THE IMPORTANCE OF STOCK MARKET RETURNS IN ESTIMATED MONETARY POLICY RULES: A STRUCTURAL APPROACH *

Jesús Vázquez*, †
Universidad del País Vasco**

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†Correspondence to: Jesús Vázquez, Departamento de Fundamentos del Análisis Económico II, Universidad del País Vasco, Av. Lehendakari Aguirre 83, 48015 Bilbao, Spain. Phone: (34) 94-601-3779, Fax: (34) 94-601-7123, e-mail: jesus.vazquez@ehu.es

ABSTRACT

This paper estimates a standard version of the New Keynesian Monetary (NKM) model augmented with financial variables in order to analyze the relative importance of stock market returns and term spread in the estimated U.S. monetary policy rule. The estimation procedure implemented is a classical structural method based on the indirect inference principle. The empirical results show that the Fed seems to respond to the macroeconomic outlook and to the stock market return but does not seem to respond to the term spread. Moreover, policy inertia and persistent policy shocks are also significant features of the estimated policy rule.

1 INTRODUCTION

The analysis of how monetary policy reacts to financial markets news has started to receive considerable attention in recent years. On the one hand, there is a strand of literature (Gerlach-Kristen, 2004; Rudebusch and Wu, 2004; Ang, Dong and Piazzesi, 2005; and María-Dolores and Vázquez, 2005) estimating monetary policy rules that include the term spread (or a long-term interest rate) in addition to the traditional determinants (inflation and output gap) using quarterly data.[1] On the other hand, Rigobon and Sack (2003) estimate the reaction of U.S. monetary policy to the stock market using daily data whereas Rigobon and Sack (2004) study the impact of monetary policy on stock prices.

The aim of this paper is to analyze the relative importance of term spread and stock market returns in the characterization of the estimated U.S. monetary policy rule. A major problem in estimating the reaction of monetary policy to financial variables is that these variables are by nature endogenous due to the simultaneous response of financial markets to policy decisions. As pointed out by Rigobon and Sack (2003, 2004), the policy reaction is difficult to identify using traditional approaches for dealing with the endogeneity problem such as instrumental variables because it is hard to find any good instrument (i.e. an instrument very closely correlated with financial variables without being correlated with monetary policy shocks). Rigobon and Sack propose an identification scheme based on the heteroskedasticity of stock market returns at the daily frequency. By contrast, this paper estimates the U.S. policy rule using quarterly data to study the importance of financial variables in the policy rule. The sample frequency may matter when estimating the monetary policy reaction functions for two reasons. First, financial vari-

[1] Two key aspects distinguish these papers: (i) the way term structure is introduced and (ii) the structural econometric approach followed. Gerlach-Kristen (2004) uses a maximum-likelihood approach to directly estimate a reduced form policy rule that includes the term spread in addition to the explanatory variables considered in a standard Taylor rule. Rudebusch and Wu (2004) build upon a typical affine no-arbitrage term structure representation with two latent factors (level and slope) by linking, (admittedly) in an ad-hoc fashion, these two factors to macroeconomic variables (inflation and output gap) which are determined by a New Keynesian Monetary (NKM) model. They also follow a maximum-likelihood approach. In a similar vein, using little macroeconomic structure, Ang, Dong and Piazzesi (2005) consider a single latent factor interpreted as a transformation of Fed policy actions on the short rate. In their model, persistent policy shocks are allowed but policy inertia is not. Ang et al. (2005) implement a Bayesian estimation approach to estimate their macro-finance model of the term structure. In contrast to these papers, María-Dolores and Vázquez (2005) introduce term structure by simply considering a representative agent optimization problem allowing the agent to have access to bonds of different maturities. Moreover, they follow an indirect inference estimation approach.

ables may display quite different dynamics at alternative data frequencies. For instance, Diebold (1988) has shown analytically that ARCH effects tend to disappear as sample frequency decreases. Second, since the Federal Open Market Committee (FOMC) meets every six weeks, the estimated monetary policy rule based on quarterly data averages the policy decisions made at two FOMC meetings and the estimated policy rule is expected to be smoother as the sample frequency becomes smaller.

As noticed by Rigobon and Sack (2003), there is a recent debate in the relevant literature on the Fed motivation for reacting to movements in stock prices. On the one hand, Cecchetti, Genberg, Lipsky and Wadhwani (2000) argue that the monetary authority should react to perceived stock price misalignments in order to prevent stock market bubbles. On the other hand, Bernanke and Gertler (2001) suggest that the Fed should react to stock process just because they anticipate future movements in inflation and output.

Closely related with this debate, there is another major problem in estimating monetary policy rules that consider financial variables in addition to the standard variables entering a Taylor rule: the issue of disentangling the independent effect of financial variables on the policy rule from the indirect effect of these variables through expected inflation and expected output gap.

One possible way of overcoming these problems is to specify and structurally estimate a general equilibrium model in order to measure the reaction of monetary policy to alternative financial variables. We consider a model that builds upon the now-standard New-Keynesian Monetary (NKM) model by considering that the representative agent can accumulate stocks and bonds of different maturities. More precise, we build on the NKM model augmented with term structure studied by María-Dolores and Vázquez (2005) to include stock market returns. We also follow María-Dolores and Vázquez (2005) by considering (i) a structural econometric approach based on the *indirect inference* principle and (ii) three alternative specifications for the monetary policy rule called the standard, forward-looking and backward-looking Taylor rules. Considering these alternative policy specifications characterized by different degrees of forward-looking behavior allows us to assess whether monetary policy reacts independently to alternative financial variables or reacts to financial variables simply because these variables anticipate expected movements in output and inflation.

Using U.S. data for the Greenspan period, the empirical results show that the Fed seems to respond to the stock market excess return in addition to the standard macroeconomic indicators in a standard Taylor rule.[2] However,

[2]Given an investment horizon, the stock market excess return is defined in this paper

the Fed does not seem to respond to the term spread, confirming the results obtained by María-Dolores and Vázquez (2005). Moreover, the fact that the excess return is significant under a backward-looking and standard Taylor rule but not under a forward-looking rule suggests that the Fed may respond to the information content of the excess return about future inflation and real activity, but does not seem to respond independently to the excess return. Hence, the empirical results seem to support Bernanke and Gertler's (2001) argument that the Fed responds to stock market movements only to the extent that they affect expectations about future inflation and output. Furthermore, the empirical results show that policy inertia and persistent policy shocks are also significant features of the estimated policy rule.

The rest of the paper is organized as follows. Section 2 introduces the log-linearized approximation of a standard version of the NKM augmented with term spread and stock returns. Section 3 describes the structural estimation method used in this paper. Section 4 presents and discusses the estimation results. Section 5 provides diagnostic tests and comovement analyses to identify features of the data that the augmented NKM model does (not) account for. Section 6 concludes.

2 A NEW KEYNESIAN MONETARY MODEL WITH FINANCIAL VARIABLES

The model analyzed in this paper is a now-standard version of the NKM model augmented with financial variables (NKMMFV), which is given by the following set of equations:

$$y_t = E_t y_{t+1} - \tau(i_t - E_t \pi_{t+1}) + g_t, \tag{1}$$

$$y_t = E_t y_{t+4} - \tau(i_t^{\{4\}} - E_t \pi_{t+4}) + c_t, \tag{2}$$

$$y_t = E_t y_{t+4} - \tau(r_t^{\{4\}} - E_t \pi_{t+4}) + s_t, \tag{3}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa y_t + z_t, \tag{4}$$

$$i_t = \rho i_{t-1} + (1-\rho)[\psi_1 \pi_t + \psi_2 y_t + \psi_3 (i_t^{\{4\}} - i_t) + \psi_4 (r_t^{\{4\}} - i_t^{\{4\}})] + v_t. \tag{5}$$

where y, π, $i^{\{4\}}$ and $r_t^{\{4\}}$denote the log-deviations from the steady states of output, inflation, nominal interest rate associated with the four-period bond and expected nominal return associated with a stock that is sold four periods

as the difference between the stock market return and the interest rate associated with a Treasury bond.

after its time of purchase (i.e. the expected payoff at time $t+4$), respectively. E_t denotes the conditional expectation based on the agents' information set at time t. g, c and s, denote aggregate demand shocks associated with the three alternative IS-curves whereas z and v denote aggregate supply and monetary policy shocks, respectively. Each of these shocks is further assumed to follow a first-order autoregressive process

$$g_t = \rho_g g_{t-1} + \epsilon_{gt}, \tag{6}$$

$$c_t = \rho_c c_{t-1} + \epsilon_{ct}, \tag{7}$$

$$s_t = \rho_s s_{t-1} + \epsilon_{st}, \tag{8}$$

$$z_t = \rho_z z_{t-1} + \epsilon_{zt}, \tag{9}$$

$$v_t = \rho_v v_{t-1} + \epsilon_{vt}, \tag{10}$$

where ϵ_{gt}, ϵ_{ct}, ϵ_{st}, ϵ_{zt} and ϵ_{vt} denote i.i.d. random shocks. We further allow for correlation between ϵ_{gt}, ϵ_{ct} and ϵ_{st} shocks.

As discussed by Ireland (2004), there is a long standing tradition (that goes back at least to Sargent, 1989) of introducing additional disturbances into dynamic stochastic general equilibrium models until the number of shocks equals the number of data series used in the estimation. The reason is that models of this type are quite stylized and introduce fewer shocks than observable variables, which implies that models are stochastically singular. That is, the model implies that certain combinations of endogenous variables are deterministic. If these combinations do not hold in the data, any approach attempting to estimate the complete model will fail. To cope with this stochastic singularity problem, we consider that the shocks are different due to measurement errors and the approximation error that results from the log-linear approximation implemented.[3]

Equations (1) (2) and (3) are the log-linearized Euler conditions obtained from the representative agent optimization plan associated with the one-period bond rate, the four-period bond rate and the four-period stock return, respectively. More precisely, for any asset i the agent optimal plan requires the basic pricing equation to hold:

$$E_t \left[\beta^j \frac{U'(C_{t+j})}{U'(C_t)} R_{it}^{\{j\}} \right] = 1,$$

where j is the horizon of the payoff of asset i, C_t is consumption at t, and $R_{it}^{\{j\}}$ is the j-period realized return from t to $t+j$ of asset i. The parameter $\tau > 0$

[3]See also Hamilton (1994, p.426) for a lucid discussion on the need to add error terms to behavioral equations and its consequences on econometric identification.

in equations (1)-(3) represents the intertemporal elasticity of substitution obtained when assuming a standard constant relative risk aversion utility function

$$U(C_t) = \frac{1}{1-\frac{1}{\tau}} C_t^{1-\frac{1}{\tau}}.$$

As shown by Andrés, López-Salido and Nelson (2004), implicitly in the Euler equations associated with bond holdings at different maturities is a term structure relationship linking the interest rates on short- and long-term bonds. Similarly, by considering stock holdings in addition to bond holdings, the set of asset pricing equations (1)-(3) is implicitly linking bond yields and stock returns.[4]

Equation (2) is the new Phillips curve that is obtained in a sticky price à la Calvo (1983) model where monopolistically competitive firms produce (a continuum of) differentiated goods and each firm faces a downward sloping demand curve for its produced good. The parameter $\beta \in (0, 1)$ is the agent discount factor and κ measures the slope of the New Phillips curve.[5]

Equation (5) is a standard Taylor-type monetary rule where the nominal interest rate exhibits inertial behavior, captured by parameter ρ, for which there are several motivating arguments in the relevant literature.[6] Moreover, the monetary policy rule (5) assumes that the nominal interest rate responds to (i) current deviations of output and inflation from their respective steady state values; (ii) term spread, $i_t^{\{4\}} - i_t$; and (iii) excess return of stocks $r_t^{\{4\}} -$

[4] Most papers in the relevant literature use the one-period asset pricing equation (1) to derive recursively the prices of all assets in the economy by assuming that state variables are log-normal instead of considering a set of asset pricing equations associated with alternative financial assets. By considering a set of asset pricing equations, our approach allows the researcher to deviate from the log-normality setup by applying high-order approximation techniques to solve the model. The disadventage is that the consideration of long-term investment horizons implies that the number of state variables increases dramatically. For instance, if we consider the 10-year maturity bond rate Γ_0 and Γ_1 defined below would be 90×90 matrices. Nevertheless, the approach carried out in this paper is rather similar in practice to the one followed in the literature because state-variables are also lognormal by construction: (i) a log-linear approximation is used for solving the model and (ii) the shocks are assumed to follow normal distributions.

[5] See, for instance, Galí (2002) for a detailed analytical derivation of the New Phillips curve.

[6] These arguments range from the traditional concern of central banks for the stability of financial markets (see Goodfriend, 1991 and Sack, 1997) to the more psychological argument posed by Lowe and Ellis (1997) that there might be a political incentive for smoothing whenever policymakers are likely to be embarrassed by reversals in the direction of interest-rate changes if they believe that the public may interpret them as repudiations of previous actions. By contrast, a series of interest-rate changes in the same direction looks like a well-designed programme, and that may give rise to the sluggish behavior of the intervention interest rate.

$i_t^{\{4\}}$. For the sake of simplicity we further assume that the one-period bond and the policy interest rate are the same.[7]

Alternatively, we also consider a forward-looking Taylor rule

$$i_t = \rho i_{t-1} + (1-\rho)[\psi_1 E_t \pi_{t+1} + \psi_2 E_t y_{t+1} + \psi_3 (i_t^{\{4\}} - i_t) + \psi_4 (r_t^{\{4\}} - i_t^{\{4\}})] + v_t, \quad (11)$$

and a backward-looking Taylor rule

$$i_t = \rho i_{t-1} + (1-\rho)[\psi_1 \pi_{t-1} + \psi_2 y_{t-1} + \psi_3 (i_{t-1}^{\{4\}} - i_{t-1}) + \psi_4 (r_{t-1}^{\{4\}} - i_{t-1}^{\{4\}})] + v_t. \quad (12)$$

By considering alternative policy rule specifications, the term spread in the estimated policy rule and a structural estimation procedure, we expect to shed light on a relevant question: does the Fed respond only to the information content of financial variables about future inflation and real activity, or does it respond independently to them?

The use of a structural econometric strategy to estimate monetary policy rules can be further motivated as follows. As pointed out by Clarida, Galí and Gertler (1999), the forward-looking Taylor rule can be solved in order to get a reduced-form for the interest rate in terms of predetermined variables. At first sight, this reduced-form looks like standard and backward-looking Taylor rules, but the difference is that the coefficients associated with the reduced-form of the forward-looking rule are cumbersome functions linking structural and policy parameters. More precisely, the reduced-form coefficients associated with the forward-looking rule must satisfy a set of cross-equation restrictions imposed by the rational expectations assumption. Therefore, alternative policy rules are not likely to be statistically identical and a structural (system-based) econometric procedure is then required to discriminate between alternative monetary policy rules. Later on, Section 5 provides evidence that the alternative policy rules lead to different dynamic features in terms of persistence and the comovement dynamics exhibited by pairs of variables.

The system of equations (1)-(10) (together with eight extra identities involving forecast errors) can be written in matrix form as follows

$$\Gamma_0 X_t = \Gamma_1 X_{t-1} + \Psi \epsilon_t + \Pi \eta_t, \quad (13)$$

[7] This assumption is not very harmful when using quarterly data since the 3-month T-bill rate dynamics are similar to the Fed rate dynamics, which is the short-term rate used by the Fed to monitor monetary policy. More precisely, the sample correlation between these two interest rates is 0.994 during the Greenspan era.

where[8]

$$
\begin{aligned}
X_t &= (y_t, \pi_t, i_t, i_t^{\{4\}}, r_t^{\{4\}}, E_t y_{t+1}, E_t y_{t+2}, E_t y_{t+3}, E_t y_{t+4}, E_t \pi_{t+1}, \\
&\quad E_t \pi_{t+2}, E_t \pi_{t+3}, E_t \pi_{t+4}, g_t, c_t, s_t, z_t, v_t)'
\end{aligned}
$$

$$
\epsilon_t = (\epsilon_{gt}, \epsilon_{ct}, \epsilon_{st}, \epsilon_{zt}, \epsilon_{vt})',
$$

$$
\begin{aligned}
\eta_t &= (y_t - E_{t-1}[y_t], E_t[y_{t+1}] - E_{t-1}[y_{t+1}], E_t[y_{t+2}] - E_{t-1}[y_{t+2}], \\
&\quad E_t[y_{t+3}] - E_{t-1}[y_{t+3}], \pi_t - E_{t-1}[\pi_t], E_t[\pi_{t+1}] - E_{t-1}[\pi_{t+1}], \\
&\quad E_t[\pi_{t+2}] - E_{t-1}[\pi_{t+2}], E_t[\pi_{t+3}] - E_{t-1}[\pi_{t+3}])'.
\end{aligned}
$$

Equation (13) represents a linear rational expectations (LRE) system. It is well known that LRE systems deliver multiple stable equilibrium solutions for certain parameter values. Lubik and Schorfheide (2003) characterize the complete set of LRE models with indeterminacies and provide a numerical method for computing them that builds on Sims' (2002) approach.[9] In this paper, we deal only with sunspot-free equilibria.[10]

3 ESTIMATION PROCEDURE

In order to estimate the structural and policy parameters of the NKMMFV, we follow the *indirect inference* principle proposed by Gouriéroux, Monfort and Renault (1993), Smith (1993), and Gallant and Tauchen (1996). Following Smith (1993), an unrestricted VAR representation is considered as the auxiliary model. More precisely, we first estimate a five-variable VAR with four lags in order to summarize the joint dynamics exhibited by U.S. quarterly data on output gap, inflation, Fed funds rate, 1-year Treasury constant maturity rate and 1-year ex-post Standard & Poor's stock market returns.

[8] Appendix 1 displays the matrices Γ_0, Γ_1, Ψ and Π.

[9] The GAUSS code for computing equilibria of LRE models can be found on Frank Schorfheide's website.

[10] Lubik and Schorfheide (2003) deal with multiple equilibria by assuming that agents observe an exogenous sunspot shock ζ_t, in addition to the fundamental shocks, ϵ_t. Since an LRE system such as (13) is linear, the forecast errors, η_t, can be expressed as a linear function of ϵ_t and ζ_t : $\eta_t = A_1\epsilon_t + A_2\zeta_t$, where A_1 is 8×5 and A_2 is 8×1 in this model. There are three possible scenarios: (i) no stable equilibrium; (ii) a unique stable equilibrium in which A_1 is completely determined by the structural parameters of the model and $A_2 = 0$; and (iii) multiple stable equilibria in which A_1 is not uniquely determined by the structural parameters of the model and A_2 can be non-zero. In this last case, one can deal only with a stable sunspot-free equilibrium by imposing $A_2 = 0$ and then the corresponding equilibrium can be understood as a sunspot equilibrium with no sunspots.

Second, we apply the simulated moments estimator (SME) suggested by Lee and Ingram (1991) and Duffie and Singleton (1993) to estimate the underlying structural and policy parameters of the NKMMFV.[11]

This estimation strategy is especially appropriate in this context for three main reasons.[12] First, we must emphasize that the NKMMFV is a highly stylized model of a complex world. Therefore, maximum-likelihood (ML) estimation of the model will impose strong restrictions which are not satisfied by the data and inference will be misleading. In the words of Cochrane (2001, p. 293) "[*ML*] *does the "right" efficient thing if the model is true. It does not necessarily do the "reasonable" thing for "approximate" models.*" We believe that one of the main virtues of the indirect inference approach is that the econometrician has in principle the possibility of choosing an auxiliary model that imposes looser restrictions than those imposed by ML. Second, we consider an unrestricted VAR instead of matching the structural impulse responses because a reduced form VAR does not require the arbitrary identification of structural shocks. Moreover, applications of the minimum distance estimator based on impulse response functions use a diagonal weighting matrix that includes the inverse of each impulse response's variance on the main diagonal. This weighting matrix delivers consistent estimates of the structural parameters, but it is not asymptotically efficient since it does not take into account the whole covariance matrix structure associated with the set of moments.[13] By considering the VAR coefficients as the set of moments to implement the minimum distance estimator, an estimator of the efficient weighting matrix is found to be straightforward.[14] Finally, the unrestricted VAR auxiliary model nests the NKMMFV model considered. As shown by Gallant and Tauchen (1996), if the auxiliary model nests the structural model then the estimator is as efficient as ML. Moreover, the estimation approach based on the indirect inference principle may help to identify which structural parameter estimates are forced outside the economically reasonable support (for instance, the prior distribution support

[11] In this vein, Rotemberg and Woodford (1997), Amato and Laubach (2003), Christiano, Eichenbaum and Evans (2005), and Boivin and Giannoni (2006) use a minimum distance estimator based on impulse-response functions instead of VAR coefficients. See Gutiérrez and Vázquez (2004), Ruge-Murcia (2003), María-Dolores and Vázquez (2005) for other recent applications of this estimation strategy based on VAR coefficients.

[12] At this point, the reader may have the following three questions in mind. Why do we not estimate the NKM model by maximum-likelihood directly? Why do we use a VAR as the auxiliary model? What do we learn from the estimation of the NKM model based on the indirect inference principle? This paragraph answers these three questions.

[13] Boivin and Giannoni (2006) indicate this drawback, but provide no alternative.

[14] See Duffie and Singleton (1993, p.939) for a discussion on the choice of a weighting matrix in order to obtain asymptotic efficient estimates.

used by Bayesian estimator applications) to achieve a better fit of the model.

The SME makes use of a set of statistics computed from the data set used and from a number of different simulated data sets generated by the model being estimated, i.e. the statistics used to carry out the SME are the coefficients of the five-variable VAR with four lags, which is considered as the auxiliary model in this paper. The lag length considered is fairly reasonable when using quarterly data. To implement the method, we construct a $p \times 1$ vector with the coefficients of the VAR representation obtained from actual data, denoted by $H_T(\theta_0)$, where p in this application is 120,[15] T denotes the length of the time series data, and θ is a $k \times 1$ vector whose components are the model parameters. The true parameter values are denoted by θ_0. In the NKMMFV, the structural and policy parameters are $\theta = (\tau, \beta, \rho, \kappa, \psi_1, \psi_2, \psi_3, \psi_4, \rho_g, \rho_c, \rho_s, \rho_z, \rho_v, \rho_{cg}, \rho_{sg}, \sigma_g, \sigma_c, \sigma_s, \sigma_z, \sigma_\varepsilon, \pi^*)$ and then $k = 21$. ρ_{cg} and ρ_{sg} denote the coefficients characterizing the noisy linear relationships between ϵ_{gt} and ϵ_{ct} shocks and between ϵ_{gt} and ϵ_{st} shocks, respectively.[16]

As pointed out by Lee and Ingram (1991), the randomness in the estimator is derived from two sources: the randomness in the actual data and the simulation. The importance of the randomness in the simulation to the covariance matrix of the estimator can be decreased by simulating the model a large number of times. For each simulation a $p \times 1$ vector of VAR coefficients, denoted by $H_{N,i}(\theta)$, is obtained from the simulated time series of output gap, inflation, interest rates and stock return generated from the NKMMFV, where $N = nT$ is the length of the simulated data. Averaging the m realizations of the simulated coefficients, i.e. $H_N(\theta) = \frac{1}{m}\sum_{i=1}^{m} H_{Ni}(\theta)$, we obtain a measure of the expected value of these coefficients, $E(H_{Ni}(\theta))$.

The choice of values for n and m deserves some attention. Gouriéroux, Renault and Touzi (2000) suggest that is important for the sample size of synthetic data to be identical to T (that is, $n = 1$) to get identical size of finite sample bias in estimators of the auxiliary parameters computed from actual and synthetic data. After checking for robustness, we make $n = 1$ and $m = 500$ in this application.

To generate simulated values of output gap, inflation, interest rates and stock returns we need the starting values of these variables. For the SME to be consistent, the initial values must have been drawn from a stationary distribution. In practice, to avoid the influence of the starting values we generate a realization from the stochastic processes of the five variables of

[15] We have 105 coefficients from a four-lag, five-variable system and 15 extra coefficients from the non-redundant elements of the variance-covariance matrix of the VAR residuals.

[16] We have also allowed for correlation between ϵ_{gt} shock and ϵ_{zt}, but the correlation parameter turns out to be non-significant.

length $200 + T$, discard the first 200 simulated observations, and use only the remaining T observations to carry out the estimation. After two hundred observations have been simulated, the influence of the initial conditions must have disappeared.

The SME of θ_0 is obtained from the minimization of a distance function of VAR coefficients from actual and simulated data. Formally,

$$\min_{\theta} \; J_T = [H_T(\theta_0) - H_N(\theta)]' W [H_T(\theta_0) - H_N(\theta)],$$

where W^{-1} is the covariance matrix of $H_T(\theta_0)$.

Denoting the solution of the minimization problem by $\hat{\theta}$, Lee and Ingram (1991) and Duffie and Singleton (1993) prove the following results:

$$\sqrt{T}(\hat{\theta} - \theta_0) \to N \left[0, \left(1 + \frac{1}{m} \right) (B'WB)^{-1} \right],$$

$$\left(1 + \frac{1}{m} \right) T J_T \to \chi^2(p - k),$$

where B is a full rank matrix given by $B = E(\frac{\partial H_{Ni}(\theta)}{\partial \theta})$.[17]

4 EMPIRICAL EVIDENCE

This section starts by briefly describing the data set considered, then goes on to discuss the estimation results.

4.1 The data

We consider quarterly U.S. data for the output gap, the inflation rate obtained for the implicit GDP deflator, the Fed funds rate, the 1-year Treasury constant maturity rate and the 1-year ex-post return from the Standard &

[17] The objective function J_T is minimized using the optimization package OPTMUM programmed in GAUSS language. The Broyden-Fletcher-Glodfard-Shanno algorithm is applied. To compute the covariance matrix we need to obtain B. Computation of B requires two steps: first, obtaining the numerical first derivatives of the coefficients of the VAR representation with respect to the estimates of the structural parameters θ for each of the m simulations; second, averaging the m-numerical first derivatives to get B. The GAUSS programs for estimating the NKMMFV are available from the author upon request.

Poor's stock market indexes during the Greenspan era.[18] We focus on the Greenspan period for several reasons. First, it allows a more straightforward comparison of the estimated monetary policy rules of Gerlach-Kristen (2004), Rudebusch and Wu (2004) and María-Dolores and Vázquez (2005). Second, the Taylor rule seems to fit better in this period than in the pre-Greenspan era. Third, considering the pre-Greenspan era opens the door to many other issues studied in the relevant literature, including the presence of macroeconomic switching regimes and the existence of switches in monetary policy (see for instance, Sims and Zha, 2004, and references therein). These issues are outside the scope of this paper. Figure 1 shows the time series studied in this paper.

4.2 Estimation results

Table 1 shows the estimation results under the standard, forward-looking and backward-looking Taylor rules. The values of the goodness-of-fit statistic, $\left(1+\frac{1}{m}\right)TJ_T$, which is distributed as a $\chi^2(p-k)$,[19] confirm the hypothesis stated above that the NKMMFV is too stylized to be supported by actual data. The best fit is obtained under a backward-looking Taylor rule.

At this point the reader may wonder why we should consider a model that does not fit the data well. Moreover, he/she may wonder why it is of interest to look at parameter estimates when the model is misspecified. I believe it is a worthwhile econometric exercise to estimate misspecified models because we can gain confidence on which parameters can be robustly estimated by estimating the model under alternative specifications (for instance, under alternative specifications of the policy rule).[20]

In order to discriminate between alternative policy rules it is also important to look at the parameters measuring shock persistence. Since the estimation procedure forces the shock processes to be stationary, the finding of a near-random walk process may indicate that the specified model is flawed. Except for ρ_s, the coefficients measuring the persistence of shocks

[18] U.S. output gap is measured as the percentage deviation of GDP from the real potential GDP time series constructed by the U.S. Congressional Budget Office. Appendix 2 describes the data sources.

[19] For the NKMMFV the goodness-of-fit statistic is distributed as a $\chi^2(99)$ since the number of VAR coefficients is $p = 120$ and the number of parameters being estimated is $k = 21$.

[20] This econometric exercise is valuable for precisely the same reason that policy analysis is believed to be worthwhile when performed in a misspecified framework. That is, one gains confidence on the policy prescriptions implied by a misspecified model only if they are fairly robust to alternative specifications.

are significantly different from a stationary, but highly persistent, alternative hypothesis (such as, $\rho_i = 0.99$ for $i = g, c, z, v$) at any standard significance level under the backward-looking and forward-looking Taylor rules. However, this is not the case for the monetary policy shock under the standard rule.

Focusing on the parameter estimates, we observe that (i) the relative aversion parameter, τ, and the Phillips curve slope parameter, κ, are poorly estimated for all three policy rule specifications since their standard errors are large; (ii) the estimate of the discount factor, β, is reasonable (implying a 3% real interest rate) for all policy rules considered and significantly different from one; (iii) the size of the policy response to inflation, output gap and stock market excess return depend on the policy rule considered. Result (iii) is not surprising at all since the Fed is reacting to different information sets under the alternative policy rule specifications; (iv) the coefficients associated with policy inertia (ρ) and the persistency of policy shocks (ρ_v) are significant at any standard significance level. However, the coefficient associated with the term spread (ψ_3) is not significant under any policy rule; in fact the point estimate is zero; (v) the fact that the excess return is significant under backward-looking and standard Taylor rules but not under a forward-looking rule suggests that the Fed may respond to the information content of the excess return about future inflation and real activity, but does not seem to respond independently to the excess return. Apart from the estimation results related to the stock market return, the empirical results obtained in this paper are qualitatively similar to those found by María-Dolores and Vázquez (2005) for the NKM model augmented with term structure.

5 MODEL PERFORMANCE

Based on the J-Wald test, we have concluded above that the overall performance of the alternative versions of the NKM considered is not good. This result does not mean that the model fails in all interesting dimensions. In this section, we consider diagnostic tests and comovement analysis to identify features of the data that the NKMMFV does (not) account for.

5.1 Diagnostic tests

The components of the vector $[H_T(\theta_0) - H_N(\theta)]$ contain information on how well the NKMMFV accounts for the estimates of the VAR (auxiliary) model. Larger components point to the estimates of the auxiliary model that the NKMMFV has trouble accounting for. As suggested by Gallant, Hsieh and

Tauchen (1997) the following quasi-t-ratio diagnostic statistics can identify sources for model failure:

$$\sqrt{1+\frac{1}{n}}\sqrt{T}\left[\left(diag(W_T^{-1})\right)_i^{1/2}\right]^{-1}[H_T(\theta_0)-H_N(\theta)]_i \quad \text{for} \quad i=1,...,p, \quad (14)$$

where W_T is a consistent estimate of W, $\left(diag(W_T^{-1})\right)_i$ denotes the i-th element of the diagonal of matrix W_T^{-1} and $[H_T(\theta_0)-H_N(\theta)]_i$ is the i-th element of $[H_T(\theta_0)-H_N(\theta)]$. In particular, a large i-th diagnostic statistic indicates that the NKMMFV does a poor job of fitting the i-th coefficient of the VAR model.

The second and third columns in Table 2 show the VAR estimates and the corresponding standard errors, respectively. The remaining columns in Table 2 show the corresponding quasi-t-ratio diagnostic statistic (14) for the alternative policy rules studied. Looking at Table 2 three general conclusions emerge. First, the qualitative results from the diagnostic statistics are quite robust to alternative specifications of the policy rule. Second, the NKMMFV has trouble in accounting for output gap, inflation, Fed rate and the 1-year rate persistence since for each of these equations some of the diagnostic statistics associated with dependent variable lags are large. However, the NKMMFV under the forward- and the backward-looking Taylor rule is capable of capturing the persistent dynamics exhibited by the 1-year stock return.

5.2 Comovement analysis

Den Haan (2000) proposes using correlations of *VAR* forecast errors at different horizons to analyze the comovement between pairs of variables. As discussed by Den Haan (2000), this method has two main advantages. First, variables need not be stationary for their comovement to be analyzed, so prior filtering is not required. Second, it avoids the type of *ad-hoc* assumptions necessary to compute impulse response functions. Since the comovement between a pair of variables is an equilibrium outcome (that is, an outcome resulting from the interaction between supply and demand shocks that is observed in the data with no need for any identifying assumption) comovement dynamics are good statistics for analyzing a model's performance.

We apply the method suggested by Den Haan to analyze the comovement between (i) the level of economic activity measured by the output gap and inflation; and (ii) the Fed funds rate and the 1-year stock return. The goal is to analyze the ability of the NKMMFV to replicate the type of comovement between pairs of variables observed in U.S. data.

Figures 2-4 show the comovement between output gap and inflation for the NKMMFV under the standard, backward-looking and forward-looking Taylor rules, respectively. Similarly, Figures 5-7 show the comovement between the Fed funds rate and the 1-year stock return under the standard, backward-looking and forward-looking Taylor rules, respectively.[21] In each figure, the solid line represents the estimated correlations at different forecast horizons using U.S. data, the lines with long dashes are 95% confidence bands computed using bootstrap methods and the line with short dashes is the correlation coefficients implied by the model. Figures 2-4 show the presence of a weak comovement between output and inflation in the U.S. Moreover, Figure 2 shows that the NKMMFV under the standard Taylor rule fails to reproduce the weak negative comovement between output gap and inflation at the short-term forecast horizons (up to six quarters). Figures 3-4 show that results are much worse for the NKMMFV under the backward- and forward-looking rules: the model generates a strong negative comovement between output and inflation that is not displayed by actual U.S. data.

Figures 5-7 show a weak comovement between the Fed rate and the 1-year stock return for the U.S. data at any forecast horizon that it is well reproduced by the NKMMFV under the alternative policy rules.

6 CONCLUSIONS

This paper follows a system-based econometric approach to analyze the importance of stock market returns in the characterization of the estimated U.S. monetary policy rule. The framework considered is an NKM model augmented with financial variables (NKMMFV) where the monetary policy rule is one of the building blocks. A structural econometric approach based on the *indirect inference* principle is implemented. In order to study the robustness of the empirical results, three alternative specifications for the monetary policy rule are considered, called standard, forward-looking and backward-looking Taylor rules.

The paper also investigates the ability of the NKMMFV to reproduce two features observed in U.S. data, namely the weak comovement between output and inflation and the persistent dynamics exhibited by output gap, inflation, interest rates and stock market returns.

The empirical results show that the Fed seems to respond to the stock market excess return in addition to the macroeconomic indicators in a standard Taylor rule. However, the Fed does not seem to respond to the term

[21] See Den Haan (2000) for details on this method of analyzing comovement.

spread, confirming the results obtained by María-Dolores and Vázquez (2005). Moreover, the fact that the stock market excess return is significant under backward-looking and standard Taylor rules but not under a forward-looking rule suggests that the Fed may respond to the information content of stock returns about future inflation and real activity, but does not seem to respond independently to the stock return movements. The empirical results then seem to support Bernanke and Gertler's (2001) view that the Fed responds to stock market movements only to the extent that they affect expectations about future inflation and output. Furthermore, the empirical results show that policy inertia and persistent policy shocks are also significant features of the estimated policy rule.

Finally, we show that the NKMMFV under a standard Taylor rule is able to reproduce well the weak comovement between output and inflation at medium- and long-term forecast horizons but fails to mimic the weak negative comovement at the short-term forecast horizons. Moreover, the model is able to mimic the weak comovement between the Fed funds rate and the 1-year stock return observed in actual data. Furthermore, diagnostic tests show that the model fails to reproduce the highly persistent dynamics characterizing U.S. output gap, inflation, Fed rate and 1-year rate time series, but it is able to reproduce the persistent dynamics exhibited by the actual 1-year stock market return.

Our empirical results should be interpreted with caution since the structural NKMMFV studied, like any other dynamic stochastic general equilibrium model, is likely to be misspecified in several dimensions. As is well known (see, for instance, Lubik and Schorfheide, 2005), overall model specification is important since it may lead to biased estimates, prevent identification of the true structural parameters and affect model selection. In spite of these warnings, the estimation of the NKMMFV looks like a reasonable approach for empirically analyzing the interaction between monetary policy, the macroeconomy and financial markets.

APPENDIX 1

This appendix shows the matrices involved in equation (13).

$$
\Gamma_0 = \begin{pmatrix}
1 & 0 & \tau & 0 & 0 & -1 & 0 & 0 & 0 & -\tau & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & \tau & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & -\tau & 0 & -1 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & \tau & 0 & 0 & 0 & -1 & 0 & 0 & 0 & -\tau & 0 & 0 & -1 & 0 & 0 \\
-\kappa & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\beta & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 0 \\
\Gamma_0^{51} & \Gamma_0^{52} & \Gamma_0^{53} & \Gamma_0^{54} & \Gamma_0^{55} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0
\end{pmatrix},
$$

$$
\Gamma_1 = \begin{pmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \rho & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_g & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_c & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_s & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_z & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_v \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0
\end{pmatrix},
$$

$$
\Pi = \begin{pmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix},
$$

$$
\Psi = \begin{pmatrix}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix},
$$

where $\Gamma_0^{51} = -(1-\rho)\psi_2$, $\Gamma_0^{52} = -(1-\rho)\psi_1$, $\Gamma_0^{53} = 1 + (1-\rho)\psi_3$, $\Gamma_0^{54} = -(1-\rho)(\psi_3 - \psi_4)$ and $\Gamma_0^{55} = -(1-\rho)\psi_4$.

APPENDIX 2

This appendix describes the time series considered.

Economic activity indexes:

- GDP: quarterly, seasonally adjusted data. Period: 1987:3-2004:3. Source: U.S. Department of Commerce, Bureau of Economic Analysis.
- Real potential GDP: quarterly data. Period: 1987:3-2004:3. Source: U.S. Congress, Congressional Budget Office.

Price level index:

- U.S. implicit price deflator of GDP: quarterly, seasonally adjusted data. Period: 1987:3-2004:3. Source: U.S. Department of Commerce, Bureau of Economic Analysis.

Interest rates and stock returns:

- Federal funds rate: monthly and quarterly data. Period: 1986:8-2004:6. Source: Board of Governors of the Federal Reserve System.
- 1-year Treasury constant maturity rate: monthly and quarterly data. Period: 1986:8-2004:6. Source: Board of Governors of the Federal Reserve System.
- 1-year ex-post real return: monthly and quarterly data. Period: 1986:8-2004:6. Source: Robert Shiller's web-site.

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Table 1. Estimation results for the five-variable model

	Backward-Looking	Forward-Looking	Standard Taylor rule
J_T	5.7683	7.5223	7.1932
τ	0.9987	0.9991	0.9987
	(0.2077)	(0.3649)	(0.3687)
β	0.9973	0.9924	0.9940
	(0.0004)	(0.0005)	(0.0008)
ρ	0.9568	0.3297	0.3156
	(0.0069)	(0.0744)	(0.0487)
κ	0.9987	0.9979	0.9988
	(0.1396)	(0.3426)	(0.2992)
ψ_1	0.0000	0.6017	0.9226
	(0.1307)	(0.1125)	(0.0180)
ψ_2	5.4196	0.6276	0.0725
	(1.0130)	(0.2210)	(0.0200)
ψ_3	0.0000	0.0000	0.0000
	(0.0720)	(0.0933)	(0.0611)
ψ_4	0.5614	0.0557	0.0645
	(0.0849)	(0.0415)	(0.0094)
ρ_g	0.7826	0.8898	0.9158
	(0.0510)	(0.0501)	(0.0169)
ρ_c	0.8655	0.9575	0.9388
	(0.0325)	(0.0249)	(0.0148)
ρ_s	0.9921	0.9330	0.9384
	(0.0016)	(0.0335)	(0.0135)
ρ_z	0.9231	0.9775	0.9820
	(0.0117)	(0.0091)	(0.0061)
ρ_v	0.9702	0.9857	0.9999
	(0.0127)	(0.0142)	(0.0080)
ρ_{cg}	0.9984	0.9987	0.6320
	(0.1305)	(0.2902)	(0.0801)
ρ_{sg}	0.0000	0.0000	0.9992
	(0.1163)	(0.1988)	(1.5819)

Note: Standard errors in parentheses.

Table 1. (Continued)

	Backward-Looking	Forward-Looking	Standard Taylor rule
σ_g	0.0151	0.0082	0.0238
	(0.0053)	(0.0044)	(0.0103)
σ_c	0.0043	0.0106	0.0008
	(0.0009)	(0.0032)	(0.0008)
σ_s	0.2079	0.1960	0.3920
	(0.0467)	(0.0825)	(0.1654)
σ_z	0.1215	0.0618	0.0407
	(0.0237)	(0.0276)	(0.0126)
σ_ϵ	0.0003	0.0000	0.0000
	(0.0009)	(0.0019)	(0.0009)
π^*	0.8166	1.8865	1.9076
	(0.1260)	(0.1682)	(0.2285)

Table 2. VAR estimates and diagnostic tests

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	Output	**gap**	**equation**		
constant	−0.5577*	0.3298	1.0718	1.2013	0.6857
outputgap(1)	1.1505***	0.1442	2.4783	1.3138	1.1124
outputgap(2)	−0.0045	0.2163	−1.2023	−0.7821	−0.3292
outputgap(3)	−0.4329**	0.1984	−2.2091	−2.2631	−2.2291
outputgap(4)	0.1641	0.1411	1.5381	1.6350	1.5600
inflation(1)	0.0849	0.0872	0.5680	0.7044	1.2905
inflation(2)	−0.0695	0.0869	−2.9584	−2.2775	−0.8261
inflation(3)	−0.0597	0.1004	−1.7138	−1.9282	0.3110
inflation(4)	0.0059	0.0975	−0.9845	−1.1844	−3.0503
Fed rate(1)	0.2030	0.2774	2.8705	2.7278	3.1931
Fed rate(2)	−0.0787	0.3521	0.2981	−0.3064	−1.7936
Fed rate(3)	−0.1264	0.3304	−0.5941	−0.5781	0.2562
Fed rate(4)	−0.0673	0.1734	0.6173	0.7865	1.3604
1-year rate(1)	−0.0129	0.1167	−1.9118	−2.0120	−2.1259
1-year rate(2)	0.0846	0.1496	−1.3682	−1.1704	−0.6162
1-year rate(3)	−0.2174	0.1439	−3.2246	−3.3211	−2.1890
1-year rate(4)	0.2530	0.1521	1.5668	1.5259	0.4822
1-year return(1)	0.0246**	0.0093	2.3132	2.2350	3.3848
1-year return(2)	0.0000**	0.0000	−1.8376	−1.8469	−3.0197
1-year return(3)	0.0000**	0.0000	0.1572	0.1746	0.5017
1-year return(4)	0.0000	0.0000	2.2930	2.2730	1.6943

Table 2. (Continued)

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	Inflation	**equation**			
constant	1.2805**	0.5305	2.7724	2.9328	2.8030
outputgap(1)	0.2497	0.2320	1.5612	1.1983	0.8518
outputgap(2)	−0.3147	0.3479	−0.5477	−0.2992	0.0077
outputgap(3)	0.2523	0.3192	−0.0431	0.0776	0.1465
outputgap(4)	−0.1990	0.2269	−1.0222	−0.8727	−0.8482
inflation(1)	0.1698	0.1402	−3.8813	−2.3362	−1.8393
inflation(2)	0.0315	0.1398	−0.0451	−0.0253	0.3806
inflation(3)	0.0982	0.1616	0.51635	0.5131	1.0359
inflation(4)	0.3664**	0.1568	3.7835	4.0241	4.7389
Fed rate(1)	−0.0810	0.4462	−0.8252	−1.6569	−2.1464
Fed rate(2)	0.1541	0.5664	0.5447	0.7045	1.2109
Fed rate(3)	0.6847	0.5314	1.8982	1.9706	1.6543
Fed rate(4)	−0.1584	0.2789	−1.6697	−1.7270	−1.9915
1-year rate(1)	0.1793	0.1877	0.8605	1.4377	1.1608
1-year rate(2)	−0.0678	0.2406	0.0577	0.3527	0.3843
1-year rate(3)	−0.4307*	0.2315	−2.0861	−1.9690	−1.9217
1-year rate(4)	−0.3032	0.2446	−1.7535	−1.6514	−1.5221
1-year return(1)	−0.0220	0.0149	−2.6845	−2.7198	−2.7562
1-year return(2)	0.0000	0.0000	1.7414	1.7432	2.0363
1-year return(3)	0.0000	0.0000	0.0195	−0.0014	0.2760
1-year return(4)	0.0000	0.0000	−0.7452	−0.8857	−0.5783

Table 2. (Continued)

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	Fed	**rate**	**equation**		
constant	−0.3142*	0.1746	−0.9249	−3.7030	−1.0865
outputgap(1)	0.3308***	0.0764	2.8401	2.1388	−0.5706
outputgap(2)	−0.0315	0.1145	−0.9737	−1.1862	2.1447
outputgap(3)	−0.1294	0.1051	−1.2633	0.0352	−0.6109
outputgap(4)	−0.0005	0.0747	−0.5855	−1.4568	−2.2931
inflation(1)	0.0409	0.0462	−0.7019	−0.1965	−1.8146
inflation(2)	0.1772***	0.0460	0.7378	1.6280	3.2193
inflation(3)	0.0655	0.0532	−2.1937	−0.8251	−1.6260
inflation(4)	0.0636	0.0516	0.0536	−2.2120	−0.9399
Fed rate(1)	0.8553***	0.1469	1.6169	−0.8624	−1.5248
Fed rate(2)	−0.5025***	0.1865	−2.4207	−1.0849	−0.3978
Fed rate(3)	0.2447	0.1749	2.3847	2.1566	2.7193
Fed rate(4)	−0.1901**	0.0918	−1.5658	−1.0142	−2.0646
1-year rate(1)	0.3363***	0.0618	0.3276	3.4774	2.2097
1-year rate(2)	0.1039	0.0792	0.3405	0.8791	0.7645
1-year rate(3)	0.1055	0.0762	1.1526	1.0840	0.7799
1-year rate(4)	−0.0687	0.0805	−1.2198	−1.8478	−1.7009
1-year return(1)	0.0078	0.0049	3.4555	3.2396	−1.3947
1-year return(2)	0.0000**	0.0000	−3.8730	−4.1576	−0.8335
1-year return(3)	0.0000	0.0000	0.5421	0.6537	0.9184
1-year return(4)	0.0000	0.0000	0.8495	1.0766	0.0293

Table 2. (Continued)

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	1-year	**rate**	**equation**		
constant	0.0454	0.4349	−0.5193	−3.5549	0.0857
outputgap(1)	0.3767*	0.1902	2.6564	2.1170	0.5319
outputgap(2)	−0.0448	0.2852	−0.5695	−1.3088	0.3057
outputgap(3)	−0.0954	0.2617	−1.1491	0.1320	−1.2290
outputgap(4)	−0.1130	0.1860	−0.0792	−1.5115	−1.1446
inflation(1)	−0.0217	0.1150	−0.0222	−2.0608	−2.9835
inflation(2)	0.2741**	0.1146	2.7634	3.6504	1.7924
inflation(3)	0.0098	0.1324	0.2616	1.9702	−1.0967
inflation(4)	0.0404	0.1286	0.3097	−0.8568	−1.3725
Fed rate(1)	0.2612	0.3658	0.5399	−0.1712	−0.0507
Fed rate(2)	−0.5048	0.4643	−0.2586	0.4767	0.4746
Fed rate(3)	0.2355	0.4356	0.3410	0.0255	0.9785
Fed rate(4)	−0.0777	0.2286	−0.0615	−0.1376	0.0447
1-year rate(1)	0.6209***	0.1539	−3.2290	−1.0660	−1.7187
1-year rate(2)	0.2818	0.1973	1.1362	1.1235	0.5304
1-year rate(3)	0.2434	0.1898	1.0227	1.1894	0.6306
1-year rate(4)	−0.2232	0.2005	−1.5513	−2.0642	−2.1953
1-year return(1)	0.0067	0.0123	−0.7969	−0.5962	−3.8225
1-year return(2)	0.0000	0.0000	1.0339	0.6112	2.4048
1-year return(3)	0.0000	0.0000	−0.4701	−0.4939	−1.1270
1-year return(4)	0.0000	0.0000	1.2671	2.1028	0.7255

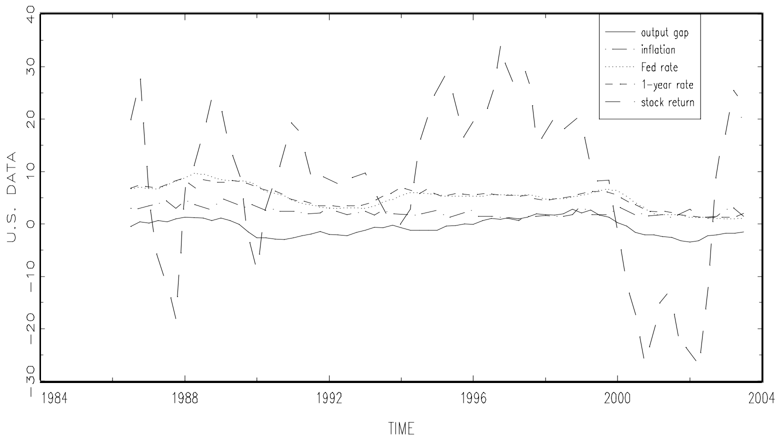
Table 2. (Continued)

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	1-year	**ex-post**	**stock**	**return**	**equation**
constant	9.9034**	4.3557	−1.7241	−1.0574	−1.1898
outputgap(1)	−2.2855	1.9048	3.5257	3.6352	3.3730
outputgap(2)	2.4115	2.8560	−1.3039	−1.9294	−1.3599
outputgap(3)	−1.7836	2.62039	−0.5502	−0.7805	−2.2802
outputgap(4)	−0.0571	1.8632	1.6615	0.5983	2.3892
inflation(1)	−0.6010	1.1513	0.6436	−1.0885	0.8559
inflation(2)	−1.8431	1.1475	−0.1557	−1.9313	−2.6921
inflation(3)	−0.9214	1.3264	4.0583	0.7764	2.2096
inflation(4)	−1.5965	1.2876	2.3605	−0.1162	0.1340
Fed rate(1)	3.6430	3.6634	−1.5105	−0.4387	−0.7753
Fed rate(2)	2.7068	4.6502	1.2119	1.7381	2.0566
Fed rate(3)	−1.9574	4.3626	−2.0874	−1.9007	−2.8735
Fed rate(4)	0.1942	2.2897	0.6565	0.6755	1.7482
1-year rate(1)	−2.8936*	1.5409	−1.7778	−0.4172	−0.3054
1-year rate(2)	−1.1741	1.9754	1.3615	0.8074	0.7094
1-year rate(3)	−0.0050	1.9005	0.6977	−0.9629	−0.5232
1-year rate(4)	1.0486	2.0081	1.7899	1.1453	1.1866
1-year return(1)	0.5443***	0.1227	2.7688	1.2124	0.9940
1-year return(2)	0.0000**	0.0000	0.2782	−0.1389	−0.0622
1-year return(3)	0.0000	0.0000	−0.6836	−0.5474	−0.6501
1-year return(4)	0.0000	0.0000	−0.2778	−0.3397	−0.4484

Table 2. (Continued)

Variable	Estimate	Standard error	Diag. stat. for (5)	Diag. stat. for (11)	Diag. stat. for (12)
	VAR residuals	**variance**	**matrix**		
s11	0.1399	0.1989	6.1782	6.2207	6.0996
s21	−0.0665	0.2303	−2.5969	−2.5280	−2.3833
s31	0.0144	0.0673	1.8330	1.8450	1.9093
s41	0.0366	0.1848	2.0302	1.5914	1.2939
s51	0.6242	2.2869	2.5840	2.4391	2.4311
s22	0.3438	0.4887	6.1051	6.1116	5.7093
s23	0.00755	0.1033	0.2425	1.1889	0.6136
s24	−0.0141	0.2843	0.4769	0.7220	1.3965
s25	−0.5996	3.4997	−1.0787	−1.4753	−1.5023
s33	0.0305	0.0434	4.5432	4.6280	5.9687
s34	0.0348	0.0916	4.6788	−0.5050	3.1506
s35	−0.2036	1.0477	−2.2076	−2.0436	−1.7111
s44	0.2321	0.3299	2.6926	0.2747	2.6323
s45	0.2382	2.8425	−2.4145	0.2520	0.2367
s55	4.2240	48.6414	1.7180	6.0083	1.6932

Note: ***,**,* denote that the corresponding coefficients are statistically significant at the 1%, 5% and 10% levels, respectively.



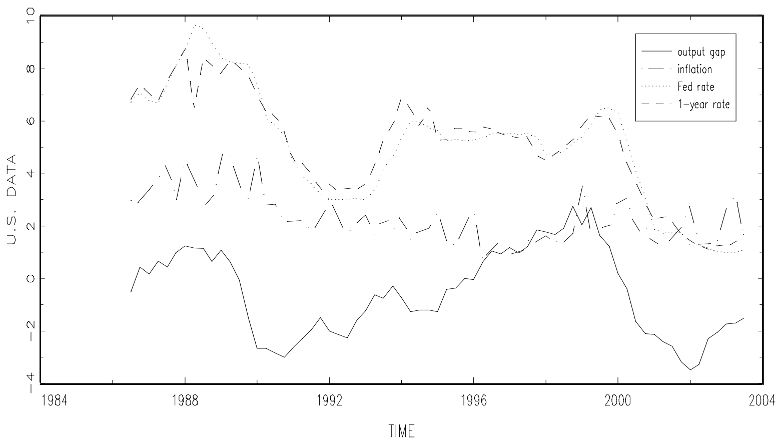


Figure 1: U.S. time series

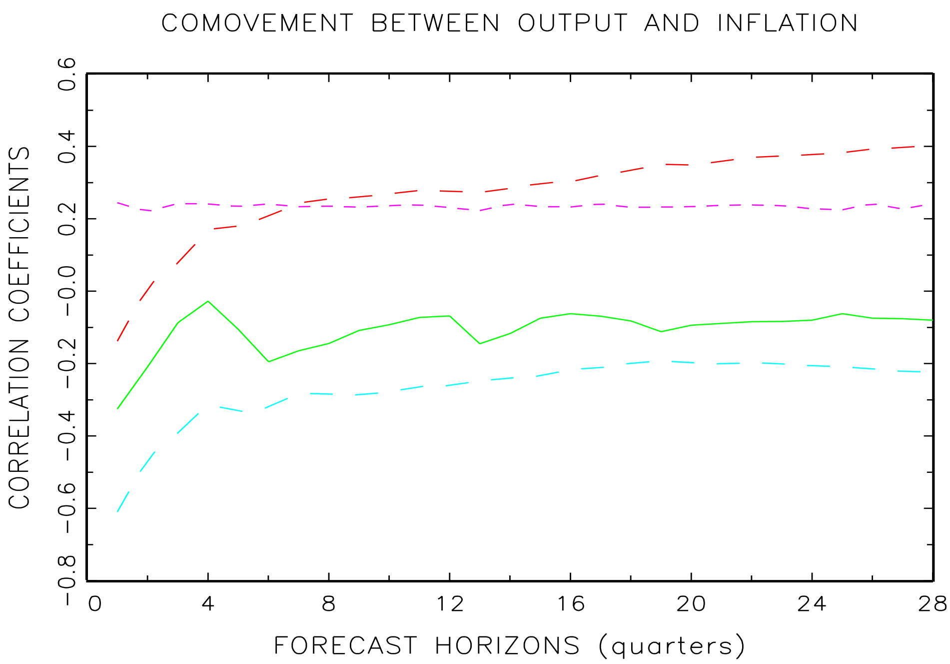


Figure 2: Comovement between output gap and inflation under the standard Taylor rule

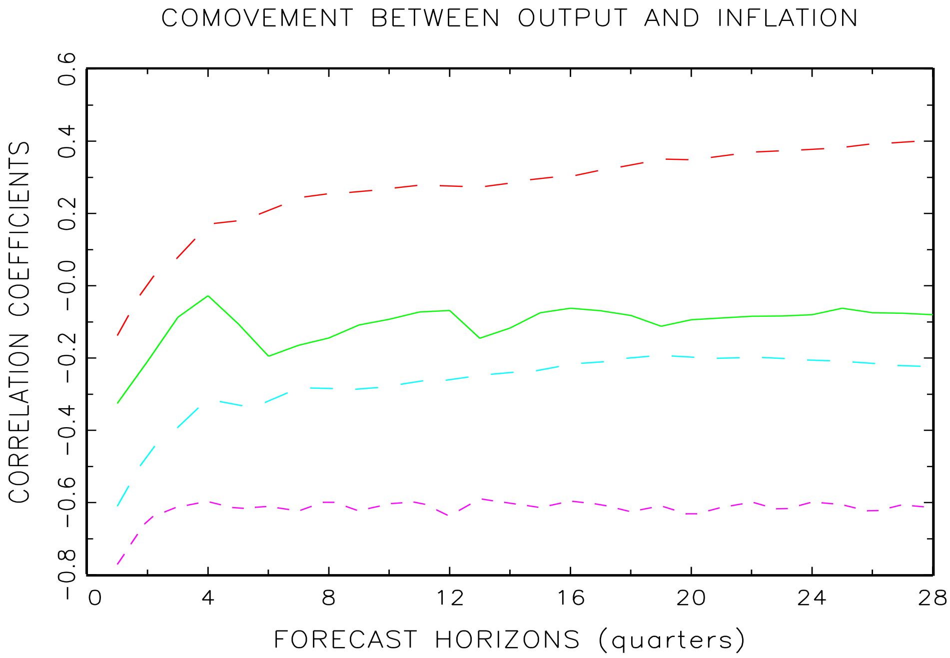


Figure 3: Comovement between output gap and inflation under the backward-looking Taylor rule

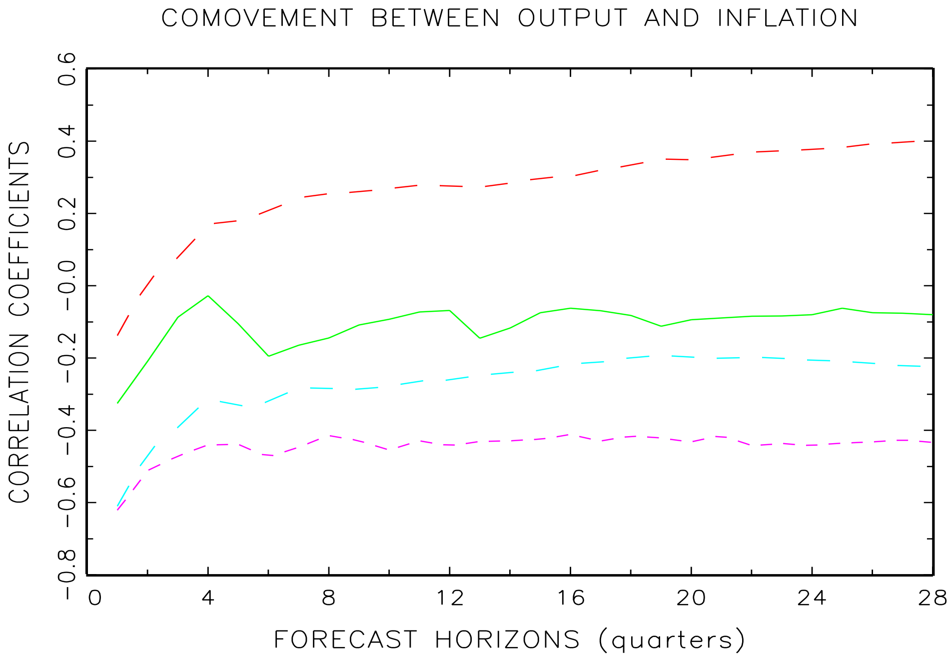


Figure 4: Comovement between output gap and inflation under the forward-looking Taylor rule

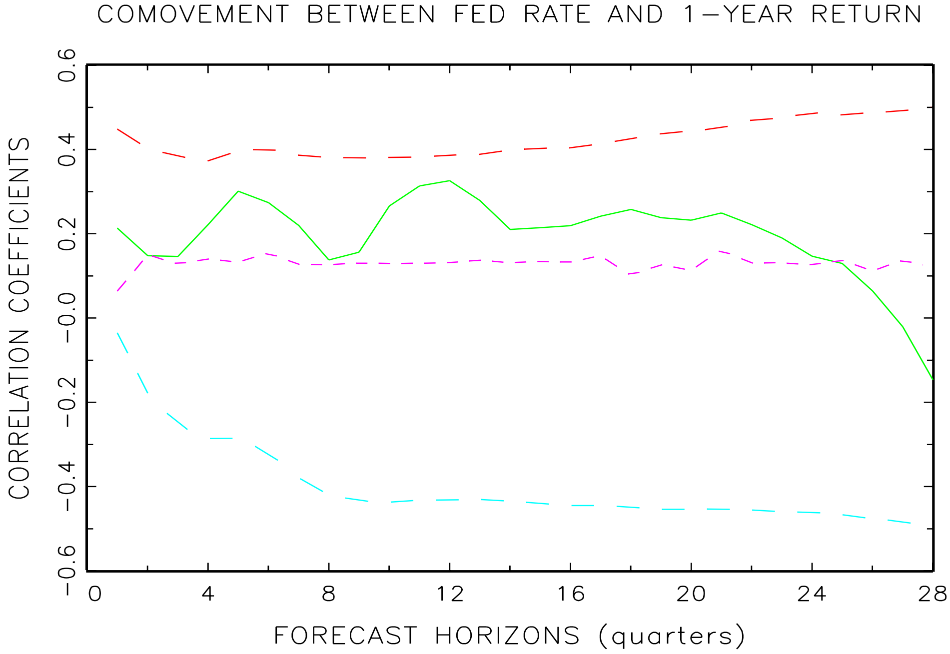


Figure 5: Comovement between Fed rate and 1-year stock return under the standard Taylor rule

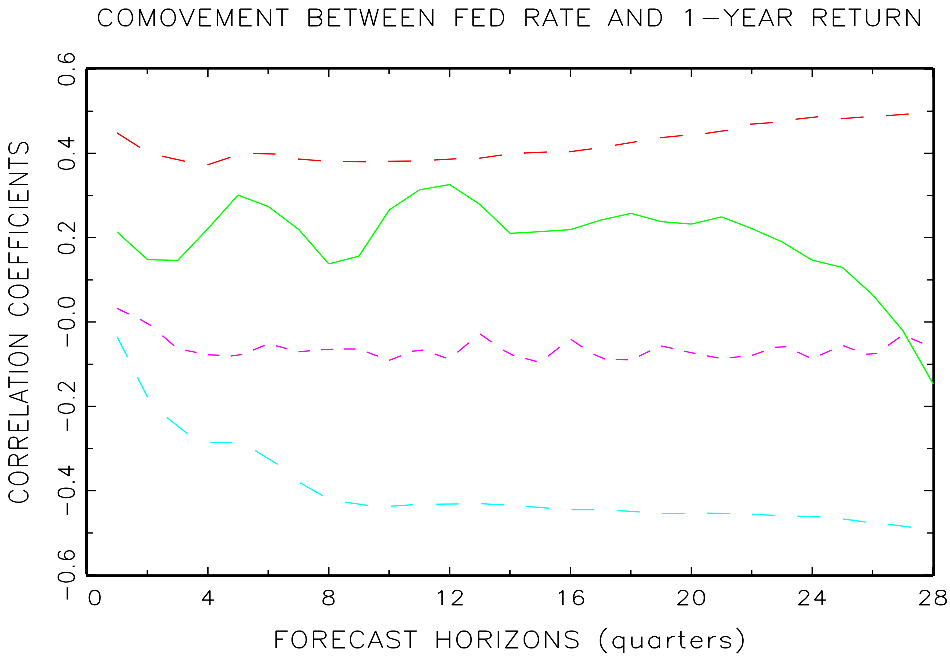


Figure 6: Comovement between Fed rate and 1-year stock return under the backward-looking Taylor rule

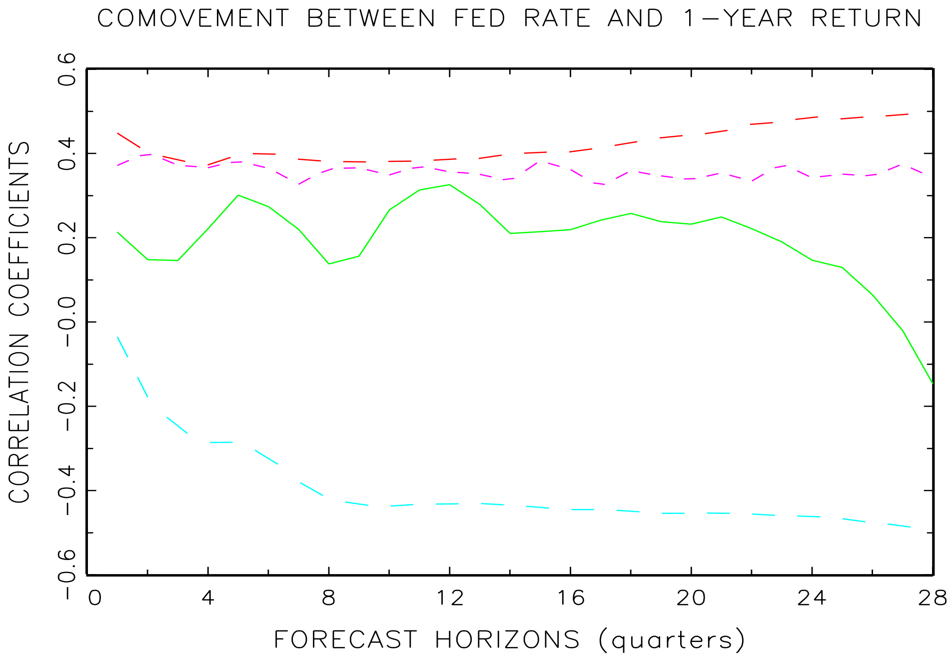


Figure 7: Comovement between Fed rate and 1-year stock return under the forward-looking Taylor rule