Real-time vs ex-post monetary policy evaluation under opportunistic policy

Steven P. Cassou†  Jesús Vázquez‡
Kansas State University Universidad del País Vasco (UPV/EHU)

November 4, 2016

Abstract

In this paper we show that there are striking differences in impulse response results when using revised and real-time data under opportunistic threshold structures. Notably, the impulse responses using revised data show almost no threshold behavior differences between the two sides of an opportunistic threshold structure while real-time data show significant differences between the two sides. This result is important to recognize since policy makers do not have ex-post revised data during their decision deliberations. As a result, economists using revised data may misread policy making behavior that can only be revealed using real-time data.

JEL Classification: C32, E32, E52

Keywords: Real-time vs revised data, threshold models, opportunistic monetary policy, local projections

*We are very grateful to Dean Croushore, Isabel Casas and Iqbal Ahmed for comments and suggestions. The authors acknowledge financial support from the Spanish Ministerio de Economía y Competitividad (research projects ECO2013-43773-P and ECO2016-78749-P). The second author also acknowledges financial support from the Basque Government and the University of the Basque Country (research grant codes IT-793-13 and UFI11/46, respectively).

†Department of Economics, 327 Waters Hall, Kansas State University, Manhattan, KS, 66506 (USA), (785) 532-6342, Fax:(785) 532-6919, email: scassou@k-state.edu.
‡Corresponding author: Depto. Fundamentos del Análisis Económico II, Facultad de Economía y Empresa, Universidad del País Vasco (UPV/EHU), Av. Lehendakari Aguirre 83, 48015 Bilbao (SPAIN), Phone: +34 946013779, Fax: +34 946017123, email: jesus.vazquez@ehu.es.
1 Introduction

In a seminal paper, Orphanides (2001) showed that monetary policy evaluation based on estimated policy reaction functions using ex post revised data can be misleading because it ignores behavior suggested by information available to the Federal Reserve Bank (Fed) in real time. Since then there is a rather large literature (see Croushore, 2011, and references therein) analyzing the consequences of policy evaluation when data is revised. However, one issue with this work is that most has focused on the reaction of monetary policy to the output gap, which is problematic because this measure of economic activity is strongly revised—e.g. Orphanides and van Norden (2002), Orphanides (2003), Kozicki, (2004) and Kamada (2005).

This paper contributes to the real-time data literature in two important ways. First, we investigate differences in Fed behavior conclusions drawn from revised and real-time data when the Fed operates using an opportunistic monetary policy structure. This opportunistic monetary policy structure has been suggested by Meyer (1996), Rudebusch (1996), Bomfim and Rudebusch (2000), Aksoy et al. (2006) and Bunzel and Enders (2010) and posits that Fed behavior differs when the inflation rate is accelerating than when it is stable or falling (non-accelerating). In particular, during non-accelerating inflation, the Fed has the opportunity to be accommodative toward output, while during accelerating inflation, the Fed does not have this opportunity. To model this structure, we follow Bunzel and Enders (2010) and use a threshold time series model which implies nonlinear behavior. Second, we use local projection methods suggested by Jordà (2005) for computing impulse responses under the two scenarios described by the threshold model. This combination allows us to investigate policy without reference to the problematic output gap data, which can hardly be measured in real time, and to isolate opportunistic policy differences that may arise during the two alternative inflation scenarios. We find that the conclusions one would draw about monetary policy are quite different if one were to use real-time instead of revised data when estimating the impulse responses.
Jordà’s (2005) methodology for computing impulse responses based on local projections has many general advantages highlighted in his paper. Its impulse responses are robust to data generating process misspecification and, therefore, they are well suited to handle unknown forms of nonlinearities. Moreover, it is simple to implement, requiring only least squares estimation. Furthermore, it provides appropriate inference that does not require asymptotic delta-method approximations or bootstrap techniques for its calculation. For our purpose of monetary policy evaluation, this approach is particularly useful for the following reasons. First, the method is well suited to deal with the nonlinear Fed opportunistic structure used here. Second, there is no need to rely on a conceptual measure, such as the output gap, which is hardly observable in real time, as is pursued in the related literature which estimate Taylor rules. Taken together, this method allows us to analyze the impulse responses to alternative shocks in the presence of policy reaction asymmetries. Furthermore, it allows a rather straightforward comparison of policy evaluation based on ex-post revised data and policy evaluation based on real-time data.

Our estimation results show important differences in the response of the federal funds rate to output and inflation shocks during accelerating and non-accelerating inflation. More importantly, for the goal of this paper, we find that the assessment of policy reactions depends on whether this assessment is based on ex-post revised data or on the information available to the Fed in real time. Furthermore, we find these differences are most striking when analyzing the federal funds rate response to an output shock during accelerating inflation episodes. These findings are important because the Fed truly operates in a real-time world, thus revised data analysis may conceal the Fed’s true behavior.

The rest of the paper is organized as follows. Section 2 describes how we compute impulse response functions using the local projection methods suggested in Jordà

---

1 Jordà’s methodology has been implemented in the empirical literature to address a wide range of issues such as the estimation of New Keynesian Phillips curve (Jordà and Kozicki, 2010), the analysis of government spending multipliers (e.g. Owyang, Ramey and Zubairy, 2013; and Kraay, 2014), the analysis of productivity spillovers across firms (Stoyanov and Zubanov, 2012) and the impact of consumer confidence on durable goods spending (Ahmed and Cassou, 2016), among others.
(2005). The sources of revised and real-time data are described in Section 3. Section 4 presents the estimation results and discusses them. A robustness analysis is carried out in Section 5 along a few dimensions. Finally, Section 6 concludes.

2 Econometric method

The econometric method makes use of several recent developments in time series econometrics. These include threshold models, which allow parameters to change depending on whether a state variable is above or below a threshold, and local projection methods suggested in Jordà (2005) for finding impulse response functions (IRF). The local projection methods are attractive because they are flexible enough to handle nonlinear models, such as threshold models, which conventional impulse response methods based on vector autoregressions (VAR) are unable to handle.

In our analysis we use three variables that are popular in monetary policy evaluation and include US real gross domestic product (GDP), inflation and the federal funds interest rate. We denote these variables generically by \( y_t, \pi_t \) and \( i_t \) respectively, but in addition we investigate two alternative data sets: one set includes revised data for \( y_t \) and \( \pi_t \) while the other includes real-time data for these two variables. In both sets we include the same federal funds rate series, \( i_t \), which we regard as the real-time policy variable that is never revised.

Jordà’s (2005) procedure generates impulse responses by projecting linear models one-period ahead at a time. We can formulate this method within our threshold structure as

\[
X_{t+s} = I_t \left[ C_a^s + \sum_{i=1}^{p} B_{i,a}^{s+1} X_{t-i} \right] + (1-I_t) \left[ C_r^s + \sum_{i=1}^{p} B_{i,r}^{s+1} X_{t-i} \right] + U_{t+s}^s \quad s = 0, 1, ..., h, \tag{1}
\]

where \( X_t = [y_t \quad \pi_t \quad i_t]' \) is a vector of the model variables which we wish to forecast \( s \)-steps ahead for \( h \) different forecast horizons using a forecasting model consisting of only \( p \) lags of the variables in the system. The variable \( I_t \) is the threshold indicator, which we define shortly using an opportunistic monetary structure and we denote
these two states with notations of $a$ when there is concern for accelerating inflation by the monetary authority and $\tau$ when inflation in the economy is tranquil and thus there is less concern. The parameters in the model are straightforward, with $C_j^a$ denoting a $3 \times 1$ vector of constants for the two threshold states $j = a, \tau$ and $B_{s+1}^j$ denoting $3 \times 3$ square matrices of parameters corresponding to the $i$-th lag, $X_{t-i}$, in the $s$-step ahead forecasting model for the two threshold states $j = a, \tau$. Finally, $U_{t+s}$ is a moving average of the forecast errors from time $t$ to time $t+s$. As shown by Jordà (2005), this method is robust to specifications with nonstationary or cointegrated data, so for our application the components of $X_t$ are level data with (the log of) GDP, $y_t$, being the only component with an obvious trend.

Jordà (2005) shows that IRFs generated by the local projections are equivalent to the ones that are calculated from a VAR when the true data generating process (DGP) is a VAR, but that the IRFs for other DGPs that are not true VARs are better estimated using this local projection method. Jordà’s key insight is that a VAR can be viewed as a linear global approximation to the unknown DGP and is optimally designed for one-period ahead forecasting. Furthermore, even when the model is misspecified, a VAR may still produce reasonable one-period ahead forecasts—see Stock and Watson (1999). However, as emphasized below, an impulse response function is defined for increasingly distant horizons, and therefore misspecification errors are compounded with the forecast horizon when using a fixed set of VAR coefficients. Due to its flexibility and performance, Jordà (2005) suggests that it is preferable to use a sequence of projections using the same regressors as in the VAR, each making one-step ahead forecasts (which he termed local projections) for computing each impulse response horizon, rather than extrapolating into increasingly distant horizons from a set of VAR coefficients. Moreover, Jordà (2005) provides Monte Carlo experiments showing that local projections result in only small efficiency losses when the true underlying model is a VAR.

The IRFs for our opportunistic threshold model are given by
\[
\tilde{IR}^a(t, s, d_i) = \tilde{B}_{1,a}^s d_i \quad s = 0, 1, ..., h,
\]

and

\[
\tilde{IR}^r(t, s, d_i) = \tilde{B}_{1,r}^s d_i \quad s = 0, 1, ..., h,
\]

with normalizations \(B_{1,a}^0 = I\) and \(B_{1,r}^0 = I\), where \(I\) is a 3 \times 3 identity matrix, and \(d_i\) is a 3 \times 1 column vector that contains the mapping from the structural shock for the \(i\)-th element of \(X_t\) to the reduced-form shocks. We construct this mapping matrix using methods suggested in Jordà (2005), which essentially follows methods used in the traditional VAR literature and begins by estimating a linear VAR and applying a Cholesky decomposition to the variance-covariance matrix. In particular, define \(d_i\) by

\[
d_i = A_0^{-1}\Omega_\varepsilon \delta_i,
\]

where \(\delta_i\) is a column vector with a one in the \(i\)-th position and zeros elsewhere, \(A_0\) is a coefficient matrix from a structural form VAR and \(\Omega_\varepsilon\) is the diagonal variance-covariance matrix associated with the structural shocks.

One can compute confidence bands using estimates of the standard deviations for the impulses. One issue that needs to be recognized in doing this is that because the DGP is unknown, there could be serial correlation in the error term of (1) induced by the successive leads of the dependent variable. Jordà (2005) addresses this issue by using Newey and West (1987) standard errors which correct for heteroskedasticity and autocorrelation (HAC) of least-squares residuals. Letting \(\hat{\sum}_{s,j}\) be the estimated HAC corrected variance-covariance matrix of the coefficients \(\hat{B}_{i,j}\), a 95\% (or two-standard deviation) confidence interval for each element of the IRF at horizon \(s\) can be constructed by \(\tilde{IR}^d(t, s, d_i) \pm 2\sigma(d_i\hat{\sum}_{s,j}d_i)\), where \(\sigma\) is a 3 \times 1 column vector of ones.

Now that the local projection approach for computing IRFs has been described,
it may be useful to highlight some of its advantages. The primary advantage over
the standard VAR approach is its lack of structure from one horizon to the next.
This can be understood by reviewing the IRF computation from the typical VAR
model. The VAR approach uses the VAR parameters to generate the moving average
representation from which the IRFs are generated at each horizon, thus the IRFs at
all horizons are directly connected to these VAR parameters. Thus, if the VAR is
misspecified, then errors are compounded with the forecast horizon. On the other
hand, the local projection method computes the IRFs for each response horizon from
a different forecast equation and thus the structure of the IRFs can vary over the
horizon. This allows flexibly when the DGP is nonlinear. So for instance, if the DGP
is given by the highly nonlinear structure in (1), the linear VAR structure will not
be able to handle this as well as the local projection approach which imposes less
structure on the IRF. Moreover, the local projection approach estimates parameters
that are based on data that can be in either state of the world. Thus these para-

deters have an averaging effect and the projections based on these estimates can
be interpreted as weighted averages of the two separate state IRFs. Furthermore,
the local projection system (1) can be easily extended by incorporating nonlinear
components of $X_t$ (quadratic, cubic, and higher order) to account for unknown forms
of nonlinearities present in the data. In particular, in our empirical application we
included the terms $X_{t-1}^2$ and $X_{t-1}^3$ in the local projection.

Before we define the threshold indicator, let us point out two important remarks.
First, the IRF approach followed in this paper to analyze the Fed’s behavior comple-
ments the Taylor-rule approach followed in the related literature. On the one hand,
the two approaches share a similar set of observables: inflation, a short-term interest
rate (e.g. the federal funds rate) and a measure of economic activity (the log level

\[ \text{The local projection method is also attractive relative to methods proposed by Auerbach and Gorodnichenko (2012). In the switching threshold VAR approach suggested by Auerbach and Gorodnichenko (2012), it is assumed that the economy stays in the current state over the horizon in which the impulse responses are calculated. Ramey and Zubairy (2014), for example, argues that this type of assumption is inconsistent with the fact that the average NBER recession period typically last 3.3 quarters, much shorter than the horizons over which one estimates IRFs.} \]
of output or a measure of the output gap). On the other hand, our IRF approach is able to address different policy responses depending on the shocks hitting the economy. Of course, there is no free lunch. The cost is that our IRF approach does not allow us to identify the reaction coefficients featured in a Taylor-type rule. Second, the computation of the Jordà type IRFs is rather straightforward when using revised data. However, the computation of these IRFs with real-time data is slightly more complicated because when computing the local projections of \( X_{t+s} \) at time \( t \), one has to take into account the lagged values, \( X_{t-i} \), corresponding to the latest (real-time) vintage of data available at \( t \).

**The threshold indicator**

According to the Federal Reserve Bank’s dual mandate, the Fed aims at keeping (i) inflation low, and (ii) production and employment close to their long-run potential levels.\(^3\) Consistent with this dual mandate, Meyer (1996), Rudebusch (1996), Bommim and Rudebusch (2000), and Aksoy et al. (2006) suggested a Fed opportunistic disinflation policy featured by the presence of an *interim* inflation target, defined by the recent history of inflation, that can be gradually adjusted as a consequence of exogenous shocks—positive (negative) supply (demand) shocks—to achieve the Fed’s low inflation target in the long-run. Thus, the Fed focuses only on output stabilization when there is no short-term inflationary pressures (i.e. when current inflation is below the interim inflation target) and only actively reacts to inflation when inflation accelerates.

We look at several opportunistic threshold variable formulations, but focus on one suggested in Bunzel and Enders (2010), which is given by

\[
I_t = \begin{cases} 
1 & \text{for } \pi_{t-1} > (\pi_{t-5} + \pi_{t-9})/2, \\
0 & \text{otherwise.} 
\end{cases}
\]  

\(^{3}\)In 1977, Congress amended The Federal Reserve Act, establishing the monetary policy goals of the Federal Reserve as follows: "The Board of Governors of the Federal Reserve System and the Federal Open Market Committee shall maintain long run growth of the monetary and credit aggregates commensurate with the economy’s long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices and moderate long-term interest rates."
In this formulation, the interim inflation target is represented by a simple average of the inflation rate prevailing 1 and 2 years ago.\textsuperscript{4} The indicator takes a value of 1 when there is an increase in inflation beyond an average of recent inflation and takes a value of 0 otherwise. It is the zero value that is interpreted as the opportunistic disinflation case, where the central bank has the opportunity to be accommodative for output because of the diminishing average inflation rate. This opportunistic structure implies a nonlinearity to the inflation-output tradeoff since the loss from even a small deviation of output from its potential level is of greater importance to the Fed than the loss due to a small increase of inflation whenever inflation is below the interim inflation target. We sometimes call this the tranquil case of inflation and use the notation $\tau$ to indicate it. On the other hand, the unit value of the indicator occurs when inflation is rising in the short-run and would indicate that the central bank does not have the opportunity to be accommodative for output. This active disinflation case also results in a nonlinearity to the inflation-output tradeoff, but completely different from the one implied in the opportunistic case. In the active disinflation case, the loss of slightly positive deviations of inflation from its interim target are of much greater importance to the Fed than any loss due to output fluctuations. We sometimes call this the accelerating inflation case and use the notation $\alpha$ to indicate it. As discussed below, estimation results are robust to alternative specifications of the threshold indicator.

3 Data

We consider both revised and real-time quarterly data for GDP and the GDP deflator as well as data for the federal funds rate.\textsuperscript{5} Revised data on GDP and the GDP deflator, and the federal funds rate were obtained from the Federal Reserve Economic \footnote{As a robustness check, we considered other plausible specifications for the interim inflation target described as $\pi_{t-1} > \lambda \pi_{t-5} + (1 - \lambda) \pi_{t-9}$ for alternative weights $\lambda \in [0, 1]$. Results from these alternative specifications were fairly similar to those shown in the empirical analysis below.}

\footnote{At times we will refer to GDP as output and the federal funds rate as simply the interest rate or the policy variable when those names seem useful.}
Data (FRED) base maintained by the St. Louis Federal Reserve Bank whereas the real-time data series for GDP and the GDP deflator were obtained from the real-time data base maintained by the Philadelphia Federal Reserve Bank. Because our empirical model requires inflation rates rather than price indexes, the inflation rates were obtained as the first difference of the log of the GDP deflator, which was then multiplied by 4 to obtain the annualized inflation rate in line with the federal funds rate and GDP, which are also annualized.

The real-time data base proved to be the binding constraint for the first period of the analysis, as this data is only available beginning in the third quarter of 1965. On the other hand, the revised data proved to be the binding constraint for the end period of the analysis. Although data that is called revised data was available up to 2015:4 when we started to carry out our empirical analysis, the earlier end date for the long sample was chosen so as to be consistent with the timing of the last revision for the data, ignoring comprehensive or benchmark revisions that can be carried out in the future.\(^6\) In particular, there is a three-year lag before GDP data is revised for the last time. This lag means that only the data up to 2012:4 can be considered as truly revised data. Together these data constraints implied a data set which ran from 1965:3 to 2012:4.

4 Empirical results

Figures 1-3 display the IRF of GDP, inflation and interest rates to an output shock, an inflation shock and an interest rate shock respectively using revised data (left column graphs) and real-time data (right column graphs). In these exercises, we use four lags (i.e. \( p = 4 \)), or one year’s worth of lags, in the local projection computation because this is a relatively common number in VAR studies. Each graph shows the IRF when inflation is accelerating (solid line) and when inflation is tranquil (dashed

---

\(^{6}\) Apart from data revisions taken place up to three years after the first release, US National Accounts are further revised due to benchmark revisions. These benchmark revisions take place every five years and involve changing methodologies or statistical changes such as base years. See Croushore (2011), and references therein, for further details.
lines) together with the 95% confidence interval (dotted lines) associated with the latter.

Looking across the figures, notice that mainly output shocks (Figure 1) produce IRFs that are sharply different between the real-time data graphs and the revised data graphs. These sharp differences to output shocks imply interesting economic insights, so we will begin by discussing the Figure 1 graphs.

First, let us note one common characteristic between the two columns of graphs in Figure 1. Both show that when inflation is accelerating, a positive output shock produces a relatively strong increase in the interest rate, relative to the case when inflation is tranquil. Where things begin to differ is that the real-time data imply policy increases during the accelerating inflation state that are outside the two-standard error band for the tranquil period and can be interpreted as implying a significantly different policy for the two states, while the revised data imply policy increases during the accelerating inflation state right at the edge of the confidence band. To account for this difference, look at the plots for the output responses. The real-time data imply that output has a long and persistent increase during the accelerating inflation state, with output reaching a peak five quarters later and that peak is roughly twice the size of the initial impulse. On the other hand, the revised data imply output has a more mild increase for the accelerating inflation state. Next note, that the real-time data imply that inflation also has a relatively large increase during the accelerating inflation state, breaking out of the confidence band for the tranquil state roughly around the third quarter and staying above the confidence band until the ninth quarter, while the revised data imply that inflation is hardly different between these two states. Taking all these things together, we interpret the real-time data as showing that during the accelerating inflation state, an output shock produces a relatively strong and persistent response in output and inflation and, following a similar logic to the one driven by a Taylor policy reaction function, this results in a much stronger policy action than is revealed by the revised data.

These results suggest that the evaluation of the monetary policy response to
an output shock in times of accelerating inflation are much different depending on whether this evaluation is made using revised data, or by taking into account the real-time information that was available to the Fed at the time they were implementing monetary policy. Overall, monetary policy looks much more aggressive when reacting to output shocks during accelerating inflation episodes using data available at the time policy is implemented than when revised data become available, roughly three years later.

Next consider Figure 2, which shows the responses to an inflation shock. Most notable is that the real-time data and the revised data show similar results, unlike the output shock. The exception here is that the interest rate responses during the accelerating inflation state are significantly different than the tranquil state using real-time data, while using revised data the policy response hardly differs between the two states. To understand the economics driving the plots, begin with the inflation impulse responses. The revised data plots show that during both the accelerating and tranquil state, an inflation shock leads to a modest short-term increase in inflation, but rather quickly inflation reverts to its mean with responses nearing zero in both states. When using real-time data, the inflation response is rather different. An inflation impulse also leads to a modest short-term increase in inflation, but the responses of inflation are much stronger and persistent during tranquil times. In contrast, output shows a delayed increase which is short lived for both states and for both real-time and revised data. Again, consistent with a Taylor rule logic, the difference in the policy response for the real-time data is then driven by the strong and persistent response of inflation perceived in real time during tranquil times. The intuition is simple: a sudden inflation innovation is perceived in real-time as having long lasting effects and thus point toward abandoning an accommodative monetary policy in the tranquil state, which results in a strong and persistent response of the federal funds rate. However, in an accelerating inflation state, a positive inflation shock does not call for further policy action since policy is already tight and thus the federal funds rate response is much weaker. While the differences between the
real-time and revised data analysis for the inflation impulse might be viewed as more modest than those found for an output shock in Figure 1, they are important and this exercise also points to a potential miss diagnosis when a researcher is using revised data.

The responses to a policy shock, presented in Figure 3, show that there are only small differences between revised and real-time data. Both types of data show some marginal differences between the two states, but these differences between the two states are similar for both data types. So for instance, in the accelerating inflation state, a federal funds rate increase is a bit more persistent for both types of data than in the tranquil state. This accords well with one’s understanding of policy in that one would expect policy makers to be more vigilant during accelerating inflation. This higher vigilance is motivated by the differences in the inflation persistence between the two states where the impulses show that during the accelerating inflation state there is greater persistence. Overall, the similarities in the plots for the real-time and revised data under the policy response impulse do not provide the level of motivation for considering real-time data to the extent seen in the output and inflation shock impulse responses.

Finally, it is useful to reemphasize the added value of our policy reaction empirical approach using the local projection methodology advocated in Jordà (2005) that somewhat complements the Taylor rule type approach commonly used in the recent literature. As seen in the discussion above, the policy reactions depend on the origin of the economic shocks as well as the economic state (accelerating or non-accelerating inflation) of the economy and the data used (revised versus real-time), and the methods used here can reveal these details. Meanwhile, the Taylor rule method focuses on the systematic part of monetary policy and thus overlooks how policy responses are connected to the alternative macroeconomic shocks driving business cycles.
Figure 1: IRF to an output shock
Figure 2: IRF to an inflation shock
Figure 3: IRF to a federal funds rate shock
5 Robustness and other considerations

At this point the reader may ask whether differences in the information contained in revised and real-time data are really driving the different impulse response behavior? Or could the threshold indicator have something to do with the results? To address these questions, we undertook a few exercises. The first was to see whether differences between the real-time and revised data where organizing the data into the two threshold groups in exactly the right way so as to produce the results. To address this we ran a counterfactual exercise where the threshold indicator computed with revised inflation data is used to estimate the IRFs using real-time data and vice versa. The estimated responses obtained in these counterfactual exercises (not shown for the sake of brevity) are almost identical to those displayed above. Moreover, the correlation coefficient between the two threshold indicators obtained with revised and real-time inflation data is only moderately high at 0.52. We interpret this as showing that it is not that a particular indicator is cherry picking data values to produce the results, but rather that there are differences in the information content of the revised and real-time data and that other algorithms for organizing the data will reveal these differences.

A related investigation is to study the full-opportunistic model discussed in Bunzel and Enders (2010). For our exercise we deviate slightly from their definition and define the threshold indicator by

\[ I_t = \begin{cases} 
1 & \text{for } (\pi_{t-1} > (\pi_{t-5} + \pi_{t-9})/2) \text{ and } (g_{t-1} < g_{t-2}), \\
0 & \text{otherwise},
\end{cases} \quad (6) \]

where \( g_t \) is the growth rate in GDP between time \( t - 1 \) and time \( t \). In contrast to Bunzel and Enders (2010), who use the lagged output gap, a measure of economic performance which is hardly observable in real time, as the second part of their definition of the threshold indicator, we choose the more readily observable measure of decelerating output growth.\(^7\) Both the Bunzel and Enders (2010) definition and our

\(^7\)Bunzel and Enders (2010), by constructing a real-time measure of the output gap using the Hodrick-Prescott filter (i.e. for each time period \( t \) they computed the percentage difference between
definition can be interpreted as showing that when the economy is in an accelerating inflation situation and, in addition, economic activity is slowing down, the Fed is torn about whether to be restrictive to reduce inflation or expansionary to stimulate output. In contrast to the threshold indicator (5), the full-opportunistic threshold (6) places a somewhat higher priority on output growth for the $I_t = 0$ case than in the $I_t = 1$. To see this, note that basic logic implies that the inflation and output growth space is cut into four parts. The $I_t = 1$ case is clearly defined in (6) and corresponds to when there is conflict among the Fed’s statutory objectives of low inflation and output growth. In this case there is no room for opportunism toward output stimulus because of the high inflation. On the other hand, the $I_t = 0$, case has two parts in which inflation is low and the Fed takes the opportunity to remain accommodative for output, as well as a third part in which both output growth and inflation are high and thus the Fed is unlikely to be very accommodative toward output. Since this case has two out of three parts which are accommodative for output, overall this case reflects the opportunity to be accommodative toward output. Bunzel and Enders (2010) referred to this $I_t = 0$ case as the fully accommodative case since here the Fed is generally more favorable toward output growth than the $I_t = 1$.

Figures 4-6 show the results for the three impulse types for revised and real-time data, where we refer to the conflicted or torn case, $I_t = 1$, as a time of concern. These figures show that the primary point of the paper, that there are differences in the conclusions one would draw when using revised and real-time data, is robust. For instance, the output shock impulse responses show that policy is very restrictive during times of concern using real-time data relative to revised data and both show

---

---

---

---

---

---
more restrictive policy in this scenario relative to the opportunistic case given in (5). One can interpret these stronger policies during times of concern as showing that policy makers focus on fighting inflation during this conflicted case. Similarly, the inflation shock impulse responses again show a strong and long lived contractionary policy response during tranquil times using real-time data while the revised data shows an initial contractionary policy which is followed by a stimulative policy four quarters later. Finally, the policy shock shows much bigger differences between the tranquil times and times of concern cases for both revised and real-time data, but more importantly they show that the differences between the revised and real-time impulses are also important. Overall we interpret these exercises as further showing that it is not simply the indicator that is cherry picking data values to produce the results, but rather that there are important differences in the information content of the revised and real-time data.

We also considered two constant-threshold indicators identified by Jordà (2005) using Hansen’s (2000) test. His estimated thresholds divided the data into a high-inflation state associated with the period between the 1970s and the mid-1980s and the rest of the sample, which was in a low inflation state. According to his test results, Jordà (2005) suggested two alternative thresholds: (i) a threshold in the third lag of inflation at 4.75% and (ii) a threshold in the third lag of the federal funds rate at 6%. The impulse responses associated with these two thresholds (available from the authors upon request) basically tell us the same story as the impulse responses associated with the time-varying threshold structures considered above.

6 Conclusion

This paper considers a semi-parametric approach using local projection methods advocated in Jordà (2005) for estimating impulse response functions based on real-time data instead of relying on estimated Taylor rules as has been standard in the recent literature. Our results show important differences in the response of the policy vari-
Figure 4: IRF to an output shock (Full opportunistic model)
Figure 5: IRF to an inflation shock (Full opportunistic model)
Figure 6: IRF to a federal funds rate shock (Full opportunistic model)
able, the federal funds interest rate, depending on whether the economy has economic performance issues (e.g. accelerating inflation) or is tranquil. This switching structure is consistent with one suggested by Bunzel and Enders (2010) and is designed to capture what is called an opportunistic monetary policy.

Most importantly for the purpose of this paper, we find that policy reactions depend on whether this evaluation relies on ex-post revised data or on the information available to the Fed in real time. This demonstrates that the use of revised data may miss important policy behavior. Moreover, the extent to which policy evaluation results using revised data or real-time data differ depends on the combination of shocks hitting the economy as well as the state of the economy. In particular, it was shown that revised data is particularly problematic at policy behavior discovery when an output shock occurs and the economy is experiencing accelerating inflation.

References


Appendix: Robustness exercises - Some alternative threshold models (Not intended for publication)

Here we provide plots for alternative threshold indicators. First, consider the first threshold identified in Jordà (2005) which implies threshold indicator given by

\[ I_t = \begin{cases} 
1 & \text{for } \pi_{t-3} > 4.75, \\
0 & \text{otherwise}. 
\end{cases} \]

The implied impulse response plots are given below (for the sake of brevity we only plot the ones associated with an output shock) in Figure A.1.

Next consider the second threshold identified in Jordà (2005) which implies threshold indicator given by

\[ I_t = \begin{cases} 
1 & \text{for } i_{t-3} > 6, \\
0 & \text{otherwise}. 
\end{cases} \]

The implied impulse response plots are in Figure A.2.
Figure A.1. IRF to an output shock (higher than 4.5%-inflation threshold indicator)
Figure A.2. IRF to an output shock (higher than 6%-federal rate threshold indicator)