Estimating the Market-Perceived Monetary Policy Rule*

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Abstract

We introduce a novel method for estimating a monetary policy rule using macroeconomic news. We estimate directly the policy rule agents use to form their expectations by linking news' effects on forecasts of both economic conditions and monetary policy. Evidence between 1994 and 2007 indicates that the market-perceived Federal Reserve policy rule changed: the output response vanished, and the inflation response path became more gradual but larger in long-run magnitude. These response coefficient estimates are robust to measurement and theoretical issues with both potential output and the inflation target.

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1 Introduction

A large literature estimates monetary policy rules of the form proposed by John B. Taylor (1993) that relate the realized fed funds rate to past or expected future indicators of output and inflation. Examples include Charles L. Evans (1998), Richard Clarida, Jordi Gali, and Mark Gertler (2000), Glenn D. Rudebusch (2002), Michael T. Owyang and Garey Ramey (2004), Jean Boivin (2006), Andrew Ang, Sen Dong, and Monika Piazzesi (2007) and Josephine Smith and John B. Taylor (2009). That kind of estimation is well suited to describe what policy rule the Fed has actually followed.

However, there is also considerable interest in what market participants *expect* the Fed to do. Expectations of future monetary policy are a key part of the monetary transmission mechanism in virtually any macroeconomic model. The Federal Reserve's expected future policy rate influences current interest rates immediately upon the market learning about the Federal Reserve's intentions to stimulate or curtail economic behavior (see James D. Hamilton 2008). Moreover, Federal Open Market Committee (FOMC) statements provide guidance for the direction of future policy rates and are responded to instantaneously by the market upon their public release (see Donald L. Kohn and Brian P. Sack 2004).

This paper proposes a novel method that enables us to uncover the market's perceived monetary policy rule. Like many previous researchers (e.g., Refet S. Gürkaynak, Brian P. Sack, and Eric T. Swanson 2005, Jon Faust, et. al 2007, Leonardo Bartolini, Linda Goldberg, and Adam Sacarny 2008, and John B. Taylor 2010), we identify news by the difference between a macroeconomic data release value and the value expected beforehand by the market. On this news day, we measure the news' effects on forecasts of both economic fundamentals and monetary policy, the latter coming from the change in market prices for fed funds futures contracts. Our contribution is to use a Taylor-Rule structure to link the fundamentals forecast updates with the policy forecast updates in order to estimate the market-perceived parameters for a Taylor Rule.[1]

Our methodology opens up to researchers the use of daily data, which offers an opportunity to

[1]Others have also used news responses to study monetary policy, but in very different ways from that proposed here. Steven Strongin and Vega Tarhan (1990) looked at the response of interest rates at different maturities to market forecast errors of M1 to try to determine whether the response of interest rates to news represented inflation or liquidity effects. Aditi Thapar (2008) related the market's n-month-ahead forecast error to the current month's fed funds rate innovation as measured by a recursive VAR. By contrast, our approach relates today's change in an n-month-ahead fed funds futures contract to today's market error in forecasting current output and inflation.

avoid estimation problems engendered by potential output and the inflation target. Potential output is tricky to define and measure in real time (see Athanasios Oprhanides and Simon van Norden 2002), and Athanasios Orphanides (2001) argues that this can confound policy rule estimation. On the other hand, the Fed's inflation target is unobservable, and moreover a growing literature, including Peter N. Ireland (2007) and Timothy Cogley and Argia M. Sbordone (2008) among others, has postulated an important historical role for low-frequency variation in the Fed's inflation target. The latency of potential output and the inflation target poses a problem for standard policy rule estimation methods because their values are necessary for measuring the explanatory variables. Our method uses daily data to difference out these slowly moving latent variables from the estimation equations. Moreover, our approach offers a cleaner answer for how to handle real-time versus revised data sets, by focusing on market expectations formed on the basis of the information as it had actually been publicly released as of a particular calendar date.

By looking at the response of fed funds futures prices for contracts of different horizons to a new data release, we are also able to measure how long the market believes it will take the Fed to adjust interest rates in response to changing fundamentals. We can thereby obtain new measures of the nature of monetary policy inertia, something that is difficult for traditional methods to estimate. A related idea using the difference between 3-month and 6-month T-bills has been explored by Glenn D. Rudebusch (2002, 2006). We expand on Rudebusch's idea using the detailed structure of a dynamic Taylor Rule formulated at the monthly level to interpret the range of responses of 1-month through 6-month fed funds futures contracts to news events isolated at the daily level.

Our estimates imply a change in the market's perception of the Fed's policy rule in terms of both the magnitude of the ultimate response and in the degree of inertia. Since 2000, the market-perceived monetary policy rule involves an eventual response to inflation that is bigger than that associated with perceived pre-2000 behavior. On the other hand, the market also believes that the Fed is more sluggish in making its intended adjustments. We show in simulations with a simple new-Keynesian model that the first feature would tend to stabilize output, whereas the second feature would be destabilizing. These simulations suggest that the "measured pace" of monetary tightening during 2004-2006 may have been counterproductive.

The remainder of the paper is structured as follows: Section 2 introduces our framework and its testable implications. Section 3 discusses the empirical strategy based on these implications and describes the data. Section 4 presents our full-sample results, and then shows evidence of time variation in perceived policy response and estimates parameters on subsamples. Section 5 generalizes the approach to estimation of a Taylor Rule with lagged adjustment dynamics and discusses the economic significance of those dynamics. We investigate the sensitivity of our conclusions to various assumptions and variable decisions in Section 6. Section 7 concludes.

2 Framework

We begin with a standard Taylor Rule that is assumed by the market to characterize Federal Reserve decisions. Let t represent a particular month and r_t the average daily effective fed funds rate for that month. The market assumes that the Fed sets the funds rate in response to the Taylor Rule variables $\pi_t - \pi_t^*$, the deviation from target of cumulative inflation between $t-12$ and t, and $Y_t - Y_t^*$, a measure of the level of the real output gap in t:

$$r_t = r + \beta\left(\pi_t - \pi_t^*\right) + \delta\left(Y_t - Y_t^*\right) + u_t \tag{2.1}$$

where Y_t is the log of real output and Y_t^* is the log of potential real output.

Note that our baseline specification (2.1) follows the original formulation of Taylor (1993) and does not include the partial-adjustment terms that have become popular in the subsequent literature. The reason is that we will be using proxies for direct market forecasts of the variables in (2.1) at various future horizons, and will show that by comparing the differences across different horizons we can obtain direct estimates of the market-perceived adjustment lags. To explain the nature of the evidence in the data for such lags, we will first describe estimation under the assumption that no lagged terms belong in (2.1) and there is no serial correlation in u_t. Specifically, the initial maintained assumption is that u_t in (2.1) is uncorrelated with news that the market receives on a particular day i in month $t-h$, as detailed below. In Section 5.2 we will generalize to a specification in which the market perceives a dynamic path for the Fed's response to output and inflation in the form of lagged terms appearing in (2.1). For both the static and dynamic Taylor Rules we will also be assuming that market forecasts of of the inflation target π_t^* and potential output Y_t^* are little changed by news arriving on day i of month $t-h$, an assumption explored further in Section 6.2.

We will be keeping careful track in this analysis of exactly when data of different sorts arrives. Let $\Omega_{i,t}$ denote the information set that is actually available to market participants as of the ith day

Table 1: NOTATION

Symbol	Meaning
r_t	Fed funds rate during month t
π_t	inflation rate (12-month ended) during month t (π^* is inflation target)
Y_t	real output in month t (y_t is 12-month ended growth rate; Y^* is potential output)
β	parameter controlling policy response to inflation
δ	parameter controlling policy response to real output
$\Omega_{i,t}$	market information on day i of month t
$f_{i,t}^{(h)}$	Fed funds futures contract implied rate in month $t+h$, quoted on day i of month t
$w_{k,t}$	economic indicator k, pertaining to month t
τ	a month h months prior to month t ($\tau = t-h$)
$i(k,t)$	the day in month t on which $w_{k,t-1}$ is released (also $i(k)$ when t is otherwise clear)
$\tilde{w}_{k,t-1}$	market expectation of $w_{k,t-1}$ as of day $i(k,t)-1$ of month t as measured by MMS estimate
$\mathbf{x}_{k,t}$	variables useful in forecasting π and y that are known as of day $i(k,t)-1$ of month t
$\gamma_{\pi,k}$	parameter controlling how w_k forecasts π (y analogous)
$\xi_{\pi,k}$	parameter controlling how $\tilde{w}_k$ forecasts π (y analogous)
$\boldsymbol{\zeta}_{\pi,k}$	parameter controlling how $\boldsymbol{x}_{k,t}$ forecasts π (y analogous)

of month t; let $\tilde{\Omega}_{i,t}$ denote the Fed's information set at that time. The formulation (2.1) assumes that the Fed knows the values of $\pi_t - \pi_t^*$ and $Y_t - Y_t^*$ at the time it sets r_t, even though π_t and Y_t would not be known to market participants until some later time. The framework is readily generalizable to a case where the Fed instead sets r_t on the basis of information available as of some day j within month t:

$$r_t = r + \beta\mathbb{E}\left(\pi_t \middle| \tilde{\Omega}_{j,t}\right) - \beta\mathbb{E}\left(\pi_t^* \middle| \tilde{\Omega}_{j,t}\right) + \delta\mathbb{E}\left(Y_t \middle| \tilde{\Omega}_{j,t}\right) - \delta\mathbb{E}\left(Y_t^* \middle| \tilde{\Omega}_{j,t}\right) + u_t. \tag{2.2}$$

Consider the expectation of (2.1) conditional on information available to the market as of the ith day of an earlier month $\tau = t - h$:

$$\mathbb{E}\left(r_t \middle| \Omega_{i,\tau}\right) = r + \beta\mathbb{E}\left(\pi_t \middle| \Omega_{i,\tau}\right) - \beta\mathbb{E}\left(\pi_t^* \middle| \Omega_{i,\tau}\right) + \delta\mathbb{E}\left(Y_t \middle| \Omega_{i,\tau}\right) - \delta\mathbb{E}\left(Y_t^* \middle| \Omega_{i,\tau}\right) + \mathbb{E}\left(u_t \middle| \Omega_{i,\tau}\right). \tag{2.3}$$

Alternatively, if we take expectations of (2.2) conditional on the information set $\Omega_{i,\tau}$, the identical equation (2.3) follows due to the Law of Iterated Expectations.[2] In either case, we obtain the following expression for the change in expectations between the ith day and the previous day

[2] We assume that $\Omega_{i,\tau} \subseteq \tilde{\Omega}_{j,t}$.

$(i-1)$ of month τ:

$$
\begin{aligned}
& \mathbb{E}\left(r_t \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(r_t \middle| \Omega_{i-1,\tau}\right) \\
= \quad & \beta\left[\mathbb{E}\left(\pi_t \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(\pi_t \middle| \Omega_{i-1,\tau}\right)\right] + \delta\left[\mathbb{E}\left(Y_t \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(Y_t \middle| \Omega_{i-1,\tau}\right)\right] \\
& -\beta\left[\mathbb{E}\left(\pi_t^* \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(\pi_t^* \middle| \Omega_{i-1,\tau}\right)\right] - \delta\left[\mathbb{E}\left(Y_t^* \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(Y_t^* \middle| \Omega_{i-1,\tau}\right)\right] \\
& + \left[\mathbb{E}\left(u_t \middle| \Omega_{i,\tau}\right) - \mathbb{E}\left(u_t \middle| \Omega_{i-1,\tau}\right)\right].
\end{aligned} \tag{2.4}
$$

Equation (2.4) is the key to what follows, stating that updates to the market forecast of future policy are linked to updates to the market forecast of future economic conditions via the market-perceived monetary policy rule. Table 1 summarizes some of the notation used in the paper.

We will consider a set of $k = 1, 2, ..., K$ different days within month τ on which particular information becomes available. Consider first $k = 1$, which we associate with the release of, say, the CPI. Let $i(1, \tau)$ denote the day in month τ on which a new inflation number (namely, the value of $\pi_{\tau-1}$) is released. For example, for τ = December 2008, the CPI number reported on December 16 ($i(1, \tau) = 16$) was the value for November 2008 (so that $\pi_{\tau-1}$ became known on $i(1, \tau)$). Consider then the initial report of the value of $\pi_{\tau-1}$ on day $i(1, \tau)$. We propose to capture the news content of this report by comparing the value actually reported on day $i(1, \tau)$ with the value that had been expected by the market, which we denote $\tilde{\pi}_{\tau-1}$:

$$\mathbb{E}\left(\pi_{\tau-1} \middle| \Omega_{i(1,\tau),\tau}\right) - \mathbb{E}\left(\pi_{\tau-1} \middle| \Omega_{i(1,\tau)-1,\tau}\right) = \pi_{\tau-1} - \tilde{\pi}_{\tau-1}.$$

Our empirical estimates below will replace $(\pi_{\tau-1} - \tilde{\pi}_{\tau-1})$ by the difference between the initially reported value on day $i(1, \tau)$ and the median forecast from the Money Market Survey.

The CPI announcement of $\pi_{\tau-1}$ (arriving on $i(1, \tau)$) triggers an update to market participants' expectation of π_t. We assume that the expectation process is well captured by the linear projection of π_t on the basis of $\pi_{\tau-1}$, $\tilde{\pi}_{\tau-1}$, and $\mathbf{x}_{1,\tau}$, where $\mathbf{x}_{1,\tau}$ denotes a vector of other variables that would have been known to market participants prior to the day $i(1, \tau)$ of month τ:

$$\pi_t = \gamma_{\pi,1}\pi_{\tau-1} + \xi_{\pi,1}\tilde{\pi}_{\tau-1} + \boldsymbol{\zeta}'_{\pi,1}\mathbf{x}_{1,\tau} + v_{\pi,1,t}. \tag{2.5}$$

The first subscript (π) on the coefficients indicates that this is a coefficient used to forecast subsequent inflation, and the second subscript (1) indicates that the forecast is formed on the day on which the first information variable (the CPI) is released. Note that the coefficients in equation

(2.5) are defined as linear projection coefficients, so that $v_{\pi,1,t}$ is uncorrelated with $\pi_{\tau-1}$, $\tilde{\pi}_{\tau-1}$, and $\mathbf{x}_{1,\tau}$ by the definition of $\gamma_{\pi,1}$, $\xi_{\pi,1}$, and $\boldsymbol{\zeta}'_{\pi,1}$. The consequences of the month τ, day $i(1,\tau)$ news release about $\pi_{\tau-1}$ for market expectations of π_t are then given by

$$\mathbb{E}\left(\pi_t \middle| \Omega_{i(1),\tau}\right) - \mathbb{E}\left(\pi_t \middle| \Omega_{i(1)-1,\tau}\right) = \gamma_{\pi,1}(\pi_{\tau-1} - \tilde{\pi}_{\tau-1}) \tag{2.6}$$

where we will subsume the dependence of $i(1,\tau)$ on τ when it is clear from the context.

The announcement of $\pi_{\tau-1}$ may also hold implications for market expectations about real output Y_t. We assume that output exhibits a unit root, and that the market forms a forecast of the level of output Y_t by forecasting the 12-month growth rate $y_t = Y_t - Y_{t-12}$:

$$\mathbb{E}\left(Y_t \middle| \Omega_{i(1),\tau}\right) = \mathbb{E}\left(y_t \middle| \Omega_{i(1),\tau}\right) + Y_{t-12}$$

Thus if the market forecasts output growth using a rule of the form

$$y_t = \gamma_{y,1}\pi_{\tau-1} + \xi_{y,1}\tilde{\pi}_{\tau-1} + \boldsymbol{\zeta}'_{y,1}\mathbf{x}_{1,\tau} + v_{y,1,t}$$

then the update in the forecast of the level of real output is

$$\mathbb{E}\left(Y_t \middle| \Omega_{i(1),\tau}\right) - \mathbb{E}\left(Y_t \middle| \Omega_{i(1)-1,\tau}\right) = \gamma_{y,1}(\pi_{\tau-1} - \tilde{\pi}_{\tau-1}). \tag{2.7}$$

Note that certain elements of $\boldsymbol{\zeta}'_{\pi,1}$ and $\boldsymbol{\zeta}'_{y,1}$ may be set to zero, depending on what elements of $\mathbf{x}_{1,\tau}$ forecast π_t or y_t.

Let $f^{(h)}_{j,\tau}$ denote the futures interest rate on day j of month τ for a fed funds futures contract based on r_t, the effective fed funds rate h months ahead. We propose that these fed funds futures offer us a direct observation on how the market expectation of r_t changed on day $i(1)$:

$$f^{(h)}_{i(1),\tau} - f^{(h)}_{i(1)-1,\tau} = \mathbb{E}\left(r_t \middle| \Omega_{i(1),\tau}\right) - \mathbb{E}\left(r_t \middle| \Omega_{i(1)-1,\tau}\right) + \eta_{r,1} + q_{r,1,\tau}. \tag{2.8}$$

Here $\eta_{r,1}$ captures the average change in the risk premium on fed funds futures contracts and $q_{r,1,\tau}$ any change in the risk premium relative to that average. In the absence of risk aversion in the fed funds futures markets, the terms $\eta_{r,1}$ and $q_{r,1,\tau}$ would be identically zero. There is certainly good evidence for supposing the contribution of risk aversion to daily changes in fed funds prices to be small; see Monika Piazzesi and Eric T. Swanson (2008) and James D. Hamilton (2009).[3] In

[3] Our method works if either the risk premium is constant, as implied by the common "expectations hypothesis" or under the implication of consumption-based asset pricing models that the risk premium would change little on a daily basis. Piazzesi and Swanson's (2008) results indicate that "[these] risk premia seem to change primarily at business-cycle frequencies."

the estimation strategy adopted here, any changes in the risk premium, along with changes in the market's expectation of the residual in the Taylor Rule, changes in the market's expectation of the inflation target, and changes in the market's expectation of potential output, are incorporated into a specification error $v_{r,1,\tau}$,

$$\begin{aligned} v_{r,1,\tau} \quad = \quad & -\delta \left[\mathbb{E}\left(Y_t^* \middle| \Omega_{i(1),\tau} \right) - \mathbb{E}\left(Y_t^* \middle| \Omega_{i(1)-1,\tau} \right) \right] - \beta \left[\mathbb{E}\left(\pi_t^* \middle| \Omega_{i(1),\tau} \right) - \mathbb{E}\left(\pi_t^* \middle| \Omega_{i(1)-1,\tau} \right) \right] \\ & + \left[\mathbb{E}\left(u_t \middle| \Omega_{i(1),\tau} \right) - \mathbb{E}\left(u_t \middle| \Omega_{i(1)-1,\tau} \right) \right] + q_{r,1,\tau}. \end{aligned} \tag{2.9}$$

Substituting (2.6), (2.7), (2.8), and (2.9) into (2.4), we have

$$f_{i(1),\tau}^{(h)} - f_{i(1)-1,\tau}^{(h)} = \eta_{r,1} + (\beta\gamma_{\pi,1} + \delta\gamma_{y,1})(\pi_{\tau-1} - \tilde{\pi}_{\tau-1}) + v_{r,1,\tau}.$$

Consider next a second news release in month τ, namely the real activity indicator $y_{\tau-1}$ released on day $i(2)$. For these days we employ the auxiliary forecasting equations

$$\pi_t = \gamma_{\pi,2} y_{\tau-1} + \xi_{\pi,2} \tilde{y}_{\tau-1} + \boldsymbol{\zeta}_{\pi,2}' \mathbf{x}_{2,\tau} + v_{\pi,2,t}$$

$$y_t = \gamma_{y,2} y_{\tau-1} + \xi_{y,2} \tilde{y}_{\tau-1} + \boldsymbol{\zeta}_{y,2}' \mathbf{x}_{2,\tau} + v_{y,2,t}$$

where $\mathbf{x}_{2,\tau}$ is known prior to day $i(2,\tau)$. From these we derive

$$f_{i(2),\tau}^{(h)} - f_{i(2)-1,\tau}^{(h)} = \eta_{r,2} + (\beta\gamma_{\pi,2} + \delta\gamma_{y,2})(y_{\tau-1} - \tilde{y}_{\tau-1}) + v_{r,2,\tau}.$$

In general, if some indicator $w_{k,\tau-1}$ is released on day $i(k,\tau)$, we have the following three equations:

$$\pi_t = \gamma_{\pi,k} w_{k,\tau-1} + \xi_{\pi,k} \tilde{w}_{k,\tau-1} + \boldsymbol{\zeta}_{\pi,k}' \mathbf{x}_{k,\tau} + v_{\pi,k,t} \tag{2.10}$$

$$y_t = \gamma_{y,k} w_{k,\tau-1} + \xi_{y,k} \tilde{w}_{k,\tau-1} + \boldsymbol{\zeta}_{y,k}' \mathbf{x}_{k,\tau} + v_{y,k,t} \tag{2.11}$$

$$f_{i(k),\tau}^{(h)} - f_{i(k)-1,\tau}^{(h)} = \eta_{r,k} + (\beta\gamma_{\pi,k} + \delta\gamma_{y,k})(w_{k,\tau-1} - \tilde{w}_{k,\tau-1}) + v_{r,k,\tau}. \tag{2.12}$$

Let $\mathbf{z}_{1,\tau} = (1, \pi_{\tau-1}, \tilde{\pi}_{\tau-1}, \mathbf{x}_{1,\tau}')'$ denote the vector including the day $i(1)$ release of $\pi_{\tau-1}$ and the information available as of the day before, where we assume that $\mathbf{z}_{1,\tau}$ is uncorrelated with $v_{\pi,1,t}$, $v_{y,1,t}$, and $v_{r,1,\tau}$. Similarly, we take $\mathbf{z}_{k,\tau} = (1, w_{k,\tau-1}, \tilde{w}_{k,\tau-1}, \mathbf{x}_{k,\tau}')'$ to be uncorrelated with $v_{\pi,k,t}$, $v_{y,k,t}$, and $v_{r,k,\tau}$, for $k = 1, 2, \ldots, K$. Thus our identifying assumption is that the following vector has expectation zero:

$$\begin{bmatrix} \left(\pi_t - \gamma_{\pi,1} w_{1,\tau-1} - \xi_{\pi,1}\tilde{w}_{1,\tau-1} - \boldsymbol{\zeta}'_{\pi,1}\mathbf{x}_{1,\tau}\right)\mathbf{z}_{1,\tau} \\ \left(y_t - \gamma_{y,1} w_{1,\tau-1} - \xi_{y,1}\tilde{w}_{1,\tau-1} - \boldsymbol{\zeta}'_{y,1}\mathbf{x}_{1,\tau}\right)\mathbf{z}_{1,\tau} \\ \left[f^{(h)}_{i(1),\tau} - f^{(h)}_{i(1)-1,\tau} - \eta_{r,1} - (\beta\gamma_{\pi,1} + \delta\gamma_{y,1})(w_{1,\tau-1} - \tilde{w}_{1,\tau-1})\right]\mathbf{z}_{1,\tau} \\ \vdots \\ \left(\pi_t - \gamma_{\pi,K} w_{K,\tau-1} - \xi_{\pi,K}\tilde{w}_{K,\tau-1} - \boldsymbol{\zeta}'_{\pi,K}\mathbf{x}_{K,\tau}\right)\mathbf{z}_{K,\tau} \\ \left(y_t - \gamma_{y,K} w_{K,\tau-1} - \xi_{y,K}\tilde{w}_{K,\tau-1} - \boldsymbol{\zeta}'_{y,K}\mathbf{x}_{K,\tau}\right)\mathbf{z}_{K,\tau} \\ \left[f^{(h)}_{i(K),\tau} - f^{(h)}_{i(K)-1,\tau} - \eta_{r,k} - (\beta\gamma_{\pi,K} + \delta\gamma_{y,K})(w_{K,\tau-1} - \tilde{w}_{K,\tau-1})\right]\mathbf{z}_{K,\tau} \end{bmatrix}. \tag{2.13}$$

Note that the ability to distinguish β from δ results from using at least $K \geq 2$ different news releases during month τ. A single release such as the inflation number could in principle have implications both for future inflation (as captured by $\gamma_{\pi,1}$) and future output (as captured by $\gamma_{y,1}$). Hence any response of the fed funds futures prices to that news could come from either the policy rule inflation coefficient (β) or output coefficient (δ). However, $\gamma_{\pi,1}$ and $\gamma_{y,1}$ are each separately observable (from the differing responses of π_t and y_t to $\pi_{\tau-1}$), so the change in the futures price on $i(1)$ tells us one linear combination (namely $\beta\gamma_{\pi,1} + \delta\gamma_{y,1}$) of the policy rule parameters β and δ. But the separate response to the output release on day $i(2)$ gives us a second linear combination $(\beta\gamma_{\pi,2} + \delta\gamma_{y,2})$. Thus, the $3K$ equations above are sufficient to identify β and δ separately.

3 Estimation

We begin this section by describing the formal estimation strategy, which is Lars P. Hansen's (1982)Hansen's (1982) generalized method of moments. Then we describe the data used.

3.1 Method

Recall that $\tau + h = t$. Denoting

$$\boldsymbol{\zeta}^{(h)}_t = \left(1, \pi_t, y_t, f^{(h)}_{i(1),\tau}, w_{1,\tau-1}, \tilde{w}_{1,\tau-1}, \mathbf{x}'_{1,\tau}, \mathbf{z}'_{1,\tau}, \ldots, f^{(h)}_{i(K),\tau}, w_{K,\tau-1}, \tilde{w}_{K,\tau-1}, \mathbf{x}'_{K,\tau}, \mathbf{z}'_{K,\tau}\right)',$$

we rephrase (2.13) as the following population orthogonality condition for each $\boldsymbol{\theta}^{(h)}$, $h = 1, 2, \ldots,$

$$\mathbb{E}\left[\mathbf{g}\left(\boldsymbol{\theta}^{(h)}, \boldsymbol{\zeta}^{(h)}_t\right)\right] = 0, \tag{3.1}$$

where $\boldsymbol{\theta}^{(h)}$ collects the auxiliary forecasting parameters $(\boldsymbol{\gamma}', \boldsymbol{\xi}', \boldsymbol{\zeta}')'$ along with the main parameters of interest, the policy rule coefficients $(\beta, \delta, \boldsymbol{\eta}'_r)'$. Let $\mathcal{Y}^{(h)}_T \equiv \left(\boldsymbol{\zeta}^{(h)\prime}_T, \boldsymbol{\zeta}^{(h)\prime}_{T-1}, \ldots, \boldsymbol{\zeta}^{(h)\prime}_1\right)'$ be the vector of all observations for each choice of horizon h. Then we have the sample average

$$\overline{\mathbf{g}}\left(\boldsymbol{\theta}^{(h)};\mathcal{Y}_T^{(h)}\right)\equiv T^{-1}\sum_{t=1}^{T}\mathbf{g}\left(\boldsymbol{\theta}^{(h)},\boldsymbol{\zeta}_t^{(h)}\right)$$

and the GMM estimator (see Hansen 1982) for each horizon h minimizes

$$Q\left(\boldsymbol{\theta}^{(h)},\mathcal{Y}_T^{(h)}\right)=\overline{\mathbf{g}}\left(\boldsymbol{\theta}^{(h)};\mathcal{Y}_T^{(h)}\right)'\mathbf{W}_T^{(h)}\overline{\mathbf{g}}\left(\boldsymbol{\theta}^{(h)};\mathcal{Y}_T^{(h)}\right). \tag{3.2}$$

As usual, the optimal weighting matrix $\mathbf{W}_T^{(h)}$ is given by the inverse of the asymptotic variance of the sample mean of $\mathbf{g}\left(\boldsymbol{\theta}^{(h)},\boldsymbol{\zeta}_t^{(h)}\right)$. In turn, we calculate a heteroskedasticity and autocorrelation robust estimate[4] $\hat{\mathbf{S}}_T^{(h)}$ of this asymptotic variance, and the efficient GMM estimator uses the inverse of this HAC estimate as the weighting matrix, with the following asymptotic approximations:

$$\hat{\boldsymbol{\theta}}^{(h)}\approx\mathcal{N}\left(\boldsymbol{\theta}^{(h)},T^{-1}\hat{\mathbf{V}}_T^{(h)}\right)\quad,\quad\hat{\mathbf{V}}_T^{(h)}=\left([\hat{\mathbf{D}}_T^{(h)}][\hat{\mathbf{S}}_T^{(h)}]^{-1}[\hat{\mathbf{D}}_T^{(h)}]'\right)^{-1}$$

$$\text{and}\quad[\hat{\mathbf{D}}_T^{(h)}]'=\left.\frac{\partial\overline{\mathbf{g}}\left(\boldsymbol{\theta};\mathcal{Y}_T^{(h)}\right)}{\partial\boldsymbol{\theta}'}\right|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}^{(h)}}.$$

Since $\mathbf{g}(\cdot)$ is nonlinear in $\boldsymbol{\theta}^{(h)}$, the minimization of (3.2) is achieved numerically. Our results are calculated by two-step GMM starting from an initial guess provided by a simple two-stage OLS procedure and with other initial conditions considered to obtain some assurance that the global optimum has been found. The inconsistent two-stage OLS procedure would instead first estimate the auxiliary forecasting equations independently, then use these forecast parameter estimates to generate regressors for the Taylor Rule regression.[5] Joint estimation by (nonlinear) two-step GMM is consistent and efficient – see Whitney K. Newey and Daniel McFadden (1986). We estimate each horizon h independently from the others so that nothing other than the original data links these estimates to one another.

As mentioned, identification is achieved by considering at least two indicators w, in which case the system (3.2) in general is just-identified. When we use more than two indicators, the system naturally delivers overidentifying restrictions. Additionally, we can impose cross-equation restrictions that create overidentification. Our baseline specification is overidentified for both reasons.

[4]Our HAC estimator is that of Whitney K. Newey and Kenneth D. West (1987) with 13 lags.

[5]Since our framework introduces a generated-regressor, the two-stage OLS procedure is inefficient – see Adrian Pagan (1986).

3.2 Data

Fed funds futures are accurate predictors of the effective fed funds rate, as documented in numerous studies including Evans (1998), Refet S. Gürkaynak, Brian P. Sack, and Eric T. Swanson (2007), Piazzesi and Swanson (2008), and Hamilton (2009). These contracts were first traded on the Chicago Board of Trade in October of 1988, though volume, especially for the longer-horizon contracts, was initially light. For example, there were no recorded trades in 6-month-ahead futures contracts during the entire month of February 1990. Volume increased substantially after the Federal Open Market Committee began announcing the fed funds target in 1994 (see Figure 1), a policy change that may have also altered the way market participants formed expectations of future Fed policy. For this reason, we follow Gürkaynak, Sack, and Swanson (2007) in beginning our analysis in 1994. We end our sample in the summer of 2007 in order to avoid the period of major financial disruptions that started following the fund freezes by BNP Paribas that August. Our data set thus consists of K particular days for each month over the period 1994:M1 through 2007:M6.

We require measures of inflation and real activity as the dependent variables in our forecasting equations. Note that it is the initial real-time inflation release that appears on the right side of these regressions, and so we will use real-time values on the left. We measure inflation by the year-over-year growth rate of the Core-PCE price index from the BEA. This has been the Federal Reserve's key inflation indicator over the sample we consider. We measure output growth by the year-over-year growth rate of industrial production from the Federal Reserve Board. Both of these series' real-time values are obtained from the ALFRED collection maintained by the Federal Reserve Bank of St. Louis. To use as much data as possible we stay at the monthly frequency and therefore require a monthly output series. Industrial production growth has been used by previous studies to proxy for overall output growth (e.g. James H. Stock and Mark W. Watson 2002) and is a natural candidate for our baseline.

The economic indicators we consider are data releases from various government agencies that are followed by the Money Market Survey (MMS).[6] Following Gürkaynak, Sack, and Swanson (2005),

[6] In the middle of the 2000s, this survey was taken over by Action Economics.

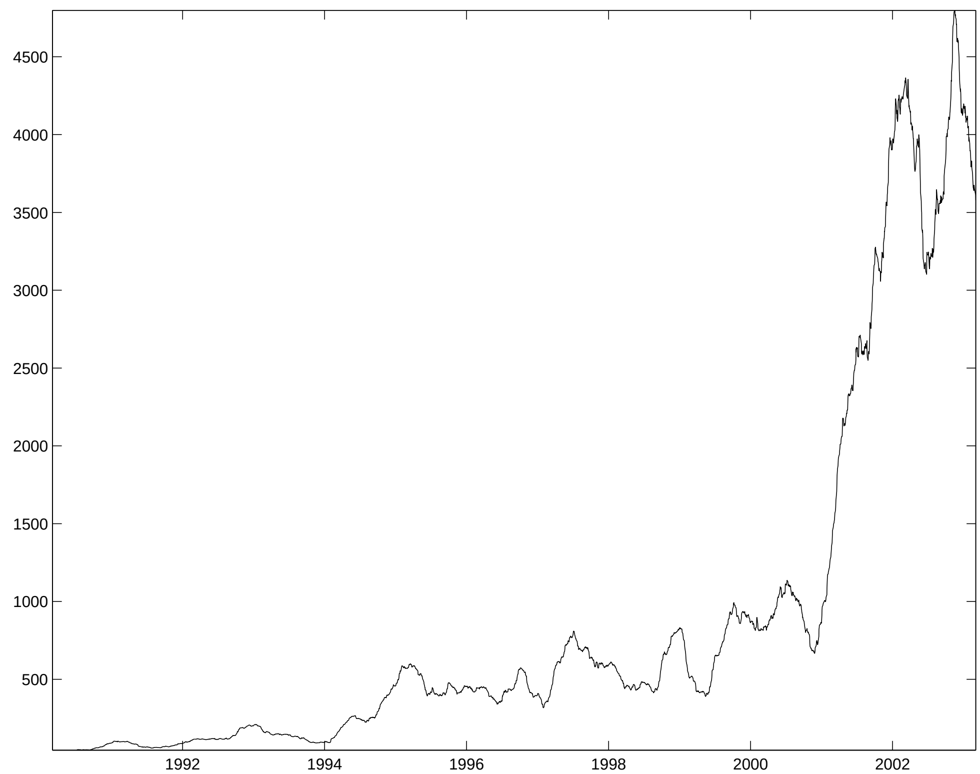

Figure 1: Trading Volume on Fed Funds Futures Contracts
Notes: Data from Chicago Board of Trade, 1992–2003. Trading volume in number of contracts, shown as 90-day moving average.

the median forecast provides a proxy for each variable's market expectation. MMS provides market expectations for several candidate economic indicators. Our choice is guided by asking which economic variables might be most helpful for forecasting output growth and core PCE inflation. It is natural for this purpose to use core CPI inflation (CPIXFE) and industrial production (INDPRD) themselves.[7] In principle, all available indicators could be used, however so doing might well lead to problems with weak instruments. With this and a desire for parsimony in mind, we look for a few additional economic indicators to include which may provide a reasonable amount of variation to our data. Previous literature has noted that financial market participants scrutinize and respond strongly to nonfarm payroll employment: for instance, see Torben G. Andersen and Tim Bollerslev

[7] MMS does not survey forecasts for Core-PCE inflation, hence our reliance on Core-CPI inflation. Fortunately, Core-CPI forecasts Core-PCE inflation well, as shown in the web appendix.

(1998), Torben G. Anderson, et al. (2003), Gürkaynak, Sack, and Swanson (2005), Bartolini, Goldberg, and Sacarny (2008), and Taylor (2010). Therefore, we include that indicator (NFPAY) as well. We also find that the report of new home sales (NHOMES) provides good forecasting power, and in particular is necessary when we rely on just the post-2000 data in some split-sample estimates reported later. Thus the values we use for $\tilde{w}_{k,\tau-1}$ in equation (2.13) are the median MMS forecasts of core CPI inflation, industrial production, nonfarm payrolls, and new home sales. The values we use for $w_{k,\tau-1}$ are the actual values as released at the time (month τ).

In terms of the variables entering the auxiliary forecasting equations, we set

$$\mathbf{x}_{k,\tau} = \left(\pi_{\tau-2}, y_{\tau-2}, f^{(h)}_{i(k)-1,\tau}, 1\right)'.$$

The lagged values of inflation and output growth are included to control for their autoregressive nature. For parsimony, we set to zero the first element of $\boldsymbol{\zeta}_{y,k}$, the coefficient on $\pi_{\tau-2}$ in indicator k's auxiliary forecasting equation for y_t; likewise, we zero out the second element of $\boldsymbol{\zeta}_{\pi,k}$, the coefficient on $y_{\tau-2}$ in indicator k's auxiliary forecasting equation for π_t. The fed funds futures value for the day before $i(k)-1$ is included to control for the predictive content (vis-a-vis each Taylor Rule variable) of the futures price that has already been priced into the contract.

4 Results

First we present our full sample results using four indicators. We then show that statistical tests of our overidentifying restrictions reject our model, and so we run tests for breaks in the policy rule parameters and find evidence of their variation over time. Placing the break around the beginning of the year 2000, we present subsample estimates suggesting the market-perceived monetary policy rule has changed over time, and repeat the overidentification tests on the separate subsamples.

4.1 Baseline

Our baseline results use four indicators – CPIXFE, INDPRD, NFPAY, and NHOMES – and impose the cross-equation restriction that the average risk premium change is identical across indicators:

$$\eta_{r,k} = \eta_r, k = 1, 2, ..., K. \tag{4.1}$$

This cross-equation restriction embodies the assumption that the different economic indicators systematically affect the forecasted policy rate only through changes to forecasted inflation and

Table 2: Market-Perceived Monetary Policy Rule Estimates, baseline

	h					
	1	2	3	4	5	6
β	0.345***	0.817***	1.134***	1.090***	1.633	1.687***
	0.083	*0.262*	*0.388*	*0.283*	*1.356*	*0.362*
δ	0.046***	0.057***	0.098**	0.098**	0.067**	0.117**
	0.009	*0.021*	*0.041*	*0.046*	*0.032*	*0.046*

Notes: The policy rule coefficient on inflation is β and on the output gap is δ. HAC standard errors in *italics*. The markers *,** and *** denote significance at 10%, 5% and 1% levels, respectively. There are 160 observations for $h = 1$, 159 for $h = 2$, etc. The indicators are CPIXFE, INDPRD, NFPAY and NHOMES. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7.

output, and it adds statistical precision to our estimates; we further discuss and test this restriction in Section 6. The policy rule response coefficient estimates are presented in Table 2.[8]

All horizons but one exhibit inflation response coefficients that are significant at the 1% level. The output response coefficient is statistically significant and positive at the 5% level for all horizons. These results suggest that our empirical methodology effectively extracts information from market forecast updates that occur in response to macroeconomic news.

Our results further suggest that the market does not expect the Fed to implement changes immediately. The response coefficients at longer horizons tend to be larger than the response coefficients at shorter horizons, and 95% confidence intervals for β or δ often exclude the point estimates obtained for different h: we denote the response coefficients estimated for a certain horizon h as $\beta^{(h)}$ or $\delta^{(h)}$. To perform the most powerful tests of hypotheses comparing estimates across different h we would need to estimate the system jointly, which due to the large number of parameters we refrain from doing. However, some informative conservative calculations are easy to perform despite the fact that we have estimated parameters for each horizon h separately. Notice that for any estimates A and B,

$$\text{Var}(A - B) = \sigma_A^2 + \sigma_B^2 - 2\rho_{AB}\sigma_A\sigma_B. \tag{4.2}$$

Because ρ_{AB}, the correlation between A and B, cannot be less than -1, it follows that

$$\text{Var}(A - B) \leq \sigma_A^2 + \sigma_B^2 + 2\sigma_A\sigma_B \tag{4.3}$$

[8]Estimates of the constant are reported in the web appendix.

with equality only if A and B are perfectly negatively correlated. One can thus obtain a very conservative test of the null hypothesis that A and B are estimating the same object by dividing $A - B$ by the square root of the right-hand side of (4.3) and rejecting H_0 if the result exceeds 2 in absolute value. The test is conservative in the sense that the asymptotic probability of rejecting H_0 when it is true is less than 5%. Using this test, we conclude that $\beta^{(1)}$ is statistically less than $\beta^{(4)}$ or $\beta^{(6)}$.

In fact the estimates $\beta^{(h)}$ are almost surely positively rather than negatively correlated, since the futures rates for contracts of different horizons h almost always move in the same direction each day. If we are willing to assume that the correlation between A and B is strictly positive, then equation (4.2) implies

$$\text{Var}(A - B) < \sigma_A^2 + \sigma_B^2.$$

If we adopt this alternative conservative test, we find that $\beta^{(1)}$ is statistically significantly less than $\beta^{(3)}$, $\beta^{(4)}$, and $\beta^{(6)}$.

We thus conclude that the market believes the Fed responds to inflation more aggressively at longer horizons than it does over the next few months. The market perceives some sluggishness or inertia in the Fed's response to news – the news warrants an immediate increase in a rational forecast of inflation and output, but the Fed is not going to respond fully to that news until several months later. The fact that β and δ are estimated to be different when we base the estimation on different horizons h implies that something in our original model was misspecified. We will show in Section 5 below how the different estimates of β and δ for different h can be used to infer parameters of a dynamic generalization of equation (2.1) representing the market's perceived inertia in the response of monetary policy to news. Before doing so, however, we first report some further specification tests on the baseline static model.

4.2 Overidentification and Break Tests

This section conducts further tests of the assumptions motivating these estimates. We first investigate Hansen's (1982) J-tests of overidentifying restrictions given by

$$TQ\left(\hat{\boldsymbol{\theta}}^{(h)}, \mathcal{Y}_T^{(h)}\right) \approx \chi^2(m) \tag{4.4}$$

for m the number of overidentifying restrictions. The p-values for this test are presented in Table 3. Recall that our baseline specification overidentifies the model both by using four indicators and by

Table 3: OVERIDENTIFICATION TESTS, BASELINE

	h					
	1	2	3	4	5	6
(1) BASELINE	0.026	0.027	0.027	0.027	0.032	0.025
(2) BASELINE, PRE	0.316	0.331	0.314	0.339	0.313	0.318
(3) BASELINE, POST	0.204	0.194	0.192	0.220	0.200	0.165

Notes: p-values from Hansen's (1982) J-test of overidentifying restrictions, for the baseline specifications. BASELINE is the baseline specification estimated over the full sample. BASELINE, PRE and BASELINE, POST are the baseline specifications estimated over the pre-2000 and post-2000 subsamples, respectively.

imposing that the policy rule specification error means are identical for these indicators (equation (4.1)). Row 1 displays the p-values associated with the J-statistics for the baseline specification. We reject at the 5% level the overidentifying restrictions for every horizon h, causing some concern that our basic framework is not consistent with the data.

A large literature has investigated changes over time in U.S. monetary policy. Clarida, Gali, and Gertler (2000), Giorgio E. Primiceri (2006), and Boivin (2006) all documented a significant increase in the Fed's response to inflation after 1979. More recently, Andrew Ang et al. (2009) found a sharp decline in the Fed's immediate response to inflation after 2001, while John B. Taylor (2007) has argued that the Fed deviated from its historical practice in waiting too long to raise interest rates between 2002 and 2005. For this reason, it is of substantial interest to see whether market participants' perception of the monetary policy rule changed over our sample period.

To answer this question, we test for a break in the parameters of interest. Using Donald W. K. Andrews' (1993)(Andrews 1993) break test, we test the null hypothesis that all parameters are constant against the alternative that the policy rule coefficients β, δ, and η_r experienced a break.[9] Letting the policy rule coefficient vector be $\mathbf{b} = (\beta, \delta, \eta_r)'$, we test:

$$H_0 : \mathbf{b}_t = \mathbf{b}_0 \quad \forall t \geq 1 \text{ for some } \mathbf{b}_0 \in \mathbf{R}^3$$
$$H_1(\varpi) : \mathbf{b}_t = \left\{ \begin{array}{ll} \mathbf{b}_1(\varpi) & \text{for } t = 1, \dots, T\varpi \\ \mathbf{b}_2(\varpi) & \text{for } t = T\varpi + 1, \dots, T \end{array} \right\} \text{ for some constants } \mathbf{b}_1(\varpi), \mathbf{b}_2(\varpi) \in \mathbf{R}^3$$

for values of ϖ in (0.25,0.75). We use the sup-Wald statistic and tabulated critical values in Andrews (1993).

[9]The vector of parameters taken to be constant under both the null and the alternative is the vector of auxilliary forecasting parameters $(\boldsymbol{\gamma}', \boldsymbol{\xi}', \boldsymbol{\zeta}')'$.

For each horizon considered, there is strong evidence of a break in the policy rule coefficients $\mathbf{b}$. In particular, for our application the 1% critical value is 16.6: the sup-Wald statistic is estimated to be 24.9, 17.5, 29.0, 201.1, 17.1 and 258.2 for horizons 1 through 6, respectively. Moreover, each horizon's maximal statistic occurs at similar times, near the beginning of the year 2000. In light of this evidence, we re-estimate our baseline model on the pre-2000 and post-2000 subsamples.

Returning to the overidentification test results of Table 3, rows 2 and 3 display the p-values for the model estimated across horizons on each subsample. We now find that the model is readily accepted for each subsample. Evidently, the break in the policy parameters was the major factor in the low full-sample p-values in row 1. Once the parameters are allowed to differ by sub-period, we find no evidence against our framework.

4.3 Time Variation

Table 4 displays the estimation results for the two subsamples. Note that these estimates were obtained from completely separate estimation applied to each subsample. We thus allow all the coefficients to change, including the forecasting parameters γ, ξ, and $\boldsymbol{\zeta}$. Hence the different estimates are not attributable to changes in the way markets may have processed news between the two samples. We now discuss the output and inflation response coefficients estimated in each subsample and how they differ from one another.

Looking at the output response coefficients, the output response during the 1990s is moderate but tightly estimated. At all horizons but one the point estimates are positive and significant at the 1% level. The response is around 0.14 in the first month, rising to 0.43 by the fourth month. By the alternative test, $\delta^{(1)}$ and $\delta^{(2)}$ are statistically less than $\delta^{(3)}$ or $\delta^{(4)}$. Hence the policy response exhibits signs of gradual adjustment. However, during the 2000s the response to output changes dramatically. The output response is tightly estimated but economically insignificant. Taken together, this evidence suggests that during the 1990s the market perceived a moderate output gap response that essentially vanished during the 2000s.

Looking now at the inflation responses, we see that the estimates in both subsamples are significant at conventional levels for all horizons but one. Moreover, two noteworthy distinctions between the subsamples are apparent. In the 1990s the inflation response is quick: by the third month the response coefficient adheres to the Taylor principle of being greater than one, and

Table 4: Market-Perceived Monetary Policy Rule Estimates, baseline pre-2000 and post-2000

		h					
		1	2	3	4	5	6
Pre-2000	β	0.356*	0.830**	1.144**	1.285**	1.571***	1.423**
		0.191	*0.373*	*0.508*	*0.647*	*0.610*	*0.637*
	δ	0.141***	0.115***	0.318***	0.420***	0.127*	0.275***
		0.027	*0.037*	*0.078*	*0.143*	*0.066*	*0.101*
Post-2000	β	–0.494**	0.554***	0.405	0.420***	1.057***	2.031***
		0.198	*0.170*	*0.297*	*0.073*	*0.233*	*0.630*
	δ	0.267***	–0.066**	0.108***	–0.037**	–0.053*	–0.182***
		0.056	*0.026*	*0.022*	*0.017*	*0.031*	*0.051*

Notes: The policy rule coefficient on inflation is β and on the output gap is δ. HAC standard errors in *italics*. The markers *,** and *** denote significance at 10%, 5% and 1% levels, respectively. pre-2000, there are 69 observations for $h = 1$, 68 for $h = 2$, etc.; post-2000, there are 88 observations for $h = 1$, etc. The indicators are CPIXFE, INDPRD, NFPAY and NHOMES. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7

thereafter stays in a range remarkably like the original Taylor rule value of 1.5. Indeed, we cannot reject the hypothesis that these response coefficients are the same, using either the conservative or alternative tests. On the other hand, in the 2000s the inflation response is gradual: it is only by the fifth month that the response is barely greater than one. Moreover, we see that in the sixth month the response jumps to 2.03, which is rather precisely estimated. This means that $\beta^{(6)}$ is statistically greater than $\beta^{(1)}, \beta^{(2)}, \beta^{(3)}$ and $\beta^{(4)}$ by the alternative test.[10]

Together, these observations suggest that the market-perceived policy response to inflation changed over time in two distinct ways: during the 1990s the response adjusted at a quicker pace with a moderate long-run magnitude, while during the 2000s the response adjusted at a slower pace with a larger long-run magnitude.

5 Dynamic Analysis of the Policy Response

Up to this point in the paper we have been investigating our baseline specification: a static Taylor Rule of the form of equation (2.1). We found that the implied market expectations of how the Fed would respond to news turned out to be a function of the horizon h. News that warrants a 1%

[10] $\beta^{(1)}$ and $\beta^{(4)}$ by the conservative test.

increase in a forecast of output or inflation for $h = 1$ to 3 months ahead results in a smaller increase in the expected fed funds rate for that horizon than would news that warrants a 1% increase in the output or inflation forecast for $h = 4$ to 6 months ahead. This difference in the estimated values for β or δ associated with different horizons h is inconsistent with the maintained hypothesis of a static Taylor Rule, and suggests instead that the market perceives some inertia in the Fed's response to news about output and inflation. In this section we will postulate a dynamic Taylor Rule that is consistent with this observed inertia. The essential property of a dynamic Taylor Rule is that the future responses to current news vary with the horizon. Since we have already estimated that fundamental object – future implications of current news as a function of the horizon – it turns out that the set of estimates for different values of h that we have already obtained provide all the information needed to infer parameters of a dynamic Taylor Rule. We now describe the details of how this can be done.

5.1 Dynamic Forecasting Equations

We first modify the earlier notation to make the dependence on the horizon h explicit, rewriting the h-period-ahead forecasting equations (2.11) and (2.10) as

$$y_t = \gamma_{y,k}^{(h)} w_{k,t-h} + \xi_{y,k}^{(h)} \tilde{w}_{k,t-h} + \boldsymbol{\zeta}_{y,k}^{(h)\prime} \mathbf{x}_{k,t-h+1} + v_{y,k,t}^{(h)} \tag{5.1}$$

$$\pi_t = \gamma_{\pi,k}^{(h)} w_{k,t-h} + \xi_{\pi,k}^{(h)} \tilde{w}_{k,t-h} + \boldsymbol{\zeta}_{\pi,k}^{(h)\prime} \mathbf{x}_{k,t-h+1} + v_{\pi,k,t}^{(h)}. \tag{5.2}$$

We will also now need a version of equations (5.1) and (5.2) for the case $h = 0$, in order to keep track of the implication of the release of one indicator for the values of other indicators to be released later that month. Suppose that the first indicator released in month $t+1$ is NHOMES, denoted here as $w_{1,t}$, followed by NFPAY, denoted here as $w_{2,t}$. These releases could cause us to update our expectation of the values for INDPRD ($y_t = w_{3,t}$) and CPIXFE ($\pi_t = w_{4,t}$) that will be reported later that same month $t+1$ according to

$$y_t = \gamma_{y,1}^{(0)} w_{1,t} + \xi_{y,1}^{(0)} \tilde{w}_{1,t} + \boldsymbol{\zeta}_{y,1}^{(0)\prime} \mathbf{x}_{1,t+1} + v_{y,1,t}^{(0)} \tag{5.3}$$

$$\pi_t = \gamma_{\pi,1}^{(0)} w_{1,t} + \xi_{\pi,1}^{(0)} \tilde{w}_{1,t} + \boldsymbol{\zeta}_{\pi,1}^{(0)\prime} \mathbf{x}_{1,t+1} + v_{\pi,1,t}^{(0)} \tag{5.4}$$

$$y_t = \gamma_{y,2}^{(0)} w_{1,t} + \xi_{y,2}^{(0)} \tilde{w}_{2,t} + \boldsymbol{\zeta}_{y,2}^{(0)\prime} \mathbf{x}_{2,t+1} + v_{y,2,t}^{(0)} \tag{5.5}$$

$$\pi_t = \gamma_{\pi,2}^{(0)} w_{2,t} + \xi_{\pi,2}^{(0)} \tilde{w}_{2,t} + \boldsymbol{\zeta}_{\pi,2}^{(0)\prime} \mathbf{x}_{2,t+1} + v_{\pi,2,t}^{(0)}. \tag{5.6}$$

Thus for example estimates of $\gamma_{y,1}^{(0)}$ and $\gamma_{\pi,1}^{(0)}$ could be obtained by OLS estimation of (5.3) and (5.4), and $\gamma_{y,2}^{(0)}$ and $\gamma_{\pi,2}^{(0)}$ could be obtained by OLS estimation of (5.5) and (5.6). Later in month $t+1$ when the output indicator $w_{3,t}$ is released, that allows us to know the value of y_t with certainty, which to preserve the general notation we would represent by $\gamma_{y,3}^{(0)} = 1$, and would also induce an update to the forecast for $w_{4,t}$ $(= \pi_t)$,

$$\pi_t = \gamma_{\pi,3}^{(0)} w_{3,t} + \xi_{\pi,3}^{(0)} \tilde{w}_{3,t} + \boldsymbol{\zeta}_{\pi,3}^{(0)\prime} \mathbf{x}_{3,t+1} + v_{\pi,3,t}^{(0)} \tag{5.7}$$

When $w_{4,t}$ is finally released, it has no implications for $w_{3,t}$ which is already known ($\gamma_{y,4}^{(0)} = 0$) and changes our forecast of inflation one-for-one ($\gamma_{\pi,4}^{(0)} = 1$).

5.2 A Dynamic Taylor Rule

Consider now the following dynamic generalization of (2.1):

$$r_t = r + \beta_1(\pi_{t-1} - \pi_{t-1}^*) + \beta_2(\pi_{t-2} - \pi_{t-2}^*) + \cdots + \delta_1(Y_{t-1} - Y_{t-1}^*) + \delta_2(Y_{t-2} - Y_{t-2}^*) + \cdots + u_t. \tag{5.8}$$

Unlike our earlier expression (2.2), equation (5.8) is strictly a backward-looking formulation, presuming that the Fed responds dynamically to the history of available information; note that π_{t-1} and Y_{t-1} are the most recent values available as of the end of month t.

Recall that the value of $w_{k,t-h-1}$ is released on day $i(k, t-h)$, and let $f_{i(k),t-h}^{(h)}$ denote the interest rate implied by a futures contract for settlement based on the value of r_t, and quoted as of the end of trading on day $i(k, t-h)$. For example, $f_{i(k),t}^{(0)}$ would reflect an expectation of the current month's fed funds rate on the day that the indicator $w_{k,t-1}$ is released. Take the expectation of (5.8) conditional on market information available on day $i(k, t-h)$ and subtract from it the expectation formed the day before:

$$f_{i(k),t-h}^{(h)} - f_{i(k)-1,t-h}^{(h)} = \eta_{r,k}^{(h)} + \tag{5.9}$$
$$\left[\beta_1 \gamma_{\pi,k}^{(h)} + \delta_1 \gamma_{y,k}^{(h)} + \beta_2 \gamma_{\pi,k}^{(h-1)} + \delta_2 \gamma_{y,k}^{(h-1)} + \cdots + \beta_{h+1} \gamma_{\pi,k}^{(0)} + \delta_{h+1} \gamma_{y,k}^{(0)}\right] (w_{k,t-h-1} - \tilde{w}_{k,t-h-1}) + v_{r,k,t-h}^{(h)}.$$

For comparison, recalling that $\tau = t - h$, we can rewrite equation (2.12) as

$$f_{i(k),t-h}^{(h)} - f_{i(k)-1,t-h}^{(h)} = \eta_{r,k}^{(h)} + (\beta^{(h)} \gamma_{\pi,k}^{(h+1)} + \delta^{(h)} \gamma_{y,k}^{(h+1)})(w_{k,t-h-1} - \tilde{w}_{k,t-h-1}) + v_{r,k,t-h}^{(h)} \tag{5.10}$$

where $\beta^{(h)}$ and $\delta^{(h)}$ denote the original parameters whose estimates we reported in column h of Tables 2 or 4. Comparing equations (5.9) and (5.10), the values of the dynamic parameters $\{\beta_j, \delta_j\}$

in (5.8) are related to our baseline estimates $\{\beta^{(h)}, \delta^{(h)}\}$ according to

$$\beta_1\gamma_{\pi,k}^{(h)} + \delta_1\gamma_{y,k}^{(h)} + \beta_2\gamma_{\pi,k}^{(h-1)} + \delta_2\gamma_{y,k}^{(h-1)} + \cdots + \beta_{h+1}\gamma_{\pi,k}^{(0)} + \delta_{h+1}\gamma_{y,k}^{(0)} = \beta^{(h)}\gamma_{\pi,k}^{(h+1)} + \delta^{(h)}\gamma_{y,k}^{(h+1)}. \quad (5.11)$$

To arrive at estimates of the dynamic parameters, we chose $\{\beta_j, \delta_j\}_{j=1}^{6}$ so as to minimize the equally-weighted sum of squared differences between the LHS and RHS of (5.11) across indicators $k = 1, 2, 3, 4$ and horizons $h = 0, 1, 2, ..., 6$. On the RHS, the values for $\{\beta^{(h)}, \delta^{(h)}, \gamma_{\pi,k}^{(h)}, \gamma_{y,k}^{(h)}\}$ for $h = 1, ..., 6$ were taken from the earlier split-sample GMM estimation reported in Table 4, while values for $h = 0$ were obtained from GMM estimation of $\beta^{(0)}$, $\delta^{(0)}$, $\gamma_{y,1}^{(0)}$, $\gamma_{\pi,1}^{(0)}$, $\gamma_{y,2}^{(0)}$, $\gamma_{\pi,2}^{(0)}$, and $\gamma_{\pi,3}^{(0)}$ based on the moment conditions

$$\begin{bmatrix} \left(y_t - \gamma_{y,1}^{(0)} w_{1,t} - \xi_{y,1}^{(0)}\tilde{w}_{1,t} - \boldsymbol{\zeta}_{y,1}^{(0)\prime}\mathbf{x}_{1,t+1}\right)\mathbf{z}_{1,t+1} \\ \left(\pi_t - \gamma_{\pi,1}^{(0)} w_{1,t} - \xi_{\pi,1}^{(0)}\tilde{w}_{1,t} - \boldsymbol{\zeta}_{\pi,1}^{(0)\prime}\mathbf{x}_{1,t+1}\right)\mathbf{z}_{1,t+1} \\ \left[f_{i(1),t+1}^{(0)} - f_{i(1)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)}\gamma_{\pi,1}^{(0)} + \delta^{(0)}\gamma_{y,1}^{(0)})(w_{1,t} - \tilde{w}_{1,t})\right]\mathbf{z}_{1,t+1} \\ \left(y_t - \gamma_{y,2}^{(0)} w_{2,t} - \xi_{y,2}^{(0)}\tilde{w}_{2,t} - \boldsymbol{\zeta}_{y,2}^{(0)\prime}\mathbf{x}_{2,t+1}\right)\mathbf{z}_{2,t+1} \\ \left(\pi_t - \gamma_{\pi,2}^{(0)} w_{2,t} - \xi_{\pi,2}^{(0)}\tilde{w}_{2,t} - \boldsymbol{\zeta}_{\pi,2}^{(0)\prime}\mathbf{x}_{2,t+1}\right)\mathbf{z}_{2,t+1} \\ \left[f_{i(2),t+1}^{(0)} - f_{i(2)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)}\gamma_{\pi,2}^{(0)} + \delta^{(0)}\gamma_{y,2}^{(0)})(w_{2,t} - \tilde{w}_{2,t})\right]\mathbf{z}_{2,t+1} \\ \left(\pi_t - \gamma_{\pi,3}^{(0)} w_{3,t} - \xi_{\pi,3}^{(0)}\tilde{w}_{3,t} - \boldsymbol{\zeta}_{\pi,3}^{(0)\prime}\mathbf{x}_{3,t+1}\right)\mathbf{z}_{3,t+1} \\ \left[f_{i(3),t+1}^{(0)} - f_{i(3)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)}\gamma_{\pi,3}^{(0)} + \delta^{(0)}\gamma_{y,3}^{(0)})(w_{3,t} - \tilde{w}_{3,t})\right]\mathbf{z}_{3,t+1} \\ \left[f_{i(4),t+1}^{(0)} - f_{i(4)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)}\gamma_{\pi,4}^{(0)} + \delta^{(0)}\gamma_{y,4}^{(0)})(w_{4,t} - \tilde{w}_{4,t})\right]\mathbf{z}_{4,t+1} \end{bmatrix} \quad (5.12)$$

where as before $\mathbf{z}_{k,t+1}$ denotes information available the day prior to release of $w_{k,t}$. This last GMM estimation resulted in the estimates $\hat{\beta}^{(0)} = 0.194, \hat{\delta}^{(0)} = 0.113$ for the pre-2000 subsample, and $\hat{\beta}^{(0)} = -.104, \hat{\delta}^{(0)} = 0.002$ after 2000. For all the above calculations, the values $\gamma_{y,3}^{(0)} = 1$, $\gamma_{y,4}^{(0)} = 0$, and $\gamma_{\pi,4}^{(0)} = 1$ were imposed throughout.

The resulting values of β_j and δ_j are reported in Table 5. In the last column is the sum of the parameter values across all j, which gives the long-run response to the inflation or output pressure. Recall from Section 3.1 that the parameter vector $\boldsymbol{\theta}^{(h)}$ for horizon h was estimated completely independently from any other horizon. This approach of leaving the dynamics implied by $\{\boldsymbol{\theta}^{(h)}\}_{h=0}^{6}$ completely unrestricted offers at least three benefits. First, nothing in our procedure requires that the long-horizon responses should be bigger than the short-horizon responses. The fact that we nonetheless find them to be increasing in h is strong evidence that the market perceives policy to respond only gradually to changing conditions. Second, if we allowed only the policy parameters to change but not those for the forecasting dynamics, it would be possible for changes in the forecasting

Table 5: Dynamic Taylor Rule Parameters

		j 1	2	3	4	5	6	7	*sum*
Pre-2000	β_j	0.30	0.01	0.15	0.50	0.53	0.11	0.00	*1.60*
	δ_j	0.17	–0.02	0.10	0.20	0.00	–0.10	0.10	*0.45*
post-2000	β_j	–0.63	0.70	0.26	0.35	0.00	0.46	1.05	*2.19*
	δ_j	0.30	–0.22	0.00	–0.02	–0.05	–0.02	–0.02	*–0.03*

Notes: from minimum-distance method described in text, using subsample parameter estimates across all horizons.

dynamics to show up spuriously as policy rule changes. By allowing both to change together we are able to estimate the changes in the policy dynamics alone. Third, our procedure allows the adjustment to inflationary pressures to differ from the adjustment to real activity, similar to the policy rules of Lawrence J. Christiano, Martin Eichenbaum, and Charles L. Evans (1996, 2005). This flexibility in the rule's process is greater than that permitted by including only lags of the policy rate itself, and our estimates suggest this greater flexibility may be warranted by the data.

5.3 An example of the implication of rule changes

We now explore the economic implications of the estimated changes in the Taylor Rule in a simple model. These results are particular to the parsimonious three equation model we choose, but this model has been well-studied previously in the literature and therefore we consider it of some interest.

Following Clarida, Gali, and Gertler (2000), we use a standard sticky-price, rational expectations model whose equilibrium conditions, log-linearized around a zero inflation steady state, are

$$\pi_t = \lambda_1 \mathbb{E}_t(\pi_{t+1}) + \lambda_2(Y_t - z_t) \tag{5.13}$$

$$Y_t = \mathbb{E}_t(Y_{t+1}) - \lambda_3^{-1}\left(r_t - \mathbb{E}_t\left(\pi_{t+1}\right)\right) + g_t \tag{5.14}$$

$$r_t = \beta(L)\pi_t + \delta(L)(Y_t - z_t) \tag{5.15}$$

The first equation (5.13) says that inflation today is a function of the output gap and the expectation of next period's inflation, which in turn can be derived from an underlying Calvo pricing structure. With relative risk aversion measured by λ_3, equation (5.14) is an IS schedule where today's output depends on the ex ante real rate and the expectation of next period's output gap. Equation (5.15)

Table 6: Effects of Changing Inflation Policy Response on the Volatility of Output Growth and Inflation

Variable	Inflation Coefficients: Post-Path Pre-LR	Pre-Path Post-LR	Post-Path Post-LR
	Both Shocks		
Inflation	–6.0	–28.1	–32.1
Output	9.0	–12.6	–3.2
	Supply Shocks Only		
Inflation	–6.0	–28.0	–32.0
Output	–0.2	1.0	0.7
	Demand Shocks Only		
Inflation	–6.0	–28.1	–32.0
Output	12.6	–18.8	–4.9

Notes: Differences in model-implied volatility of macro variables, caused by changing the inflation-response parameters $\beta(L)$, relative to the pre-2000 benchmark. We consider two possible changes: (1) a change in the Path, the shape of the dynamic response; and (2) a change in the LR magnitude, the sum of the response coefficients. Output coefficients $\delta(L)$ are held at pre-2000 values. See the text for further details.

is a dynamic Taylor Rule that closes the model. The model's shocks are autocorrelated demand shocks g_t and supply shocks z_t. We take parameter values from Clarida, Gali, and Gertler (2000) and set $\lambda_1 = 0.9967$, $\lambda_2 = 0.3$, $\lambda_3 = 1$, and the shocks' autocorrelation to 0.9655 for our monthly model. Clarida, Gali, and Gertler (2000) give supply and demand shocks the same unconditional volatility, but we note the sensitivity of following this choice and so also report results for economies that are only buffeted by only supply or only demand shocks, respectively.

Our goal is to characterize what difference the inflation-response parameters $\beta(L)$ might make for the volatility of macro variables according to this model. To do so, we fix $\delta(L)$ at the pre-2000 values,[11] and calculate the difference in volatilities using pre-2000 and post-2000 values for $\beta(L)$. We find that in the model the post-2000 dynamics imply a 32% reduction in the variance of inflation, as reported in the last column of Table 6, regardless of the source of fluctuations in the economy. The effect on output is small: if there are demand shocks, the volatility drops 3–5% while if there are no demand shocks the volatility rises modestly.

We next wanted to see what it was about the post-2000 inflation response that helped stabilize inflation. Was it the overall magnitude of the inflation response, as reflected in the sum of the β_j coefficients, or was it the more gradual post-2000 response, as reflected in the shape of the dynamic

[11] Very similar results were obtained if we instead fix $\delta(L)$ at the post-2000 values.

response? To find out, we explored the consequences of changing just one of these two elements at a time. Let β_j^{PRE} denote the pre-2000 inflation responses and β_j^{POST} the post-2000 responses. We calculated what would happen if the inflation responses were given by

$$\beta_j = \beta_j^{\text{POST}} \frac{[\beta_0^{\text{PRE}} + \beta_1^{\text{PRE}} + \ldots + \beta_6^{\text{PRE}}]}{[\beta_0^{\text{POST}} + \beta_1^{\text{POST}} + \ldots + \beta_6^{\text{POST}}]}$$

so that the sum of the coefficients β_j was restricted to be the same as for the pre-2000 estimates, while the shape of $\beta(L)$ was that for the post-2000 estimates. These results are reported in the column labeled "Post-Path, Pre-LR" in Table 6. Such a change would have modestly reduced the volatility of inflation by 6%. If supply shocks are the only source of economic fluctuation, the effect on output would have been negligible, but if there are demand shocks output volatility rises 9–13%.

On the other hand, if we change just the long-run response, but leave the dynamics the same as for the pre-2000 rule,

$$\beta_j = \beta_j^{\text{PRE}} \frac{[\beta_0^{\text{POST}} + \beta_1^{\text{POST}} + \ldots + \beta_6^{\text{POST}}]}{[\beta_0^{\text{PRE}} + \beta_1^{\text{PRE}} + \ldots + \beta_6^{\text{PRE}}]},$$

as reported in the "Pre-path, Post-LR" column of Table 6, inflation volatility would be reduced about 28%. Output would have been stabilized by 12–19% if there are demand pressures, but becomes 1% more volatile if there are supply shocks alone.

These calculations suggest that increasing the long-run magnitude of inflation response, as the market perceives the Fed to have done, achieves the lion's share of the reduction of inflation volatility; making the inflation response more gradual, as the market *also* perceives the Fed to have done, detracts from output's stabilization. [12] We provide this example primarily to illustrate the kinds of uses that could be made of the more detailed inference about dynamics that our estimation approach makes possible, rather than to offer a definitive answer to the question of whether the estimated changes in monetary policy subsequent to 2000 have been helpful for purposes of economic stabilization.

It should also be acknowledged that a key source of the inertia we find is due to the limited response in the immediate months following new economic information. Rudebusch (2006) acknowledges the existence of this kind of short-run inertia in Fed decision-making but thinks it is

[12] Note, however, that the beneficial component of the post-2000 change is entirely attributed to the large estimated value of $\beta^{(6)}$ in Table 4. If this were dropped from the analysis, there would be no perceived improvement in the long-run inflation response.

less interesting than longer adjustment delays:

> Such short-term partial adjustment of the funds rate involves cutting the policy rate by two 25-basis-point moves in fairly quick succession, rather than reducing the rate just once by 50 basis points. This smoothing likely reflects various institutional rigidities, such as a fixed monthly meeting schedule and perhaps certain sociological and political factors. However, short-term partial adjustment within a quarter is essentially independent of whether there is monetary policy inertia over the course of several quarters, and this latter issue is the one that is relevant to the empirical monetary policy rules.

However, we would argue that the decision of the Greenspan Fed to increase the funds rate by only 25 basis points at each FOMC meeting over 2004-2006 is very much an issue deserving review and likely part of the reason we estimate an increased sluggishness in the post-2000 period. Moreover, our simple model uses exactly the inertia we find in the data to derive the result that this form of gradual adjustment indeed can be counterproductive.

6 Sensitivity Analysis

We next test the cross-equation restrictions imposed, and look for corroboration of the identifying assumptions from other data sources.

6.1 Tests of Cross-Equation Restrictions

In addition to the average change in the risk premium on fed funds futures contracts, the constant term $\eta_{r,k}$ in equation (2.12) would incorporate any non-zero mean for the specification error that represented day-to-day changes in the market forecasts of potential output, the inflation target, and the policy rule residual (see expression (2.9)). If this constant term turned out to be different for different indicators k, that could be evidence of general mis-specification. For example, if the indicators were in part providing signals about changes in potential output, and if the value of this signal differed across indicators, that might show up as differences in $\eta_{r,k}$ across different k.

It is easy to conduct tests of the restriction (4.1) that the policy rule constant is identical across indicators based again on Hansen's J-statistic

$$TQ\left(\hat{\boldsymbol{\theta}}_R^{(h)}, \mathcal{Y}_T^{(h)}\right) - TQ\left(\hat{\boldsymbol{\theta}}_U^{(h)}, \mathcal{Y}_T^{(h)}\right) \approx \chi^2(2)$$

where $\hat{\boldsymbol{\theta}}_R$ is the GMM parameter estimate subject to the cross-equation restriction $\eta_{r,1} = \eta_{r,2} = \eta_{r,3}$ and $\hat{\boldsymbol{\theta}}_U$ is the unrestricted estimate. The resulting estimates are placed in the web appendix and summarized here. The restrictions are quite consistent with the data.

The associated unrestricted policy parameter estimates suggest that nothing substantive is lost, and statistical precision is noticeably gained, by imposing the cross-equation restriction that the policy rule constant is identical across economic indicators. Estimating separate policy rule constants reduces the statistical precision with which we estimate the policy rule response coefficients, in particular the inflation response coefficients at longer horizons.

6.2 Potential Output and the Inflation Target

A challenge for standard methods of estimating monetary policy rules is the difficulty in measuring potential output Y_t^* and the inflation target π_t^*. We have argued that our approach can avoid these problems to the extent that the daily news items of which we make use have negligible consequences for Y^* or π^*. Here we provide additional evidence on why we believe that is a reasonable assumption.

To explore this issue empirically, we will be looking at the properties of the Congressional Budget Office's series for quarterly potential real GDP growth, denoted y_q^* where q indexes quarters. If one looks at the historical values of this series as reported in the January 2009 vintage, y_q^* is an extremely smooth and highly predictable series (see the top panel of Figure 2). However, over time the CBO will make many revisions to its estimate of the value of y_q^* for a given historical quarter q. For example, on April 17, 1996, CBO estimated the growth rate of potential GDP for $q = 1995\text{:Q4}$ to be 1.98% (at an annual rate), whereas by January 8, 2009, they had revised the estimate for $y^*_{1995:Q4}$ up to 2.76%. Orphanides (2001) and Orphanides and van Norden (2002) demonstrated that such revisions can pose a big problem for traditional Taylor Rule estimates. Is it reasonable to assert that the daily news events exploited in our analysis had negligible implications for these subsequent revisions of potential GDP?

Let $\Omega(q)$ denote the information set available to the public as of the 20th calendar day of the first month of quarter $q + 1$. For example, for $q = 1995\text{:Q4}$, $\Omega(q)$ would represent information publicly reported as of January 20, 1996. By this date, values for the percentage growth in nonfarm

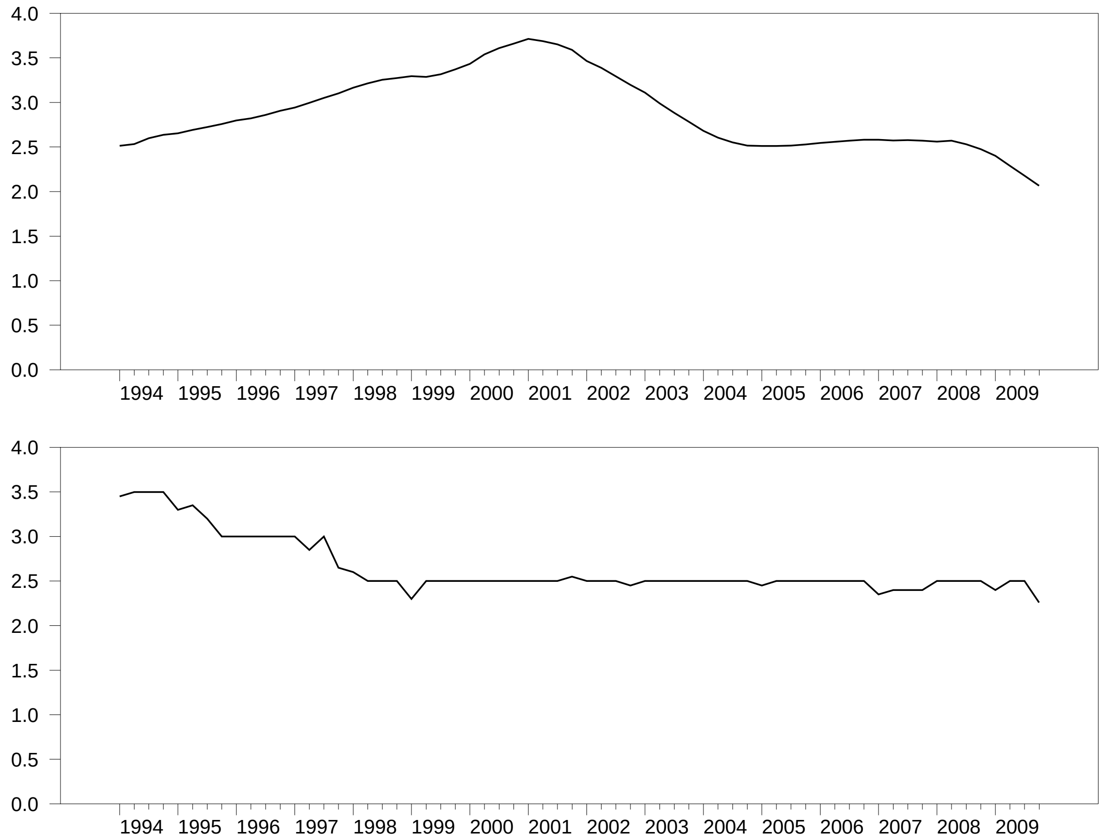

Figure 2: Potential GDP growth and long-run inflation expectations
Notes: Top panel: quarterly growth (at an annual rate) of potential GDP as estimated by the CBO as of January 2009. Bottom panel: average CPI inflation rate expected over the next 10 years according according to the median response from professional forecasters surveyed in each individual quarter.

payrolls for each month of quarter q would have been reported, denoted $x_{1q|\Omega(q)}$, $x_{2q|\Omega(q)}$, and $x_{3q|\Omega(q)}$, though the actual GDP growth rate for quarter q would not yet be known. Thus for example for $q =$ 1995:Q4, $x_{1q|\Omega(q)}$ would be the growth rate of seasonally adjusted nonfarm payroll employment during the month of October 1995 as reported by the Bureau of Labor Statistics on January 6, 1996, while $x_{2q|\Omega(q)}$ would be the November 1995 growth rate as reported on January 6. Let $\{y^*_{q-1|\Omega(q)}, \ldots, y^*_{q-4|\Omega(q)}\}$ denote the four most recent quarterly growth rates for potential GDP as they would have been reported by CBO prior to date $\Omega(q)$; for example, for $q =$ 1995:Q4, $y^*_{q-1|\Omega(q)}$ is the potential growth rate for 1995:Q3 as estimated by CBO on February 1, 1995 (the most recent CBO estimate released prior to January 20, 1996). Finally, let $y^*_{q|T}$ denote the potential GDP growth rate for quarter q as reported on January 8, 2009. Vintage values for $x_{iq|\Omega(q)}$ and

$y^*_{q-j|\Omega(q)}$ were obtained from ALFRED, the real-time archived data set maintained by the Federal Reserve Bank of St. Louis.

We then estimated the following regression by OLS for q = 1994:Q1 to 2007:Q3:

$$y^*_{q|T} = \alpha_0 + \sum_{j=1}^{3} \alpha_j x_{jq|\Omega(q)} + \sum_{j=1}^{4} \gamma_j y^*_{q-j|\Omega(q)} + \epsilon_q.$$

The coefficients α_j can tell us the extent to which the values of nonfarm payroll growth that arrive during quarter q could help predict the potential GDP growth rate for quarter q as it would ultimately be reported, relative to information about potential GDP that had arrived prior to the quarter's actual GDP report. We fail to reject the null hypothesis that $\alpha_1 = \alpha_2 = \alpha_3 = 0$ ($F(3, 46) = 0.27, p = 0.85$). On the other hand, a parallel regression for predicting the actual real GDP growth rates as eventually reported,

$$y_{q|T} = \tilde{\alpha}_0 + \sum_{j=1}^{3} \tilde{\alpha}_j x_{jq|\Omega(q)} + \sum_{j=1}^{4} \tilde{\gamma}_j y_{q-j|\Omega(q)} + \tilde{\epsilon}_q,$$

leads to rejection of $H_0 : \tilde{\alpha}_1 = \tilde{\alpha}_2 = \tilde{\alpha}_3 = 0$ ($F(3, 46) = 3.37, p = 0.03$). Nonfarm payrolls contain useful information about the current quarter's actual GDP growth but little information about the current quarter's potential GDP growth.

We repeated the same calculations using monthly industrial production growth rates or monthly core CPI inflation rates in place of nonfarm payroll employment growth.[13] We again found that industrial production is of no use in predicting potential GDP ($F(3, 46) = 0.98, p = 0.41$), but is helpful for predicting actual GDP ($F(3, 46) = 4.06, p = 0.01$), while real-time core CPI releases do not help predict either actual or potential GDP growth. Our maintained assumption that markets are responding to news about near-term economic conditions Y_{t+h} and not potential output Y^*_{t+h} is thus fully consistent with these hypothesis tests.

In fact, even the actual growth of GDP itself as reported at the time has little correlation with potential GDP growth as currently assessed by the CBO. In a regression of $y^*_{q|T}$ on the GDP rate initially reported for quarter q, 4 lags of $y^*_{q-j|\Omega(q)}$, 4 lags of $y_{q-j|\Omega(q)}$, and a constant, one fails to reject the hypothesis that the coefficient on initially reported GDP growth is zero ($p = 0.92$).

Alternatively, one might view the market's perception of potential GDP as constructed mechanically from some filtering algorithm on incoming data, which would imply that news of any sort

[13] Release of the December 1995 value for industrial production was delayed until January 24, 1996. We used this January 24, 1996 release for q =1995:Q4. ALFRED's real-time coverage of the core CPI begins in 1996:M12

by definition has some impact on perceived potential GDP. The size of this impact would depend on the particular filter used, though in general it should be small. For example, if one associates potential GDP with the trend component of a Hodrick-Prescott filter, a choice of $\lambda = 1600$ implies that a 1% increase in observed real GDP warrants a 0.2% increase in estimated potential GDP.[14] Using $\lambda = 129,600$ as recommended by Morten O. Ravn and Harald Uhlig (2002) for monthly data would imply that an indicator that raised perceived monthly industrial production by 1% would raise expected potential industrial production by 0.07%. If, for illustration, a 1% increase in $\mathbb{E}(Y_t)$ coincides with a 0.07% increase in $\mathbb{E}(Y_t^*)$, our estimate of δ would be understated by a factor of 0.93. Although such a perspective might warrant small numerical changes in the interpretation of our estimated coefficients, we do not think it materially affects our broad conclusions.

As far as the inflation target is concerned, Sharon Kozicki and P. A. Tinsley (2001) and Gürkaynak, Sack, and Swanson (2005) have produced evidence that some of the response of interest rates to daily news events represents a market belief that the Fed's long-run inflation target is poorly anchored. Nevertheless, the suggestion that the FOMC is changing its long-run inflation target on a daily basis in response to the latest economic news would seem quite strange to those who actually implemented recent U.S. monetary policy. Apart from the discrete effects of personnel changes, some would argue that the Fed's long-run inflation target should be by definition an even smoother series than potential GDP, particularly over the period we study. Marvin Goodfriend (2005) observed

> a measure of inflation favored by the Fed, core PCE inflation, has remained in the 1 to 2 percent range since the mid-1990s. It is difficult to imagine circumstances that would cause the Greenspan Fed to deliberately target core PCE inflation above 2 percent in either the long run or the short run.... Likewise, it is hard to imagine any circumstances in which the Greenspan Fed would deliberately target core PCE inflation below 1 percent.

[14] Andrew C. Harvey and Albert Jaeger (1993) note that one can implement Hodrick-Prescott smoothing using Kalman smoothing from a state-space model for which (in the notation of James D. Hamilton 1994).

$$\mathbf{F} = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \mathbf{Q} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \mathbf{H}' = \begin{bmatrix} 1 & 0 \end{bmatrix} R = \lambda.$$

The limiting value for the Kalman gain vector $\mathbf{K}_t$ can be found by iterating on equations [13.2.22] and [13.2.23] in Hamilton (1994) until convergence, which produce $\mathbf{K}' = \begin{bmatrix} 0.201 & 0.178 \end{bmatrix}$ for $\lambda = 1600$ and $\mathbf{K}' = \begin{bmatrix} 0.072 & 0.069 \end{bmatrix}$ for $\lambda = 129,600$.

The 10-year expected CPI inflation rate reported by the median respondent in the Survey of Professional Forecasters has certainly behaved in a way consistent with Goodfriend's perception; (see the bottom panel of Figure 2).

We investigated the extent to which changes in the expected inflation rate from the SPF might be responding to the specific news events on which we focus in a similar exercise to that described above. Let π_q denote the 10-year expected CPI inflation rate that respondents reported in quarter q and let $x_{q|\Omega(q)}$ denote the most recent 12-month growth rate for nonfarm payrolls as it would have been reported as of the middle of quarter q. We estimated the following by OLS:

$$\pi_q = \alpha_0 + \theta_0 x_{q|\Omega(q)} + \sum_{j=1}^{2} \gamma_j \pi_{q-j} + \epsilon_q.$$

The test of the null hypothesis that long-run inflation expectations did not respond to the most recent nonfarm payroll numbers ($\theta_0 = 0$) fails to reject ($p = 0.44$). P-values for analogous tests that inflation expectations did not respond to the most recent industrial production ($p = 0.73$) and core CPI ($p = 0.76$) also fail to reject.

If it were the case that market participants did revise their perception of the long-run inflation target π_t^* in response to the daily news events we analyze, the implication would be that the market-perceived increase in $\pi_t - \pi_t^*$ would be smaller than that of π_t, resulting in a potential underestimate of β. If the nature of the revision is similar to that implied by a monthly Hodrick-Prescott filter, the magnitude of the bias should be relatively minor for reasons of the algebra noted above.

7 Conclusion

It is important to be able to measure market participants' beliefs, manifest through their behavior, about how monetary policy is conducted. Previous work has found fed funds futures contracts to be excellent predictors of future Federal Reserve policy. This paper proposed that market participants forecast future policy along with future economic conditions, and linked the two by the Taylor Rule. This enabled us to measure the market's beliefs about how the Federal Reserve responds to inflation and the output gap. Additionally, by focusing on daily forecast updates, we are able to nearly eliminate the impact of potential output and the inflation target on our main focus: the market-perceived monetary policy response to inflation and output.

Our baseline results for the 1994–2007 sample suggest the market perceives that the Federal

Reserve gradually responds to inflation and real activity. Similar to previous literature working on post-Volcker data, we find the Federal Reserve follows the Taylor Principle, a greater than one-for-one response to inflation. We also find evidence that the market-perceived monetary policy rule changed over our sample: estimating response and forecasting coefficients separately for each subsample leads to our baseline specification being readily accepted by the data. During the 1990s market-perceived policy responded robustly to output and quickly to inflation; during the 2000s market-perceived policy doesn't respond to output and responds at a more measured pace to inflation, though its long-run inflation response is greater than before. We quantify the importance of the inflation response path and long-run magnitude in a standard model, and find that raising the long-run magnitude is effective at lowering inflation volatility while making the path more gradual is counterproductive.

References

Andersen, Torben G. and Tim Bollerslev, "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies," *Journal of Finance*, 02 1998, *53* (1), 219–265.

——, ——, **Francis X. Diebold, and Clara Vega**, "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," *American Economic Review*, March 2003, *93* (1), 38–62.

Andrews, Donald W. K., "Tests for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica*, 1993, *61*, 821–856.

Ang, Andrew, Jean Boivin, Sen Dong, and Rudy Loo-Kung, "Monetary Policy Shifts and the Term Structure," NBER Working Paper 15270, National Bureau of Economic Research, Inc August 2009.

——, **Sen Dong, and Monika Piazzesi**, "No-Arbitrage Taylor Rules," NBER Working Papers 13448, National Bureau of Economic Research, Inc September 2007.

Bartolini, Leonardo, Linda Goldberg, and Adam Sacarny, "How Economic News Moves Markets," *Current Issues in Economics and Finance*, August 2008, *14* (6), 1–7. Federal Reserve Bank of New York.

Boivin, Jean, "Has US Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data," *Journal of Money, Credit, and Banking*, August 2006, *38* (5), 1149–1173.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L. Evans, "The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds," *The Review of Economics and Statistics*, February 1996, *78* (1), 16–34.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, February 2005, *113* (1), 1–45.

Clarida, Richard, Jordi Gali, and Mark Gertler, "Monetary Policy Rules And Macroeconomic Stability: Evidence And Some Theory," *The Quarterly Journal of Economics*, February 2000, *115* (1), 147–180.

Cogley, Timothy and Argia M. Sbordone, "Trend Inflation, Indexation, and Inflation Persistence in the New Keynesian Phillips Curve," *American Economic Review*, December 2008, *98* (5), 2101–26.

Evans, Charles L., "Real-time Taylor rules and the federal funds futures market," *Economic Perspectives*, 1998, pp. 44–55.

Faust, Jon, John H Rogers, Shing-Yi B Wang, and Jonathan H Wright, "The High-Frequency Response of Exchange Rates and Interest Rates to Macroeconomic Announcements," *Journal of Monetary Economics*, May 2007, *54* (4), 1051–68.

Goodfriend, Marvin, "Inflation Targeting in the United States," in Ben S. Bernanke and Michael Woodford, eds., *The Inflation Targeting Debate*, The University of Chicago Press, 2005, chapter 8, pp. 311–352.

Gürkaynak, Refet S., Brian P. Sack, and Eric T. Swanson, "The Sensitivity of Long-Term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models," *American Economic Review*, March 2005, *95* (1), 425–436.

____ , ____ , and ____ , "Market-Based Measures of Monetary Policy Expectations," *Journal of Business & Economic Statistics*, April 2007, *25*, 201–212.

Hamilton, James D., *Time Series Analysis*, Princeton University Press, 1994.

____ , "Daily monetary policy shocks and new home sales," *Journal of Monetary Economics*, 2008, *55*, 1171–1190.

____ , "Daily Changes in Fed Funds Futures Prices," *Journal of Money, Credit, and Banking*, 2009, *41*, 567–582.

Hansen, Lars P., "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 1982, *50*, 1029–1054.

Harvey, Andrew C. and Albert Jaeger, "Detrending, Stylized Facts and the Business Cycle," *Journal of Applied Econometrics*, 1993, *8*, 231–247.

Ireland, Peter N., "Changes in the Federal Reserve's Inflation Target: Causes and Consequences," *Journal of Money, Credit and Banking*, December 2007, *39* (8), 1851–1882.

Kohn, Donald L. and Brian P. Sack, "Central bank talk: does it matter and why?," in "Macroeconomics, Monetary Policy, and Financial Stability," Bank of Canada, 2004, pp. 175–206.

Kozicki, Sharon and P. A. Tinsley, "Shifting endpoints in the term structure of interest rates," *Journal of Monetary Economics*, 2001, *47* (3), 613–652.

Newey, Whitney K. and Daniel McFadden, "Large sample estimation and hypothesis testing," in R. F. Engle and D. McFadden, eds., *Handbook of Econometrics*, Vol. 4 of *Handbook of Econometrics*, Elsevier, 06 1986, chapter 36, pp. 2111–2245.

____ and Kenneth D. West, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, May 1987, *55* (3), 703–708.

Orphanides, Athanasios, "Monetary Policy Rules Based on Real-Time Data," *American Economic Review*, September 2001, *91* (4), 964–985.

____ and Simon van Norden, "The Unreliability of Output-Gap Estimates in Real Time," *Review of Economics and Statistics*, Nov 2002, *84* (4), 569–583.

Owyang, Michael T. and Garey Ramey, "Regime switching and monetary policy measurement," *Journal of Monetary Economics*, November 2004, *51* (8), 1577–1597.

Pagan, Adrian, "Two Stage and Related Estimators and Their Applications," *Review of Economic Studies*, August 1986, *53* (4), 517–38.

Piazzesi, Monika and Eric T. Swanson, "Futures prices as risk-adjusted forecasts of monetary policy," *Journal of Monetary Economics*, May 2008, *55* (4), 677–691.

Primiceri, Giorgio E, "Why Inflation Rose and Fell: Policy-Makers' Beliefs and U.S. Postwar Stabilization Policy," *Quarterly Journal of Economics*, August 2006, *121* (3), 867–901.

Ravn, Morten O and Harald Uhlig, "On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations," *The Review of Economics and Statistics*, 2002, *84*, 371–380.

Rudebusch, Glenn D., "Term structure evidence on interest rate smoothing and monetary policy inertia," *Journal of Monetary Economics*, September 2002, *49* (6), 1161–1187.

——, "Monetary Policy Inertia: Fact or Fiction?," *International Journal of Central Banking*, December 2006, *2* (4), 85–135.

Smith, Josephine and John B Taylor, "The Long and Short End of the Term Structure of Policy Rules," *Journal of Monetary Economics*, October 2009, *56* (7), 907–917.

Stock, James H. and Mark W. Watson, "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business & Economic Statistics*, 2002, *20* (2), 147–62.

Strongin, Steven and Vefa Tarhan, "Money Supply Announcements and the Market's Perception of Federal Reserve Policy," *Journal of Money, Credit and Banking*, May 1990, *22* (2), 135–153.

Taylor, John B., "Discretion versus Policy Rules in Practice," *Carnegie-Rochester Conference Series on Public Policy*, 1993, *XXXIX*, 195–214.

——, "Housing and Monetary Policy," in "Housing, Housing Finance, and Monetary Policy," Federal Reserve Bank of Kansas City, 2007.

Taylor, Nicholas, "The Determinants of Future U.S. Monetary Policy: High-Frequency Evidence," *Journal of Money, Credit and Banking*, 2010, *42* (2-3), 399–420.

Thapar, Aditi, "Using private forecasts to estimate the effects of monetary policy," *Journal of Monetary Economics*, May 2008, *55* (4), 806–824.

A Web Appendix– Not for Publication

Table A1: Policy Rule Constant Estimates

	h					
	1	2	3	4	5	6
Baseline	–0.421	–0.493	–0.578	–0.518	–0.547	–0.195
	0.068	*0.092*	*0.114*	*0.125*	*0.139*	*0.139*
Baseline, pre	–0.412	–0.489	–0.580	–0.492	–0.667	–0.624
	0.109	*0.091*	*0.080*	*0.199*	*0.132*	*0.186*
Baseline, post	–0.380	–0.469	–0.517	–0.448	–0.686	–0.644
	0.070	*0.082*	*0.119*	*0.124*	*0.200*	*0.145*

Notes: η_r is the average risk premium change. HAC standard errors in *italics*. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7. Pre period is 1994–1999, Post period is 2000–2007.

Table A2: Tests of Cross-Equation Restriction

	h					
	1	2	3	4	5	6
(4) Cross, pre	0.988	0.969	0.925	0.967	0.987	0.994
(5) Cross, post	0.999	0.997	0.996	0.957	0.999	0.976

Notes: p-values from Hansen's (1982) J-test of cross-equation restriction that the average risk premium change is identical across indicators. Pre period is 1994–1999, Post period is 2000–2007.

Table A3: Market-Perceived Monetary Policy Rule Estimates, No Cross-Equation Restriction

		h					
		1	2	3	4	5	6
(4) Cross, pre	β	0.286	0.845	1.160	1.340	1.490	1.502
		0.207	*0.687*	*0.611*	*0.745*	*0.752*	*0.975*
	δ	0.137	0.128	0.348	0.434	0.130	0.305
		0.046	*0.049*	*0.248*	*0.354*	*0.085*	*0.112*
(5) Cross, post	β	–0.499	0.603	0.398	0.445	1.023	2.196
		0.365	*0.457*	*0.376*	*0.397*	*0.680*	*0.854*
	δ	0.257	–0.101	0.088	0.002	–0.040	0.105
		0.057	*0.154*	*0.068*	*0.024*	*0.038*	*0.689*

Notes: The policy rule coefficient on inflation is β and on the output gap is δ. HAC standard errors in *italics*. See the notes for Table A2. Point estimates and standard errors are from two-step nonlinear GMM. Data run over 1994:M1-2007:M7. Pre period is 1994–1999, Post period is 2000–2007.

Table A4: Core Inflation Predictability

	h					
	1	2	3	4	5	6
R^2	91.5%	90.7%	89.5%	88.0%	86.2%	84.1%
t-stat	60.9	58.9	55.9	52.8	49.8	47.0

Notes: R^2 and slope coefficient t-stat (robust), from regressions of Core-PCE inflation on Core-CPI inflation, both as annual logarithmic rates, monthly 1960–2007.