} + \\ &\quad \theta(Y^p_{t-1} - Y^p_{t-2}) + \zeta_t + \eta_t + \alpha\nu_t, \end{aligned} \tag{15}$$

which implies

$$\begin{aligned} \Delta Y_t &= \psi' + (1-\delta)^2 t - (1-\delta) Y_{t-1} + \theta \Delta Y_{t-1} + \zeta_t + \eta_t + \alpha\nu_t - \\ &\quad \delta\left(\alpha\nu_{t-1} + \eta_{t-1}\right) - \theta\left(\alpha\Delta\nu_{t-1} + \Delta\eta_{t-1}\right). \end{aligned} \tag{16}$$

Equations (13) or (14) along with (16) were estimated jointly using a maximum likelihood estimation (MLE) procedure

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- Sample period: 1965:4-2011:2

Getting real-time data to have the same trend

Computing the GDP revisions as in (6) is not a straightforward exercise because the two series have different benchmark revision characteristics and thus different trends. Both of these features mean that simple differencing of (the logs of) the two raw series to get the revision series is more likely to reflect these differences rather than the non-benchmark revision process. To remedy this, we compute $\widehat{Y}_t^r = \left[1 + \ln\left(\frac{Y_t^r}{Y_{t-1}^r}\right)\right] * Y_{t-1}^{HP}$ where Y_{t-1}^{HP} is the trend component of the revised GDP data, Y_t^r is the real time output data at date t and $\widehat{Y}_t^r$ is our notation for the recomputed real-time GDP data

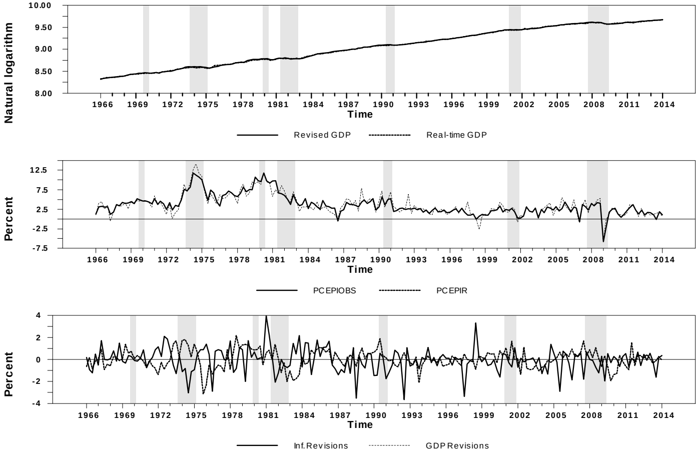

Figure 1. U.S. real-time and revised output and inflation

As noted in Croushore (2011), real-time and revised data would not be an issue if revisions are not predictable in some way

Table 1. Estimation of revision process

	output	inflation
constant	0.001	0.124*
	(0.001)	(0.034)
$AR(1)$	0.347*	0.055
	(0.070)	(0.080)
$AR(2)$	0.252*	
	(0.070)	
$AR(3)$		
$AR(4)$		
real-time variable		-0.143*
		(0.037)
R^2	0.268	0.130
Durbin-Watson statistic	2.016	1.749

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    1. Using the "original" residuals from raw data series regressions
    2. Using "standardized" residuals from a first step multivariate $GARCH(1,1)$ model
- Table 2 shows several facts. First, although none of the original series show significant conditional heteroskedasticity, the revised data and real-time series do show a higher degree of conditional heteroskedasticity than the revision series. Second, the GARCH model generating the standardized residuals reduce the conditional heteroskedasticity for all series, which implies that conditional variances obtained from the $GARCH(1,1)$ model do contain useful information

Table 2. LM tests for neglected ARCH

Squared residuals	No. of lags 1	2	3	4	5	6
	Revised Output Data					
Original	0.87	4.68[†]	4.82	7.24	7.41	7.44
Standardized	1.78	2.25	3.22	5.01	6.31	9.97
	Real-time Output Data					
Original	0.88	1.20	4.30	5.13	5.44	5.42
Standardized	0.09	1.76	2.01	2.75	2.81	2.84
	Output Revisions					
Original	0.89	1.21	2.07	2.31	3.34	3.23
Standardized	0.08	0.38	2.56	2.67	3.09	4.54

Estimation

- Table 3 shows the MLE results using PCE inflation (while Table 4 uses GDP deflator inflation) for the four versions of the model that result from combining the nonstationary and trend-stationary versions of the reduced form of output process together with the two versions of the empirical equation of inflation (i.e. the baseline version based on revised output and the alternative version based on real-time output)

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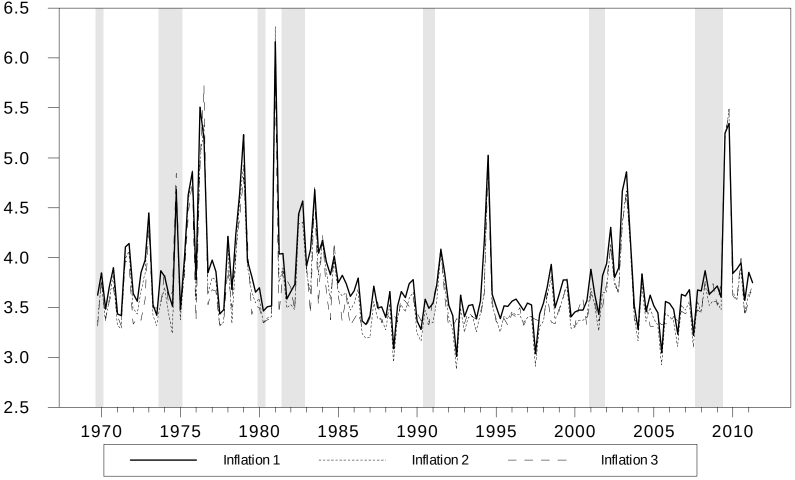
- The nonstationary models, denoted as $ARIMA(1,1,2)$ correspond to δ values of 1, which means that first differences of some of the output variables in (16) were taken
- The stationary versions correspond to values of $\delta < 1$, denoted as $ARIMA(2,0,2)$. This meant that there was a deterministic time trend. The time trend was estimated from a simple regression of real-time output on a constant and a time trend in a preliminary regression. This regression found $\delta = 0.992$ and was the value used for the MLE procedure

Table 3. PCE inflation.

	ARIMA(1,1,2) model		ARIMA(2,0,2) model	
Coefficient	Revised output	Real-time output	Revised output	Real-time output
a	2.496^{*}	2.884^{*}	2.516^{*}	2.749^{*}
	(0.631)	(0.570)	(0.650)	(0.550)
b	0.0	0.0	0.0	0.0
	.	.	.	.
c_1	10.316^{*}	$5.650^{\dagger}$	9.628^{*}	$7.279^{\dagger}$
	(5.134)	(3.274)	(4.718)	(3.727)
d	0.0	0.0	0.0	0.0
	.	.	.	.
λ_1	0.862^{*}	0.853^{*}	0.840^{*}	0.865^{*}
	(0.208)	(0.217)	(0.203)	(0.205)
λ_2	0.580	$0.895^{\dagger}$	0.5	0.5
	(0.470)	(0.471)	.	.
log likelihood	0.952	0.946	0.938	0.933
t-statistics				
H_0: $\lambda_1 = 0.5$	$1.740^{\dagger}$	1.627	$1.675^{\dagger}$	$1.780^{\dagger}$
H_0': $\lambda_2 = 0.5$	0.170	1.051	.	.

Table 4. GDP deflator inflation.

	ARIMA(1,1,2) model		ARIMA(2,0,2) model	
Coefficient	Revised output	Real-time output	Revised output	Real-time output
a	2.361*	2.708*	2.412*	2.706*
	(0.651)	(0.570)	(0.698)	(0.575)
b	0.0	0.0	0.0	0.0
	.	.	.	.
c_1	10.934†	6.203†	10.005†	5.999†
	(6.098)	(3.180)	(5.421)	(3.207)
d	0.0	0.0	0.038	0.0
	.	.	(0.044)	.
λ_1	0.814*	0.779*	0.806*	0.784*
	(0.182)	(0.210)	(0.172)	(0.209)
λ_2	0.569	0.951*	0.5	0.985*
	(0.432)	(0.436)	.	(0.451)
log likelihood	1.051	1.044	1.030	1.026
t-statistics				
H_0: $\lambda_1 = 0.5$	1.725†	1.329	1.779†	1.359
H_0': $\lambda_2 = 0.5$	0.160	1.034	.	1.075


6.5
6.0
5.5
5.0
4.5
4.0
3.5
3.0
2.5
1970
1975
1980
1985
1990
1995
2000
2005
2010
Inflation 1
Inflation 2
Inflation 3

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- Our model identifies several new potential sources of inflation bias due to data revisions in addition to those featured by surprise inflation à la Barro-Gordon (1983) and by asymmetric central bank preferences as suggested by Ruge-Murcia (2003)
- Our empirical results suggest that the Federal Reserve Bank mainly focuses on targeting revised data, but it does weigh real-time data too
- As a consequence, the inflation bias induced by real-time data increases by 12.6 basis points on average, but this figure becomes roughly twice as large at the start of recessions