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ABSTRACT

We explore the effects of official targeting policy on the term-structure of nominal interest rates, adapting relevant insights from theoretical work on "peso problems" to account for realistic infrequency of target changes. Our analysis of daily U.S. interest rates and newly available historical targets provides an interpretation for persistent spreads between short-term money-market rates and overnight fed-funds targets, and for the poor performance of expectations-hypothesis tests: it is the policy-induced component of fed funds dynamics that appears to be erroneously anticipated by the market. Still, allowance for serial correlation in target changes makes it possible to extract from interest-rate data an expected-knoll series which is quite consistent with the assumptions of the model, indicating that some features of the interest-rate-targeting process are incorporated by market expectations.

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1 Introduction

In many models of the nominal term structure, the monetary authorities affect interest rates mainly through inflationary expectations, and perhaps through short-term liquidity effects as well. In practice, however, market participants attach particular significance to the stance of monetary policy when assessing the outlook for short-term interest rates. The present paper takes this perspective seriously. At the theoretical level, we formalize the idea that short-term interest rates are mainly determined by the current and expected future pattern of monetary policy. We also relate empirical interest-rate dynamics to a newly available historical series of interest-rate targets.

We view the overnight rate of interest on fed funds as the prime instrument of monetary policy, and we model it as the sum of two components: the "target," which is changed infrequently by the monetary authority in a way that imparts martingale-like behavior to interest rates; and the deviations from the target, which are the outcome of continuous market equilibrium and exhibit mean reversion toward zero. Longer-term yields are then driven by three factors: the current target, the fluctuations of overnight rates about the target, and the expectations of future target changes.

We document the existence of long-memory spreads between overnight and longer-term interest rates when the former were the immediate instrument, and the latter the intermediate target, of monetary policy. The simple model we propose formalizes the idea that the Fed's style of intervention may only loosely control even short-term interest rates, and allows us to extract from interest-rate and target data an estimate of the market's expected size and direction of target changes. Our approach is closely related to that of recent and less recent work on "peso problems" and interest-rate differentials in the exchange rate literature.[1] Like most contributions to that literature, we focus on expectational relations between nominal interest rates of different maturities, and do not explicitly address more substantial policy

[1]The references most relevant to our work are Bertola and Svensson (1992), Rose and Svensson (1991), and Lindberg, Svensson, and Söderlind (1991), where the notion of stochastic "devaluation risk" is introduced and empirically implemented on exchange- and interest-rate data.

issues. Still, our theoretical approach does offer insights on many issues of academic and non-academic interest, especially in light of renovated emphasis, both by monetary authorities and the press, on interest-rate targeting and discount rate changes.

Section 2 proposes a simple model based on relevant institutional information and literature. The model formalizes Mankiw and Miron's (1986) "martingale" view of interest-rate-targeting policies, but extends their framework to account for the infrequent character of real-life target changes at a daily time scale, while allowing for possible misunderstandings between market participants and monetary authorities. Section 3 confronts the model with recent U.S. money-market data. Our modeling approach provides an interpretation of the poor performance of tests of the expectations hypothesis, suggesting that it is the policy-induced component of fed funds dynamics to be erroneously anticipated by the market. In Section 4 we consider two specific models of expectation formation, and extract a series of expected target changes from historical targets and short-term interest rates. The estimated series have statistical properties which are consistent with modeling assumptions, and predict well the direction of realized changes. On average, however, short-term rates appear to anticipate target changes of much larger size than those actually implemented; the problem is lessened, but not eliminated, if "martingale" assumptions are relaxed to account for the observed serial correlation of target changes. Section 5 summarizes what is learned from our theoretical and empirical work, and concludes outlining directions for further research.

2 A simple model of interest-rate targeting

It is well understood that the process for short-term interest rates has displayed very long memory since the Federal Reserve System ("the Fed") was established in the 1920s. Mankiw and Miron (1986) and others show that previously important interest-rate seasonals have disappeared after the Fed's inception, and that short-term nominal interest rates have approximately followed a martingale process. The long memory in interest rates is viewed as the result of direct or indirect intervention of the Fed with the objective of stabilizing the economy. Goodfriend (1990) relates this view to institutional information on interest-rate-targeting practices. Historically, the Fed has indeed used direct targeting of overnight rates to stabilize longer-term interest rates. Goodfriend notes that targets are changed infrequently in practice, and surveys empirical evidence showing the Fed's influence on interest rates.

Accordingly, we model the process followed by the overnight fed funds rate, r_t, as the sum of a target-rate process $\bar{r}_t$, and deviations from it. The resulting perspective on the term structure of interest rates is quite different from that afforded by the customary decomposition of nominal rates in (expected) inflation and real interest rates. The two views are complementary, however, and the one we choose in this paper has a number of novel implications. First, it reverses the usual view of the relation between inflation and interest rates: it is the stabilization policy, implemented by interest-rate targeting, which induces long memory in nominal interest rates and *thus* inflation [Goodfriend (1990)]. Second, it allows us to do without inflation data, whose quality and frequency fail to match those of interest-rate data. Third, it points to the core of the effects of monetary intervention on interest rates at the short end of the term structure: from this perspective, explaining interest rates requires understanding the character of interest-rate targeting on the part of the Fed.

The model outlined in the rest of this section, while admittedly oversimplified, formalizes ideas which feature prominently in the relevant theoretical and empirical literature. We model the limited and mean-reverting nature of fed funds-rate fluctuations around the target by the first-order stochastic difference equation

$$r_t - \bar{r}_t = (1 - k)(r_{t-1} - \bar{r}_{t-1}) + \epsilon_t, \tag{1}$$

where ϵ_t is a white-noise error, and $0 < k < 1$ is a given constant. The r_t process is more tightly targeted the smaller the standard deviation σ of ϵ_t, and the higher the mean-reversion parameter k.

As to the behavior of the target $\bar{r}_t$, we do not fully specify the way in which the Fed decides target changes. We model the process of target changes in a minimal fashion as it is actually implemented *and* perceived by the market: we take target changes to be independent from the process (1), and to be *infrequent*, with $\nu < 1$ the known probability of a target change on any day t. We also assume in this section that, when a target change occurs, all adjustment "pressure" is released, and only the accrual of new information leads the Fed to contemplate a new target change in either direction. This rather extreme assumption incorporates Mankiw and Miron's (1986) idea that Fed targeting is responsible for martingale-like behavior of short-term rates.

In the following, we focus on *market expectations* of future target changes, which we model in an equally minimal fashion. We denote with $z_t = E_t(\Delta\bar{r}_{\hat{t}})$ the market's expectation, as of t, of the size of the *next* target-change realization, occurring at time $\hat{t} > t$. In reality, of course, such expectations presumably depend in complex ways on a variety of detailed policy-relevant information. By definition, however, the expectation revisions represented by changes in z_t are unpredictable: only new information should induce the market to revise its expectation of future target changes occurring at time $\hat{t}$. Together with the "pressure release" assumption above, such unpredictability implies a simple univariate representation for the $\{z_t\}$ process:

$$z_t = \begin{cases} z_{t-1} + \text{error}_t, & \text{when } t \neq \hat{t}; \\ \text{error}_t, & \text{when } t = \hat{t}, \end{cases} \qquad (2)$$

where the error is unpredictable on the basis of the market's past information (which obviously includes z_{t-1}). The expectational nature of z_t implies that it should follow a martingale when target changes are *not* realized and, by assumption, z_t is reset to zero (or, more generally, to a value drawn from an independent, mean-zero distribution) at every time $\hat{t}$ when a target change is realized. Before proceeding, we note that the process (2) is meant to describe expectations *as formed by the market.* We do not presume in what follows that the $\{z_t\}$ process is necessarily consistent with the process governing actual target changes. Systematic discrepancies between the two may arise for at least one reason: The Fed may not follow a stable policy or may hide the one it follows, so as to enhance the effectiveness of policy actions by surprising the market. As a result, the changing array of parameters characterizing the process of target changes is not known to the market, requiring potentially endless learning on their part.

To link the dynamics of overnight rates (and targets) to longer-maturity yields, we suppose that arbitrage keeps the interest rates on longer-term maturities in line with the average overnight fed funds rate *as expected by the market.* A linear expectations-hypothesis term structure is then a fair description of the equilibrium relation between short-term and overnight fed funds rates:

$$R_t = \sum_{s=t}^{t+\tau-1} \frac{E_t(r_s)}{\tau}, \tag{3}$$

i.e., the yield R_t on a τ days-maturity loan at time t is the average of the future overnight rates $\{r_s\}$ expected to prevail during the life of the credit instrument.[2]

In the Appendix we calculate each term of the summation in (3) using our assumptions, to obtain

$$R_t = \bar{r}_t + \left[1 - \frac{1-(1-\nu)^\tau}{\nu\tau}\right] z_t + \left[\frac{1-(1-k)^\tau}{k\tau}\right] (r_t - \bar{r}_t)\,. \tag{4}$$

The resulting term structure features three factors: the target $\bar{r}_t$, which follows a generalized random walk on random time steps; the expectation of the next target change's size z_t, which is stationary but has local martingale dynamics between target changes; and the deviation $r_t - \bar{r}_t$ of overnight rates from current targets, which is stationary and reverts linearly towards zero.

As the time to maturity shortens, the yield converges to the overnight fed funds rate, $R_t(1) = r_t$: thus, day-by-day fluctuations in the very short end of the term structure reflect mainly expected movements around the current target $\bar{r}_t$. At the other extreme, $R_t(\infty) = \bar{r}_t + z_t$ if $\nu > 0$. The further into the future one looks, the less important is the current deviation from target (k is the relevant parameter for the fading relevance of this factor),

[2]See Cook and Hahn (1990) and Campbell and Shiller (1991) for recent surveys of theoretical and empirical issues relevant to (3).

and the more relevant the possibility of a target change (by z_t, given current information). This "expected target change" factor is novel and peculiar to our interest-rate-targeting setup.

The simple model of this section is quite close in spirit to Mankiw and Miron's (1986) framework of analysis but, as is appropriate at the very fine time scale we wish to consider, it accounts for *infrequency* of target changes. Only if $\nu = 1$ would target changes occur every day, to imply that the overnight rate itself would behave as a martingale (plus a mean reverting process). *Expectations* of future target changes play a separate and very important role in our model, and we shall see in Section 4.1 that our perspective leads quite naturally to a relaxation of the resetting assumptions above.

3 Taking the model to the data

We now turn to confront the simple model outlined above with real-world data which may be generated by a similar mechanism.

New daily historical fed funds targets were made available to us by the Federal Reserve Bank of New York (FRBNY). The target data are those on which the trading desk's open market operations were based on any given day, or "indications of the fed funds rate expected to be consistent with the degree of reserve pressure specified by the Federal open market committee (where a trading range was indicated, the midpoint of that range is provided)." While professional "fed watchers" are usually able to infer current targets from a variety of economic and policy variables, the historical data we use were not previously disclosed. In line with evidence of renewed emphasis on fed funds rates, however, from 1991 the FRBNY publishes target data in the Spring issue of its Quarterly Review, resuming a practice interrupted in 1983.

As to overnight and longer-term interest rate data, we obtained from the Board of Governors of the Fed daily closing-quote series for overnight interest rates on fed funds and for three-month "term fed funds" of comparable liquidity and risk characteristics.[3]

Figure 1

Figure 1 plots the target fed funds rate, the overnight fed funds rate, and the three-month fed funds rate from January, 1985 through December, 1991. All three series are translated on a continuously compounded basis,[4] and market holidays are filled with observations from the last day the market was open.

We see in the Figure that target changes are indeed infrequent on a daily time scale. There are 66 target changes in the seven-year span of Figure 1, hence the target is changed (on average) only every five weeks or so. The data also tell us that targets are most often specified in quarter points (before continuous compounding), so that realized target changes are usually 25 or 50 basis points in absolute value. In principle, this is not a problem for the simple model specified above: as long as the market attaches positive probability to different quarter-point increments, the *expected* size z_t of target changes can be a continuous random variable even when target-change realizations (hence expectational errors) have discrete distributions. Indeed, such lumpiness in target changes may be naturally associated to their infrequency. The Fed might conceivably intervene using a finer single-tick mesh, but usually decides to specify targets in quarter-point (eight ticks) increments. Specifying "round" targets might well facilitate communications between policy makers and the New York desk and, to the extent that the Fed intends to clearly signal its policy moves, between the desk and the market as well. The timing of target changes would then be determined by rounding to the closest quarter-point of an underlying, continuously updated "shadow" target process.

[3]While similar theoretical and empirical work could be performed on T-bill or commercial-paper yields, the liquidity, tax, and default characteristics of such securities are quite different from those of interbank instruments, and the time-varying effects introduced by such features [for which see, e.g., Simon (1990) and Bernanke (1990)] would spoil our analysis of expectational factors.

[4]Let r^q be the quoted overnight fed funds rate, the corresponding continuously compounded rate r is given by $r = 100[\ln(1 + r^q/360000)365]$. The same formula applies to quoted fed-funds-rate targets. Similarly, quoted three-month fed funds rates R^q are converted to their continuously-compounded counterpart according to $R = 100[\ln(1 + R^q\ 91/360000)365/91]$.

The overnight rate is quite volatile around the current target, reflecting the inherent difficulty of controlling a price target by quantity intervention in a turbulent market: in general, the change in reserve assets implemented by the desk's open-market operations is not exactly consistent with the specified overnight-rate target. Further, desk operations are implemented shortly after 11 AM in New York, and no coincident market-rate series is available to us. Our interest-rate data are 5 PM closing rates, and time lag introduces additional noise in the spread between measured overnight rates and targets.

Fed funds rates also display pronounced spikes in the last two days of "reserve maintenance periods," when banks must meet reserve requirements calculated over two-week "computation periods" ending on Monday. Every other Tuesday and Wednesday, the banking sector as a whole may be trying to increase net reserve positions or to unload excess reserves. The resulting market tensions impart wide fluctuations to the overnight fed funds rate: our empirical work below takes such seasonal effects into account.[5]

Official documents suggest that the interest-rate targeting perspective of our model may not be equally applicable to all available data. Chairman Volcker's anti-inflationary policies officially focused on monetary-aggregate rather than interest-rate targets. Quantity targets were de-emphasized starting in 1982, and gradually replaced by the semi-official interest-rate targets plotted by the step function of Figure 1. It is apparent in the Figure, however, that targets were not strictly implemented in the first part of the available sample. Indeed, only in 1987 did the Fed stop declaring targets for M1, a clear indication of the mounting difficulty of controlling aggregates rather than interest rates. Recent official Fed documents reflect a prevalence of price over quantity targets which was also typical of monetary policy in the 1970s [e.g., Hetzel (1981)].[6] As it is apparent from Figure 1, however, tight targeting was

[5]Biweekly clearing of the market for reserve assets might in principle invalidate our assumption that innovations to the overnight rate/target spread are independent of those in target-change expectations: market-clearing overnight rates might conceivably themselves reflect anticipations of target changes if banks distribute reserve requirements towards times of expected lower cost within the maintenance period. However, the evidence in Campbell (1987) indicates such anticipation effects are not apparent in overnight-rate data. They would only operate at biweekly horizons anyway, and we abstract from them in our theoretical models and empirical work on 3-month term fed funds rates.

[6]In their section on policy implementation, recent issues of the Quarterly Review of the FRBNY (Spring

de facto abandoned in the aftermath of the 1987 stock market crash (no formal fed funds-target rate was indicated from October 19, 1987 through November 3, 1987) and during the highly volatile Gulf War period (from August 1990 through February 1991).

This institutional information confirms that the *modus operandi* of monetary policy is far from constant over time. We choose to work on data from November 4, 1987 through August 1, 1990, when the character of monetary policy appears relatively homogeneous: the period roughly coincides with the tenure of Alan Greenspan as Chairman of the Fed, but excludes obvious sources of instability such as the 1987 stock market crash period and the highly volatile period following the invasion of Kuwait. It will become apparent below, however, that even during this sub-period interest rates need not have been based on a stable expectational structure, and appear to incorporate the likelihood of future and ongoing "monetary regime" shifts.

Figure 2

For this period, Figure 2 displays the autocorrelation functions of overnight and three-month interest rates (both decay very slowly, as is also apparent from the long cycles of these series in Figure 1), as well as autocorrelations of their spread from contemporaneous targets.

Autocorrelations of the spread between overnight rates and targets display biweekly seasonality corresponding to the maintenance period, but otherwise decay very quickly, consistently with the mean-reverting dynamics postulated in equation (1). Conversely, the spread between three-month rates and targets is just as persistent as the level of the three-month interest rate. Such long-lived spreads are qualitatively consistent with the simple theoretical model outlined above, where deviations of longer-term interest rates from the overnight rates and targets are driven by target-change expectations z_t as well as by mean-reverting

1990; Spring 1991, pp.66–71; Spring 1992, p.84) lament instability of the relation between fed funds rates and the amount of borrowing. In 1990, for example, the trading desk of the FRBNY was prompted to signal policy moves so clearly as to minimize possibility of misunderstanding, because it was considered paramount to fix the right rate rather than adjust the reserves.

dynamics around the current target. With z_t a martingale between target changes and relatively infrequent target changes, the spread between short-term and overnight interest rates should indeed display long memory to the extent that intervals between target changes are long relative to the life of the credit instrument.[7]

3.1 Data analysis

We now estimate the law of motion of overnight interest rates around the target. To account for the biweekly seasonal effects which are apparent in Figures 1 and 2, we use ten level dummies (one for each working day of the maintenance period) and ten mean-reversion dummies. We estimate the model

$$r_t - \bar{r}_t = d_t + (1 - k_t)(r_{t-1} - \bar{r}_{t-1} - d_{t-1}) + \epsilon_t, \tag{5}$$

where r_t is the overnight fed funds rate; $\bar{r}_t$ is the target; $d_t = d_{t+10}$ is a time-varying intercept with biweekly periodicity, which captures seasonality in the conditional mean of r_t; $k_t = k_{t+10}$ is a time-varying mean-reversion parameter, also with biweekly periodicity, meant to capture variations in targeting intensity. As not only the level, but also the volatility of the fed funds rate is affected by the maintenance-period cycle, we allow the standard deviation $\{\sigma_t\}$ of the serially uncorrelated error ϵ_t to vary over time, and impose a seasonal pattern with $\sigma_{t+10} = \sigma_t$.[8] We estimate the process in (5) by maximum likelihood, assuming ϵ_t to be normally distributed. The results are reported in Table 1.

Table 1

[7] These findings are not specific to the limited period we consider. Indeed, sizable and persistent spreads between 3-month fed funds rates and contemporaneous targets are quite apparent in Figure 1, indicating that "expected target change" term-structure factors are quantitatively important for all recent U.S. monetary policy.

[8] The stochastic seasonality exhibited by the fed funds rate could alternatively be captured by an autoregressive process with ten lags. However, the coefficients of our simple AR(1) process with seasonal variation are much easier to interpret.

The model fits the data well, and the residuals have satisfactory statistical properties. Biweekly patterns are statistically significant for levels ($\{d_t\}$), serial correlations ($\{k_t\}$), and volatilities ($\{\sigma_t\}$). These parameters are precisely estimated, and offer insights into the nature of targeting and seasonal patterns during the period under scrutiny.[9] The intercept parameters $\{d_t\}$ are all close to zero, indicating that systematic seasonal effect on the level of the fed funds rate are economically (if not statistically) insignificant. Conversely, the intensity of mean-reversion changes quite dramatically over the biweekly period: we find *diversion* from the target on day 3 of the biweekly cycle, the Wednesday closing the maintenance period, while strong reversion towards the target is induced on the following Thursday and Friday. The variability of innovations in the fed funds rate also follows a marked seasonal pattern. The standard deviations $\{\sigma_t\}$ are higher on average during the first week of the period, especially between Tuesday and Thursday, with a peak on Wednesday.

Next, we assess the empirical validity of a key assumption leading to the simple theoretical results above. In Section 2 we assumed target-change events to occur with constant daily probability, and to be independent of all other elements of randomness. Hence, the length of constant-target spells should be binomially distributed with parameter ν, and unrelated to other observable data.

Figure 3

Figure 3 plots the sample spells' empirical distribution function, along with their theoretical counterpart based on the empirical frequency of target-change events. The two panels of the Figure measure time in calendar days (as in our theoretical model) and in business days, respectively. In both cases, the empirical and theoretical distributions are quite close in shape and position: formally, the Kolmogorov-Smirnov goodness-of-fit statistic [see, e.g., De Groot (1986), p.556] fails to reject the null hypothesis at conventional significance levels (p-values are 29.01% and 24.05% for the distributions of Figure 3.a and 3.b, respectively).

[9]See Campbell (1987) for similar empirical evidence on weekly seasonals in fed funds rates in 1980-83, when reserve maintenance periods were weekly.

Consistently with the empirical evidence of Figure 3, the data reveal no pattern of serial correlation in the length of constant-target spells, indicating that the daily target-change probability ν is well approximated by a constant in this sample.[10] We have also informally tested for correlation between the target changes' size and timing. The sample contains very little information on such issues: target-change sizes do not vary much around their quarter-point mode, and are essentially unrelated to the length of the previous no-change spell length.

We conclude that data provide no evidence against the simple model's timing assumptions, and proceed to seek evidence on the basic expectational relation (3) by estimating the regression model

$$\sum_{s=t}^{t+\tau-1} \frac{r_s}{\tau} - r_t = \alpha\,[R_t - r_t] - \phi_t + \eta_{t+\tau-1}, \tag{6}$$

where R_t is the interest rate on a loan of maturity τ, ϕ_t is a time-varying intercept which may capture liquidity and term effects, and η_t is an expectational error. Under the premium-augmented expectations hypothesis,

$$R_t = \sum_{s=t}^{t+\tau-1} \frac{E_t(r_s)}{\tau} + \phi_t \tag{3'}$$

and, assuming unbiasedness of expectations, the coefficient α of the regression should equal one.

Table 2

In Table 2 we present results from estimation of (6) on R_t, the three-month fed funds rate. We allow for an intercept ϕ_t with biweekly seasonal periodicity, i.e., we impose $\phi_t = \phi_{t+10}$ for every t. The hypothesis that $\phi_t = 0$ is not rejected. This is remarkable in light of the

[10] It would not be difficult to specify and solve a model where this probability is time-varying (and at least partially reset upon target-change realizations). The model would have interesting implications for the yield curve's shape. However, such an extension does not appear to be called for by our data, and is better left to further research.

very pronounced "maintenance period" seasonal pattern, and the result provides support for maintaining the premium-free expectations hypothesis of (3).

The spread between three-month and overnight rates has substantial predictive power for future behavior of the latter, but the slope coefficient α is estimated to be significantly lower than the unitary value implied by (3) in large samples. Unexplained time-variation in unobservable term premia could of course be responsible for biasing α towards zero, in the way suggested by Mankiw and Miron's (1986) work on quarterly data of three- and six-month maturity. However, given the daily periodicity of our data and the shorter maturities we consider, our empirical findings give some support to the notion that $\phi_t = 0$. We take the absence of term premia as a maintained identifying assumption and, in light of the theoretical structure of Section 2, we proceed to examine the origin of the bias in tests of (3′) in terms of expectational errors.

3.2 The performance of the expectations hypothesis

As in Section 2, we suppose that longer-term interest rates correctly embody the market's expectations of future overnight rates. However, we relax the standard requirement that the data-generating process is completely known to economic agents, and reinterpret the performance of tests of the expectations hypothesis from the vantage point of our simple theoretical framework and newly-available target data. As argued above, imperfect knowledge of policy rules is indeed likely to be important in real-life settings, and market expectations of future fed funds rates may well be biased, as documented by Simon (1990) with quarterly data from the Goldsmith-Nagan Survey for various recent periods. While Simon does not attribute expectational errors to specific features of interest-rate dynamics, our target data and estimated fed funds process help us identify the source of expectational biases.

Under the maintained expectations hypothesis, the regressor of equation (6) can be decomposed as follows:

$$\begin{aligned} R_t - r_t &= E_t\left(\frac{\sum_{i=0}^{t+\tau-1}\bar{r}_{t+i}}{\tau} - \bar{r}_t\right) + E_t\left[\frac{\sum_{i=0}^{t+\tau-1}(r_t - \bar{r}_{t+i})}{\tau} - (r_t - \bar{r}_t)\right] \\ &\equiv E_t\left(\Delta_{\bar{r}_t}\right) + E_t\left(\Delta_{r_t - \bar{r}_t}\right). \end{aligned}$$

Thus, $E_t\left(\Delta_{\bar{r}_t}\right)$ denotes the market's forecast of relevant future target-change variations, and $E_t\left(\Delta_{r_t-\bar{r}_t}\right)$ denotes the forecast of the relevant variations around future targets.

Projecting (5) forward, we have $E_t(r_s - \bar{r}_s) = d_s + (r_t - \bar{r}_t - d_t)\prod_{j=1}^{s-t}(1 - k_{t+j})$, where the index on d and k now refers to calendar time rather than to business days (seasonal parameters are set to zero on weekend days). Hence,

$$E_t\left(\Delta_{r_t-\bar{r}_t}\right) = \sum_{i=0}^{\tau-1}\frac{d_{t+i}}{\tau} + \frac{1}{\tau}\left[1 + \sum_{s=t+1}^{t+\tau}\prod_{j=1}^{s-t}(1 - k_{t+j})\right].$$

We maintain the hypothesis that the process driving fed funds rates around current targets is well understood by market participants, who know its form and the parameters $\{d_t, k_t, \sigma_t\}$. We can then isolate the expectational component reflecting target-change forecasts:

$$\begin{aligned} E_t\left(\Delta_{\bar{r}_t}\right) &= R_t - r_t - E_t\left(\Delta_{r_t-\bar{r}_t}\right) \\ &= R_t - r_t - [L_{r_t-\bar{r}_t} - 1](r_t - \bar{r}_t - d_t) - L_{d_t}, \end{aligned} \tag{7}$$

where

$$L_{r_t-\bar{r}_t} \equiv \frac{1}{\tau}\left[1 + \sum_{s=t+1}^{t+\tau}\prod_{j=1}^{s-t}(1 - k_{t+j})\right]$$

is the term-structure loading on seasonally adjusted deviations from target, and

$$L_{d_t} \equiv \sum_{i=0}^{\tau-1} d_{t+i}/\tau$$

is a time-varying (but empirically rather small) intercept induced by seasonal effects.

A sample counterpart of $E_t\left(\Delta_{r_t-\bar{r}_t}\right)$ can be computed from (7) inserting estimates of $\{k_t, d_t\}$ in the factor-loading expressions $L_{r_t-\bar{r}_t}$ and L_{d_t}. The resulting expectational series can then be compared to the realized target-change series. For such comparisons to be statistically meaningful, we need to account for the fact that the factor-loading expressions are (highly nonlinear) functions of the parameters given in Table 2. We therefore implement a simple Monte Carlo procedure (see the Appendix) based on the estimated asymptotic covariance matrix of the estimates, and report empirical standard errors for each of the point-estimate comparisons below.

When we regress $\Delta_{\bar{r}_t}$ on the sample counterpart of $E_t(\Delta_{\bar{r}_t})$ and a constant, we obtain a slope coefficient $\alpha' = 0.520$, with empirical standard error 0.009. Recalling that we had $\alpha = 0.576$ in Table 2, where the test was run on raw data, we find that the expectations-hypothesis test uncovers an even *more pronounced* bias when focused on the target component of fed funds dynamics.

To interpret this result, consider that the theoretical value of α' (to which the estimated parameter should converge in probability) is given by

$$\frac{\text{cov}^* \left[\Delta_{\bar{r}_t}, E_t(\Delta_{\bar{r}_t})\right]}{\text{var}^* \left[E_t(\Delta_{\bar{r}_t})\right]},$$

where an asterisk (*) denotes moments calculated with respect to the *true* target-change process. Note that our model does not impose $E_t(\Delta_{\bar{r}_t}) = E_t^*(\Delta_{\bar{r}_t})$. Hence, in general

$$\text{cov}^* \left[\Delta_{\bar{r}_t}, E_t(\Delta_{\bar{r}_t})\right] \neq \text{var}^* \left[E_t(\Delta_{\bar{r}_t})\right],$$

and the theoretical value of α' can indeed be lower than one. Moreover, if the population value of α' is less than one, then it is a simple matter of algebra to show that it should also be less than the theoretical value of α,

$$\frac{\text{cov}^* \left[\Delta_{\bar{r}_t}, E_t(\Delta_{\bar{r}_t})\right] + \text{var}^* \left[E_t(\Delta_{r_t - \bar{r}_t})\right]}{\text{var}^* \left[E_t(\Delta_{\bar{r}_t})\right] + \text{var}^* \left[E_t(\Delta_{r_t - \bar{r}_t})\right]},$$

as we find for their sample counterparts. Thus, our modeling approach is consistent with the empirical finding of a more pronounced bias of the expectations-hypothesis test for the target component of fed funds.

As suggested by Mankiw and Miron (1986), time-varying term premia can certainly rationalize below-unity estimates of regression coefficients like α and α'. However, we show in the Appendix that, under standard rational-expectations assumptions, such alternative specifications may well (counterfactually) imply that α is estimated to be *smaller* than α'. In fact, stationary term premia need not covary strongly with the highly persistent expected-target-change component $E_t^*(\Delta_{\bar{r}_t})$ which our data and modeling approach make it possible to identify. Inasmuch as premia covary little with expectations of policy changes, it would be hard for them to strongly bias the estimated coefficient α' below one. Conversely, term premia (especially if liquidity-motivated) might well correlate positively with the overnight rate's spread from its currently targeted level, or with $E_t(\Delta_{r_t-\bar{r}_t}) = E_t^*(\Delta_{r_t-\bar{r}_t})$. Such correlation could easily imply that the estimated α coefficient differs from one by a more substantial quantity than α' does.

4 Expected target changes

The stylized formal model presented in Section 2 makes it possible to extract target-change expectations from observable series: the parameters determining the factor loadings in (4) are readily estimated from our data and, for given factor loadings, the theoretical relation lets us infer expected target changes z_t from historical targets and observed term-structure spreads.

As in the derivation of (4), we proceed under the maintained assumption that (3) holds (so that longer-term rates reflect the market's expectations of future overnight rates) to obtain:

$$R_t = \bar{r}_t + L_{r_t-\bar{r}_t}(r_t - \bar{r}_t - d_t) + L_{z_t} z_t + L_{d_t}, \tag{8}$$

where the loadings $L_{r_t-\bar{r}_t}$ and L_{z_t} are as defined above, and

$$L_{z_t} \equiv \left[1 - \frac{1-(1-\nu)^{\tau}}{\nu\tau}\right]$$

is the loading on target-change expectations z_t. The estimate of the daily probability ν of a target change, which determines the factor loading L_{z_t}, is given by the empirical frequency of target changes. The target changes 24 times in our sample of 1001 calendar days. Since the term-structure model above presumes a constant probability of target changes on every calendar day in the relevant forecasting horizon, we use the estimate $\nu = 24/1001 = 0.024$ and appropriate asymptotic standard errors (see the Appendix).[11]

Using the parameter estimated in Table 2 to compute the deviations factor loading $L_{r_t-\bar{r}_t}$ and the time-varying intercept L_{d_t}, the term-structure model (8) yields point estimates of the target-change expectation series $\{z_t\}$,

$$z_t = \frac{R_t - \bar{r}_t - (r_t - \bar{r}_t - d_t)\, L_{r_t-\bar{r}_t} - L_{d_t}}{L_{z_t}}, \tag{9}$$

and associated standard errors from Monte Carlo experiments based on estimated parameters' standard errors.

By equation (2), z_t and its sample counterparts should follow a martingale process between target changes, and be reset to zero (on average) on days when target changes are realized. Regressing $z_t - z_{t-1}$ on a constant and z_{t-1} only *between* target changes, we find that the intercept and slope coefficients (which should both be zero under the null) are −0.002 and 0.036, with small empirical standard errors (0.001 and 0.0001 respectively). The process followed by the estimated series of expected target changes is indeed economically (if not statistically) close to a martingale between target changes.[12] As to the stochastic resetting feature, the extracted $\{z_t\}$ series averages to 0.012 across the 24 days following a target change, with an empirical standard error of 0.034. The data do not reject the hypothesis that future target-change expectations have *unconditional* mean zero the day after a target

[11] In reality, of course, target changes could only be observed on the days during which the monetary market was actually open. Implicitly, we are allowing the "shadow" target process triggering target changes to be continuously updated during weekends and holidays, at the same speed as on business days. The evidence of Figure 3 indicated that this does not do violence to our data: more realistic assumptions would have only minor effects on our results.

[12] Realistic time-variation in ρ and/or ν, which we do not model, could potentially account for departures from strict martingale behavior of the extracted $\{z_t\}$ series.

change. However, if we regress $z_{\bar{t}+1}$ on $\Delta\bar{r}_{\bar{t}}$, we obtain a coefficient of 1.080 with empirical standard error of 0.361: realized target changes carry information as to expectations of future ones, rejecting the stylized model's hypothesis that future target-change expectations have *conditional* mean zero after a target change.

Figure 4

Figure 4 plots the point estimate of the z_t series and empirical two-standard-error bands. The extracted $\{z_t\}$ series predicts well the sign of the next target change, but often quite substantially *overestimates* its actual size.

4.1 Serially correlated target changes

The lack of conditional resetting of the empirical $\{z_t\}$ series and its rather dramatic "overshooting" of subsequent target changes prompt us to reconsider the stylized assumption of uncorrelated target changes. This assumption was motivated invoking Mankiw and Miron's (1986) martingale-policy ideas: the specification of Section 2, however, turns out to be too stringent for the period and time scale we consider. In our sample period, target changes were quite clearly *correlated* over time (see Figure 1). The thirteen positive target changes occurring in 1988 and early 1989 are followed by nine negative ones, and such sign runs are of course extremely unlikely in our small sample of target changes. This feature sheds light on the source of the simple model's empirical shortcomings. On a day-to-day basis, the extracted expectational series plotted in Figure 1 substantially overestimates the following realized target changes. In absolute value, target changes only rarely exceed 25 basis points, yet their expectational counterpart plotted in Figure 3 is about twice as large on average. Such overshooting of the $\{z_t\}$ series extracted from three-month yields is readily explained, of course, if the market on average expects a *series* of target changes in the same direction.

We maintain Section 2's assumption that the expectational $\{z_t\}$ process has martingale dynamics between target changes, but we relax its resetting assumption writing

$$\Delta\bar{r}_j = \rho\Delta\bar{r}_j + \text{error}_j, \tag{10}$$

where j indexes the j-th target change and the constant ρ denotes the correlation of target changes over the random time steps of the target change's process. As noted above, realized target changes most often have 25- or 50-point size; this simply induces a discrete probability distribution on the error term in (10), which is inconsequential to our modeling of expectations as a continuous process.[13]

If the law of motion (10) is rationally incorporated into the market's expectations, the univariate representation of the next target change's expected size z_t is:

$$z_t = \begin{cases} z_{t-1} + \text{error}_t, & \text{when } t \neq \hat{t}; \\ \rho\Delta\bar{r}_{t-1} + \text{error}_t, & \text{when } t = \hat{t}. \end{cases} \tag{2'}$$

Target-change expectations are indeed reset at $\hat{t}$ if $\rho = 0$, but persist across target-change realizations, as the data suggest, if $\rho > 0$.

The time-varying seasonal intercept L_{d_t} and the loading $L_{r_t - \bar{r}_t}$ on the deviations are unaffected by serial correlation in target-change realizations, but the loading on the next target-change expectation z_t (derived in the Appendix) is now

$$L^a_{z_t} \equiv \frac{1}{\tau} \sum_{s=t+1}^{t+\tau-1} \left[\sum_{n=1}^{s-t} \binom{s-t}{n} \nu^n (1-\nu)^{s-t-n} \frac{1-\rho^n}{1-\rho} \right], \tag{11}$$

a rather formidable, but easily programmed function of ν and of the newly introduced parameter ρ. Once the latter is estimated from the sample of realized target changes (see Appendix for details), extraction of the $\{z_t\}$ series from term-structure and target data can

[13]An alternative approach would recognize such discreetness explicitly and model the process for target changes in terms of the transition probabilities of, say, seeing a target change of +.25 after a target change of −.25 has occurred. The refinement is best left to further work on a larger data set. In our current sample, target-change realizations are too few in number and too serially correlated to allow meaningful inference on a matrix of transition probabilities.

proceed as in the previous section.

Figure 5

The extracted $\{z_t\}$ series and empirical standard error bands are reported in Figure 5. Quite intuitively, $L^a_{z_t} > L_{z_t}$ for $\rho > 0$: thus, allowing for serially correlated target changes reduces the absolute size of z_t point estimates, and brings them much closer to subsequent target-change realizations. As ρ is rather imprecisely estimated, the model now features wide error bands, covering many more realizations than in Figure 4. Recognizing that target changes are serially correlated delivers the internal consistency between data-generating and expectation-formation structures that was elusive for the simpler model of Section 2. Indeed, a regression of $z_{\hat{t}+1}$ on $\Delta\bar{r}_{\hat{t}}$ across the 24 days after a realignment yields a coefficient that is statistically indistinguishable from the estimate of ρ, 0.737, which is used in the expectational factor-loading of expression (11): the estimate of the difference between the two parameters is an economically insignificant 0.075, and its empirical standard error is 0.372. Also, between target changes the extracted z_t behaves quite closely to a martingale, with parameters virtually identical to those estimated in Section 3.1.

The amended model, where $\Delta\bar{r}_{\hat{t}}$ carries information on the direction and size of future target changes as anticipated by the market, makes it possible to capture some aspects of the market's expectation-formation process in a way that is consistent with the empirical law of motion of target changes. Still, the market appears to only inefficiently accumulate and process new information: the sign of future policy actions is most often correctly predicted, but their size is substantially overestimated at times. Consistently with the evidence from the expectations-hypothesis test, the point estimate of the expectational series often "overshoots" subsequent target-change realizations.

Most strikingly, the three-month fed funds rate surged much higher than overnight market rates and targets at the end of 1987. In our framework, this indicates that the market was expecting sharply higher interest rates in the very near future, yet the events of late 1987 lie outside of the error bands implied by our estimated model's parameters. Was the market "irrational" in entertaining such expectations, i.e., were arbitrage opportunities open to "smart" investors during that period? The question is of course very difficult to answer with a single string of data, as it is well understood in the related literature on "peso" problems [see e.g. Lewis (1991)]. No surge in overnight rates was realized *ex post,* as the Fed successfully injected liquidity to control the market turbulence induced by the stock market crash (which, despite our *a priori* sample selection, does affect our data). Yet, a replay of the events which led to the Great Depression in 1929 was certainly possible in 1987: on the basis of what is essentially a single observation, no objective statistical procedure can ascertain whether the probability attached to the event by the market was in any sense irrational. The expectational overshooting of mid-1989, though not as sharp, can be similarly interpreted in terms of the market's misperceptions of the extent to which the Fed would be prepared to ease monetary policy after the interest-rate peak of early 1989.

5 Concluding comments

This paper's framework of analysis formalizes and extends the views of Mankiw and Miron (1986) on the effects of interest-rate targeting on the term structure of interest rates. While we do not offer an economic theory of how expectations of future target changes are formed, our approach does afford meaningful measurement with minimal theory. We account for a number of well-known stylized facts on interest-rate behavior, and we find that the infrequency of policy (target) changes leads to persistent expectations of unrealized events which, in turn, generate long-memory spreads between money-market rates and overnight-rate targets. At a general level, our perspective and data offer insights into the nature of the bias found by tests of the expectations hypothesis: given that the variation in the fed funds rate is generated mainly by changes in targets rather than by fluctuations about the target, and since the latter fluctuations are easily modeled and should be well understood by the market, we gather evidence indicating that the bias pertains to the policy-induced dynamics of the fed funds rate.

At a more practical level, we propose stylized models of expectations formation, and use their parametric structure to infer market expectations from interest-rate data. When we explicitly model the (autocorrelated) style of Fed intervention, we find that target-change expectations appear quite consistent with theoretical assumptions. Such findings indicate that at least some features of interest rate targeting are rationally incorporated into market expectations. Of course, more complex parameterizations of the type of model we consider could capture yet other features, such as time variation in target-change probabilities or correlations, and might better fit historical experience. Yet, the negative evidence on the expectations hypothesis holds regardless of specific parameterizations: in the relatively large and homogeneous sample we consider, the process of target changes is *not* well anticipated by the market. This suggests that specification searches on more sophisticated mechanisms of expectation formation and data generation may never eliminate expectation biases, but only yield insights on their source.

Our theoretical and empirical work does suggest several directions for further research. First, we may want to ask whether the expected target changes we measure are consistent with the Fed's *desiderata*. In its effort to anticipate future policy, the public accumulates information, and this translates into highly persistent spreads between overnight targets and longer-term rates (see the evidence of Section 3). Such slack between the instruments and objectives of monetary policy may or may not be desirable from the authorities' point of view. The variability of the innovations in z_t is an indicator of how frantic is the information-acquisition process, and of how successful is the Fed in keeping its intentions secret and preserving a discretionary role for policy. At the same time, however, a higher variability of the innovations in z_t means looser control on longer-term money market rates. A trade-off could arise between secrecy and interest-rate control, of which the authorities should be (and probably are) aware. In the same spirit, it would be important to evaluate different monetary regimes in terms of the features of the fed funds rate process and, through the lenses of our model, compare the market's understanding of monetary policy across different periods.

Finally, we have shown that realistic specifications of interest-rate targeting processes have distinctive implications for the joint behavior and serial correlation properties of money market rates of different maturities. For example, deviations of shorter-term rates from the target mainly reflect the short-lived variability of the fed funds rate about the target, and should exhibit short memory; deviations of longer-term rates from the target are mainly driven by expectations of proximate target changes, and should be long-lived. These and other implications deserve to be formally tested in further work on interest rates of different maturities, and such testing may provide additional measures of our framework's descriptive validity.

Appendix

A The simple term structure model

Each of the expectations on the right-hand side of (3) can be conditioned on whether or not a target change occurs in the relevant forecast horizon:

$$\begin{aligned} E_t(r_s) &= \Pr(\hat{t} > s)E_t(r_s|\hat{t} > s) + \Pr(\hat{t} \leq s)E_t(r_s|\hat{t} \leq s) \\ &= E_t(r_s - \bar{r}_s) + \Pr(\hat{t} > s)E_t(\bar{r}_s|\hat{t} > s) + \Pr(\hat{t} \leq s)E_t(\bar{r}_s|\hat{t} \leq s) \qquad \text{(A.1)} \\ &= (r_t - \bar{r}_t)(1-k)^{s-t} + \Pr(\hat{t} > s)E_t(\bar{r}_s|\hat{t} > s) + \Pr(\hat{t} \leq s)E_t(\bar{r}_s|\hat{t} \leq s), \end{aligned}$$

where we make use of the assumption that deviations of the fed funds rate at s are independent of target change dynamics to obtain the second equality, while we calculate $E_t(r_s - \bar{r}_s)$ from (1) to obtain the last equality.

Our assumptions yield simple expressions for the expectations of future targets appearing on the right-hand side of (A.1). If no target changes have occurred as of time s, we obviously have

$$E_t(\bar{r}_s|\hat{t} > s) = \bar{r}_t. \qquad \text{(A.2)}$$

As to the terms where $s > \hat{t}$ is the conditioning event, we have

$$\begin{aligned} E_t(\bar{r}_{\hat{t}+s}) &= \bar{r}_t + E_t(\bar{r}_{\hat{t}} - \bar{r}_t) \\ &= \bar{r}_t + E_t(z_{\hat{t}-1}) \\ &= \bar{r}_t + z_t, \qquad \text{for all } s \geq 0; \qquad \text{(A.3)} \end{aligned}$$

the first equality follows from the assumption that the target is expected to remain constant after $\hat{t}$ [formally, $E_t(z_{\hat{t}}) = 0$ and z_t follows a martingale after $\hat{t}$], and the second equality is implied by z_t's martingale behavior between t and $\hat{t}$.

Using (A.2) and (A.3) in (A.1), and noting that $\Pr(\hat{t} > s) = (1-\nu)^{s-t}$, we obtain:

$$E_t(r_s) = (r_t - \bar{r}_t)(1-k)^{s-t} + (1-\nu)^{s-t}\bar{r}_t + [1 - (1-\nu)^{s-t}](\bar{r}_t + z_t). \qquad \text{(A.4)}$$

The nominal yield on instruments of any maturity is now straightforward to calculate using (A.4) in the summations on the right-hand side of (3):

$$R_t = \bar{r}_t + \left[1 - \frac{1-(1-\nu)^\tau}{\nu\tau}\right] z_t + \left[\frac{1-(1-k)^\tau}{k\tau}\right] (r_t - \bar{r}_t)\,. \tag{4}$$

B Empirical standard errors

All statistics which depend on estimates of the parameters $\{k_t, d_t\}$, ν, and ρ are subject to randomness due to variability of the estimates around the true values. We account for this by drawing 100 samples from the estimated joint asymptotic distribution of the estimates, and compute the empirical standard errors of the quantities of interest. By standard results, the asymptotic distribution of the $\{k_t, d_t, \sigma_t\}$ estimates in Table 2 is multivariate normal and, by our independence assumption, is independent of ν and ρ estimates. The sample frequency $\hat{\nu}$ is bounded between zero and one and has asymptotic Beta distribution. To simplify programming, we draw Monte Carlo samples from the asymptotic distribution of the monotone log-odd ratio transformation $\ln(\hat{\nu}/(1-\hat{\nu}))$. Asymptotic maximum likelihood estimation of the log-odds ratio yields the sampling frequency as the $\hat{\nu}$ point estimate, and a normal asymptotic distribution. (The log-odds ratio point estimate is -3.708, with standard error 0.250.)

We use a similar approach to account for sampling variability in estimation of the target-change correlation parameter ρ introduced in Section 4.1. We estimate the model

$$\Delta\bar{r}_j = \frac{e^\xi}{1+e^\xi}\Delta\bar{r}_{j-1} + \text{error}_j,$$

by nonlinear least squares, thus ensuring that the estimate of $\rho = e^\xi/(1+e^\xi)$ lies between zero and one. We obtain an estimate $\xi = 1.030$ (or $\rho = 0.737$). The standard error of the (asymptotically normal) ξ estimate is 0.742.

C Performance of the expectations hypothesis

We consider an alternative framework where:

$$E_t(\Delta_{\bar{r}_t}) = E_t^*(\Delta_{\bar{r}_t}).$$

We further allow for time-varying premia ϕ_t which we assume to covariate positively with $E_t(\Delta_{\bar{r}_t})$ and $E_t(\Delta_{r_t-\bar{r}_t})$. Under these additional assumptions, when we regress the realized $\Delta_{\bar{r}_t}$ on our model's estimate of $E_t(\Delta_{\bar{r}_t})$, we obtain a slope coefficient, α', whose theoretical value is

$$\frac{\text{var}^*[E_t(\Delta_{\bar{r}_t})] + \text{cov}^*[\phi_t, E_t(\Delta_{\bar{r}_t})]}{\text{var}^*[E_t(\Delta_{\bar{r}_t})] + \text{var}^*(\phi_t) + 2\text{cov}^*[\phi_t, E_t(\Delta_{\bar{r}_t})]}.$$

Similarly, the theoretical coefficient of the expectations-hypothesis regression, α, becomes

$$\frac{\text{var}^*[E_t(\Delta_{\bar{r}_t})] + \text{var}^*[E_t(\Delta_{r_t-\bar{r}_t})] + \text{cov}^*[\phi_t, E_t(\Delta_{\bar{r}_t})] + \text{cov}^*[\phi_t, E_t(\Delta_{r_t-\bar{r}_t})]}{\text{var}^*[E_t(\Delta_{\bar{r}_t})] + \text{var}^*[E_t(\Delta_{r_t-\bar{r}_t})] + \text{var}^*(\phi_t) + 2\text{cov}^*[\phi_t, E_t(\Delta_{\bar{r}_t})] + 2\text{cov}^*[\phi_t, E_t(\Delta_{r_t-\bar{r}_t})]}.$$

Straightforward algebra shows that the theoretical value of α' is *greater* than the theoretical value of α if

$$\begin{aligned}\text{cov}^*[\phi_t, E_t(\Delta_{r_t-\bar{r}_t})] \quad & (\text{var}^*[E_t(\Delta_{\bar{r}_t})] - \text{var}^*(\phi_t)) \\ & > \text{var}^*[E_t(\Delta_{r_t-\bar{r}_t})](\text{var}^*(\phi_t) + \text{cov}^*[\phi_t, E_t(\Delta_{\bar{r}_t})]).\end{aligned}$$

This inequality is satisfied, for example, when the variability of $E_t(\Delta_{\bar{r}_t})$ is substantially greater than that of ϕ_t and $E_t(\Delta_{r_t-\bar{r}_t})$, while ϕ_t covariates strongly with $E_t(\Delta_{r_t-\bar{r}_t})$ and weakly with $E_t(\Delta_{\bar{r}_t})$.

D Serially correlated target changes

For any $s > t$ we have the definitional relation

$$E_t(r_s) \equiv E_t\left[(r_s - \bar{r}_s) + \bar{r}_t + \sum_{j=1}^{N_s-N_t} \Delta\bar{r}_j\right], \tag{D.1}$$

where N_s is the number of target changes between time zero and time s and $\Delta\bar{r}_j$ is the j-th target change after time t. Since changes occur with fixed daily probability ν, and their timing is independent of z_t, we can condition on their total number N_s and implement the known (binomial) form of the distribution of N_s:

$$E_t\left(\sum_{j=1}^{N_s-N_t}\Delta\bar{r}_j\right)=\sum_{n=1}^{s-t}\binom{s-t}{n}\nu^n(1-\nu)^{s-t-n}\,E_t\left(\sum_{j=1}^{n}\Delta\bar{r}_j\middle|N_s=N_t+n\right). \tag{D.2}$$

Using the law of iterated expectations on equation (4.1), the expected size of the jth target-change realization is

$$E_t(\Delta\bar{r}_j|n\geq j\geq 1)=\rho^{j-1}z_t, \tag{D.3}$$

hence

$$\begin{aligned}E_t\left(\sum_{j=1}^{N_s-N_t}\Delta\bar{r}_j\middle|N_s=N_t+n\right)&=\sum_{n=1}^{s-t}\binom{s-t}{n}\nu^n(1-\nu)^{s-t-n}\sum_{j=1}^{n}\rho^{j-1}z_t\\&=z_t\sum_{n=1}^{s-t}\binom{s-t}{n}\nu^n(1-\nu)^{s-t-n}\frac{1-\rho^n}{1-\rho}.\end{aligned} \tag{D.4}$$

Substituting (D.4) in (D.1), we find that

$$E_t(\bar{r}_s)=\bar{r}_t+z_t\left[\sum_{n=1}^{s-t}\binom{s-t}{n}\nu^n(1-\nu)^{s-t-n}\frac{1-\rho^n}{1-\rho}\right]. \tag{D.5}$$

Averaging this expression over the horizon relevant to an instrument of maturity τ yields a counterpart to (8)'s term-structure expression, with a loading on the next target-change expectation z_t given by

$$L^a_{z_t}\equiv\frac{1}{\tau}\sum_{s=t+1}^{t+\tau-1}\left[\sum_{n=1}^{s-t}\binom{s-t}{n}\nu^n(1-\nu)^{s-t-n}\frac{1-\rho^n}{1-\rho}\right]. \tag{11}$$

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Table 1. The fed funds-rate process: maximum likelihood estimates.

We estimate the model

$$r_t - \bar{r}_t - d_t = (1 - k_t)(r_{t-1} - \bar{r}_{t-1} - d_{t-1}) + \epsilon_t,$$

where r_t is the overnight fed funds rate; $\bar{r}_t$ is the target; d_t is a time-varying intercept parameter with biweekly periodicity; k_t is a time-varying parameter which regulates mean reversion towards the target, also with biweekly periodicity. The white-noise error term ϵ_t is allowed to display a biweekly seasonal heteroskedasticity pattern. The model is estimated by maximum likelihood under the assumption of normality, using daily data for the period 1987:11:05–1990:08:01. We report the Ljung-Box portmanteau statistic, Q, distributed chi-square (degrees of freedom in parenthesis). For each of the three sets of parameters $\{d_t\}$, $\{k_t\}$, and $\{\sigma_t\}$, we report likelihood-ratio test statistics λ_{LR} for the hypothesis of no biweekly seasonality. These statistics have chi-square distributions (degrees of freedom in parenthesis).

Statistics

$\bar{R}^2$	0.308
D-W	1.979
$Q(80)$	160.3

Parameter estimates

	Coefficient (s.e.)		Coefficient (s.e.)		Coefficient (s.e.)
k_1	0.274	d_1	0.053	σ_1	0.130
	(0.134)		(0.011)		(0.019)
k_2	0.476	d_2	-0.009	σ_2	0.138
	(0.107)		(0.012)		(0.019)
k_3	-0.213	d_3	0.081	σ_3	0.398
	(0.295)		(0.033)		(0.052)
k_4	0.759	d_4	0.104	σ_4	0.190
	(0.051)		(0.016)		(0.025)
k_5	0.763	d_5	0.043	σ_5	0.115
	(0.062)		(0.010)		(0.014)
k_6	0.120	d_6	0.084	σ_6	0.094
	(0.079)		(0.007)		(0.016)
k_7	0.297	d_7	0.070	σ_7	0.115
	(0.096)		(0.009)		(0.017)
k_8	0.349	d_8	0.019	σ_8	0.073
	(0.051)		(0.005)		(0.013)
k_9	0.577	d_9	0.026	σ_9	0.094
	(0.101)		(0.007)		(0.014)
k_{10}	0.103	d_{10}	0.003	σ_{10}	0.062
	(0.070)		(0.005)		(0.014)
$\lambda_{LR}(9)$	131.9	$\lambda^2_{LR}(9)$	62.8	$\lambda_{LR}(9)$	459.9

Table 2. A test of the expectations hypothesis

We estimate the model

$$\sum_{s=t}^{t+90} \frac{r_s}{91} - r_t = \alpha \left[R_t - r_t\right] - \phi_t + \eta_{t+90},$$

where R_t is the interest rate on a loan of maturity 91 days, ϕ_t is a time-varying intercept with biweekly seasonal periodicity which captures liquidity and term effects, and η_{t+90} is an expectational error. We use daily overlapping observations, and the standard errors (in parentheses) are adjusted for heteroskedasticity and serial correlation of moving-average form in the residuals η_{t+90} [see Hansen (1982)]. We report the Wald test statistic λ_W for the null hypothesis that $\phi_t = 0 \; \forall \; t$. The statistic is based on an adjusted estimated covariance matrix [Newey and West (1987)] and is distributed *chi*-square (degrees of freedom in parenthesis). The sample period is 1987:11:04–1990:05:04.

Statistics

R^2	0.371

Parameter estimates

	Coefficient (s.e.)
α	0.576
	(0.182)
ϕ_1	-0.003
	(0.068)
ϕ_2	0.035
	(0.068)
ϕ_3	-0.004
	(0.083)
ϕ_4	-0.019
	(0.067)
ϕ_5	0.007
	(0.063)
ϕ_6	-0.009
	(0.070)
ϕ_7	-0.002
	(0.070)
ϕ_8	0.018
	(0.068)
ϕ_9	0.018
	(0.068)
ϕ_{10}	0.024
	(0.057)
$\lambda_W(10)$	16.38

Figure 1. Overnight and Three-month Fed Funds Rates and Target

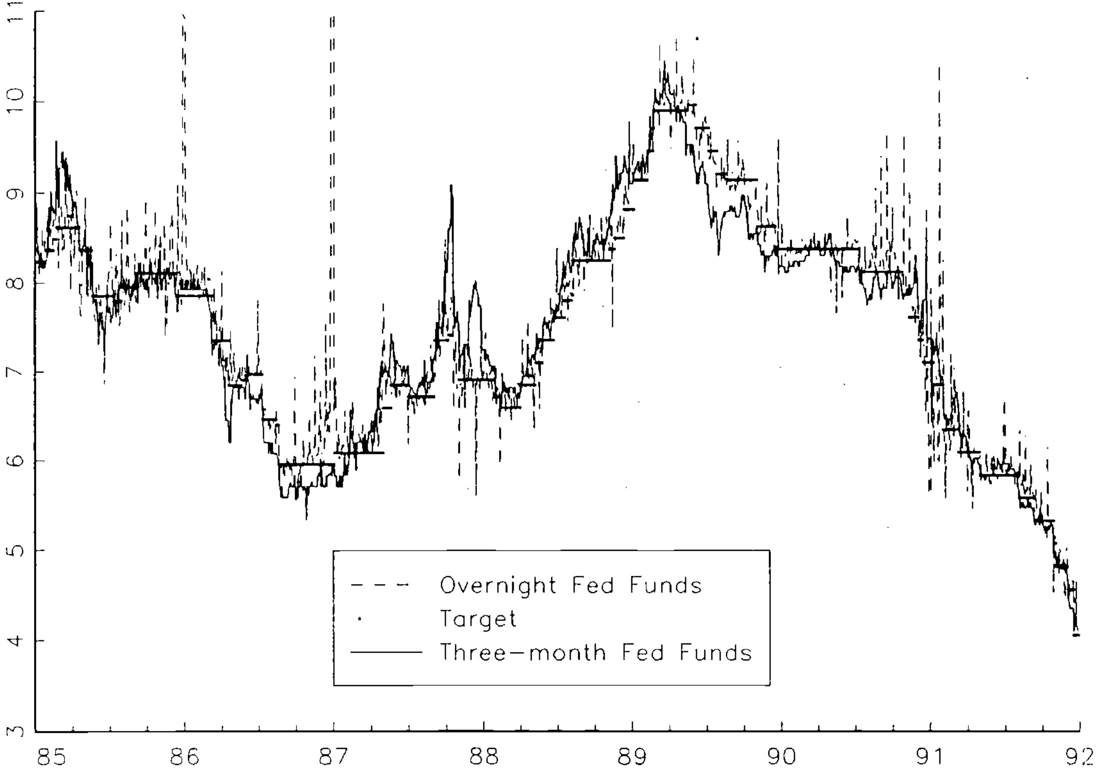


Figure 2. Autocorrelation Functions

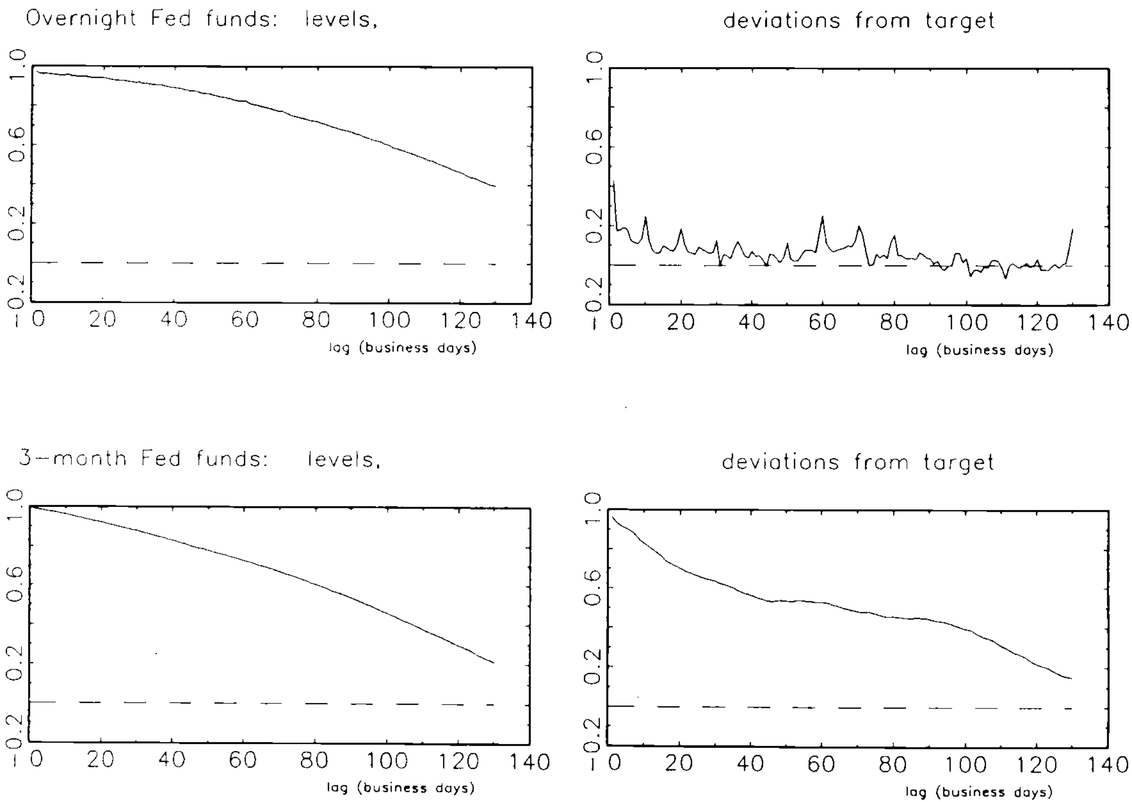
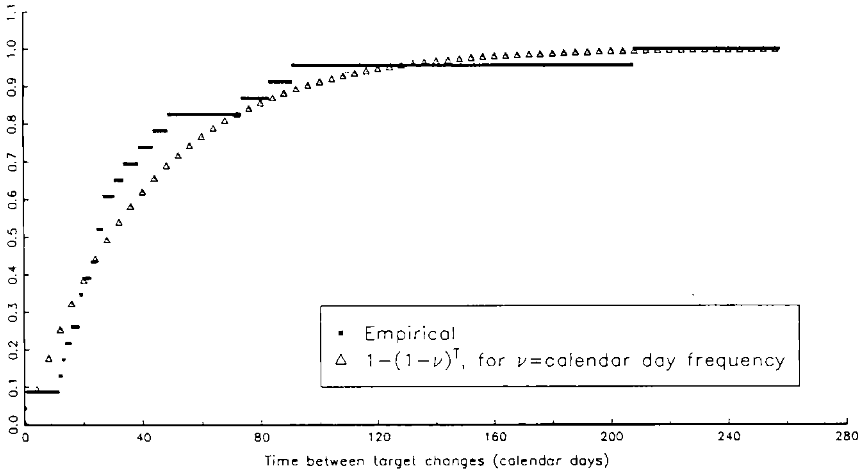


Figure 3: Empirical vs theoretical CDF of no-change spells

3.a: Calendar time

Kolmogorov–Smirnov statistic=0.71, p–value=29.81%



3.b: Business time

Kolmogorov–Smirnov statistic=0.67, p–value=24.05%

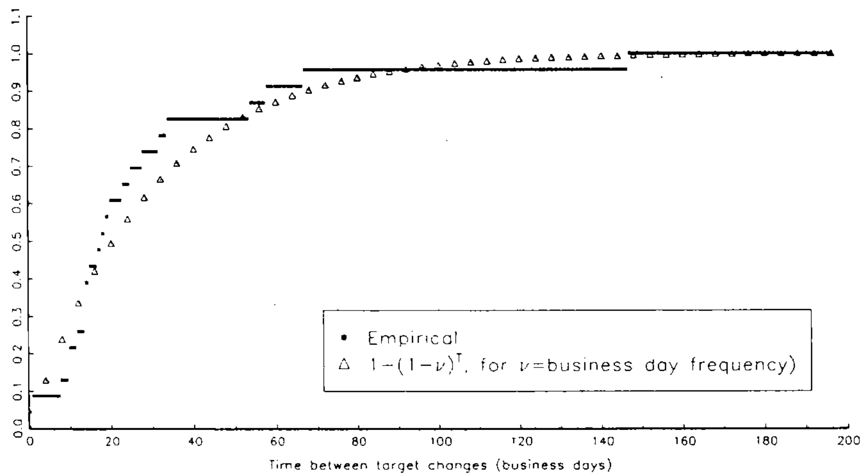


Figure 4. Expected Target Change

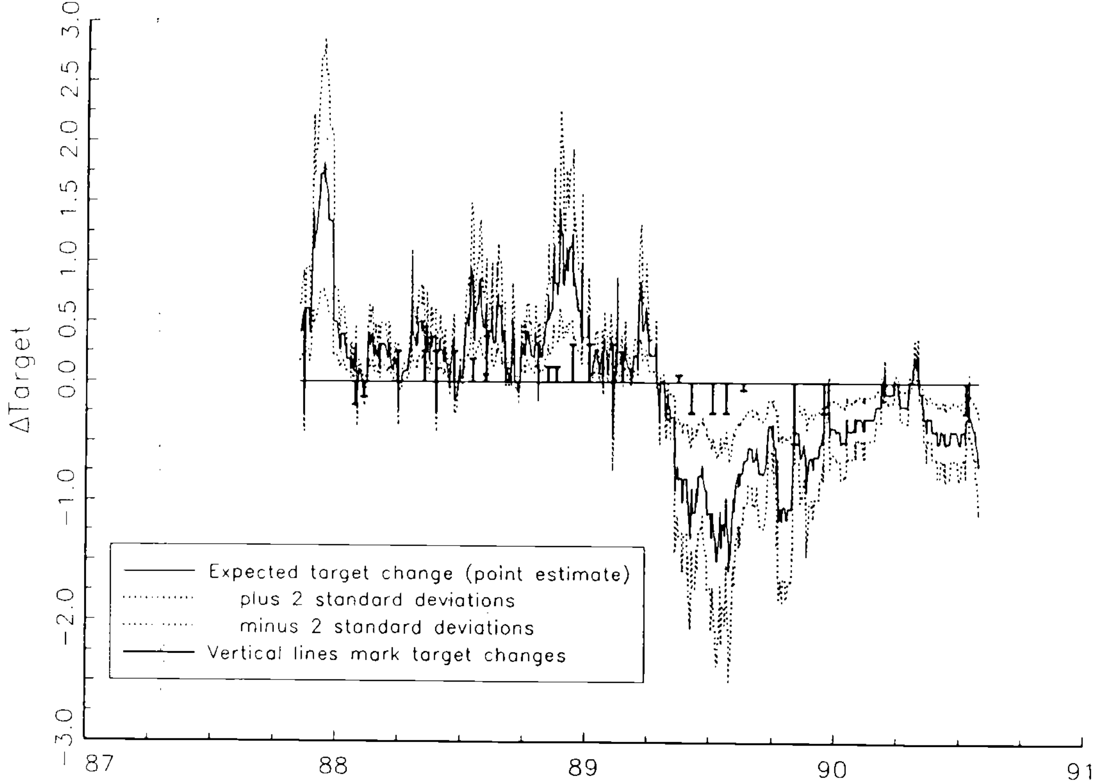


Figure 5. Expected Target Change. Autocorrelated Interventions