Frequency Dependence in a Real-Time Monetary Policy Rule

Richard Ashley **Virginia Tech**

Kwok Ping Tsang **Virginia Tech**

Randal J. Verbrugge **Bureau of Labor Statistics***

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Abstract

We estimate a monetary policy rule for the US allowing for possible frequency dependence - i.e., allowing the central bank to respond differently to persistent innovations than to transitory innovations, in both the real-time unemployment rate and the real-time inflation rate. The estimation method we use is flexible, and requires no strong a priori assumptions on the pattern of frequency dependence or on the nature of the data-generating process; it also allows for the use of real-time data and allows for possible feedback in the relationship. The data convincingly reject linearity - i.e., coefficients independent of frequency and symmetry - in the monetary policy rule, as suggested by theory. Our approach provides useful insights into how the nature of the central bank's monetary response has varied over time.

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*First draft: December 2008. The authors would to thank participants at a presentation at the University of Hong Kong. Ashley: Department of Economics, Virginia Tech, Pamplin Hall (0316), Blacksburg, VA 24061-0316. Email: ashleyr@vt.edu. Tsang (Corresponding author): Department of Economics, Virginia Tech, Pamplin Hall (0316), Blacksburg, Virginia, 24061. Email: byront@vt.edu. Verbrugge: Division of Price and Index Number Research, Bureau of Labor Statistics, 2 Massachusetts Ave. NE, Washington, DC 20212. Email: verbrugge.randal@bls.gov.

1 Introduction

Following Taylor (1993), there has been an intense focus on Taylor-type monetary policy rules, such as:

$$i_t = \rho + \phi_\pi \pi_t + \phi_u u_t + e_t \tag{1}$$

where i_t is the federal funds rate, π_t is the annualized inflation rate from period $t-1$ to period t, u_t is a measure of real activity (output gap or unemployment rate) in period t, and e_t is a stationary exogenous monetary shock. There are many variants of (1). Theory often suggests forward-looking versions (e.g. Clarida, Gali and Gertler (2000)); real-time lags in data collection motivate the use of lagged inflation and real activity, i.e., a backward-looking monetary policy rule (e.g. McCallum (1997)); and interest rate smoothing considerations (as well as the statistical properties of i_t) motivate adding lags of i_t to the right-hand side of (1).[1] Using variants of (1), many studies have concluded that the Fed's policy changed markedly after Volcker; see, e.g. Clarida, Gali and Gertler (2000) and Judd and Rudebusch (1998).[2]

Taylor originally developed the monetary policy rule as a descriptive device; more recently, with appropriate parameter values, a Taylor-type rule is found to be optimal in a dynamic, optimizing New Keynesian macroeconomic model - see Woodford (2003) or Gali (2009) for a textbook treatment. Decades ago, however, Friedman (1968) and Phelps (1968) introduced the concept of a natural rate of unemployment, and a related literature on the Phillips curve argues for the existence of a time-varying natural rate of unemployment. If there is a time-varying natural rate, it implies that not all unemployment rate movements are economically equivalent; a reasonable central bank will respond differently to natural rate movements than to fluctuations about the natural rate. Hence, linear policy rules such as (1) are profoundly misspecified.

In particular, it is now quite typical to place an "unemployment gap" for u_t in (1), as in Ball and Tchaidze (2002) and McCulloch (2007). To calculate the unemployment gap, one

[1] Rudebusch (2002) disagrees with the interest rate smoothing interpretation. Using evidence from the term structure, he shows that monetary policy inertia is more likely due to persistent shocks that the central bank faces. Consolo and Favero (2009) argues, in the forward-looking context, that the inertia is an artifact of a weak-instrument problem for expected inflation.

[2] Using the the time-varying parameter framework, Boivin (2001), Cogley and Sargent (2005), Kim and Nelson (2006) and McCulloch (2007) come to a similar conclusion. However, Sims (2001) and Sims and Zha (2006) find that there is less evidence for significant changes in the reaction coefficients ϕ if one allows for time-varying variance in the monetary policy shock.

needs an explicit estimate of the natural rate of unemployment. Such estimates are inherently problematic in that 1) they are estimated with error, 2) they typically hinge upon auxiliary assumptions about the data generating process (such as the degree of persistence of the natural rate), which may well be incorrect; and 3) they are often based upon two-sided filters, which are known to distort the dynamics of time series relationships (See Ashley and Verbrugge (2009)). Using an output gap instead of an unemployment gap in (1) does not improve matters.

This misspecification conclusion is reinforced when it is recognized that the central bank will likely respond differently to permanent innovations in inflation than to transitory innovations.[3] Here, the distinction between transitory and persistent innovations in inflation has motivated the use of "core inflation" measures in (1), e.g. by removing the food and energy components in CPI. But this expedient is valid only if all movements in the "core inflation" are identically persistent, which is emphatically not the case (for example, see Bryan and Meyer (2010)).

There are two prominent recent studies that use variants of (1) to understand monetary policy behavior and its evolution over time. Orphanides (2002) uses real-time data and shows that the Federal Reserve's forecast of inflation is biased during the Great Inflation period. While reacting aggressively to the biased forecast, the Federal Reserve behaves *as if* it is soft on inflation when analyzed using *ex post* data. Ball and Tchaidze (2002) ask if the Federal Reserve behaves differently between the "old economy" period from 1987 to 1995, and the "new economy" period from 1996 to 2000. Using a monetary policy rule that contains only inflation and the unemployment rate, they find that the estimates differ considerably between the two periods. Under the "old economy", the Federal Reserve reacts strongly to both inflation and unemployment; for each one-percentage-point rise in inflation, the Federal Reserve raises the interest rate by 1.4 or 1.6 points, depending on the definition of inflation; and for each one-percentage-point rise in unemployment rate, the Federal Reserve cuts the interest rate by almost 2 points. In the "new economy" period, the fit drops substantially, and the reaction to unemployment is much smaller. Ball and Tchaidze argue that the results are driven not by a change in policy but by a change in the non-accelerating-inflation rate of unemployment (NAIRU) in this later period. Allowing the estimated NAIRU to change over time and replacing unemployment with unemployment gap in the monetary policy rule, Ball and Tchaidze find that

[3] This issue with regard to two-sided fourier transforms is certainly discussed in Ashley and Verbrugge (2009).

the Federal Reserve's behavior does not change between the two periods.

In this paper, we estimate the central bank's monetary policy rule using a new method proposed by Ashley and Verbrugge (2009) (described in Section 2). The method is robust to the kind of specification error highlighted above. It is also flexible in that it does not impose an assumption that all fluctuations in unemployment rate and inflation rate are identically persistent, and in that it does not require the use of strong auxiliary assumptions about the nature of the data-generating process. In particular, the method allows us to estimate whether (and how) the central bank differentially responds in real time to perceived permanent or transitory innovations in either the unemployment rate or the inflation rate. We are thus able to get a much more detailed picture of the actual policy rule being followed by the central bank.

Notably, the method is designed to use only one-sided filter. Consequently, it is feasible for use in the present setting, which features real-time data on a relationship in which feedback is likely. The two-sided filters inherent in the usual cross-spectral analysis are incompatible with feedback relationships - see Ashley and Verbrugge (2009); they are also incompatible with the real-time data available for estimating a monetary policy rule. For these reasons, cross-spectral results are not quoted here.

In keeping with theory, we find that the central bank responds differently to highly persistent innovations in the unemployment rate - largely identified with natural rate fluctuations - than it does to transitory innovations. Similarly, its response to inflation-rate innovations is also frequency-dependent. We find differences between the Martin-Burns-Miller period and the Volcker-Greenspan-Bernanke period, mostly in keeping with previous research, but with some surprises as well. The central bank responds much more aggressively to persistent innovations in inflation, but we find that it actually accommodates transitory fluctuations during the Volcker-Greenspan-Bernanke period, in the sense that the coefficients in the unemployment rate is significantly negative at the lowest frequency (i.e., permanent fluctuations) but significantly positive at higher frequencies (i.e. relatively transitory fluctuations). And we find that the central bank responds more aggressively to transitory fluctuations in the unemployment rate during the Volcker-Greenspan-Bernanke period than it does in the Martin-Burns-Miller period.

We do not interpret our results as suggesting that the central bank *actually* looks at fluctuations of macroeconomic variables at all frequencies. Instead, the goal of the paper is to apply a general model to *describe* the behavior of the central bank, allowing the data to better inform us as to the manner in which the central bank responds to fluctuations at low versus high frequencies: the bank no doubt acts in accordance with simple heuristics. While the original Taylor rule is attractive due to its simplicity, the frequency-dependent model broadens its generality and descriptive power, and it reveals characteristics of monetary policy which are neglected in a linear setting. [4]

2 Modeling Frequency Dependence

In this section we briefly discuss the technique used here for modeling frequency dependence in the monetary policy rule.[5] The idea of regression in the frequency domain can be traced back to Hannan (1963) and Engle (1974, 1978), and is further developed in Tan and Ashley (1999a and 1999b), who developed a real-valued reformulation of Engle's (1974) framework. The discussion most clearly begins with the Tan and Ashley (1999a and 1999b) development of a real-valued re-formulation of the Engle (1974) framework. It is based on the ordinary regression model:

$$Y^* = X\beta + e \quad e \sim N(0, \sigma^2 I) \tag{2}$$

where Y is $T \times 1$ and X is $T \times K$. Now define a $T \times T$ matrix A, whose $(s,t)^{th}$ element is given by:

$$a_{s,t} = \begin{array}{l} (\frac{1}{T})^{\frac{1}{2}} \quad \text{for } s = 1; \\ (\frac{2}{T})^{\frac{1}{2}} \cos(\frac{\pi s(t-1)}{T}) \quad \text{for } s = 2, 4, 6, ..., (T-2) \text{ or } (T-1); \\ (\frac{2}{T})^{\frac{1}{2}} \sin(\frac{\pi (s-1)(t-1)}{T}) \quad \text{for } s = 3, 5, 7, ..., (T-1) \text{ or } T; \\ (\frac{1}{T})^{\frac{1}{2}} (-1)^{t+1} \quad \text{for } s = T \text{ when } T \text{ is even} \end{array} \tag{3}$$

It can be shown that A is an orthogonal matrix; pre-multiplying the regression model (1) by A thus yields,

$$AY = AX\beta + Ae \rightarrow Y^* = X^*\beta + e^*, e^* \sim N(0, \sigma^2 I) \tag{4}$$

[4] This paper focuses on the "current-period" monetary policy rule in which the central bank responds to current inflation and real activity. We do not consider forward-looking monetary policy rules here, because doing so would require a substantial number of valid instruments for π_{t+j} and u_{t+j}. Lagged values do not provide useful instruments due to the identification problem discussed by Jondeau, Bihan and Galles (2004).

[5] See Ashley and Verbrugge (2009) for details; see Ashley and Verbrugge (2007a) and Ashley and Verbrugge (2007b) for applications.

where Y^* is defined as AY, X^* is defined as AX, and e^* is defined as Ae. The dimensions of the of Y^*,X^*, and e^*arrays are the same as those of Y, X, and e in (1), but the T components of Y^* and e^* and the rows of X^* now correspond to frequencies instead of time periods.

Next, the T frequency components are partitioned into M frequency bands, and M $T \times 1$ dimensional dummy variable vectors, $D^{*1}, ..., D^{*M}$, are defined as follows: for elements that fall into the s^{th} frequency band, $D^{*s,j}$ equals $X^*_{\{j\}}$, and the elements are zero otherwise. The regression model can then be written as:

$$Y^* = X^*_j \beta_j + \sum_{m=1}^{M} \beta_{j,m} D^{*m,j} + e^* \tag{5}$$

where X^*_j is the X^* matrix with its j^{th} column deleted and β_j is the β vector with its j^{th} component deleted.

To test whether the j^{th} component of β is frequency-dependent, or whether the effect of the j^{th} variable in X on Y is frequency-dependent, one can then simply test the null hypothesis that $H_0 : \beta_{j,1} = \beta_{j,2} = ... = \beta_{j,M}$. Similarly, if one is interested in the frequency-dependence in more than one variable in X, say both the j and k columns, the regression equation can be written as:

$$Y^* = X^*_{j,k} \beta_{j,k} + \sum_{m=1}^{M} \beta_{j,m} D^{*m,j} + \sum_{m=1}^{M} \beta_{k,m} D^{*m,k} + e^* \tag{6}$$

To make this regression equation more intuitive, one can back-transform (4) by pre-multiplying both sides of this equation with the inverse of A, which (because A is an orthogonal matrix) is just its transpose:

$$A'Y^* = A'X^*_j \beta_j + A' \sum_{m=1}^{M} \beta_{j,m} D^{*m,j} + A'e^* \tag{7}$$

$$Y = X_j \beta_j + \sum_{m=1}^{M} \beta_{j,m} A' D^{*m,j} + e = X_j \beta_j + \sum_{m=1}^{M} \beta_{j,m} D^{m,j} + e \tag{8}$$

Note that now the dependent variable is the same time series (Y) as in the original model (1); similarly, all of the explanatory variables – except for the j^{th} – are the same as in the original model. Indeed, the only difference is that the j^{th} explanatory variable has been replaced by a weighted sum of M new explanatory variables $D^{1,j}, ..., D^{M,j}$. These M variables can be viewed as bandpass-filtered versions of the j^{th} column of the X matrix, with the nice property that they add up to precisely this j^{th} column. To test for frequency dependence in the regression coefficient on this j^{th} regressor, then, all that one need do is test the null hypothesis that $\beta_{j,1} = \beta_{j,2} = ... = \beta_{j,M}$.

However, because the A transformation mixes up past and future values (in keeping with any standard band pass filter), it can be shown that these M frequency components are correlated with the model error term e if there is feedback between Y and any of the explanatory variables, leading to inconsistent parameter estimation in that case. To avoid this problem, Ashley and Verbrugge (2009) suggest modifying the procedures described above in order to obtain one-sided transformations of the data. In particular, they suggest decomposing X_j, the j^{th} explanatory variable data vector, into frequency components by applying the transformation described above in a moving three-year window, keeping only the most recent value.[6] In essence this leads to a one-sided, rather than a two-sided bandpass filter. This moving-window approach is used in the present paper for a second reason: the moving window makes it possible to use real-time data for the values of X_j used in the window.

Restricting the length of the window in this way implies that the lowest frequency (longest period) component of X_j cannot distinguish between fluctuations with periods longer than 36 months. On the other hand, it has the nice feature that only 18 frequencies are delineated – i.e., M equals 19.[7] Thus, it is is feasible in this moving-window framework to estimate *all* of the $\beta_{j,1} = \beta_{j,2} = \cdots = \beta_{j,M}$ without making any *ad hoc* selection of "frequency bands".

When decomposing X_j using a window, one must confront the problem of "edge effects" near the window endpoints. As in Dagum (1978) and Stock and Watson (1999), this problem is dealt with by augmenting the window data with projected data for an additional 3 months; thus, the window uses the immediately previous 33 months of real time data and three projected values in order to produce the decomposed value for the current period, the 33^{rd} month of the

[6] Using a 3-year window implies that the central bank treats all fluctuations of a period longer than 3 years the same as it does the "trend". As a robustness check, in the Appendix we provide results using a 4-year window; the results are qualitatively similar to those obtained with a 3-year window. A 2-year window reduces the number of possible frequency components to 13. According to the our results, however, interesting findings would have been missed near the 3-year period of fluctuation if a 2-year window had been used. In addition, results using a 4-year window, which are available upon request, are very similar to those using a 3-year window.

[7] There are 19 bands because a quadratic trend polynomial is estimated for the X_j data within each window, providing an additional "zero-frequency" component.

window. Separately for inflation and unemployment, in each month t we use all of the real time data available up to that period to estimate an AR(4) model with monthly dummies.[8] This estimated model is used to forecast the time series for month $t+1$ to $t+3$; we then we combine the projected values with the latest 33 months of actual real time observations up to month t to form the three-year window for decomposing each variable. One should note that this projection method gives the monetary policy rule something of a forward-looking nature, evne though the central bank does not explicitly use these methods.

3 Data Description

We use monthly real-time data over the period March 1960 – April 2009 for three time series: the federal funds rate i_t, civilian unemployment rate u_t , and "headline" CPI inflation rate π_t.[9] We use real-time data so that the data we are analyzing correspond to the data the central bank had available at the time each of its policy decisions was actually made.[10] Real-time data on unemployment and inflation are obtained from the St. Louis central bank ALFRED (ArchivaL Federal Reserve Economic Data) dataset (http://alfred.stlouiscentral bank.org). Inflation is measured by the CPI for urban wage earners and clerical workers until Feb 1978, and since then is measured by the CPI for all urban consumers. Inflation is defined as twelve-month logarithmic growth rate in the CPI, expressed in percentage terms – i.e., as $100 \times \ln(P_t/P_{t-12})$, where both P_t and P_{t-12} are the data available when P_t first becomes available. The observations on the federal funds rate are not revised, so the end-of month observations available from the St. Louis FRED dataset (http://fred.stlouiscentralbank.org) are used for this variable.

The real-time ALFRED data are decomposed into frequency components in the following manner: in month $t+1$, data for month t are released and data before month t may have been revised; using month $t+1$ data, we again take the last 33 observations, forecast out for

[8]Both the unemployment rate and inflation rate are highly persistent; most of their variation is explained by these four lags. Results using additional explanatory variables for the projections indicate that the frequency decomposition (and estimation results) are not sensitive to this choice.

[9]Since the earliest real-time observation is on March 1960, we do not use the frequency components of data earlier than March 1960 in our analysis.

[10]Orphanides (2001) show that estimation of the monetary policy rule may not be robust to the vintage of the data.

3 months using the AR(4) model, and decompose the data into frequency components for each month in the resulting 36 months window; the 33^{rd} observation of each frequency component is the period t value. Using this procedure, the behavior of the central bank is modeled as using data available in real time.

There are two ways to align our inflation and unemployment data with the federal funds rate data. One can regress the value of the federal funds rate at the end of the month t on the unemployment rate and inflation rate data released in month t, assuming that the central bank obtains the data at the same time as the public. Or, alternatively, one can regress the value of the federal funds rate at the end of month t on the unemployment rate and inflation rate that are released in month $t-1$, assuming that the central bank has an informational advantage over the public. To avoid using information that the central bank probably does not have, we only report the first set of results.[11]

We consider two sub-sample periods, following Clarida, Gali, and Gertler (2000). The first is March 1960 - August 1979, which roughly corresponds to the Martin-Burns-Miller (MBM) period; see Meltzer (2005) for a discussion on the high inflation rate during the latter part of this period. The second sub-sample starts from September 1979 to April 2009; it covers the tenures of Volcker, Greenspan and part of Bernanke (VGB). Most of the second sub-sample period is also referred to as the Great Moderation - see McConnell and Perez-Quiros (2000) and Kim and Nelson (1999), as it is characterized by low variance in most macroeconomic variables; since the recent recession, of course, most macroeconomic variables have become more volatile.[12]

4 Empirical Results

4.1 Results without Frequency Decomposition

Table 2 displays the estimates of the monetary policy rule (1) as conventionally estimated, without allowing for the possibility of frequency dependence. The federal funds rate is highly persistent. The estimate of δ is around 0.9 for the full sample. For the MBM period the

[11]Nevertheless, the two sets of results are very similar and lead to qualitatively identical results..

[12]The results are very similar if we drop the 2008 and 2009 data.

interest smoothing parameter is about 0.7, and in the VGB period it is about 0.9. Adding additional lags does not substantially affect the results. Reaction to inflation varies over the two sub-sample periods. During the MBM period, reaction to inflation is modest: for every 1% increase in inflation, the central bank increases rate by only 0.743%. Reaction is far stronger during the VGB period, when the central bank raises the rate by more 1% for a 1% increase in inflation. During the MBM period, the central bank responds significantly to a change in the unemployment rate (a cut of 0.86% for every 1% increase). Conversely, the response is not significant for the VGB period, either economically or statistically.[13]

Theoretically, a more appropriate specification would have "unemployment gap" instead of the unemployment rate as an explanatory variable; that is, if the natural rate of unemployment is $u_{n,t}$, the central bank should respond to the unemployment gap $u_{c,t} \equiv u_t - u_{n,t}$. In Table 3 we estimate a linear monetary policy rule (1) using the non-accelerating-inflation rate of unemployment (NAIRU) estimate provided by the Congressional Budget Office.[14] The change in the definition of unemployment has a modest impact on estimates for the MBM period: the response to inflation drops from 0.743 to 0.686, while the response to unemployment strengthens from -0.860 to -0.924. For the VGB period, the changes are opposite: response to inflation increases from 1.028 to 1.084, while response to unemployment changes from -0.411 to 0.131 (although the estimate remains statistically insignificant). As mentioned in the introduction, the goal of this paper is to provide a less arbitrary way of describing how the central bank responds to different frequency components of macroeconomic variables. Instead of implicitly accepting the CBO's judgment about the NAIRU, using *ad hoc* detrending methods or making strong but essentially untestable assumptions about the data generating process, the method applied in this paper lets the data speak about questions such as, does the central bank distinguish

[13]Note that we use the headline CPI inflation rather than "core inflation". Some have argued that it is more appropriate to use a core inflation measure, and thus one might argue that out results are not strong evidence for a violation of the "Taylor principle" for the MBM period. However, the standard conceptualization of "core inflation" did not attract much attention until Gordon (1975); while the CPI-less-food has been produced since 1957, the CPI-less-food-and-energy was first produced in 1977 (although the BLS then retrospectively produced this index back to 1957). In any case, if an inflation measure like core inflation is preferable, then this amounts to an argument that the central bank responds differently to low-frequency inflation innovations than to high-frequency innovations; in other words, it amounts to an argument that a frequency decomposition like the one proposed here is necessary. Our method has the advantage that it does not make a judgment, *a priori*, that movements in all components of the "core inflation" are equally persistent.

[14]The estimates can be found at http://www.cbo.gov/Spreadsheets.cfm. The NAIRU estimates from CBO are quarterly, and the quadratic-average method is used to interpolate the series to monthly frequency.

between permanent and transitory fluctuations in the unemployment rate, and if so, how?

By breaking the inflation rate and unemployment rate into frequency components, the rest of the paper tests for the presence of frequency dependence in this relationship and looks for monetary policy behavior which may have been missed by the linear monetary policy rule estimation (1). We find that the linear specification leads to substantial misunderstandings about the central bank's behavior.

4.2 Is There Frequency Dependence in the Monetary Policy Rule?

The monetary policy rule allowing for frequency dependence is written as:

$$i_t = \delta i_{t-1} + (1-\delta)(\rho + \sum_{j=1}^{19} \phi_{\pi,j}\pi_t^j + \sum_{j=1}^{19} \phi_{u,j}u_t^j) + e_t \tag{9}$$

The term x_t^j stands for the j^{th} frequency component of the variable x_t, with the 1^{st} component being the zero-frequency component of the variable x_t - this component corresponds to a quadratic polynomial trend - and the 19^{th} being the component with a period of fluctuation of 2 months. We include only one lag of the federal funds rate as an additional right-hand-side variable, but our results below are robust to adding more lags.[15] The term $\left(\rho + \sum_{j=1}^{19} \phi_{\pi,j}\pi_t^j + \sum_{j=1}^{19} \phi_{u,j}u_t^j\right)$ may be interpreted as the target interest rate, with the central bank eliminating a fraction $(1-\delta)$ of the gap between the current target and the current federal funds rate.

Equation (8) implicitly assumes that the federal funds rate, inflation and unemployment rate are all stationary. Empirically, it is hard to reject the null of a unit root for the variables over the full sample, given that the variables are persistent and that unit root tests have low power. However, by partitioning the data into two sub-samples, the stationary assumption becomes more reasonable.[16] Also, as argued in Clarida, Gali and Gertler (1999), stationarity for these variables is implied by the theoretical models in which the monetary rule, as estimated

[15]Newey-West standard errors are quoted throught, with truncation lag chosen following the suggestion of Newey and West (1987), to account for heteroskedasticity and any remaining serial correlation in the model error. For all of our regressions a lag of 4 or 5 is chosen.

[16]Unit root tests do not reject the null of a unit root for the inflation and unemployment rate series. For the sub-sample periods, the null is strongly rejected for both series. By breaking the sample, we also alleviate the problem of time-varying variance mentioned in Sims and Zha (2001, 2006).

here, plays a role.

In addition, the specification allows us to find out if the central bank responds to the "unemployment gap", defined here as $u_{c,t} \equiv u_t - u_{n,t}$, as suggested in the literature. Suppose that the zero-frequency, or the most persistent, component of unemployment rate is a good measure of, or simply reflects, the natural rate of unemployment ($u_{n,t}$) and that the central bank responds to the difference between the current unemployment rate and the natural rate. If that is the case, then the coefficient on the zero-frequency component should be positive in (9) (i.e., when the natural rate increases, the central bank tightens monetary policy, holding the other frequency components constant). As a robustness check, we also estimate the following by adding the CBO's NAIRU $u_{n,t}$ into (9) as an another explanatory variable:

$$i_t = \delta i_{t-1} + (1-\delta)(\rho + \sum_{j=1}^{19} \phi_{\pi,j}\pi_t^j + \sum_{j=1}^{19} \phi_{u,j}u_t^j + \phi_n u_{n,t}) + e_t \tag{10}$$

If the central bank responds to the unemployment gap, the sign for ϕ_n should be negative. If the frequency-dependent specification (9) does a good job of capturing the idea of the unemployment gap, estimates from (9) and (10) should not be significantly different.

Table 3 tests for whether there is frequency dependence in the monetary policy rule (9): after estimating (9), we test the hypothesis that the set of coefficients $\phi_{\pi,j}$ or $\phi_{u,j}$ are the same over all frequencies, i.e., for all values of j. For the full sample, we reject the null of no frequency dependence in unemployment rate (p-value=0.00) but there is no evidence of frequency dependence in the inflation rate. Results are the same when we do not include the zero-frequency component in the test. The picture that emerges when one separately examines the sub-sample periods is quite different, however. When all frequencies are included in the regression - in the columns "with u_t^1" and "with π_t^1", where the superscript "1" indicates that the first (i.e., zero-frequency) component is included in the test - the null hypothesis of no frequency dependence is rejected for the unemployment rate for both the MBM and VGB periods; but for inflation, we reject the null only for the VGB period. In short, there is strong evidence for frequency-dependence, especially for unemployment rate, in the monetary policy rule. Next, we investigate whether the rejection is driven by a distinction between the lowest-frequency component and the rest, by testing for frequency dependence only in the non-zero-frequency components (in the columns “without u_t^1” and “without π_t^1”). For the unemployment rate, the answer is no: there is strong evidence for frequency-dependence even when one restricts attention to the non-zero-frequency components of the unemployment rate. For the inflation rate, the answer is yes: for the VGB period there is no evidence of frequency dependence for non-zero frequencies. Below we provide further discussion on the nature of frequency dependence in the policy rules.

In Table 4, we test the hypothesis that the set of coefficients $\phi_{\pi,j}$ or $\phi_{u,j}$ are all zero. While the linear monetary policy rule results in Table 2 indicate that the central bank appears to be unresponsive to the unemployment rate for the full sample and in the VGB period, we see in Table 4 that relaxing the *ad hoc* assumption of no frequency dependence leads to a different conclusion: for both the full sample and the VGB period the central bank does respond to unemployment rate. Evidently, the unresponsiveness found in the linear monetary policy rule can be an artifact of misspecification, the failure to disaggregate explanatory variables by frequency.

4.3 The Nature of Frequency Dependence in the Monetary Policy Rule

We next examine the nature of the frequency dependence in the monetary policy rule. Figures 1 to 6 display the 19 coefficient estimates (± 2 Newey-West standard errors) - first for $\phi_{u,j}$ on the unemployment rate, and then for $\phi_{\pi,j}$ on the inflation rate - for the full sample and the two sub-samples. These figures display the overall pattern of the monetary policy reaction to fluctuations at different frequencies, and convey the statistical significance of various coefficients. The picture that emerges about the nature of monetary policy over the various regimes is far more nuanced than previous studies have suggested; indeed, along some dimensions, our analysis suggests that previous findings on the monetary policy rule may be misleading.

Regarding its reaction to fluctuations in the unemployment rate, we find that during both the MBM and the VGB periods, the central bank reacts to unemployment rate for periods of fluctuation between 6 and 12 months. In addition, the response to the zero-frequency component of unemployment rate in both the full sample and the VGB period is significantly positive, but is insignificant at a value close to zero for the MBM period. This result corresponds to our earlier argument that the central bank may respond to a change in the natural rate of unemployment: when the natural rate, which is included in the zero-frequency component, increases, the central bank tightens monetary policy as the unemployment gap is smaller.

Regarding the central bank's reaction to fluctuations in inflation, our results indicate that the differences between the MBM and the VGB period are actually *understated* in the linear model, which does not allow for frequency dependence. In particular, during the MBM period the reaction to fluctuations in inflation rate is positive, though modest, at all frequencies. In sharp contrast, in the VGB period, reaction to the zero-frequency component of inflation is more aggressive, but reaction to less persistent fluctuations is actually negative, i.e., the central bank *accommodates* inflation at these frequencies.

Estimates for (10), where the CBO's estimate of NAIRU is included as an explanatory variable, are reported in Figures 7-9. If the zero-frequency component of unemployment rate contains the natural rate, including the NAIRU in the regression will change the coefficient on the zero-frequency component. Indeed, for the full sample and the two sub-samples, the coefficient on the zero-frequency component is now statistically insignificant. The coefficient on NAIRU is significantly positive for all cases, suggesting that the central bank responds to the unemployment gap. It is encouraging to see in Figures 7-9 that coefficient estimates for other frequency components are not substantially affected by the inclusion of NAIRU. We take the results as evidence that the general specification (8) is satisfactory for capturing the idea of an unemployment gap, with the additional advantage that we do not need an arbitrary measure of the natural rate of unemployment, e.g. the NAIRU estimates calculated by the CBO.

4.4 How Large is the Response at Each Frequency?

To further understand the nature of the monetary policy rule, as well as to properly compare the various regimes, an alternative presentation of the coefficient estimates is required. While Figures 1-6 accurately display the statistical significance of the coefficient estimates, their magnitudes are misleading: each of the $\phi_{\pi,j}$ or $\phi_{u,j}$ is the reaction of the federal funds rate to a 1% change in the corresponding frequency component, but in the data we rarely observe a 1% change at some frequencies. For example, for the highest-frequency component of inflation (a period of 2 months), the largest absolute value of the component is 0.06% over the full sample. On the other hand, for the zero-frequency of inflation, the largest value is 14.6%. To make the coefficient magnitudes more interpretable, we rescale them by multiplying each by the standard deviations of the frequency components, sub-sample by sub-sample. This adjustment allows us to interpret the rescaled coefficients as the reaction of the federal funds rate to a one-standard-deviation change in the frequency components.

Figure 10 displays the empirical results for the rescaled reaction to unemployment rate.[17] The central bank reacts to changes in unemployment rate at periods above 3 months; but the central bank in the VGB period is significantly more aggressive in its response to unemployment rate fluctuations. While a one-standard-deviation increase in the unemployment rate at one of these frequencies triggers a response of 0.5 to 1 percent reduction in the federal funds rate during the MBM period, during the VGB period the response is 1 percent or more. As mention above, for the full sample and the VGB period the central bank responds positively to the zero-frequency component, suggesting that the central bank is responding to the unemployment gap.

Figure 11 displays the rescaled reactions to the inflation rate. Here there is a sharp contrast between the MBM period and the VGB period. While the central bank responds in all both regimes to zero-frequency fluctuations in the inflation rate, the response in the VGB period is much stronger. More strikingly, in the MBM regime, the central bank responds to fluctuations with periods greater than 9 months, but in the post-Volcker regime the central bank actually strongly *accommodates* inflation at all frequencies except the zero-frequency.[18]

The findings above are missed in the estimated linear monetary policy rule (1). Indeed, the kind of frequency dependence we find in the coefficients of an estimated linear policy rule - while gracefully interpretable in terms of the idea of a natural rate of unemployment - is

[17] Standard errors for these estimates are not quoted for a good reason: the estimated standard error for the coefficient estimators and the standard deviation of the frequency components themselves are both random variables.

[18] The usual practice of using core inflation (i.e., headline CPI inflation, but omitting the more transitory food and energy components) in a linear monetary policy rule assumes that the central bank responds to the low frequency components of headline CPI inflation equally and does not respond at all to the high frequency components. Our finding of a positive response at the zero-frequency component of headline CPI inflation, but an accommodating response to the higher frequency components, contradicts such an assumption.

actually equivalent to detecting nonlinearity in the true regression relationship.[19] Thus, it is not surprising that the linear policy rule estimates are misleading, as they are based on a regression which is approximating a nonlinear relationship with a linear model.

4.5 Comparison with the Ball and Tchaidze (2002) Results

As mentioned in the introduction, Ball and Tchaidze (2002) find that, once a time-varying NAIRU is allowed, the Federal Reserve behaves similarly before and after the end of 1995 (the beginning of the "new economy") when the Federal Reserve holds the interest rate constant though the economy is booming. The method proposed in this paper does not require the use of an estimated measure of NAIRU, as in Ball and Tchaidze (2002). We apply this method to determine whether the Federal Reserve changed its behavior with the beginning of the "new economy". Following Ball and Tchaidze, the first period begins in September 1987 and ends in December 1995, and the "new economy" period begins in January 1996 and ends in December 2000.

Table 5 shows the results using the linear monetary policy rule (1). Since we use the headline CPI inflation, we do not get the strong reaction to inflation obtained by Ball and Tchaidze. We do find that the Federal Reserve reacts much less to unemployment rate in the second period. Will one reach the same conclusion if frequency dependence is allowed? Table 6 shows that we can strongly reject the null of zero coefficients on inflation and unemployment rate in both periods, in contrast to the zero response to unemployment found in the second period using the linear policy rule (1). In addition, while a Chow test strongly rejects the null of no breakpoint on December 1995 in the linear monetary policy rule (1) (with a p-value of 0.000), the null is not rejected in the frequency-dependent monetary policy rule (8) (with a p-value of 0.429). We take the results as evidence that the frequency-dependent framework is general enough to handle the issue raised by Ball and Tchaidze (2002) without the need to separately estimate the NAIRU.

[19] See Ashley and Verbrugge (2009).

5 Conclusions

We reach two conclusions in this paper:

1) *Frequency dependence is statistically and economically important in the monetary policy rule. The response of the federal funds rate to the frequency components is consistent with the idea of a natural rate of unemployment. The central bank distinguishes between transitory and persistent inflation developments, and has always responded aggressively to the latter.*

We find frequency dependence in the monetary policy rule. More specifically, regressing the federal funds rate on its lag, the unemployment rate, and the inflation rate, we find that decomposing unemployment rate and inflation rate into frequency components reveals nonlinear structure that is hidden in the typical specification, which does not allow for frequency dependence. Except for the MBM (Martin-Burns-Miller) period, the central bank responds positively to the lowest frequency component of unemployment, which suggests that the central bank is responding to the unemployment gap. For both the sub-sample periods we find a strong reaction to unemployment fluctuations at periods of fluctuation from 3 to 36 months, with the strongest response around 12 to 36 months. In the central bank's reaction to inflation fluctuations, we find the strongest response at the zero-frequency component of inflation in both the sub-sample periods. We also find the VGB (Volcker-Greenspan-Bernanke) central bank strongly *accommodates* inflation fluctuations with periods from 9 to 36 months.

2) *Results from the monetary policy rule without frequency dependence are misleading.*

The estimates deriving from a standard linear monetary policy rule specification imply sharply different behavior by the central bank over time. During the VGB period, the central bank appears unresponsive to the unemployment rate, and appears much more aggressive in fighting inflation. Allowing for frequency dependence in the specification leads to a different conclusion: the central bank has always aggressively responded to perceived persistent innovations in the inflation rate, and the VGB central bank is actually more responsive to transitory fluctuations in the unemployment rate. As the imposition of a linear specification produces such misleading results, we conclude that it is essential to test (and allow) for frequency dependence in descriptively quantifying the Fed's monetary rule behavior.

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Estimates for the Non-Frequency-Dependent Taylor Rule

	Interest smoothing	Constant	π Response	u Response	
Sample	δ	ρ	ϕ_π	ϕ_u	$\mathbf{R}^2$
Full Sample	0.900 (0.026)	2.694 (1.629)	0.842 (0.248)	-0.034 (0.276)	0.900
Martin-Burns-Miller	0.735 (0.088)	6.937 (0.933)	0.743 (0.113)	-0.860 (0.149)	0.884
Volcker-Greenspan-Bernanke	0.878 (0.039)	-0.315 (1.682)	1.028 (0.321)	-0.411 (0.285)	0.857

Table 1: Nonlinear least squares estimates are quoted for the regression $i_t = \delta i_{t-1} + (1-\delta)(\rho + \phi_\pi \pi_t + \phi_u u_t) + e_t$, with Newey-West standard errors in parentheses. We are regressing the federal funds rate on its lag, a constant, inflation rate and unemployment rate.

Estimates for the Non-Frequency-Dependent Taylor Rule with Unemployment Rate Gap Calculated Using CBO NAIRU Estimates

	Interest smoothing	Constant	π Response	u Response	
Sample	δ	ρ	ϕ_π	ϕ_u	$\mathbf{R}^2$
Full Sample	0.900 (0.025)	2.534 (0.869)	0.846 (0.245)	-0.263 (0.307)	0.900
Martin-Burns-Miller	0.723 (0.088)	2.098 (0.363)	0.686 (0.100)	-0.924 (0.151)	0.885
Volcker-Greenspan-Bernanke	0.886 (0.037)	1.869 (1.140)	1.084 (0.332)	0.131 (0.362)	0.905

Table 2: Nonlinear least squares estimates are quoted for the regression $i_t = \delta i_{t-1} + (1-\delta)(\rho + \phi_\pi \pi_t + \phi_u u_{c,t}) + e_t$, with Newey-West standard errors in parentheses. We are regressing the federal funds rate on its lag, a constant, inflation rate and unemployment rate.

F-Test for Frequency Dependence (p-value)

Sample	Unemployment Rate		Inflation	
	with u_t^1	without u_t^1	with π_t^1	without π_t^1
Full Sample	0.00	0.00	0.65	0.85
Martin-Burns-Miller	0.00	0.01	0.22	0.19
Volcker-Greenspan-Bernanke	0.00	0.00	0.03	0.41

Table 3: The null hypothesis is that the coefficients on the 19 components for inflation or unemployment rate are the same in (8), or that there is no frequency dependence in the monetary policy rule for inflation or unemployment rate. We report the p-value of the F-test for each variable.

F-Test for Zero Coefficients (p-value)

Sample	Unemployment Rate	Inflation
Full Sample	0.00	0.00
Martin-Burns-Miller	0.00	0.00
Volcker-Greenspan-Bernanke	0.00	0.00

Table 4: The null hypothesis is that the coefficients on the 19 components for inflation or unemployment rate are all zero. We report the p-value.

Estimates for the Non-Frequency-Dependent Taylor Rule

	Interest smoothing	Constant	π Response	u Response	
Sample	δ	ρ	ϕ_π	ϕ_u	$\mathbf{R}^2$
Sep 1987 - Dec 1995 ("Old Economy")	0.571 (0.096)	14.470 (1.842)	0.814 (0.201)	-1.876 (0.229)	0.897
Jan 1996 - Dec 2000 ("New Economy")	0.262 (0.117)	5.241 (1.037)	0.410 (0.166)	-0.115 (0.184)	0.195

Table 5: Nonlinear least squares estimates are quoted for the regression $i_t = \delta i_{t-1} + (1-\delta)(\rho + \phi_\pi \pi_t + \phi_u u_t) + e_t$, with Newey-West standard errors in parentheses. We are regressing the federal funds rate on its lag, a constant, inflation rate and unemployment rate.

F-Test for Zero Coefficients (p-value)

Sample	Unemployment Rate	Inflation
Sep 1987 - Dec 1995 ("Old Economy")	0.00	0.02
Jan 1996 - Dec 2000 ("New Economy")	0.01	0.00

Table 6: The null hypothesis is that the coefficients on the 19 components for inflation or unemployment rate are all zero. We report the p-value.

Frequency-Dependent Response to Unemployment Rate (Full Sample)

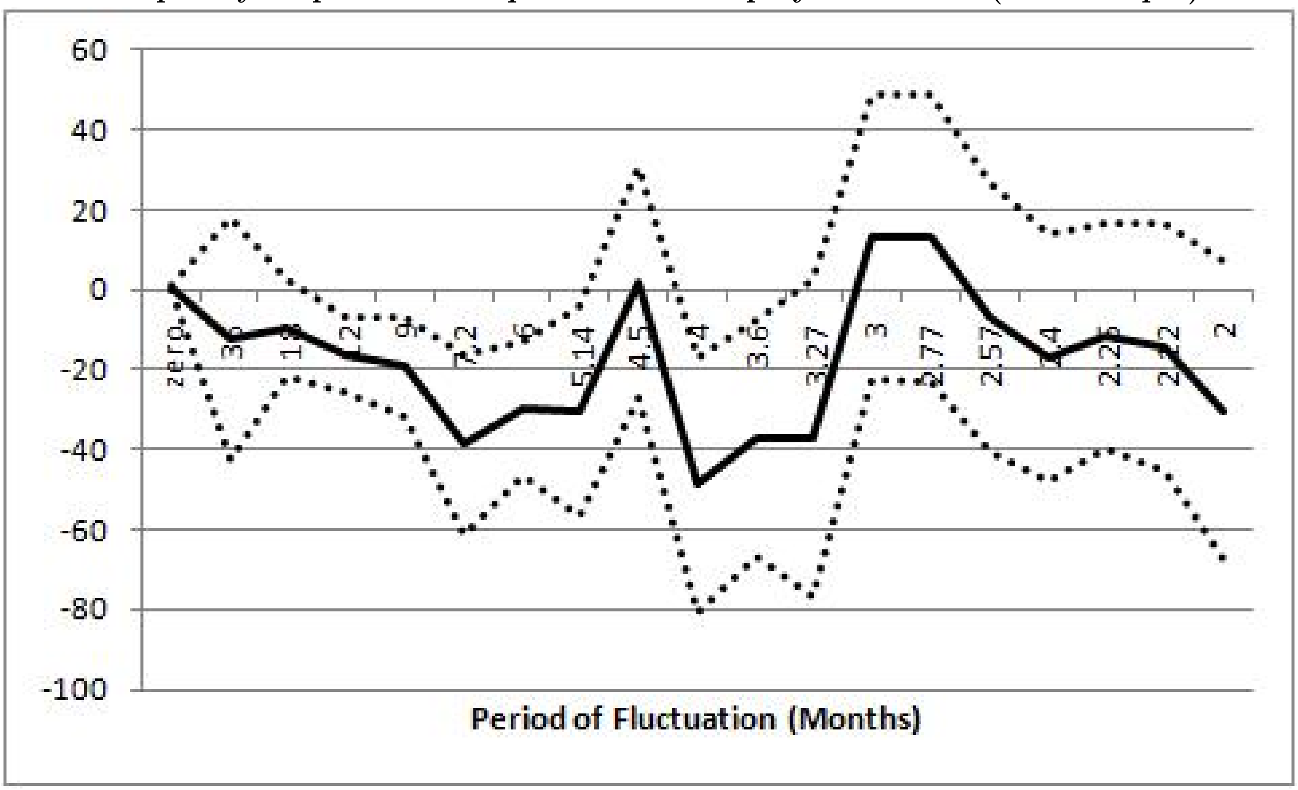

Figure 1: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Inflation (Full Sample)

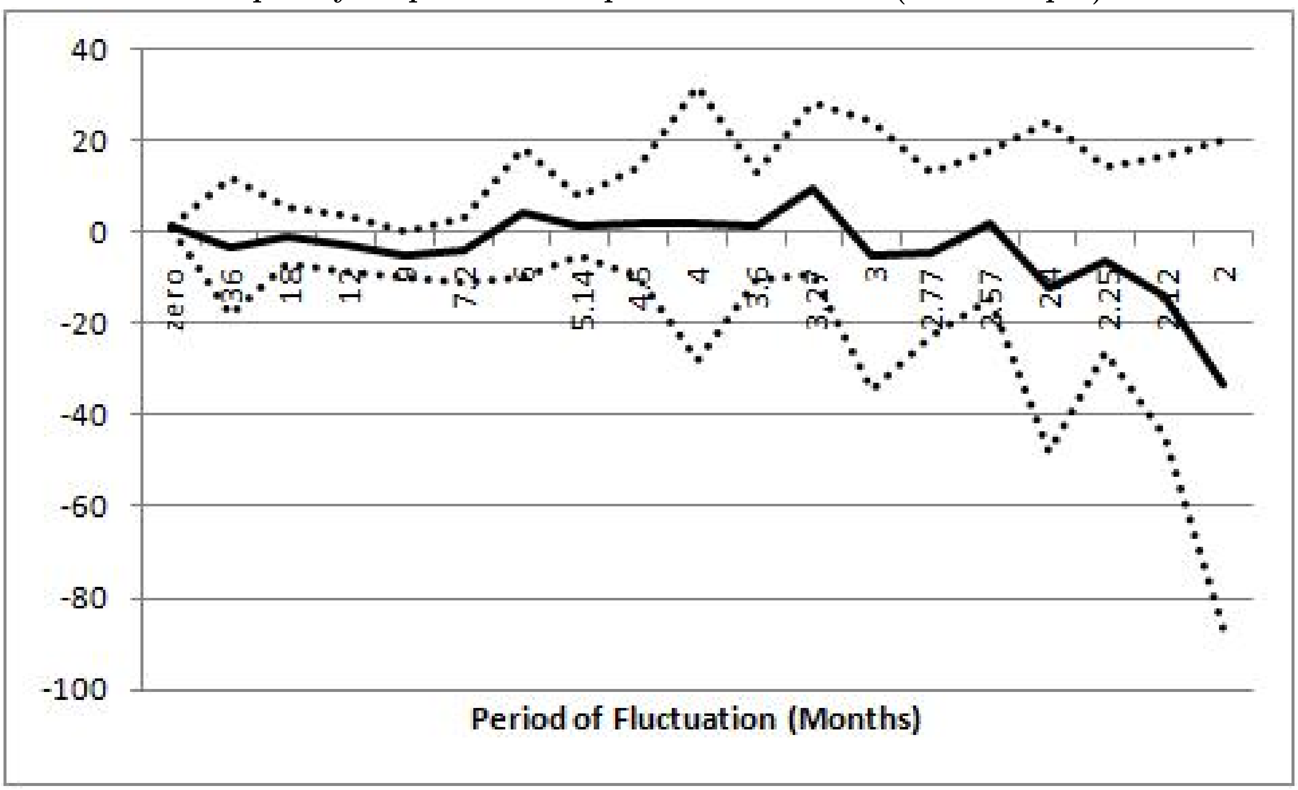

Figure 2: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Unemployment Rate (Martin-Burns-Miller Sub-Sample)

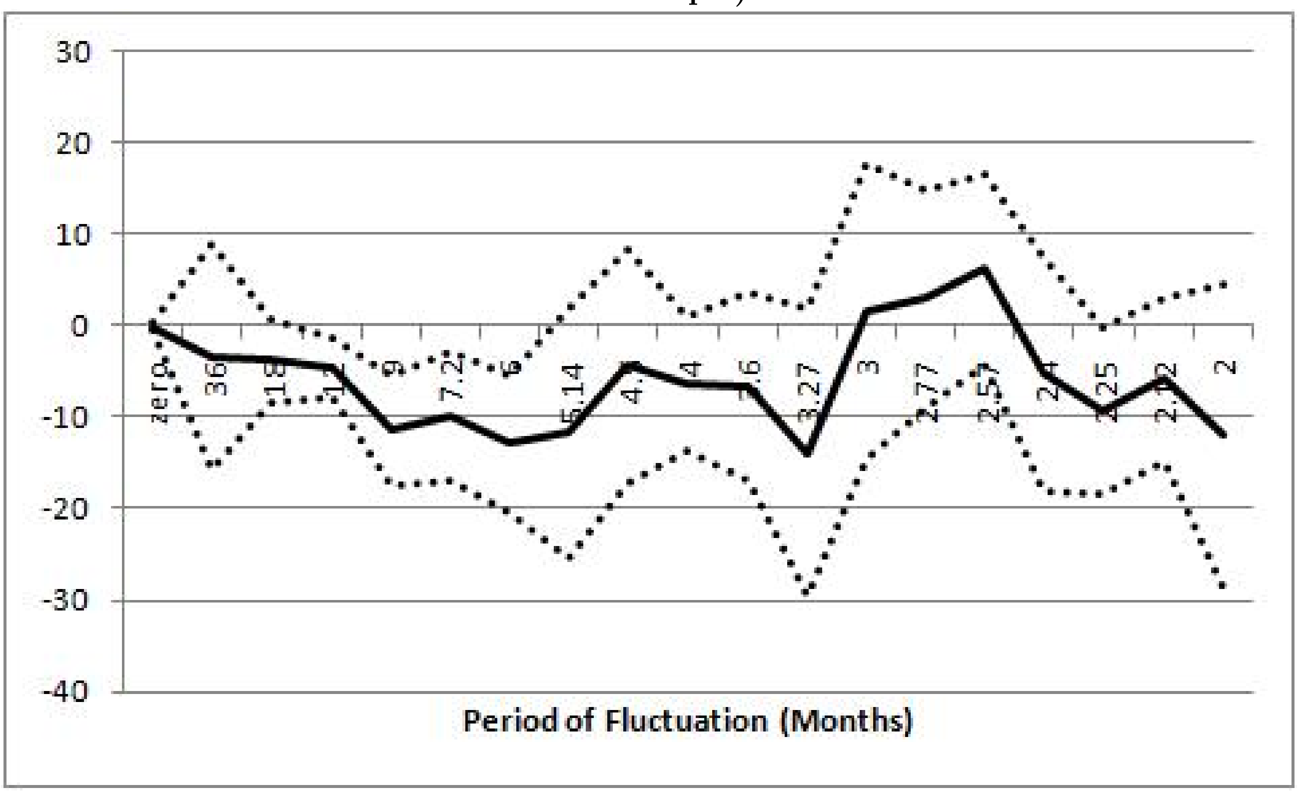

Figure 3: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Inflation (Martin-Burns-Miller Sub-Sample)

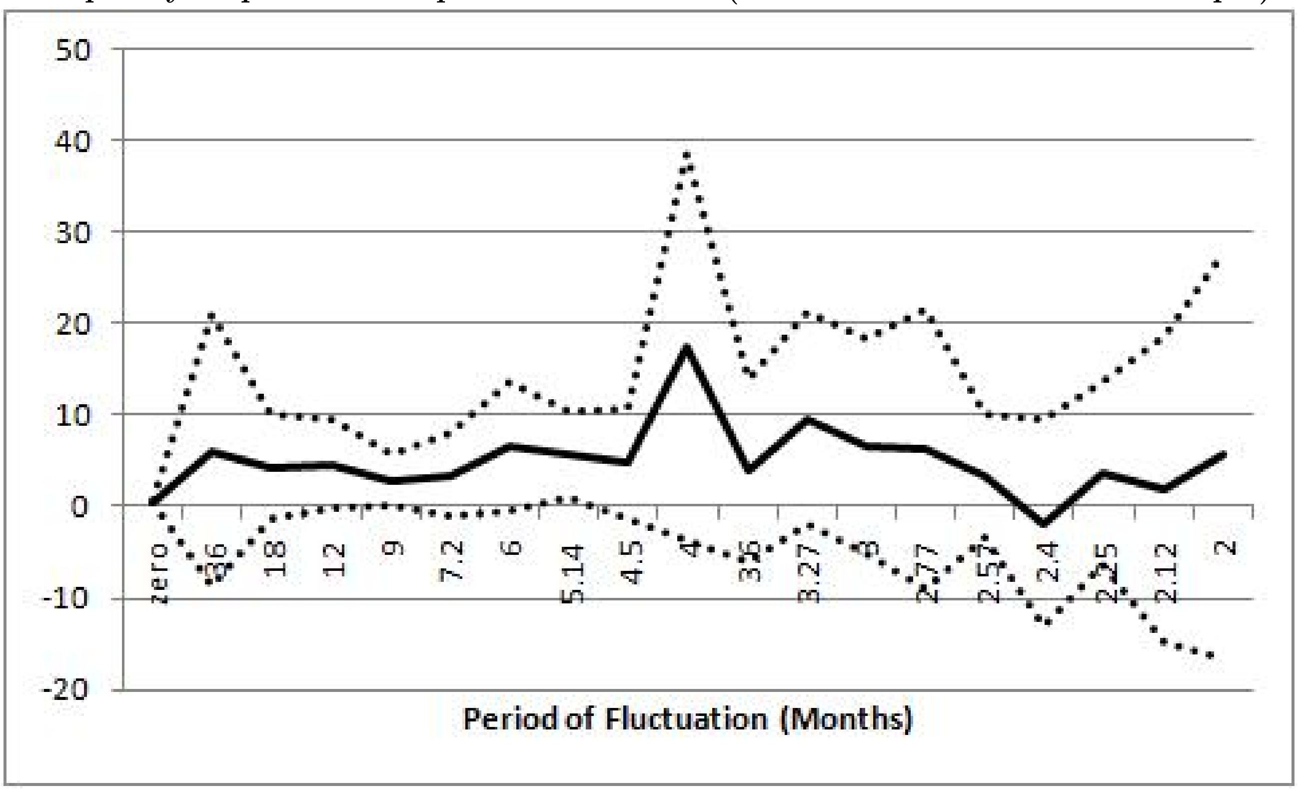

Figure 4: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Unemployment Rate
(Volcker-Greenspan-Bernanke Sub-Sample)

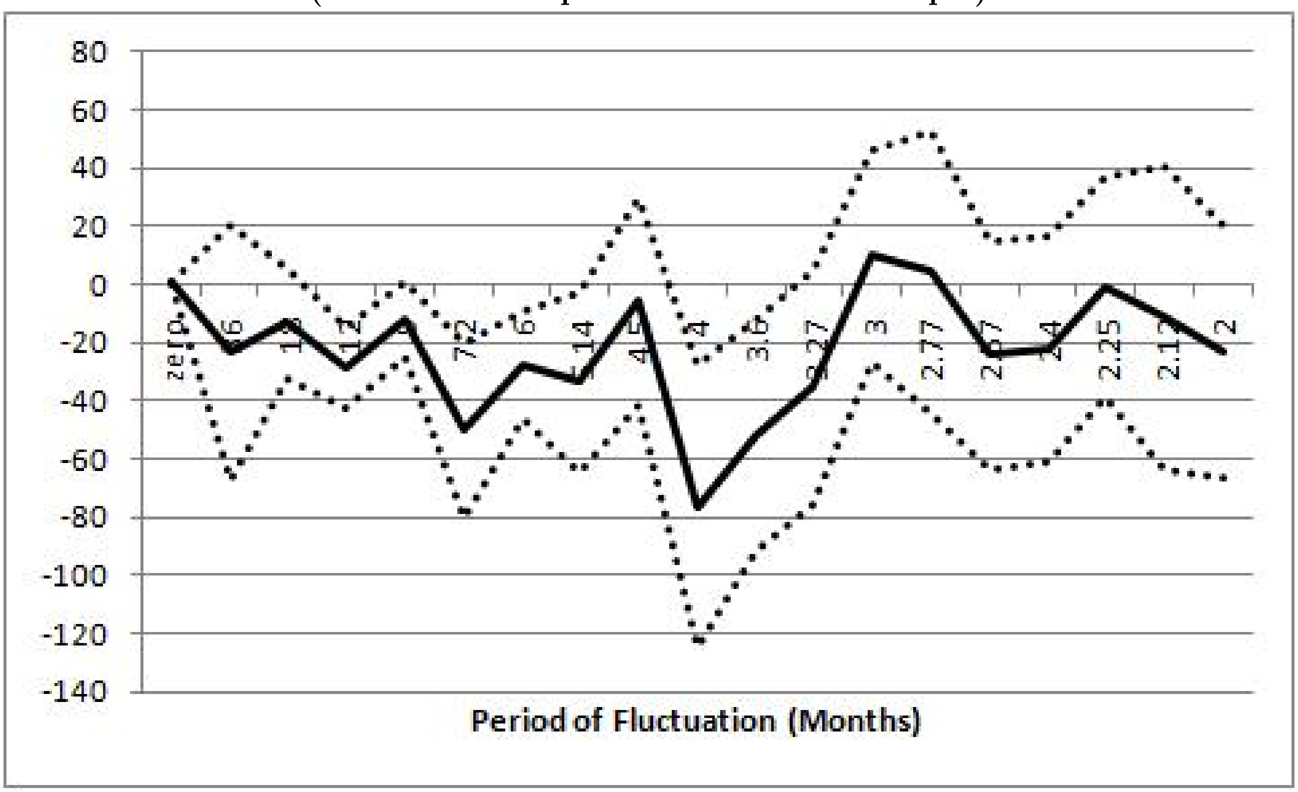

Figure 5: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Inflation (Volcker-Greenspan-Bernanke Sub-Sample)

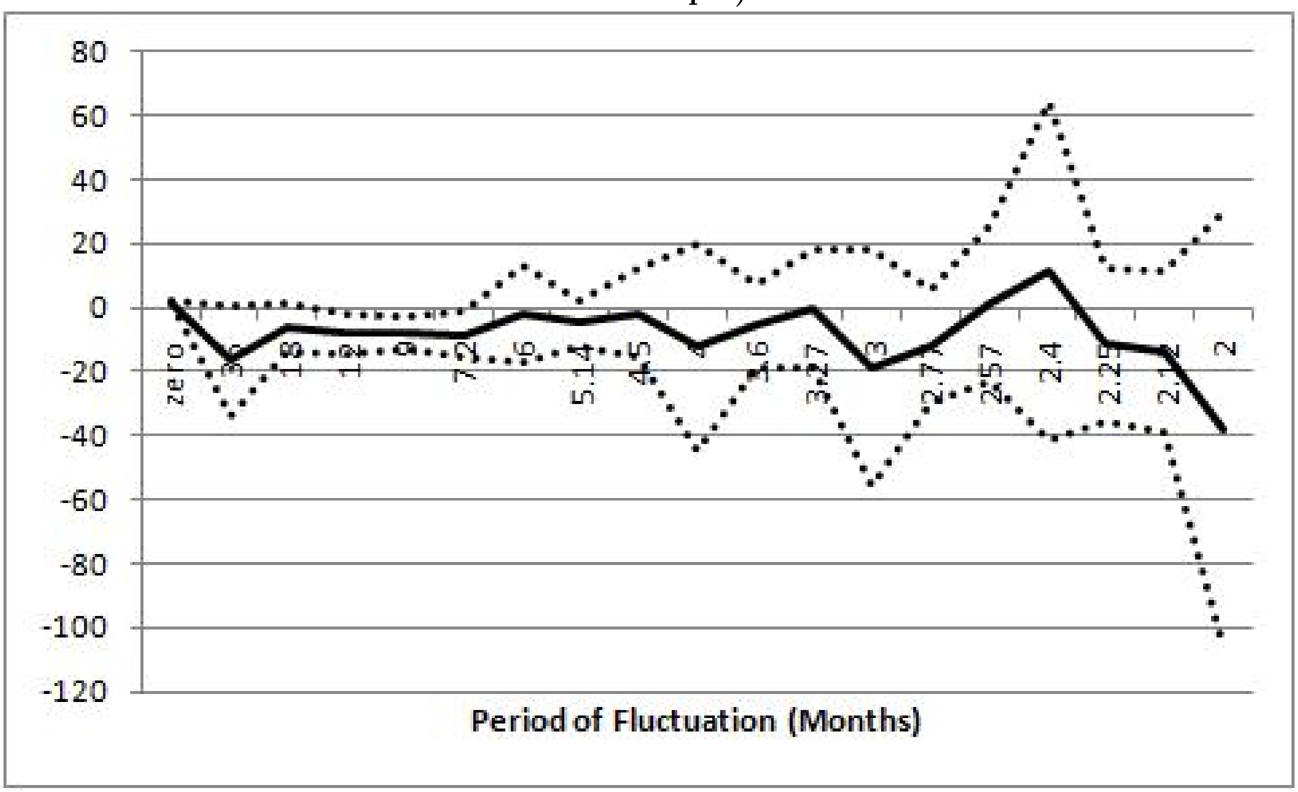

Figure 6: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ and $\phi_{\pi,j}$ from (5), the monetary policy rule allowing for frequency dependence. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Unemployment Rate With or Without the NAIRU as Explanatory Variable (Full Sample)

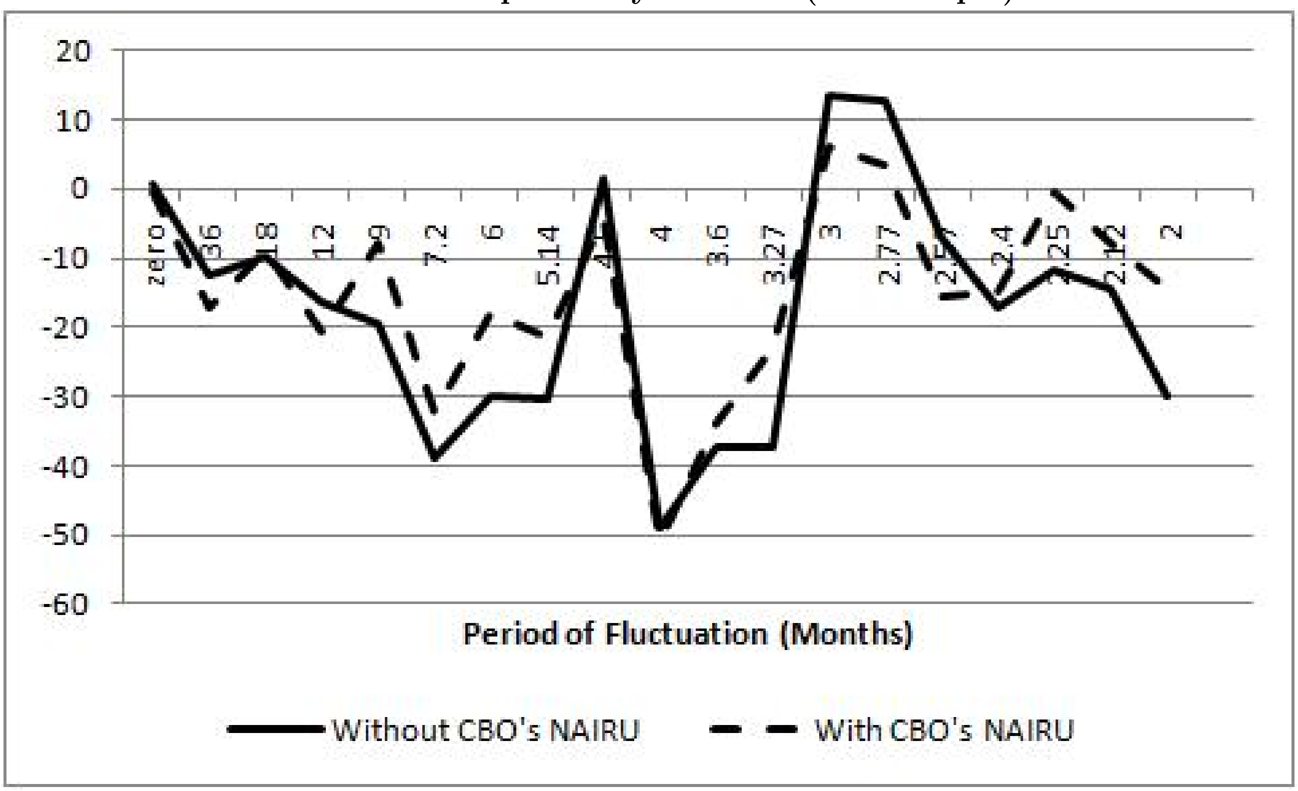

Figure 7: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ from (5), with or without the CBO's NAIRU as an explanatory variable. The coefficient on NAIRU is positive, as expected. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Unemployment Rate With or Without the NAIRU as Explanatory Variable (Martin-Burns-Miller Sub-Sample)

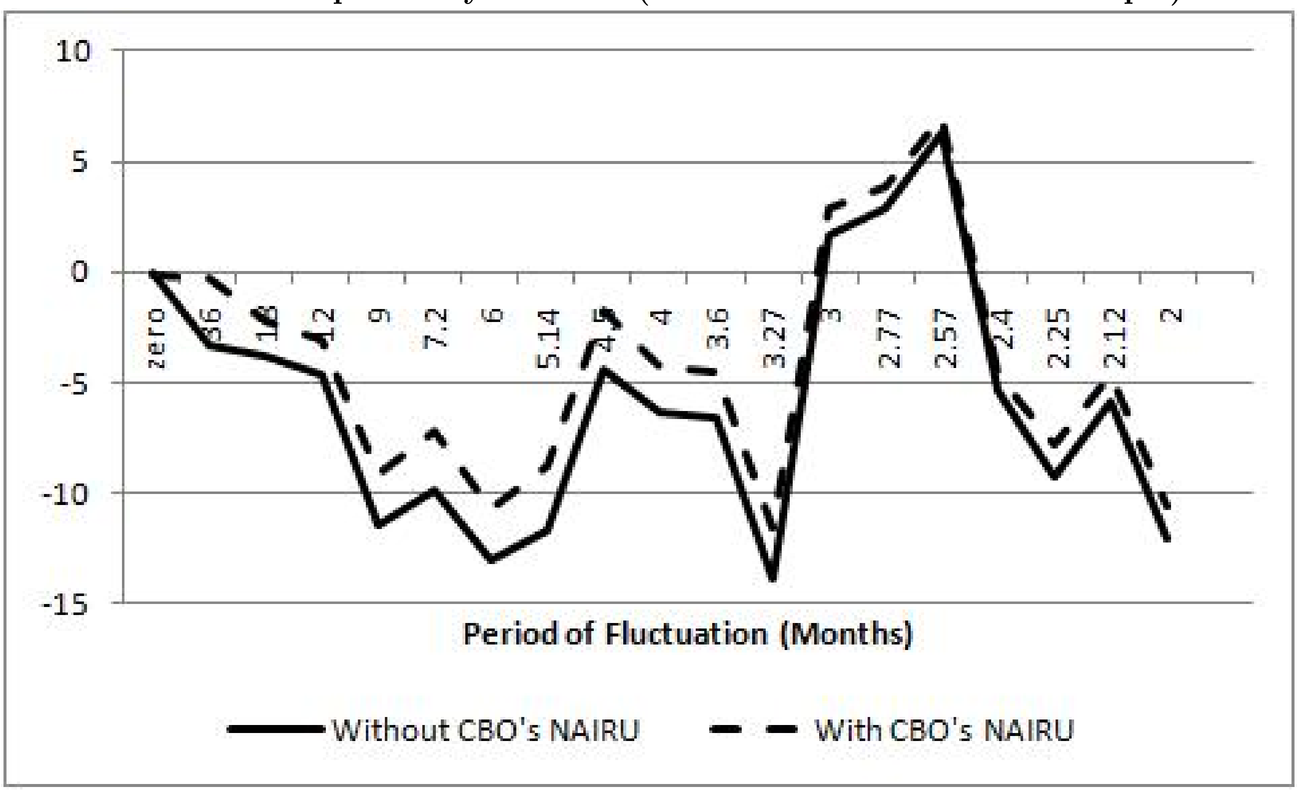

Figure 8: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ from (5), with or without the CBO's NAIRU as an explanatory variable. The coefficient on NAIRU is positive, as expected. Confidence interval is $\pm$ 2 Newey-West standard errors.

Frequency-Dependent Response to Unemployment Rate With or Without the NAIRU as Explanatory Variable (Volcker-Greenspan-Bernanke Sub-Sample)

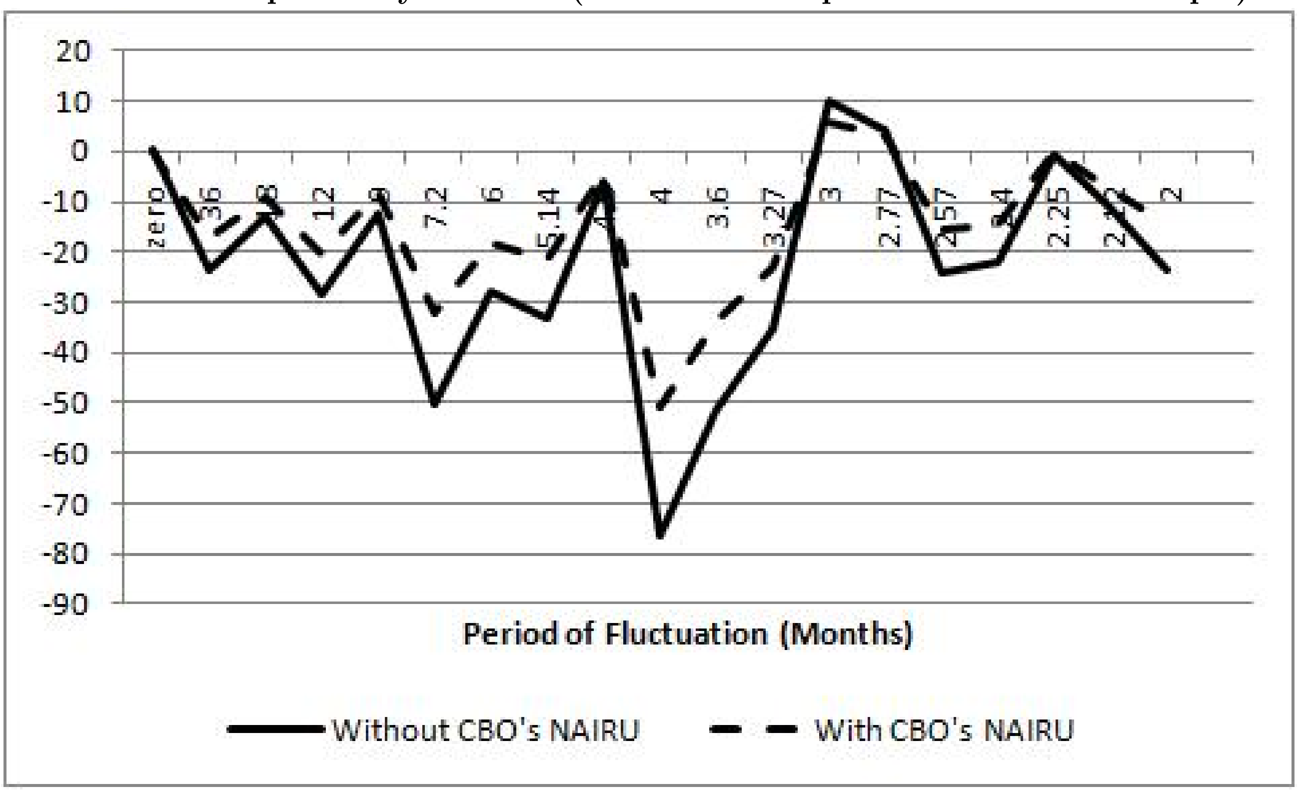

Figure 9: Nonlinear least squares estimates. We plot the estimates $\phi_{u,j}$ from (5), with or without the CBO's NAIRU as an explanatory variable. The coefficient on NAIRU is positive, as expected. Confidence interval is $\pm$ 2 Newey-West standard errors.

Reaction to 1 S.D. Change in Each Component (Unemployment Rate)

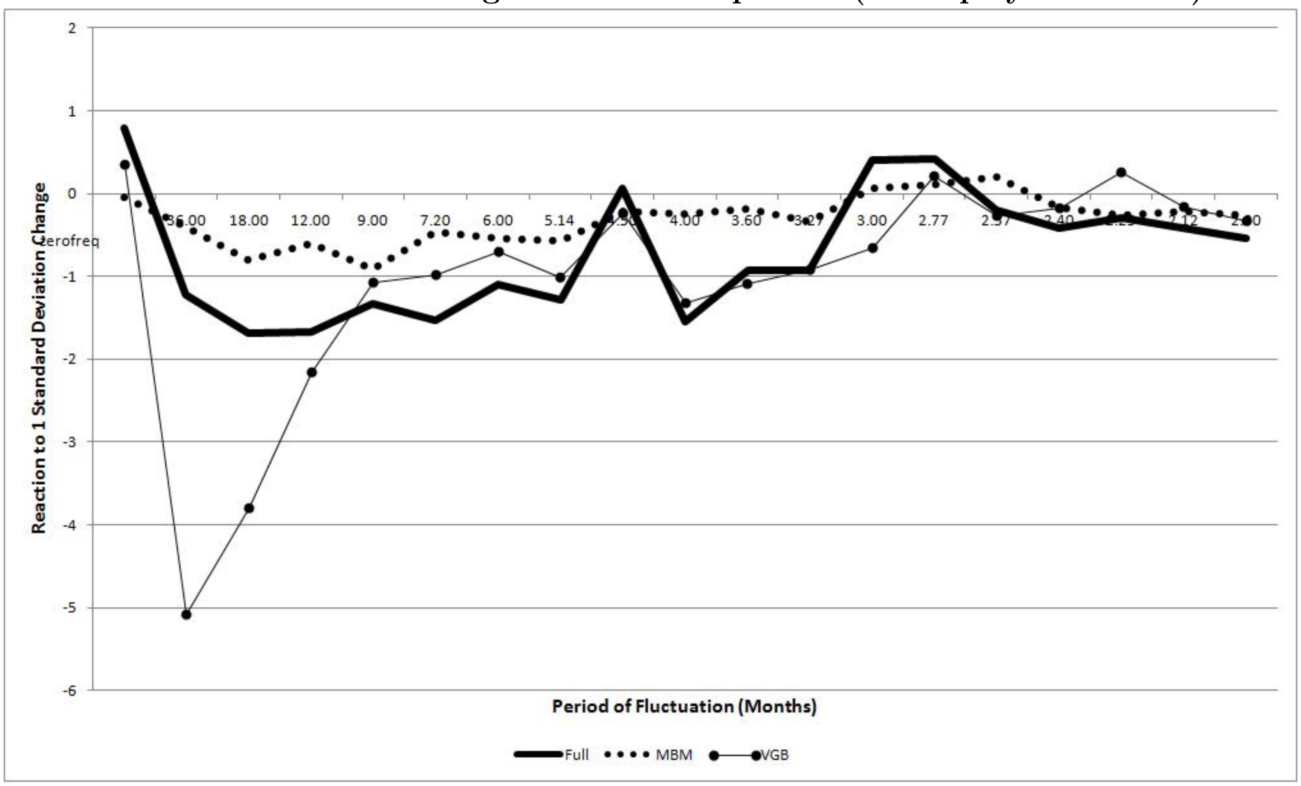

Figure 10: The coefficients $\phi_{u,j}$ and $\phi_{\pi,j}$ do not tell us the economic magnitude of the coefficients. To judge how large the coefficients are, we calculate the standard deviation of each frequency components for the relevant sample. We then standardize the coefficients by multiplying them with the corresponding standard deviation. The standardized coefficents then tell us the reponse of the federal funds rate to one standard deviation change of the frequency components.

Reaction to 1 S.D. Change in Each Component (Inflation)

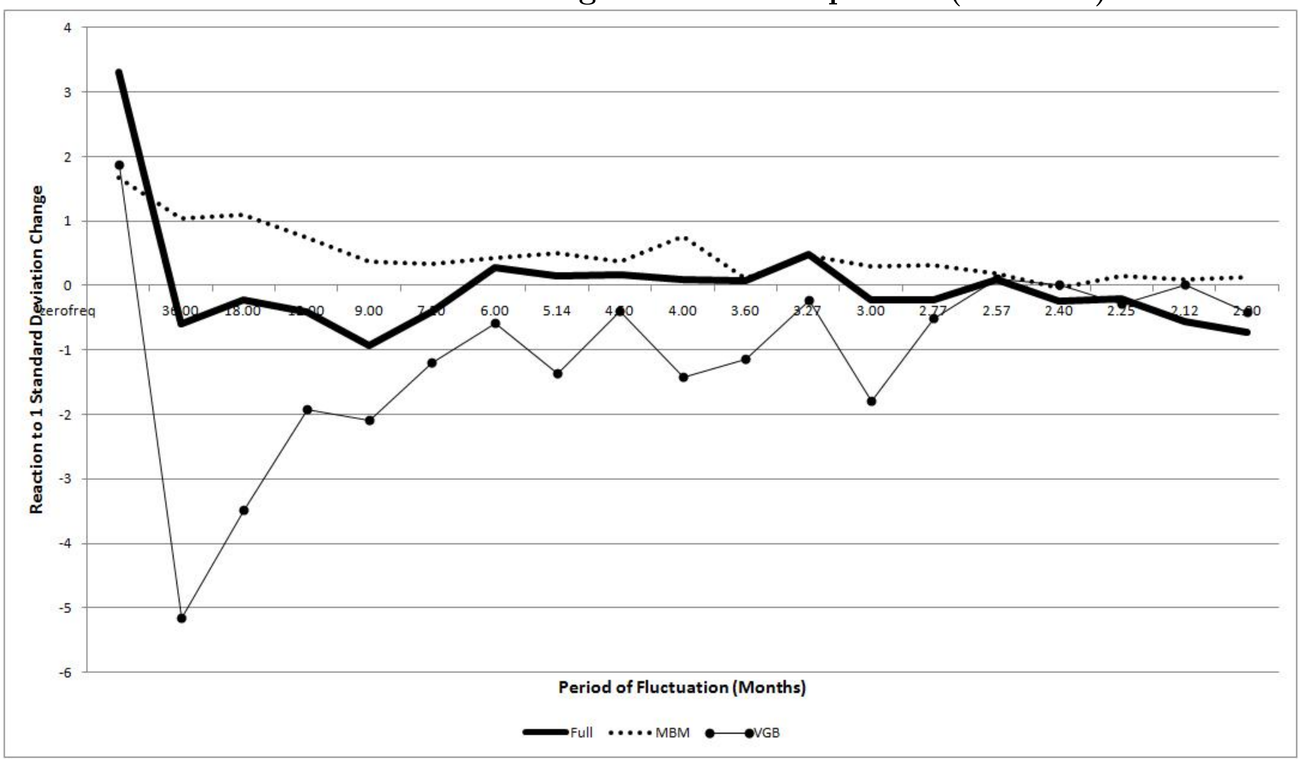

Figure 11: The coefficients $\phi_{u,j}$ and $\phi_{\pi,j}$ do not tell us the economic magnitude of the coefficients. To judge how large the coefficients are, we calculate the standard deviation of each frequency components for the relevant sample. We then standardize the coefficients by multiplying them with the corresponding standard deviation. The standardized coefficents then tell us the reponse of the federal funds rate to one standard deviation change of the frequency components.