Optimal Monetary Policy Revisited: Does Considering Real-Time Data Change Things?

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

Steven P. Cassou, C. Patrick Scott and Jesús Vázquez

Kansas State University, Missouri State University and Universidad del País Vasco

July 24, 2015
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Our models identify 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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Background

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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.
Key findings

- Main theoretical result: we identify a few additional potential sources of inflation bias due to data revisions
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- First empirical results show that output revisions are well characterized by autoregressive processes whereas inflation revisions are negatively anticipated by their initial announcement: predictability for revisions may produce persistent inflation biases.

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- Second empirical results suggest that the Fed mainly focuses on targeting revised inflation, but it also weights real-time inflation and this induces one type of new bias: increasing inflation by 12.6 basis points on average, but this figure becomes roughly twice as large at the start of recessions when discrepancies between revised and real-time data increase.
- We find weaker evidence on bias induced by output revisions.
Outline of talk

- We begin by describing the theoretical model and some theoretical results including the additional sources for inflation bias
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- Next we describe the data
- Results estimating simple autoregressive process for the revision process are presented
- Finally, we present estimates of the full theoretical model
We consider Lucas (1977) short run supply curve

\[ Y_t = Y_t^p + \alpha (\pi_t - \pi_t^e) + \eta_t, \]  

where \( Y_t \) is output produced at time \( t \), \( Y_t^p \) is permanent or potential output at time \( t \), \( \pi_t \) is inflation at time \( t \), \( \pi_t^e \) is expected inflation at time \( t \) based on information at time \( t - 1 \), \( \eta_t \) is a supply disturbance and \( \alpha \) 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 $\zeta_t$ according to the AR process

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

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


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- $\delta$ captures different types of trend possibilities. To see this, rewrite (2) as

$$Y_t^P - Y_{t-1}^P = \psi' + (1 - \delta)^2 t - (1 - \delta) Y_{t-1}^P + \theta(Y_{t-1}^P - Y_{t-2}^P) + \zeta_t,$$

where $\psi' = \psi + (1 - \delta) [1 - \theta - (1 - \delta)]$. 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 $\varepsilon_t$, and the weighted average of the revised (actual) inflation data, denoted by $\pi_t$, and the real-time inflation data, denoted by $\pi^r_{t,t+1}$

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

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

$$\lambda_2 Y_t + (1 - \lambda_2) Y^r_{t,t+1}. \quad (5)$$
Revised and Real-time relationships

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

\[ Y_t = Y_{t,t+1}^{r} + r_{t,t+s}^{Y}, \]  
\[ \pi_t = \pi_{t,t+1}^{r} + r_{t,t+s}^{\pi}, \]  

where \( r_{t,t+s}^{Y} (r_{t,t+s}^{\pi}) \) 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

\[ r_{t,t+s}^{Y} - \mu = \beta_Y (r_{t-1,t-1+s}^{Y} - \mu) + \varepsilon_{t,t+s}^{Y}, \]  
\[ r_{t,t+s}^{\pi} = \alpha_{\pi} + \beta_{\pi} \pi_{t,t+1}^{r} + \varepsilon_{t,t+s}^{\pi}, \]

where \( \varepsilon_{t,t+s}^{Y} \) and \( \varepsilon_{t,t+s}^{\pi} \) are white noise for all \( t \).
The model

The error structure

\( \tilde{\xi}_t \) 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

\[
\tilde{\xi}_t | I_{t-1} = \begin{bmatrix}
\eta_t \\
\zeta_t \\
v_t \\
(\tilde{\varepsilon}_{Y_{t,s}})'
\end{bmatrix} ~ \mathcal{N}(0, \Omega_t),
\]

(10)

where

\[
(\tilde{\varepsilon}_{Y_{t,s}})' = [\varepsilon_{Y_{t,t+s}}, \varepsilon_{Y_{t-1,t+s-1}}, \varepsilon_{Y_{t-2,t+s-2}}, \ldots, \varepsilon_{Y_{t-s,t}}]'.
\]

Under this formulation, \( \tilde{\xi}_t \) has normal distribution with mean zero and variance–covariance matrix \( \Omega_t \). So \( \tilde{\xi}_t \) could be conditionally heteroskedastic.
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

$$
\min_{i_t} E_{t-1} \left\{ \left( \frac{1}{2} \right) \left[ \lambda_1 \pi_t + (1 - \lambda_1) \pi_{t,t+1}^r - \pi_t^* \right]^2 + \left( \frac{\phi}{\gamma^2} \right) \left( \exp \left( \gamma (\pi_t^* - \lambda_2 Y_t - (1 - \lambda_2) Y_{t,t+1}^r) \right) - \gamma (\pi_t^* - \lambda_2 Y_t - (1 - \lambda_2) Y_{t,t+1}^r) - 1 \right) \right\},
$$

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

$$
Y_t^* = kE_{t-1}Y_t^p \quad \text{for} \quad k \geq 1. \quad (11)
$$

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

\[ E_{t-1} \left[ \lambda_1 \pi_t + (1 - \lambda_1) \pi_{t,t+1}^r \right] - \pi^* \]

\[ - \left( \frac{\phi \alpha}{\gamma} \right) E_{t-1} \left\{ \exp \left[ \gamma (kE_{t-1} Y_t^p - Y_t + (1 - \lambda_2) r_{t,t+s}^Y) \right] - 1 \right\} = 0. \]

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

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

is also normally distributed. This implies that

\[ \exp \left( \gamma (kE_{t-1} Y_t^p - Y_t + (1 - \lambda_2) r_{t,t+s}^Y) \right) \]

is distributed log normal.
Reduced form inflation equation

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

\[ \pi_t = a + bE_{t-1} Y_t + c_1 \sigma^2_{Y_t} + c_2 \sigma_{Y_t, r_{t,t+s}} + c_3 \sigma^2_{r_{t,t+s}} + \sigma_{r_{t-s-1,t-1}} + (1 - \lambda_1) r^\pi_{t,t+s} + e_t, \]  

(13)

where \( a = \pi^* - \left( \frac{\phi \alpha}{\gamma} \right) + \phi \alpha (1 - \lambda_2) \mu \left[ 1 - (\beta_Y)^{s+1} \right], \)

\( b = \phi \alpha (k - 1) \geq 0, \)

\( c_1 = \frac{\phi \alpha \gamma}{2} \geq 0, \)

\( c_2 = -\phi \alpha \gamma (1 - \lambda_2) \geq 0, \)

\( c_3 = \frac{\phi \alpha \gamma (1 - \lambda_2)^2}{2} \geq 0, \)

\( d = \phi \alpha (1 - \lambda_2) (\beta_Y)^{s+1} \geq 0, \)

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.

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The model

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 $\gamma$ is not identified. However, the sign of parameter $c$ is informative about central banker preferences. As in the Ruge-Murcia model, as $\gamma \to 0$ (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, $H_0 : b = 0$. 
An alternative empirical model can be found by first noting that (6) implies $Y_t - (1 - \lambda_2) r_{t,t+s}^Y = Y_{t,t+1}^r + \lambda_2 r_{t,t+s}^Y$ so following the same steps as above, one can get

$$\begin{align*}
\pi_t &= a + b E_{t-1} Y_t + c_1 \sigma_{Y_{t,t+1}}^2 + c'_2 \sigma_{Y_{t,t+1}^r, Y_{t,t+s}^r} + c'_3 \sigma_{r_{t,t+s}^Y}^2 \quad (14)
+ d r_{t-s-1,t-1}^Y + (1 - \lambda_1) r_{t,t+s}^\pi + e'_t,
\end{align*}$$

where $a$, $b$, $c_1$ and $d$ were defined above and $c'_2 = \phi \alpha \gamma \lambda_2 \geq 0$ and $c'_3 = \frac{\phi \alpha \gamma \lambda_2^2}{2} \geq 0$. 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, $\sigma_{Y_{t,t+1}^r}^2$, and the conditional covariance between real-time output and output revisions, $\sigma_{Y_{t,t+1}^r, r_{t,t+s}^Y}$. 
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

\[
Y_t = Y_{t-1}^p + \psi' + (1 - \delta)^2 t - (1 - \delta) Y_{t-1}^p + \theta (Y_{t-1}^p - Y_{t-2}^p) + \zeta_t + \eta_t + \alpha \nu_t,
\]

which implies

\[
\Delta Y_t = \psi' + (1 - \delta)^2 t - (1 - \delta) Y_{t-1} + \theta \Delta Y_{t-1} + \zeta_t + \eta_t + \alpha \nu_t - \delta (\alpha \nu_{t-1} + \eta_{t-1}) - \theta (\alpha \Delta \nu_{t-1} + \Delta \eta_{t-1}).
\]

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

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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

$$\hat{Y}_t^r = \left[ 1 + \ln \left( \frac{Y_t^r}{Y_{t-1}^r} \right) \right] \ast Y_{t-1}^{HP}$$

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 $\hat{Y}_t^r$ 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

<table>
<thead>
<tr>
<th></th>
<th>output</th>
<th>inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>0.001</td>
<td>0.124*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.347*</td>
<td>0.055</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.252*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td></td>
</tr>
<tr>
<td>AR(3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR(4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>real-time variable</td>
<td></td>
<td>-0.143*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.268</td>
<td>0.130</td>
</tr>
<tr>
<td>Durbin-Watson statistic</td>
<td>2.016</td>
<td>1.749</td>
</tr>
</tbody>
</table>
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2. Using "standardized" residuals from a first step multivariate $GARCH(1,1)$ model
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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

<table>
<thead>
<tr>
<th>Squared residuals</th>
<th>No. of lags</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Revised Output Data</td>
<td></td>
</tr>
<tr>
<td>Original</td>
<td>0.87</td>
</tr>
<tr>
<td>Standardized</td>
<td>1.78</td>
</tr>
<tr>
<td>Real-time Output Data</td>
<td></td>
</tr>
<tr>
<td>Original</td>
<td>0.88</td>
</tr>
<tr>
<td>Standardized</td>
<td>0.09</td>
</tr>
<tr>
<td>Output Revisions</td>
<td></td>
</tr>
<tr>
<td>Original</td>
<td>0.89</td>
</tr>
<tr>
<td>Standardized</td>
<td>0.08</td>
</tr>
</tbody>
</table>
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 $\delta$ values of 1, which means that first differences of some of the output variables in (16) were taken.
Estimation

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- The nonstationary models, denoted as $ARIMA(1, 1, 2)$ correspond to $\delta$ 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.**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>ARIMA(1,1,2) model</th>
<th>ARIMA(2,0,2) model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Revised output</td>
<td>Real-time output</td>
</tr>
<tr>
<td>( a )</td>
<td>2.496(^*)</td>
<td>2.884(^*)</td>
</tr>
<tr>
<td></td>
<td>(0.631)</td>
<td>(0.570)</td>
</tr>
<tr>
<td>( b )</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>( c_1 )</td>
<td>10.316(^*)</td>
<td>5.650(^\dagger)</td>
</tr>
<tr>
<td></td>
<td>(5.134)</td>
<td>(3.274)</td>
</tr>
<tr>
<td>( d )</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>0.862(^*)</td>
<td>0.853(^*)</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.217)</td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>0.580</td>
<td>0.895(^\dagger)</td>
</tr>
<tr>
<td></td>
<td>(0.470)</td>
<td>(0.471)</td>
</tr>
<tr>
<td>log likelihood</td>
<td>0.952</td>
<td>0.946</td>
</tr>
<tr>
<td>( t )-statistics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( H_0: \lambda_1 = 0.5 )</td>
<td>1.740(^\dagger)</td>
<td>1.627</td>
</tr>
<tr>
<td>( H'_0: \lambda_2 = 0.5 )</td>
<td>0.170</td>
<td>1.051</td>
</tr>
</tbody>
</table>
## Table 4. GDP deflator inflation.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>ARIMA(1,1,2) model</th>
<th>ARIMA(2,0,2) model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Revised output</td>
<td>Real-time output</td>
</tr>
<tr>
<td>$a$</td>
<td>2.361* (0.651)</td>
<td>2.708* (0.570)</td>
</tr>
<tr>
<td>$b$</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>$c_1$</td>
<td>10.934† (6.098)</td>
<td>6.203† (3.180)</td>
</tr>
<tr>
<td>$d$</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>0.814* (0.182)</td>
<td>0.779* (0.210)</td>
</tr>
<tr>
<td>$\lambda_2$</td>
<td>0.569 (0.432)</td>
<td>0.951* (0.436)</td>
</tr>
</tbody>
</table>

log likelihood: 1.051, 1.044, 1.030, 1.026

t-statistics

$H_0$: $\lambda_1 = 0.5$

$H_0': \lambda_2 = 0.5$

1.725†, 1.329, 1.779†, 1.359

0.160, 1.034, ·, 1.075
Optimal monetary policy revisited: Does considering real-time data change things?

Model estimation results

![Graph showing inflation rates from 1970 to 2010 for inflation 1, 2, and 3.](image-url)
This paper adds to the growing body of literature regarding monetary policy and real-time data analysis. A version of the Ruge-Murcia (2003) model in which the planner targets a weighted average of revised and real-time inflation and output is built to study real-time issues.
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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).
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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.