Stop-Go Monetary Policy

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Abstract

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1 Introduction

Monetary policymaking is known to be inertial. As Bernanke (2004, p.1) remarked in a well-known speech, “the Federal Reserve tends to adjust interest rates incrementally, in a series of small or moderate steps in the same direction.” Figure 1 displays a plot of the federal funds target rate over the 1993-2017 period that supports Bernanke’s assertion. The figure shows that changes in the target rate come in discrete increments. When the rate has changed, it has typically moved up or down by 25 basis points.¹ The figure also shows that the target rate has gone through stretches of time in which it has changed frequently in the same direction and other stretches in which it has not changed at all. These patterns have occurred as other macroeconomic variables, including those that should affect target interest rates, have been continually changing. Bernanke then offered three reasons for the appeal of “gradualism.” He argued that (1) uncertainty justifies caution, (2) gradual adjustment of short rates can improve control of long-term rates, and (3) gradualism can reduce financial instability.²

This paper investigates the empirical modeling of gradualism rather than the sources of gradualism. Empirical studies of monetary policymaking frequently involve the estimation of reaction functions, which explain the choice of a policy instrument as a function of variables describing macroeconomic conditions. Reaction functions based on Taylor’s (1993) rule, for example, explain the setting of an interest rate target as a function of the output gap and deviations of inflation from target values. To account for policy inertia, Taylor rule regression equations typically add several lagged values of the dependent variable to the right-hand side (e.g., Orphanides 2001). This is a conventional way of modeling “partial adjustment” or “interest-rate smoothing” motives of the policymaker. While this modeling strategy has been successful in capturing the existence of inertia, it fails to reflect fully the stylized facts depicted in Figure 1. Specifically, such a model does not reflect the fact that interest rate changes are made in discrete moves, nor does it adequately account for the prevalence of two types of policy choice sequences, those with frequent moves and those with no moves.

¹ In this period, there were 56 rate moves, 41 of which were movements of 25 basis points.
² Brainard (1967) provides an argument for small policy moves in the presence of uncertainty. Goodfriend (1991) and Woodford (1999, 2003) show that when policymakers are known to follow gradualist policies, a single small policy move can have large reinforcing effects on longer-term rates through expectations. Bernanke argues that gradualist policies are transparent and easily understood, leading to fewer disruptive effects on financial markets. Other studies, including Coibion and Gorodnichenko (2012), Rudebusch (2002), Gerlach-Kristen (2004), and Chappell and McGregor (2017), have empirically investigated sources of policy inertia.
A number of previous studies have explicitly accounted for the discreteness of policy moves. In early contributions, Eichengreen, Watson, and Grossman (1985) and Lapp and Pearce (2000) used ordered probit models to explain central bank decisions to tighten, ease, or leave monetary policy unchanged. For our work, a notable contribution using the ordered probit model was made by Hu and Phillips (2004a,b). In the Hu-Phillips model, discrete movements in the target interest rate are triggered when deviations between the prevailing target rate and an unobserved “optimal rate” are sufficiently large. If the thresholds for policy moves are large, then the Hu-Phillips model can explain the existence of inertia.

Modeling strategies broadly similar to that of Hu-Phillips have also been used by Eichengreen, Watson, and Grossman (1985), Dueker (1999), Genberg and Gerlach (2004), Gerlach (2007), Kim, Mizen, and Chevapatrakul (2008), Boeckx (2011), and Kim (2014). Unlike these studies, Hu and Phillips did not include lagged interest rates as explanatory variables in their final reaction function specification. This has two consequences. First, inertia in their model is produced solely by the existence of thresholds appearing in the ordered probit specification. Second, the model clearly separates the process determining optimal rates from the process describing adjustment toward optimal rates.\(^3\)

In this paper, we examine inertia in policymaking at the Federal Reserve using an approach that builds upon the Hu-Phillips model, but with an important modification. We find that adequately explaining the patterns depicted in Figure 1 requires us to permit time-varying inertial pressures. The term “stop-go monetary policy” has sometimes been used to describe destabilizing policy oscillations that repeatedly and abruptly shifted from ease to tightness in the 1960s and 1970s. In this paper, we appropriate the term, but with a change in meaning. In our empirical models, inertial pressures can be high, resulting in long periods without rate changes, or low, resulting in periods in which rates change frequently.\(^4\)

We find that in a variety of empirical specifications, there is support for the existence of time-varying inertia. Accounting for variations in inertia improves the fit of our models and their in-sample predictions relative to the baseline case modeled by Hu and Phillips. The

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\(^4\)We believe that the experience of the 1960s and 1970s might have better been described as “forward-reverse” monetary policy, but the latter descriptor is admittedly forgettable. In discussing the correlation between monetary instability and real instability, Hetzel (2013) describes a pattern in which the Fed first raised interest rates when it became concerned about inflation and then lowered interest rates slowly as the economy weakened in order to avoid exacerbating expectations of inflation. Hetzel (2013, p. 109) argues that the Great Recession fits this pattern in that an attempt by the Fed “to create a negative output gap to bend inflation down mirrored the stop phases of the earlier stop-go monetary policy.” Arguably, then, the descriptor “stop-go monetary policy” need not be confined to the 1960s and 1970s. See also Hetzel (2009).
in-sample prediction accuracy of our models matches or surpasses that of ordinary linear model estimates of reaction functions that capture inertia by including multiple lags of the dependent variable.

Our results support a simple and appealing characterization of changes in the FOMC’s inertial states. Movements to high-inertia states are triggered under two circumstances: (1) when the FOMC increases or decreases the target rate, inertia becomes high for possible moves in the opposite direction, and (2) when a sufficiently long time has passed without a policy move, inertia becomes high for a move in either direction.

We proceed as follows. Section II reviews the Hu-Phillips model, which provides a point of departure for our empirical models. Section III describes the data used in our analysis. In Section IV, we present estimates of the Hu-Phillips model and compare those to estimates of a conventional linear monetary policy reaction function that includes multiple lags of the dependent variable as explanatory variables. Section V introduces our extensions of the Hu-Phillips model to account for time-varying inertia. We propose different ways of modeling inertial regimes and present estimates of the models. In Section VI, we compare the performance of all models for in-sample prediction of target rate moves, and in Section VII we examine the recent history of monetary policymaking in light of the policymaking patterns revealed by our estimations. Sections VIII and IX look at extensions to the model and our sample period to account for the years in which a lower bound on interest rates applied. Conclusions are offered in Section X.

II The Hu-Phillips Model

Following Hu and Phillips (2004a,b), we assume that the central bank’s optimal target interest rate depends on existing macroeconomic conditions according to the monetary policy reaction function below:

\[ r_t^* = x_t \beta + e_t, \quad e_t \sim N(0, \sigma^2). \]  

(1)

In this equation, \( r_t^* \) is an unobserved optimal target rate of interest, \( x_t \) is a vector of macroeconomic variables, \( \beta \) is a vector of parameters, and \( e_t \) is the usual normally distributed random error term. This equation could take the form of a Taylor rule, in which measures of the output gap and inflation would be included in \( x_t \).

In each policy meeting, the central bank moves the current target rate, \( r_t \), up or down,
or chooses not to move, depending on the level of the “status quo” interest rate, \( r_t^{eq} \), relative to the optimal rate, \( r_t^* \):

\[
\begin{align*}
\text{Case I: If } r_t^* - r_t^{eq} > \mu_u, & \text{ then } \Delta r_t > 0; \quad (2a) \\
\text{Case II: If } r_t^* - r_t^{eq} < \mu_l, & \text{ then } \Delta r_t < 0; \quad (2b) \\
\text{Case III: If } \mu_l \leq r_t^* - r_t^{eq} \leq \mu_u, & \text{ then } \Delta r_t = 0. \quad (2c)
\end{align*}
\]

In these conditions, \( \mu_u \) and \( \mu_l \) are threshold parameters such that \( \mu_l < 0 < \mu_u \) (the subscripts refer to “upper” and “lower” thresholds). Condition (2a) specifies that the target rate will be increased if the optimal rate exceeds the status quo rate by an amount \( \mu_u \). Condition (2b) specifies that the target rate will be decreased if the optimal rate is below the status quo rate by an amount \( -\mu_l \). Condition (2c) says that the rate will remain unchanged if the status quo rate is “sufficiently close” to the optimal rate. Equation (1) and conditions (2) define an ordered probit model to explain the setting of the target interest rate.\(^5\)

Following Boeckx (2011), we adopt two identifying restrictions for this ordered probit model. First, the coefficient on \( r^{eq} \) is equal to one in conditions (2) above (determining the scale of the latent propensity). Second, we will require that the mean of the predicted values of \( r^* \) be equal to the sample mean of the observed target rates, \( r_t \).\(^6\) The latter assumption identifies an intercept included in \( \beta \) in equation (1). Under these assumptions, all model parameters are identified and can be estimated.\(^7\)

Hu and Phillips (2004a,b) give special attention to the case where the macroeconomic variables included in the model are non-stationary. They show that when variables are non-stationary, ordered probit estimates of threshold parameter values will depend on the sample size. However, other parameter estimates are identical to those obtained when explicitly accounting for the non-stationarity. Accordingly, we simply employ the conventional ordered probit framework throughout our analysis.\(^8\)

\(^5\)It is possible to estimate models that distinguish large rate moves from small rate moves. We follow Hu and Phillips and others in not making this distinction in the work reported here, but we have estimated models that distinguish large and small moves for some of our model variants. None of these estimations produced fundamentally different results than those we have reported.

\(^6\)We modify the Boeckx (2011) identification slightly. We require that the mean of the predicted values for \( r_t^* \) be equal to the sample mean of observed target rates over the sample of observations where the zero bound was not binding. For most of our work, the sample included only one observation (in December 2008) where the zero bound applied.

\(^7\)Boeckx (2011) provides a thorough discussion of identification in the context of the Hu-Phillips model.

\(^8\)Using a battery of tests, we generally cannot reject the null hypothesis of non-stationarity for variables included in \( x_t \) in our empirical models. While this does not affect parameter estimates, Kim, Jackson,
III Data

Our initial sample consists of 128 regularly scheduled FOMC meetings over the 1993-2008 period. It is not unusual for the FOMC to call unscheduled meetings, but we have chosen not to include those meetings in our sample. In many cases, unscheduled meetings are called precisely when unusual economic conditions have arisen, or when the Chair believes that a rate move has become necessary. If unscheduled meetings were included in the sample, then the analysis would need to model jointly both the decision to meet and the outcomes of meetings. That is a task that we will not undertake here.

We specify that the optimal interest rate, $r^*_t$, is determined by a modified Taylor rule specification. The elements of $x_t$ (explanatory variables for the optimal interest rate) will include real-time one-year ahead forecasts of the output gap and the CPI inflation rate. The forecasts are averages of quarterly rates, beginning with the current quarter and extending through the next three quarters. These forecasts were extracted from the Philadelphia Federal Reserve Bank’s real-time Greenbook data sets.\footnote{Greenbooks did not routinely report output gaps; however, the output gaps we use were available to Federal Reserve staff and the FOMC at the times of meetings in our sample.}

Following Gerlach-Kristen (2004) and Chappell and McGregor (2017), our model also adds an interest rate spread as an explanatory variable in the modified Taylor rule. This variable is intended to measure financial market stress. Our selected spread measure is the difference between Moody’s seasoned Baa corporate bond yield and the 10-year constant maturity Treasury bond yield, measured for the day preceding the FOMC meeting. The Baa spread was obtained from FRED (Federal Reserve Economic Data, Federal Reserve Bank of St. Louis).\footnote{In our estimations, all explanatory variables were expressed as deviations from sample means (for the sample excluding the December 2008 observation). This permits us to set the intercept equal to the sample mean for the dependent variable to impose the Hu-Phillips identifying restriction referred to earlier.}

The current target rate, $r_t$, was also obtained from FRED. From 1994 onward, the target rate was directly extracted from FOMC meeting transcripts and statements. FRED reports that for 1993 only, the original source of the data for $r_t$ is Thornton (2005).

\footnote{and Saba (2009) have shown that coefficient standard errors obtained with conventional ordered probit estimation will not be correct. Empirically, they found that the standard errors produced by conventional ordered probit were inflated relative to the correct values, suggesting that our use of conventional ordered probit could lead us to be conservative in assessing the significance of explanatory variables. Kim et al. concluded that non-stationarity could be an important issue if the selection of explanatory variables were based on a search based on significance levels; however, that is not the case in this paper. Kim et al. further concluded that “if one is interested in forecast accuracy only, and has a prior about the true model . . ., correcting for non-stationarity is irrelevant” (p. 148). The focus of our paper on predictive accuracy places our work in the latter category.}
The choice of our sample period, 1993-2008, requires some explanation. One consideration is that we wish to use a period when the Federal Reserve was clearly targeting the federal funds rate. From October 1979 until October 1982, the Fed targeted non-borrowed reserves. The switch back to funds rate targeting was never announced and, ex post, it is not completely clear when that switch occurred. Thornton (2006) argues that the Fed was effectively targeting the funds rate immediately after abandoning the non-borrowed reserves procedure in 1982. However, he acknowledges that others place the switch date later, perhaps as late as 1992.

There is a second reason for starting the sample period in 1993. Thornton’s (2005) data indicate that prior to this date, targets were often changed between meetings. Such changes occurred at the discretion of the Chair, a practice that by 1993 had stopped.\textsuperscript{11} This implies that the meaning of a target rate choice by the FOMC was different before 1993 (when the choice could be quickly altered by the Chair) than it was afterwards.

We end our sample period in December 2008, when the federal funds rate target hit an effective lower bound. It remained in a range from 0.00% to 0.25% until December 2015. Arguably, this period constitutes a change in regime, and we exclude it from the sample for most of our work. The model can be modified to include a zero-bound restriction, though, so in Section VIII we consider a modified model using a sample that extends to 2010. Greenbook data are subject to a 5-year release lag and, at the time the data for this paper were collected, output gap and inflation forecasts were available only through 2010. In Section IX, however, we provide model estimates obtained using alternative data sources and extend the estimation period to early 2017.

IV Empirical Results for Hu-Phillips and OLS Estimations

The first column of Table 1 displays estimates of the Hu-Phillips model for the 1993-2008 period.\textsuperscript{12} The estimates are largely in accord with expectations. Coefficients for inflation

\textsuperscript{11}The ending of this practice immediately preceded the FOMC’s decision to release post-meeting statements in 1994, a practice which is now routine. Introducing this form of monetary policy communication constrained the power of the Chair to make inter-meeting moves. Schonhardt-Bailey (2013) notes that Donald Kohn, who served as a member of the Board of Governors from 2002-2010, points to post-meeting statements “as having the effect of reducing the discretion of the Chairman during the intermeeting period to take action without a conference call among the FOMC members” (p. 437).

\textsuperscript{12}Hu and Phillips (2004a) used a different set of variables for the $x_t$ vector but employed the general form described by (1) and (2). They initially included a broad set of possible explanatory variables and proceeded to a final specification by dropping insignificant variables. Their final specification included M2 money growth, initial unemployment claims, an index of consumer confidence, and the growth of new factory orders.
and the output gap are positively signed and differ significantly from zero. The interest rate spread is negatively signed, and its coefficient is also significantly different from zero. The point estimate of the inflation coefficient is less than one and therefore fails to satisfy the “Taylor principle” required for long-run stability of inflation. Because inflation was very stable over most of our sample period, it is possible that the impact of inflation is difficult to detect. A test of the hypothesis that the inflation coefficient is equal to one is marginally rejected (p-value=0.081).\(^\text{13}\)

The threshold parameters are of special interest. The results imply that an upward move in the funds rate occurs when the optimal target rate exceeds the current rate by 122 basis points. A downward move occurs when the optimal rate is less than the prevailing rate by 146 basis points. These estimates are similar to those found by Hu and Phillips, but slightly larger in absolute value. The results indicate that there is inertia in policymaking, since moves only occur when actual and optimal rates differ by large amounts.

For purposes of comparison, the second column of Table 1 provides estimates of a conventional linear monetary policy reaction function of the form

\[
 r_t = \rho_1 r_{t-1} + \rho_2 r_{t-2} + \rho_3 r_{t-3} + \mathbf{x}_t \mathbf{\beta} + \epsilon_t.
\] (3)

The specification in (3) differs from the Hu-Phillips model in two key ways. First, the dependent variable in (3) is the actual target rate of interest, which is presumed to be both observed and continuous. Second, inertia is captured by the inclusion of lagged values of the dependent variable, rather than by a requirement that movements be generated when deviations between current and optimal rates exceed thresholds. Our choice of three lags of the dependent variable is empirically determined; when included, the coefficient of a fourth lag did not differ significantly from zero.\(^\text{14}\) To facilitate comparisons, the coefficients of the economic variables presented in Table 1 are long-run estimates, estimates that display the total impact of a variable after completion of the adjustment process captured by the lagged dependent variables.\(^\text{15}\)

Results of these two models are similar in important respects. First, the coefficients of the macroeconomic determinants of target rates are similar in the two estimations. In the Hu-Phillips model, the coefficient of inflation is smaller and the coefficient of the Baa

\(^\text{13}\)In preliminary estimations, Hu and Phillips (2004a) found no significant impact of inflation and dropped the variable from their final model.

\(^\text{14}\)Although biased in small samples, such an approach does yield consistent estimates.

\(^\text{15}\)Equation (3) can be rewritten as \( r_t = \rho_1 r_{t-1} + \rho_2 r_{t-2} + \rho_3 r_{t-3} + (1 - \rho_1 - \rho_2 - \rho_3) \mathbf{x}_t \mathbf{\beta} + \epsilon_t \), where the elements of \( \mathbf{\beta} \) are the long-run reaction function coefficients.
spread is larger (in absolute value) than those in the linear model, but signs are identical, and all coefficients differ significantly from zero. Second, both models provide evidence of substantial policymaking inertia. In the Hu-Phillips model, this is apparent in the large values of the threshold parameters; in the linear model, the sum of the coefficients of the lagged target rates is close to one (0.913).

V Models with Time-Varying Inertia

In this section, we extend the Hu-Phillips model to permit policymaking inertia to vary over time. We will consider three different ways of modeling inertial regimes. First, we consider a simple model that is based on the premise that we can judge whether inertia is high or low based on an observable indicator. We refer to this as a “Deterministic Inertia” model. Second, we consider a model in which inertia can vary continuously and is a function of multiple inertia indicators and estimated parameters. We refer to this as the “Continuous Inertia” model. Third, we develop a model in which inertial states are discrete but stochastic, and we call this the “Stochastic Inertia” model. Ultimately, results from the three specifications have broadly similar implications for descriptions of policymaking behavior.

V.1 Deterministic Inertia

We propose that policy inertia is either “high” or “low” for each of two directions for rate moves, up and down. Let $I_t^u = 1$ if inertia is “high” and let $I_t^u = 0$ if policy inertia is “low” for rate moves in an upward direction at time $t$. Similarly, let $I_t^d = 1$ if inertia is “high” and let $I_t^d = 0$ if policy inertia is “low” for rate moves in a downward direction at time $t$. We then specify that the threshold parameters in the Hu-Phillips model depend on the state of inertia as follows:

$$\mu_u = v_0 + v_1 I_t^u$$

and

$$\mu_t = \lambda_0 + \lambda_1 I_t^d.$$ 

(4a)

As long as $I_t^u$ and $I_t^d$ are observed, it is straightforward to estimate all parameters of
the ordered probit model defined by conditions (1), (2), and (4).\textsuperscript{16} Estimated parameters include the elements of $\beta$ and the parameters determining thresholds, $v_0$, $v_1$, $\lambda_0$, and $\lambda_1$.

We will consider three possible definitions for $I_t^u$ and $I_t^d$, as described below:

**Definition 1** $I_t^u = I_t^d = 1$ when the FOMC has gone at least $\overline{T}_t$ days since the last rate change; otherwise $I_t^u = I_t^d = 0$. $\overline{T}_t$ is estimated.

**Definition 2** $I_t^u = 1$ if the last rate move was in a downward direction; else $I_t^u = 0$; $I_t^d = 1$ if the last rate move was in an upward direction; else $I_t^d = 0$.

**Definition 3** $I_t^u = 1$ if (1) the last rate move was in a downward direction or (2) at least $\overline{T}_t$ days have passed since the last rate change; else $I_t^u = 0$. $I_t^d = 1$ if (1) the last rate move was in an upward direction or (2) at least $\overline{T}_t$ days have passed since the last rate change; else $I_t^d = 0$. $\overline{T}_t$ is estimated.

Under the first proposed definition, inertia in either direction is assumed to depend only on the amount of time that has elapsed since the last rate move. When more time has elapsed, a move might be viewed as a more significant event. In this case, greater caution might be warranted, and inertia would be stronger.

Under the second proposed definition, inertia depends on the direction of the last move. It implies that any rate change leads to low inertia for future moves in the same direction and high inertia for moves in the opposite direction. These inertial states persist until another rate move occurs to change them. This definition is appropriate if central banks are reluctant to reverse the direction of policy abruptly. Frequent rate changes in different directions could be viewed by the public as evidence of incoherence or inconsistency, and central banks wish to avoid such perceptions.

The third definition combines features of the first two. High inertia in a specific direction is generated either by a rate move in the opposite direction or by passage of sufficient time without a move. Otherwise inertia is low.

Table 2 reports estimates of the Deterministic Inertia model for each of these three definitions. In the two models where a value of $\overline{T}_t$ is needed, we repeatedly estimated over a range of possible values and selected that value which resulted in the highest value of the likelihood function.\textsuperscript{17} In both cases, this resulted in a value of $\overline{T}_t = 94$ days.\textsuperscript{18} For the FOMC, 94 days is roughly twice the length of a typical inter-meeting interval.

\textsuperscript{16}This generalization of the ordered probit model was proposed by Terza (1985). Terza’s model is discussed in Greene and Hensher (2010, pp. 209-210).

\textsuperscript{17}This approach has been suggested in Gannon, Harris, and Harris (2014).

\textsuperscript{18}Any $T$ between 93 and 97 splits our sample identically. We arbitrarily report a cutoff at 94.
In all estimations reported in Table 2, estimates of the economic variable coefficients are similar to the corresponding entries in Table 1. All parameters have expected signs and differ significantly from zero. All models also give ample evidence of differences in threshold parameters across inertial regimes. For example, in the third column the estimated threshold for upward moves under low inertia \( (v_0) \) is 18 basis points, but the threshold for upward moves under high inertia \( (v_0 + v_1) \) is 208 basis points. The threshold for downward moves under low inertia \( (\lambda_0) \) is -56 basis points, while the threshold for downward moves under high inertia \( (\lambda_0 + \lambda_1) \) is -176 basis points.

It is possible to test the hypothesis of time-varying inertia. Under the null hypothesis that inertia is non-varying, we should observe \( v_1 = \lambda_1 = 0 \). This implies that changes in the inertia indicators, \( I_t^u \) and \( I_t^d \), have no effect on the thresholds that regulate rate moves. In this case, the model collapses to the Hu-Phillips case. We convincingly reject this hypothesis for each of the estimations in Table 2. For each estimation, a Wald test rejects the null hypothesis that \( v_1 = \lambda_1 = 0 \) with a p-value of 0.000.

Although each inertia definition seems to work well, the model using Definition 3 provides the best fit judged by the Bayesian information criterion (BIC). This suggests that the direction of the last rate move and time elapsed since the last rate change both affect the state of policy inertia.

V.2 Continuous Inertia

It is possible that inertia that affects the FOMC varies continuously rather than discretely. Allowing this possibility leads to a generalization of the model of the last section. That model assumed that the discrete inertial states were indicated by the dummy variables \( I_t^u \) and \( I_t^d \). We now suppose that inertial states, again indicated by \( I_t^u \) and \( I_t^d \), are functions of a set of observable variables that can be continuous or discrete.

Upward and downward inertia, \( I_t^u \) and \( I_t^d \), are now given by

\[
I_t^u = \Phi (z_t \gamma) \tag{5a}
\]

and

\[
I_t^d = \Phi (z_t \omega), \tag{5b}
\]
where $\Phi(\cdot)$ is the standard normal distribution function. The selected functional form assures that the inertia indicators are bounded between zero and one. Variables determining inertia in both upward and downward directions are included in the vector $z_t$. By imposing exclusion conditions on elements of $\omega$ and $\gamma$, the set of variables influencing inertia in the two directions can differ.

As before, the threshold parameters are specified to depend on inertia according to conditions (4):

$$\mu_u = v_0 + v_1 I_t^u$$  \hspace{2cm} (4a)

and

$$\mu_l = \lambda_0 + \lambda_1 I_t^d.$$  \hspace{2cm} (4b)

Substituting conditions (5) into conditions (4) yields expressions for the (continuously varying) thresholds in the model:

$$\mu_u = v_0 + v_1 \Phi(z_t \gamma)$$  \hspace{2cm} (6a)

and

$$\mu_l = \lambda_0 + \lambda_1 \Phi(z_t \omega).$$  \hspace{2cm} (6b)

The complete model is now described by conditions (1), (2), (4), and (5).

To estimate the model, we must specify variables to be included in $z_t$. In our earlier discussion, we suggested two possible determinants of inertia: (1) the direction of the last rate move and (2) the amount of time that has elapsed since the last rate move. This suggests the following specifications for $z_t \gamma$ and $z_t \omega$:

$$z_t \gamma = \gamma_0 LM U_t + \gamma_1 LM D_t + \gamma_2 LM U_t \times T_t + \gamma_3 LM D_t \times T_t$$  \hspace{2cm} (7a)

and

$$z_t \omega = \omega_0 LM D_t + \omega_1 LM U_t + \omega_2 LM D_t \times T_t + \omega_3 LM U_t \times T_t.$$  \hspace{2cm} (7b)
where the included variables are defined below:

$LMU_t$: Dummy variable equal to 1 if the last target move before meeting $t$ was in an upward direction, else equal to 0;

$LMD_t$: Dummy variable equal to 1 if the last target move before meeting $t$ was in a downward direction, else equal to 0;

$T_t$: The number of days at time $t$ since the target rate was last changed.

The linear combination in (7a) determines the state of inertia in an upward direction. It permits upward inertia to depend on the direction of the last rate move and on time that has elapsed since the last rate move. Further, the time effects are permitted to differ depending on whether the last move was in an upward or downward direction. In symmetric fashion, equation (7b) determines inertia in a downward direction. In estimation, we impose symmetry restrictions on the parameters in (7a) and (7b). Specifically, we require that $\gamma_0 = \omega_0$, $\gamma_1 = \omega_1$, $\gamma_2 = \omega_2$, and $\gamma_3 = \omega_3$.

Results for this model are provided in column 1 of Table 3. Our discussion will focus on what the results imply about inertia for upward rate moves. Because the model specifies a symmetric process for downward moves, we will not discuss that case separately.

We first note a peculiar result—we report a value of $-\infty$ for parameter $\gamma_0$. In our estimations, $\gamma_0$ was negative and took on ever larger values as the optimization routine progressed. This has a sensible interpretation in our model. When the target rate is increased, so that $LMU_t = 1$, the immediate impact is that inertia for upward rate moves, $I_t^u$, goes to zero—a low-inertia state prevails. We also report that $\gamma_2 = -0.0106 \times \gamma_0$, implying that $\gamma_2$ tended to infinity, but in proportion to $\gamma_0$. This also has a sensible interpretation. When 94.17 (i.e., $1 \div 0.0106$) days pass without a rate move, then inertia for upward moves immediately takes a value of one. Thus, the passage of time generates high inertia for upward moves.

Now suppose that there has been a decrease in the target rate, so that $LMD_t = 1$. The large estimate for $\gamma_1$ implies that upward moves are initially subject to high inertia (at $T_t = 0$ following a downward move, we calculate that $I_t^u = 1.00$). However, because $\gamma_3$ is negative, in the absence of additional moves, upward inertia falls over time. The estimates imply that it would take 402.6 days for $I_t^u$ to reach a value of 0.50. While our sample period contains several stretches of time without a rate move that were longer than this, intervals between
moves were typically shorter.

Note that these results are similar to those presented earlier for the Deterministic Inertia model under Definition 3. In both cases, a move to a high-inertia state can be triggered either by a target rate move or by the passage of time without a move. The results generally support the idea that inertia is usually “high” or “low,” but less frequently “medium.” In 108 of 128 observations (84.4%), upward inertia is either below 0.05 or above 0.95 on a scale bounded between 0 and 1. Similarly, in 114 of 128 observations (89.1%), downward inertia is either below 0.05 or above 0.95. This suggests that it may often be reasonable to think of inertial states as discrete and dichotomous, as we did in the simpler Deterministic Inertia models.

Because the upper and lower thresholds vary over time, it is useful to plot them to visualize what the model implies. Figure 2 plots paths for $\mu_u$ and the absolute value of $\mu_t$ over the sample period. The plots reveal that the threshold for upward rate movements varies between 27 and 263 basis points and that the absolute value of the threshold for downward rate moves varies between 49 and 189 basis points.

V.3 Stochastic Inertia

We now return to the case where there are two discrete inertial states. In contrast to the preceding sections, however, we assume that determination of inertial states is stochastic rather than deterministic. In this model, the probabilities of being in high- or low-inertia states vary continuously. To our knowledge, this variant of the ordered probit model has not previously been estimated.$^{19}$

We first assume that our model retains these equations and conditions introduced in earlier sections:

$$r^*_t = \mathbf{x}_t \beta + e_t, \quad e_t \sim N(0, \sigma^2); \quad (1)$$

Case I: If $r^*_t - r^*_u > \mu_u$, then $\Delta r_t > 0$; \quad (2a)

Case II: If $r^*_t - r^*_u < \mu_l$, then $\Delta r_t < 0$; \quad (2b)

Case III: If $\mu_l \leq r^*_t - r^*_u \leq \mu_u$, then $\Delta r_t = 0$; \quad (2c)

$^{19}$Gillman, Greene, Harris, and Spencer (2017) have estimated a model in which the decisions to make a policy move and the direction of the move are treated sequentially. Although that model differs in a number of ways from the one presented here, there are similarities in the likelihood functions for the two models.
\[ \mu_u = v_0 + v_1 I_u^t, \quad (4a) \]
\[ \mu_t = \lambda_0 + \lambda_1 I_t^d. \quad (4b) \]

We now assume that \( I_u^t \) and \( I_t^d \) are discrete but not observed; our model will specify the stochastic processes that generate them.

First consider inertia for rate moves in an upward direction, i.e., inertia for target rate increases. Let \( i_t^u \) be an unobserved “propensity” for upward inertia such that

\[ \begin{align*}
  i_t^u &= \mathbf{z}_t \gamma + u_t, \\
  u_t &\sim N(0, 1). \quad (8)
\end{align*} \]

The actual state of upward inertia (high or low) depends on \( i_t^u \) according to

\[ I_t^u = 1 \quad \text{if} \quad i_t^u > 0 \quad (9a) \]

and

\[ I_t^u = 0 \quad \text{if} \quad i_t^u \leq 0. \quad (9b) \]

Similarly, there is an unobserved propensity for downward inertia, i.e., inertia for target rate decreases. That propensity, \( i_t^d \), is given by\(^2\)

\[ \begin{align*}
  i_t^d &= \mathbf{z}_t \omega + v_t, \\
  v_t &\sim N(0, 1). \quad (10)
\end{align*} \]

The actual state of inertia for downward moves depends on \( i_t^d \) according to

\[ I_t^d = 1 \quad \text{if} \quad i_t^d > 0 \quad (11a) \]

and

\[ I_t^d = 0 \quad \text{if} \quad i_t^d \leq 0. \quad (11b) \]

Conditions (1), (2), (4), (8), (9), (10), and (11) together comprise the stochastic inertia model. Although \( I_t^u \) and \( I_t^d \) are not observed, it is possible to estimate the model by the

\(^2\)As in Section V.2, exclusion conditions on elements of \( \omega \) and \( \gamma \) can be imposed so that variables determining inertia in the two directions could differ.
maximum likelihood method. See the appendix for discussion of the likelihood function for the model.

To estimate the model, we must have empirical specifications for the upward and downward inertia processes described in equations (8) and (10). Mirroring our treatment in equations (7) for the Continuous Inertia model, we adopt these forms:

\[
\mathbf{z}_t \gamma = \gamma_0 \mathbf{L} \mathbf{M} \mathbf{U}_t + \gamma_1 \mathbf{L} \mathbf{M} \mathbf{D}_t + \gamma_2 \mathbf{L} \mathbf{M} \mathbf{U}_t \times T_t + \gamma_3 \mathbf{L} \mathbf{M} \mathbf{D}_t \times T_t
\]

(12a)

and

\[
\mathbf{z}_t \omega = \omega_0 \mathbf{L} \mathbf{M} \mathbf{D}_t + \omega_1 \mathbf{L} \mathbf{M} \mathbf{U}_t + \omega_2 \mathbf{L} \mathbf{M} \mathbf{D}_t \times T_t + \omega_3 \mathbf{L} \mathbf{M} \mathbf{U}_t \times T_t.
\]

(12b)

Variables are defined in the same manner as before, and we again impose the symmetry conditions \( \gamma_0 = \omega_0, \gamma_1 = \omega_1, \gamma_2 = \omega_2, \) and \( \gamma_3 = \omega_3. \) Although conditions (7) and (12) are identical in appearance, their interpretations differ in the models for continuous inertia and stochastic inertia. In conditions (7), \( \mathbf{z}_t \gamma \) and \( \mathbf{z}_t \omega \) determined a continuous index of inertia. In conditions (12), they determine unobserved propensities which, in turn, affect probabilities of being in discrete inertial states.

Results of our estimation of the Stochastic Inertia model are provided in the second column of Table 3. Once again, we report a parameter estimate tending toward infinity; in this case, \( \gamma_1 \) tends toward infinity. This result implies that the probability of being in the high-inertia state for upward rate moves jumps to one immediately following a cut in the target rate. Also note that Table 3 indicates that \( \gamma_3 = -0.00243 \times \gamma_1. \) Following a rate cut, the probability of being in the high-inertia state for upward rate moves is equal to one, but after 411.5 \( (1 \div 0.00243) \) days, the probability drops to zero.

There are similar but less extreme results reported for parameters \( \gamma_0 \) and \( \gamma_2. \) Because \( \gamma_0 \) is large and negative, if the last move was upward, then the probability of being in a high-inertia state for upward moves will be close to zero. The point estimate of \( \gamma_2 \) is positive, so that probability will rise as time passes, as long as there are no further moves. The estimates imply that 112 days must pass in order for the probability to rise to 0.50.

Estimated coefficients for the economic variables are broadly similar to those reported for the earlier models, as are the threshold parameters \( \nu_0, \nu_1, \lambda_0, \) and \( \lambda_1. \) A minor exception is provided by the inflation coefficient, which is smaller in the Stochastic Inertia model than in others. The inflation coefficient is also not significantly different from zero.
Overall fits (as judged by the BIC) of the Continuous Inertia model, the Stochastic Inertia model, and the Deterministic Inertia model under Definition 3 are similar. The Continuous Inertia model has the best fit (lowest BIC) by a small margin over the simpler Deterministic Inertia model under Definition 3. All of the time-varying parameter models substantially outperform the Hu-Phillips specification.\textsuperscript{21}

\section{Comparative Predictions of Target Rate Moves}

In this section, we will compare the in-sample target rate predictions from the models we have estimated. These models include a conventional linear model that includes lags of the dependent variable, the Hu-Phillips specification, three variants of the Deterministic Inertia model, the Continuous Inertia model, and the Stochastic Inertia model.

To make comparisons, we generate in-sample predictions of interest rate decisions (increase, decrease, or no change).\textsuperscript{22} For all models with an ordered probit structure, our outcome for each observation is that which has the highest predicted probability given estimated parameter values. To get similar predictions from the OLS estimates, we calculated predicted values of the target interest rate, transformed those to discrete options (based on options that are spaced at 25 basis point intervals), and inferred whether a movement was required to reach that outcome. Table 4 compares prediction accuracy for the various models. The table shows prediction success rates for each of the three possible outcomes (upward rate moves, downward rate moves, and unchanged rates).

Table 4 shows that the Continuous Inertia model, the Stochastic Inertia model, and the Deterministic Inertia model (Definition 3) are the top performers, with success rates of 82.81\%, 81.25\%, and 78.91\% (the first two models have the advantage of being parameter-rich). The linear model performs comparably, with a success rate of 78.13\%. The Hu-Phillips model does well in predicting no-change outcomes, but not outcomes where the rate changes. Its overall success rate is lower at 71.88\%.

While the success rates for the various models are not dramatically different, we should keep in mind that when many observations are correctly predicted, it becomes increasingly

\textsuperscript{21}Because the linear model specification has a different dependent variable, comparisons of BIC values between that model and the various ordered probit models are not meaningful.

difficult to correctly predict even more outcomes. Some observations are necessarily close calls, where the outcome is a toss-up, and these outcomes will be difficult to predict. Also, our time-varying inertia models were not designed primarily to improve on prediction versus a linear model with lagged dependent variables; rather, our models were intended to give accurate representations of the actual decision-making process used by the FOMC.

VII The History of Monetary Policymaking

Our estimations have interesting implications about recent historical events in monetary policymaking. For this exercise, we use the Deterministic Inertia model with Definition 3, the model in which high inertia is triggered either by an opposite-direction rate change or elapsing time. The model has a good fit (judged by the likelihood function and the BIC), predicts well, and is parsimonious in parameters. Our other time-varying inertia models support similar interpretations.

Panel A of Figure 3 plots time paths of the adopted funds rate and the fitted optimal interest rate, with the latter calculated from the estimates reported in column 3 of Table 2. Panel B of Figure 3 plots the difference between actual and optimal rates. These graphs reveal several periods in which there are persistent large differences between the adopted rate and the fitted rate. In May 2000, the FOMC raised the target funds rate to 6.50%. Our estimates imply that the optimal rate started to move down at that point, but high downward inertia prevented a quick policy reversal. The rate was finally reduced in January 2001, and this was followed by a series of additional gradual rate reductions. Because the optimal rate was also falling, the actual target rate exceeded the optimal rate for a 22-month period from May 2000 until February 2002. This suggests that monetary policy was excessively tight in the period surrounding the 2001 recession.

Once the FOMC began to lower rates, it did so persistently. In June 2003, the target rate fell to 1.00%. By the very next meeting, in August, the optimal rate had increased by almost 75 basis points, and a long period in which actual target rates were below optimal rates began. The June rate drop sustained high inertia in an upward direction. By the time the actual rate was moved up a year later, in June 2004, the optimal rate exceeded the actual rate by 238 basis points. Excessive ease then continued until March 2006, as the process of gradual rate increases failed to catch up with rising optimal rates. At this point, 30 consecutive months of excessively easy monetary policy had elapsed. As is well known, in this period house prices were rising consistently at double-digit rates, and the seeds of a
future financial crisis were being sown.

Many economists have been critical of U.S. monetary policy in this period, with Taylor (2007, 2009) providing a prominent example.\textsuperscript{23} He argues that his prescribed rule called for
tighter policy in the mid-2000s that might have averted the housing bubble, the bursting of
that bubble, and the financial crisis and recession that followed. Our results indicate that
policy was too easy for too long even in terms of an optimal Fed policy that is inferred from
its own historical behavior. Although Bernanke (2004) identified good reasons for favoring a
gradualist approach, our findings suggest that the precise way in which gradualism has been
implemented bears some responsibility for poor economic outcomes in our sample period.

Panel B of Figure 3 displays one more interesting point. The last observation in our
sample is for December 2008. At that meeting, the target rate was moved to a range
centered at 0.125\%, its effective lower bound. Given the dismal outlook for the economy
and an unprecedented rise in the interest rate spread, our model indicates that the optimal
setting for the funds rate at that meeting, in the absence of a lower bound, would have been
-7.58\%. Moreover, upward rate moves would have been subject to high inertia. At that time,
increases in the target rate were unthinkable for the near future.

\section*{VIII The Lower Bound on Interest Rates}

The sample period we have analyzed so far ends in December 2008. At that point, the
target interest rate had reached an effective lower bound, with a target range set between
0.00\% and 0.25\%. While the lower-bound regime may have been unique in some respects,
the time-varying inertia models can be easily modified to account for the bound.\textsuperscript{24}

Using a sample that extends through 2010, we have re-estimated our time-varying inertia
models while properly accounting for the lower bound. We have not reported the estimates
for a simple reason—when observations through 2010 are added, model estimates are almost
identical to those reported for the sample ending in 2008. There is a reason for this, as
Figure 4 helps to demonstrate. Figure 4 displays optimal and actual levels for the funds
rate, as determined by the model of Table 2 column 3 (the best-performing Deterministic
Inertia model) with the sample now extending through 2010. Beginning in October 2008, the

\textsuperscript{23} Ahrend, Cournède, and Price (2008) lend supporting international evidence to the arguments of Taylor
(2007).

\textsuperscript{24} In our ordered probit model, there are normally three cases to consider: (1) the rate moves up, (2) the
rate moves down, or (3) the rate is unchanged. In the presence of the lower bound, there are four cases: (1)
the rate moves up, (2) the rate moves down, (3) the rate is unchanged and the current rate is not at the
lower bound, and (4) the rate is unchanged and the current rate is at the lower bound.
optimal interest rate became negative, and in December 2008 it reached a trough at -7.58%. At the end of the sample in December 2010, it had risen back to -1.71%. Throughout this two-year period where the zero bound prevailed, the actual rate of 0.125% far exceeded the optimal rate. Moreover, because the last rate change was downward, there was high inertia in an upward direction. This means that during the lower bound period through 2010, the model is routinely predicting that the rate will stay at its lower bound with a probability approaching one with the same coefficient values that were estimated for the sample period that ended in 2008. If the same coefficient values can predict the 16 new observations with perfect accuracy, then addition of the new observations will not change the estimates.

The FOMC finally increased the funds rate target in December 2015, following seven years without a move. It is not possible to extend the sample beyond 2010 while using Greenbook data for forecasts of the output gap and inflation. In the next section, we use alternative data sources to extend the sample to 2017.

IX An Extended Data Set

Although our Greenbook data extend only through 2010, it is possible to estimate our models with alternative data that include more recent observations. We have calculated inflation according to the personal consumption expenditure deflator for a one-year backward horizon, ending with the month before the month of a meeting. Instead of Greenbook estimates of the output gap, we use output gaps based on estimates of potential GDP provided by the Congressional Budget Office. Our updated gap variable is not a real-time series; each observation is a final revised estimate.25 We continue to use the most recent daily observations to measure the Baa interest rate spread.

Table 5 reports the results of this exercise, using the Deterministic Inertia model with Definition 3. For purposes of comparison, the first column reports estimates that use the original Greenbook data through 2010. These estimates are identical to those reported earlier in column 3 of Table 2. The second column of Table 5 reports estimates using the alternative data series for the same sample period (through 2010). The use of the alternative data series results in some notable changes in parameter estimates. The coefficient of inflation is now smaller and insignificantly different from zero, while the coefficient on the interest rate spread is larger in absolute value. The threshold parameters $\lambda_1$ and $\nu_1$ are both larger in absolute

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25 We have also constructed alternative real-time data series for inflation and output gap forecasts through 2017 using data from the Survey of Professional Forecasters and the Congressional Budget Office. Models estimated with these data perform relatively poorly.
value. In addition, the overall fit of the model, as judged by the likelihood function or the BIC, has worsened. This is not surprising—we should be able to explain Fed decisions better when we use the data that the Fed possessed at the time of its meetings.

Columns 3 and 4 of Table 5 update the estimation through March 2017. The results in column 3 are for the Deterministic Inertia model with Definition 3. The results in column 4 are for the same model, but with a modification to permit a downward shift in the Taylor rule intercept for the 2009-2017 period. The latter specification is appropriate if there was a one-time permanent reduction in the natural rate of interest coinciding with the beginning of the zero-bound period. Our estimates are consistent with such a shift. Results in columns 3 and 4 are similar, except that permitting the intercept shift results in smaller and more plausible estimates of threshold parameters under high-inertia states. The results in column 4 are also similar to those presented in columns 1 and 2 that provide estimates for the sample that extends only through 2010.

Figure 5 compares optimal and adopted interest rate targets through March 2017 using the estimates of our model from column 4 of Table 5 (the version of the model permitting an interest rate shift). Our estimates imply that the optimal interest rate was below the target of 0.125% from October 2008 through October 2013. Beginning in December 2013, the optimal rate exceeded the actual target rate until September 2015. In this time period, the target rate remained at 0.125%, even though the optimal rate reached a local peak at 1.59% in July 2014. Our estimates imply that the probability of a rate hike was 0.177 at that time—our model accounts for the failure to raise the target rate with a high estimate of the threshold for an upward move in a high-inertia state.

Ironically, the FOMC finally increased its target rate in December 2015, a time when our model implies the pressure for an upward move was dissipating. At that meeting, our estimate of the optimal rate was again negative, and the probability of an upward rate move was only 0.013. The FOMC then paused long enough for high inertia to return, and the next upward move in the target rate occurred in December 2016, when the optimal rate was back up to 1.683%. At that point, the FOMC paused at its next meeting, even though inertia should have been low and the difference between optimal and actual rates was large.

The behavior of the FOMC as it departed the zero-bound regime is challenging to explain. The first upward move occurred at an unlikely moment, and a typical run of consecutive upward moves has not materialized. Instead, the FOMC has made moves to eliminate the gap between actual and optimal rates more slowly than in the past.
X Conclusions

Central banks have varied institutional arrangements and practices that can affect the quality of monetary policy decisions. One common practice is to adjust target interest rates in an inertial fashion. Our research attempts to describe the inertial process that has characterized monetary policymaking in the United States.

Following Hu and Phillips (2004a,b), we have estimated an ordered probit model that assumes that discrete movements in target rates occur when the currently prevailing rate deviates sufficiently from the optimal rate. Unlike Hu and Phillips, we have developed three models that permit the inertia that affects rate changes to vary over time. The first model assumes that dichotomous inertial states are known a priori. The second model assumes that inertia varies continuously over time. The third model assumes that inertial regimes are discrete, but that they are stochastic and unobserved.

All of the time-varying inertia models fit the data well—we reject the Hu-Phillips base model in favor of varying inertia in all cases. The models also show that the direction of the last rate move, as well as the passage of time without a rate move, can affect the state of inertia. Most time-varying inertia models also offer improved in-sample predictions compared to the Hu-Phillips model and comparable or better performance relative to a conventional linear model that includes lags of the dependent variable to account for inertia.

Our models imply that target rates have sometimes diverged from optimal rates for long periods of time. Specifically, interest rates were not lowered promptly when the 2001 recession approached, and they were kept low for too long in the mid-2000s. When we used alternative data to extend the sample to 2017, we found that it is difficult to explain the FOMC’s emergence from the zero-bound regime—in particular, it is difficult to explain why the Fed delayed as long as it did, why it finally moved at a seemingly inappropriate moment, and why subsequent upward rate moves have occurred rather infrequently. Whether these most recent events indicate a fundamental change in policymaking behavior provides a question for future research.
References


Appendix: Maximum Likelihood Estimation of the Stochastic Inertia Model

Under the assumptions described by conditions (8)–(11) in the text, probabilities for the two inertial states relevant for an upward move will be given by

$$\Pr (I_t^u = 1) = \Phi (z_t \gamma)$$

(A.1a)

and

$$\Pr (I_t^u = 0) = 1 - \Phi (z_t \gamma).$$

(A.1b)

Similarly, probabilities for the two inertial states relevant for downward moves are given by

$$\Pr (I_t^d = 1) = \Phi (z_t \omega)$$

(A.2a)

and

$$\Pr (I_t^d = 0) = 1 - \Phi (z_t \omega).$$

(A.2b)

The probabilities given in conditions (A.1) and (A.2) have a form that would characterize a probit model if $I_t^u$ and $I_t^d$ were observed.

Although we do not observe $I_t^u$ and $I_t^d$, it is possible to derive the likelihood function for the stochastic inertial regimes model. First, consider the probability of observing a reduction in the target rate. This can happen when the inertial state for downward moves is either high or low. Assuming that $e_t$, $v_t$, and $u_t$ are independent, then the probability of a rate reduction is given by

$$\Pr (\Delta r_t < 0) = \Pr (\Delta r_t < 0 | I_t^d = 0) \times \Pr (I_t^d = 0)$$

$$+ \Pr (\Delta r_t < 0 | I_t^d = 1) \times \Pr (I_t^d = 1).$$

(A.3)

Equation (A.3) says that the overall probability of a rate reduction is equal to the prob-
ability of a rate reduction conditional on downward inertia being low, multiplied by the probability that downward inertia is low, plus the probability of a rate reduction conditional on downward inertia being high, multiplied by the probability that downward inertia is high.

Next consider the probability of observing no change in the target rate. This can happen in four ways: (1) inertia is low for both upward and downward moves; (2) inertia is high for both upward and downward moves; (3) inertia is high for upward moves and low for downward moves; (4) inertia is low for upward moves and high for downward moves. The probability that no rate change occurs is given by

\[
\Pr(\Delta r_t = 0) = \Pr(\Delta r_t = 0 \mid I_t^d = 0 \text{ and } I_t^u = 0) \times \Pr(I_t^d = 0) \times \Pr(I_t^u = 0) + \\
\Pr(\Delta r_t = 0 \mid I_t^d = 1 \text{ and } I_t^u = 1) \times \Pr(I_t^d = 1) \times \Pr(I_t^u = 1) + \\
\Pr(\Delta r_t = 0 \mid I_t^d = 0 \text{ and } I_t^u = 1) \times \Pr(I_t^d = 0) \times \Pr(I_t^u = 1) + \\
\Pr(\Delta r_t = 0 \mid I_t^d = 1 \text{ and } I_t^u = 0) \times \Pr(I_t^d = 1) \times \Pr(I_t^u = 0).
\] (A.4)

Finally, consider the probability of observing an increase in the target rate. This event can happen when the inertial state for upward moves is either high or low. The probability of a rate increase can therefore be written as

\[
\Pr(\Delta r_t > 0) = \Pr(\Delta r_t > 0 \mid I_t^u = 0) \times \Pr(I_t^u = 0) + \\
\Pr(\Delta r_t > 0 \mid I_t^u = 1) \times \Pr(I_t^u = 1).
\] (A.5)

The likelihood function for an observation gives the probability of the occurrence of that outcome as a function of parameter values, given the data. As equations (A.6) below illustrate, all probability expressions appearing in equations (A.3) – (A.5) can be written as functions of the data and parameter values.

\[
\Pr(\Delta r_t < 0 \mid I_t^d = 0) = \Phi\left(\frac{\lambda_0 - x_t \beta + r_t^{eq}}{\sigma}\right)
\] (A.6a)

\[
\Pr(\Delta r_t < 0 \mid I_t^d = 1) = \Phi\left(\frac{\lambda_0 + \lambda_1 - x_t \beta + r_t^{eq}}{\sigma}\right)
\] (A.6b)

\[
\Pr(\Delta r_t = 0 \mid I_t^d = 0 \text{ and } I_t^u = 0) = \Phi\left(\frac{\lambda_0 - x_t \beta + r_t^{eq}}{\sigma}\right) - \Phi\left(\frac{\lambda_0 - x_t \beta + r_t^{eq}}{\sigma}\right)
\] (A.6c)
\[
\text{Pr}(A_t = 0 \mid I_t^d = 1 \text{ and } I_t^u = 1) = \Phi \left( \frac{v_0 + v_1 - x_i \beta + r_t^{s_q}}{\sigma} \right) - \Phi \left( \frac{\lambda_0 + \lambda_1 - x_i \beta + r_t^{s_q}}{\sigma} \right) \\
\text{Pr}(A_t = 0 \mid I_t^d = 0 \text{ and } I_t^u = 1) = \Phi \left( \frac{v_0 + v_1 - x_i \beta + r_t^{s_q}}{\sigma} \right) - \Phi \left( \frac{\lambda_0 - x_i \beta + r_t^{s_q}}{\sigma} \right) \\
\text{Pr}(A_t = 0 \mid I_t^d = 1 \text{ and } I_t^u = 0) = \Phi \left( \frac{v_0 - x_i \beta + r_t^{s_q}}{\sigma} \right) - \Phi \left( \frac{\lambda_0 + \lambda_1 - x_i \beta + r_t^{s_q}}{\sigma} \right) \\
\text{Pr}(A_t > 0 \mid I_t^d = 0) = 1 - \Phi \left( \frac{v_0 - x_i \beta + r_t^{s_q}}{\sigma} \right) \\
\text{Pr}(A_t > 0 \mid I_t^d = 1) = 1 - \Phi \left( \frac{v_0 + v_1 - x_i \beta + r_t^{s_q}}{\sigma} \right) \\
\text{Pr}(I_t^d = 0) = 1 - \Phi (z_t \omega) \\
\text{Pr}(I_t^d = 1) = \Phi (z_t \omega) \\
\text{Pr}(I_t^u = 0) = 1 - \Phi (z_t \gamma) \\
\text{Pr}(I_t^u = 1) = \Phi (z_t \gamma) \\
\]

The likelihood for an observation is equal to the probability of the observed outcome’s occurrence, given parameter values and the data. Appropriately substituting equations (A.1), (A.2), and (A.6) into conditions (A.3) - (A.5) will yield the likelihood function for each observation in the sample.
Figures

Figure 1: Federal Funds Target Rate, 1993-2017

Notes: This figure plots the federal funds target adopted by the FOMC in regularly scheduled FOMC meetings from 1993 through March 2017. Source: FRED (Federal Reserve Economic Data, Federal Reserve Bank of St. Louis).
Figure 2: Time Varying Upper and Lower Thresholds for Target Rate Changes, 1993-2008

Notes: This figure displays estimated threshold values, $\mu_u$ and $\mu_l$, for upward and downward moves in the target federal funds rate. The estimate of $\mu_l$ is negative but is displayed as an absolute value. Estimated threshold values are calculated using the estimates in column 1 of Table 3 (the Continuous Inertia model).
Figure 3: Adopted Federal Funds Rate Target, Optimal Federal Funds Rate, and Difference between Target and Optimal Rates, 1993-2008

Notes: Panel A displays the target federal funds rate adopted in each regularly scheduled FOMC meeting. It also displays estimated optimal federal funds rates. Optimal rates are fitted values derived from model estimates in column 3 of Table 2 (the Deterministic Inertia model with Definition 3). Panel B displays the difference between the adopted federal funds rate target and the optimal federal funds rate.
Figure 4: Adopted Federal Funds Rate Target and Optimal Federal Funds Rate, 1993-2010

Notes: The figure displays the target federal funds rate and an estimated optimal target rate for each regularly scheduled FOMC meeting. Optimal rates are fitted values derived from model estimates in column 3 of Table 2 (the Deterministic Inertia model with Definition 3).
Figure 5: Adopted Federal Funds Rate Target and Optimal Federal Funds Rate, 1993-2017

Notes: The figure displays the target federal funds rate and an estimated optimal target rate for each regularly scheduled FOMC meeting. Optimal rates are fitted values derived from model estimates in column 4 of Table 5 (the Deterministic Inertia model with Definition 3 and permitting a one-time shift in the Taylor rule intercept).
Table 1: Ordered Probit Estimates: Hu-Phillips Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Hu-Phillips Ordered Probit</th>
<th>Linear Model OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (Intercept)</td>
<td>4.006*</td>
<td>4.042</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.971)</td>
</tr>
<tr>
<td>$\rho_1$</td>
<td>1.094</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(16.993)</td>
<td></td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>0.143</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.418)</td>
<td></td>
</tr>
<tr>
<td>$\rho_3$</td>
<td>-0.324</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.574)</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ (Inflation)</td>
<td>0.653</td>
<td>0.834</td>
</tr>
<tr>
<td></td>
<td>(3.286)</td>
<td>(3.716)</td>
</tr>
<tr>
<td>$\beta_2$ (Output Gap)</td>
<td>0.755</td>
<td>0.729</td>
</tr>
<tr>
<td></td>
<td>(8.751)</td>
<td>(5.004)</td>
</tr>
<tr>
<td>$\beta_3$ (Interest Rate Spread)</td>
<td>-1.791</td>
<td>-1.076</td>
</tr>
<tr>
<td></td>
<td>(-6.456)</td>
<td>(-3.766)</td>
</tr>
<tr>
<td>$\mu_u$</td>
<td>1.219</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.427)</td>
<td></td>
</tr>
<tr>
<td>$\mu_t$</td>
<td>-1.460</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-7.165)</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.951</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
<td></td>
</tr>
<tr>
<td>log $L$</td>
<td>-78.613</td>
<td>77.882</td>
</tr>
<tr>
<td>$\bar{R}^2$</td>
<td></td>
<td>0.994</td>
</tr>
<tr>
<td>BIC</td>
<td>93.169</td>
<td>-60.900</td>
</tr>
</tbody>
</table>

*The estimate of $\beta_0$ in the ordered probit model is set to the value that makes the average optimal interest rate equal to the sample mean of the actual target interest rate.

Notes: The parameters are defined as follows: $\beta_1$, $\beta_2$, and $\beta_3$ are Taylor rule coefficients; $\mu_u$ and $\mu_t$ are the upper and lower thresholds in the ordered probit model; and $\rho_1$, $\rho_2$, and $\rho_3$ are coefficients on the autoregressive terms in the linear monetary policy reaction function. The reported Taylor rule parameters are estimates of the long-run coefficients.
Table 2: Deterministic Inertia Models

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Deterministic 1</th>
<th>Deterministic 2</th>
<th>Deterministic 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (Intercept)</td>
<td>4.006*</td>
<td>4.006*</td>
<td>4.006*</td>
</tr>
<tr>
<td>$\beta_1$ (Inflation)</td>
<td>0.516</td>
<td>0.723</td>
<td>0.577</td>
</tr>
<tr>
<td></td>
<td>(2.821)</td>
<td>(4.184)</td>
<td>(2.341)</td>
</tr>
<tr>
<td>$\beta_2$ (Output Gap)</td>
<td>0.792</td>
<td>0.635</td>
<td>0.754</td>
</tr>
<tr>
<td></td>
<td>(10.004)</td>
<td>(8.030)</td>
<td>(8.222)</td>
</tr>
<tr>
<td>$\beta_3$ (Interest Rate Spread)</td>
<td>-1.736</td>
<td>-1.253</td>
<td>-1.435</td>
</tr>
<tr>
<td></td>
<td>(-7.133)</td>
<td>(-6.453)</td>
<td>(-4.951)</td>
</tr>
<tr>
<td>$v_0$</td>
<td>0.575</td>
<td>0.454</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>(3.043)</td>
<td>(2.357)</td>
<td>(0.726)</td>
</tr>
<tr>
<td>$v_1$</td>
<td>1.502</td>
<td>1.382</td>
<td>1.900</td>
</tr>
<tr>
<td></td>
<td>(4.178)</td>
<td>(4.649)</td>
<td>(4.373)</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>-0.907</td>
<td>-0.741</td>
<td>-0.562</td>
</tr>
<tr>
<td></td>
<td>(-3.531)</td>
<td>(-3.623)</td>
<td>(-1.763)</td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>-0.862</td>
<td>-1.235</td>
<td>-1.197</td>
</tr>
<tr>
<td></td>
<td>(-2.923)</td>
<td>(-4.165)</td>
<td>(-3.342)</td>
</tr>
<tr>
<td>$\mu_u = v_0 + v_1$</td>
<td>2.077</td>
<td>1.835</td>
<td>2.083</td>
</tr>
<tr>
<td></td>
<td>(6.185)</td>
<td>(6.348)</td>
<td>(5.808)</td>
</tr>
<tr>
<td>$\mu_l = \lambda_0 + \lambda_1$</td>
<td>-1.769</td>
<td>-1.976</td>
<td>-1.759</td>
</tr>
<tr>
<td></td>
<td>(-8.740)</td>
<td>(-8.686)</td>
<td>(-7.489)</td>
</tr>
</tbody>
</table>

$H_0: v_1 = \lambda_1 = 0$  
$\chi^2_2 = 28.363$ (Reject $H_0$)  
$\chi^2_2 = 36.887$ (Reject $H_0$)  
$\chi^2_2 = 26.833$ (Reject $H_0$)  

(p-value=0.000)  
(p-value=0.000)  
(p-value=0.000)

$\bar{T}$  
log $L$  
BIC

*The estimate of $\beta_0$ is set to the value that makes the average optimal interest rate equal to the sample mean of the actual target interest rate.

Notes: $\bar{T}$ was selected by iterating over possible values and selecting based on the highest value for the likelihood function. The parameters are defined as follows: $\beta_1$, $\beta_2$, and $\beta_3$ are Taylor rule coefficients; $v_0$ and $v_1$ are parameters that determine the upper threshold $\mu_u$; and $\lambda_0$ and $\lambda_1$ are parameters that determine the lower threshold $\mu_l$. The reported Taylor rule parameters are estimates of the long-run coefficients.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Continuous Inertia</th>
<th>Stochastic Inertia</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (Intercept)</td>
<td>4.006*</td>
<td>4.006*</td>
</tr>
<tr>
<td>$\beta_1$ (Inflation)</td>
<td>0.393</td>
<td>0.360</td>
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<td></td>
<td>(1.366)</td>
<td>(1.117)</td>
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<tr>
<td>$\beta_2$ (Output Gap)</td>
<td>0.833</td>
<td>0.861</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(8.759)</td>
</tr>
<tr>
<td>$\beta_3$ (Interest Rate Spread)</td>
<td>-1.431</td>
<td>-1.388</td>
</tr>
<tr>
<td></td>
<td>(-4.654)</td>
<td>(-4.961)</td>
</tr>
<tr>
<td>$\nu_0$</td>
<td>0.216</td>
<td>0.204</td>
</tr>
<tr>
<td></td>
<td>(0.882)</td>
<td>(0.715)</td>
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<tr>
<td>$\nu_1$</td>
<td>2.365</td>
<td>2.027</td>
</tr>
<tr>
<td></td>
<td>(3.789)</td>
<td>(4.049)</td>
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<tr>
<td>$\lambda_0$</td>
<td>-0.550</td>
<td>-0.443</td>
</tr>
<tr>
<td></td>
<td>(-2.170)</td>
<td>(-1.572)</td>
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<tr>
<td>$\lambda_1$</td>
<td>-1.395</td>
<td>-1.676</td>
</tr>
<tr>
<td></td>
<td>(-3.804)</td>
<td>(-4.381)</td>
</tr>
<tr>
<td>$\gamma_0 = \omega_0$</td>
<td>$-\infty$</td>
<td>-1.912</td>
</tr>
<tr>
<td></td>
<td>$-\infty$</td>
<td>(-1.862)</td>
</tr>
<tr>
<td>$\gamma_1 = \omega_1$</td>
<td>6.417</td>
<td>$\infty$</td>
</tr>
<tr>
<td></td>
<td>(0.565)</td>
<td>$-\infty$</td>
</tr>
<tr>
<td>$\gamma_2 = \omega_2$</td>
<td>$-0.0106 \times \gamma_0$</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>$-0.0106 \times \gamma_0$</td>
<td>(2.440)</td>
</tr>
<tr>
<td>$\gamma_3 = \omega_3$</td>
<td>$-0.016$</td>
<td>$-0.00243 \times \gamma_1$</td>
</tr>
<tr>
<td></td>
<td>(-0.597)</td>
<td>$-0.00243 \times \gamma_1$</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.796</td>
<td>0.604</td>
</tr>
<tr>
<td></td>
<td>(4.444)</td>
<td>(3.042)</td>
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<tr>
<td>log $L$</td>
<td>-47.389</td>
<td>-49.746</td>
</tr>
<tr>
<td>BIC</td>
<td>71.469</td>
<td>74.005</td>
</tr>
</tbody>
</table>

*The estimate of $\beta_0$ is set to the value that makes the average optimal interest rate equal to the sample mean of the actual target interest rate.

Notes: The parameters are defined as follows: $\beta_1$, $\beta_2$, and $\beta_3$ are Taylor rule coefficients; $\nu_0$ and $\nu_1$ are parameters that determine the upper threshold $\mu_0$; $\gamma_0$, $\gamma_1$, $\gamma_2$, and $\gamma_3$ are parameters that characterize the process determining inertia in an upward direction; $\lambda_0$ and $\lambda_1$ are parameters that determine the lower threshold $\mu_1$; and $\omega_0$, $\omega_1$, $\omega_2$, and $\omega_3$ are parameters that characterize the process determining inertia in a downward direction. The reported Taylor rule parameters are estimates of the long-run coefficients.
### Table 4: Comparison of Model Predictions

<table>
<thead>
<tr>
<th>Meeting Outcomes</th>
<th>Obs.</th>
<th>OLS</th>
<th>Hu-Phillips</th>
<th>Deterministic 1</th>
<th>Deterministic 2</th>
<th>Deterministic 3</th>
<th>Continuous</th>
<th>Stochastic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate Increases</td>
<td>30</td>
<td>26</td>
<td>16</td>
<td>20</td>
<td>19</td>
<td>24</td>
<td>26</td>
<td>25</td>
</tr>
<tr>
<td>Rate Decreases</td>
<td>23</td>
<td>14</td>
<td>12</td>
<td>17</td>
<td>12</td>
<td>14</td>
<td>16</td>
<td>17</td>
</tr>
<tr>
<td>Rate Unchanged</td>
<td>75</td>
<td>60</td>
<td>64</td>
<td>61</td>
<td>60</td>
<td>63</td>
<td>64</td>
<td>62</td>
</tr>
<tr>
<td>All Outcomes</td>
<td>128</td>
<td>100</td>
<td>92</td>
<td>98</td>
<td>91</td>
<td>101</td>
<td>106</td>
<td>104</td>
</tr>
<tr>
<td>All Outcomes %</td>
<td>100%</td>
<td>78.13%</td>
<td>71.88%</td>
<td>76.88%</td>
<td>71.09%</td>
<td>78.91%</td>
<td>82.81%</td>
<td>81.25%</td>
</tr>
</tbody>
</table>

*Notes:* Table entries indicate the number or percentage of correct predictions by the model.
### Table 5: Deterministic Inertia, Definition 3, Extended Sample

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_0$ (Intercept)</td>
<td>4.006*</td>
<td>4.006*</td>
<td>3.724*</td>
<td>4.006*</td>
</tr>
<tr>
<td>$\beta_{shift}$</td>
<td></td>
<td></td>
<td></td>
<td>-1.686 (-2.411)</td>
</tr>
<tr>
<td>$\beta_1$ (Inflation)</td>
<td>0.577</td>
<td>0.130</td>
<td>0.334</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(2.341)</td>
<td>(0.375)</td>
<td>(0.874)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>$\beta_2$ (Output Gap)</td>
<td>0.754</td>
<td>0.727</td>
<td>0.872</td>
<td>0.784</td>
</tr>
<tr>
<td></td>
<td>(8.222)</td>
<td>(4.880)</td>
<td>(4.675)</td>
<td>(5.224)</td>
</tr>
<tr>
<td>$\beta_3$ (Interest Rate Spread)</td>
<td>-1.435</td>
<td>-2.201</td>
<td>-2.557</td>
<td>-2.069</td>
</tr>
<tr>
<td></td>
<td>(-4.951)</td>
<td>(-5.352)</td>
<td>(-5.499)</td>
<td>(-5.250)</td>
</tr>
<tr>
<td>$\nu_0$</td>
<td>0.183</td>
<td>0.031</td>
<td>0.314</td>
<td>0.155</td>
</tr>
<tr>
<td></td>
<td>(0.726)</td>
<td>(0.074)</td>
<td>(0.689)</td>
<td>(0.384)</td>
</tr>
<tr>
<td>$\nu_1$</td>
<td>1.900</td>
<td>2.882</td>
<td>3.454</td>
<td>2.674</td>
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<tr>
<td></td>
<td>(4.373)</td>
<td>(3.618)</td>
<td>(3.598)</td>
<td>(3.663)</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>-0.562</td>
<td>-0.770</td>
<td>-1.057</td>
<td>-0.727</td>
</tr>
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<td>(-1.970)</td>
<td>(-1.863)</td>
<td>(-2.063)</td>
<td>(-1.779)</td>
</tr>
<tr>
<td>$\lambda_1$</td>
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<td>-1.877</td>
<td>-2.338</td>
<td>-1.988</td>
</tr>
<tr>
<td></td>
<td>(-3.342)</td>
<td>(-2.868)</td>
<td>(-2.872)</td>
<td>(-2.989)</td>
</tr>
<tr>
<td>$\mu_u = \nu_0 + \nu_1$</td>
<td>2.083</td>
<td>2.913</td>
<td>3.768</td>
<td>2.829</td>
</tr>
<tr>
<td></td>
<td>(5.808)</td>
<td>(4.270)</td>
<td>(4.820)</td>
<td>(4.429)</td>
</tr>
<tr>
<td>$\mu_l = \lambda_0 + \lambda_1$</td>
<td>-1.759</td>
<td>-2.648</td>
<td>-3.395</td>
<td>-2.715</td>
</tr>
<tr>
<td></td>
<td>(-7.489)</td>
<td>(-4.764)</td>
<td>(-5.102)</td>
<td>(-4.807)</td>
</tr>
<tr>
<td>$\chi^2_1 = \chi^2_2 = \chi^2_3 = \chi^2_4$</td>
<td>26.833</td>
<td>15.258</td>
<td>15.316</td>
<td>15.966</td>
</tr>
<tr>
<td>$H_0: \nu_1 = \lambda_1 = 0$</td>
<td>Reject $H_0$ (p-value=0.000)</td>
<td>Reject $H_0$ (p-value=0.000)</td>
<td>Reject $H_0$ (p-value=0.000)</td>
<td>Reject $H_0$ (p-value=0.000)</td>
</tr>
<tr>
<td>$\bar{T}$</td>
<td>94</td>
<td>94</td>
<td>94</td>
<td>94</td>
</tr>
<tr>
<td>log $L$</td>
<td>-52.750</td>
<td>-60.939</td>
<td>-74.461</td>
<td>-71.871</td>
</tr>
<tr>
<td>BIC</td>
<td>72.629</td>
<td>80.347</td>
<td>95.532</td>
<td>95.577</td>
</tr>
</tbody>
</table>

*The estimate of $\beta_0$ is set to the value that makes the average optimal interest rate equal to the sample mean of the actual target interest rate.

**Notes:** $\bar{T}$ was selected by iterating over possible values and selecting based on the highest value for the likelihood function. The parameters are defined as follows: $\beta_1$, $\beta_2$, and $\beta_3$ are Taylor rule coefficients; $\nu_0$ and $\nu_1$ are parameters that determine the upper threshold $\mu_u$; and $\lambda_0$ and $\lambda_1$ are parameters that determine the lower threshold $\mu_l$. The reported Taylor rule parameters are estimates of the long-run coefficients.