Fiscal Policy and Asset Markets: A Semiparametric Analysis *

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August 29, 2007

Abstract

Using a flexible semiparametric varying coefficient model specification, this paper examines the role of fiscal policy on the U.S. asset markets (stocks, corporate and treasury bonds). We consider two possible roles of fiscal deficits (or surpluses): as a separate direct information variable and as a (indirect) conditioning information variable indicating binding constraints on monetary policy actions. The results show that the impact of monetary policy on the stock market varies, depending on fiscal expansion or contraction. The impact of fiscal policy on corporate and treasury bond yields follow similar patterns as in the equity market. The results are consistent with the notion of strong interdependence between monetary and fiscal policies.

Key words: fiscal deficits; monetary policy; stock market; semiparametric estimation.

JEL Classification: C2, C5, F3

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*We would like to thank Jiti Gao and two referees for their insightful comments that greatly improved the paper. The research of Jansen and Li is partially supported by the Private Enterprise Research Center, Texas A&M University. The corresponding author: Qi Li, email: qi@econmail.tamu.edu

1 Introduction

It is well known that monetary policy actions (such as changes in the federal funds rate) exert substantial influence on financial markets. Indeed, the role of monetary policy in explaining stock returns has been extensively investigated (e.g., Jensen, Mercer, & Johnson, 1996; Patelis, 1997; Thorbecke, 1997; Bernanke and Kuttner, 2005). In general, most recent studies have confirmed the impact of monetary policy on U.S. asset markets.

Interestingly, while researchers have been primarily concerned with the impact of monetary policy on the stock market, little attention, if any, has been devoted to exploring the informational role of fiscal policy on the stock market.[1] Yet, on purely theoretical grounds, even the early literature (e.g., Blanchard, 1981) has demonstrated that both monetary and fiscal policies can have substantial effects on asset returns. While the recent literature continues to suggest a significant role for fiscal policy to affect key macroeconomic variables (e.g., Canzoneri, Cumby, and Diba, 2001)[2], it has particularly underscored the potentially complex interaction between monetary and fiscal policies (Sargent, 1999; Kutsoati, 2002; Linnemann and Schabert, 2003; Schabert, 2004). As clearly pointed out in Sargent (1999), the administrative independence of central banks does not by itself imply that monetary policy is independent of the fiscal decisions of governments. In the U.S., " the force of U.S. economic policy institutions is to leave that interdependence implicit" (Sargent, 1999, p.1465). Hence, it is natural to explore a different role of fiscal policy as a conditioning information variable, which is based on its interaction with monetary policy.

Such an investigation also contributes to the ongoing debate on fiscal discipline. Since the 1980s, balanced budgets have become increasingly uncommon in many developed countries. Instead, bond-financed deficits have become the fiscal policy tool of choice and tend to be persistent in developed countries. In the U.S., the federal budget surpluses during 1990s have turned into one of the largest peacetime budget deficits in the 2000s. The debate thus has gained momentum recently on mechanisms or institutional changes designed to improve policy outcomes. However, although

[1] A notable exception is Darrat (1990) who considers fiscal deficits in a simple linear regression framework. As we will show below, a linear regression model is likely to be a misspecified model.

[2] In particular, the fiscal theory of the price levels argues that fiscal policy, rather than monetary policy, determines the general price level and inflation. Specifically, it views the government intertemporal budget constraint as an equilibrium condition where the price level adjusts to accommodate changes in fiscal conditions. See Canzoneri, Cumby, and Diba (2001) for more references.

some recent studies (e.g., Fatas and Mihov, 2003; Catao and Terrones, 2005) have documented a negative impact of fiscal deficits on output, inflation and other macroeconomic variables, little empirical work has been conducted to investigate how fiscal deficits impact financial markets in general and the stock market in particular. Our study should shed more light on this important policy issue.

This paper contributes to the literature in two important aspects. We first examine the role of fiscal policy on the U.S. stock and bond markets, and we document the conditioning information role of fiscal policy via interactions with monetary policy, a feature that has been forcefully emphasized in the recent theoretical literature but not yet thoroughly investigated empirically. The few existing empirical works only consider the role of fiscal policy as a direct information variable separate from monetary policy. Second, we employ a flexible varying coefficient specification in our econometric analysis, which has not been commonly used in this line of research. We find that a semiparametric varying coefficient model and its variants (Cai, Fan, Yao, 2000) appear to be particularly suitable for capturing the potentially complex interactions between fiscal and monetary policies. Essentially, "monetary policy can be constrained by fiscal policy if fiscal deficits grow large enough to require monetization of government debt" (Sargent, 1999, p.1463). However, when and how such a fiscal policy works as a binding constraint on monetary policy would be difficult to model with a parametric (e.g., linear) model, as no theory has made an explicit suggestion about functional forms. The semiparametric varying coefficient model has the advantage that it allows more flexibility in functional forms than either a linear model or many parametric nonlinear models, and at the same time it avoids much of the 'curse of dimensionality' problem that occurs in fully nonparametric analysis.

The rest of this paper is organized as follows: Section 2 presents econometric methodology; Section 3 proposes a test for a varying coefficient model; Section 4 describes the data and empirical results; and finally, Section 5 concludes the paper.

2 Econometric Methodology

We start with a simple linear regression model:

$$Y_t = X_t'\alpha + Z_t'\gamma + u_t, \qquad (t = 1, ..., n), \tag{1}$$

where X_t is a $p \times 1$ vector with its first component being 1, Z_t is a $q \times 1$ vector, and α and γ are $p \times 1$ and $q \times 1$ vectors of (constant) parameters, respectively. In this paper we will first consider the case that the dependent variable Y_t is the U.S. stock return at period t. We will also consider the cases that Y_t is the U.S. treasury bond yield and that Y_t is the U.S. corporate bond yield. The explanatory variables X_t and Z_t contain lagged values of Y_t, lagged values of the growth rate, of industry production, the first difference of the federal fund rate, and changes in the fiscal deficit.

One way that the linear regression model (1) may be misspecified is when fiscal policy variables affect asset markets in a nonlinear way. To allow for a flexible functional form and also to avoid the 'curse of dimensionality', we consider a semiparametric varying coefficient model given by

$$Y_t = X_t' \beta(Z_t) + u_t, \tag{2}$$

where the coefficient function $\beta(z)$ is a $p \times 1$ vector of unspecified smooth functions of z. Under the assumption that model (2) is the correct specification, $E(u_t|X_t, Z_t) = 0$. Pre-multiplying both sides of (2) by X_t and taking conditional expectation ($E(\cdot|Z_t = z)$), then solving for $\beta(z)$ yields

$$\beta(z) = \left[E(X_t X_t' | Z_t = z)\right]^{-1} E(X_t Y_t | Z_t = z). \tag{3}$$

Replacing the conditional mean functions in (3) by some nonparametric estimators, say by the local constant or local linear kernel estimators, one obtains a feasible estimator of $\beta(z)$.

The varying coefficient model (2) is simple yet rather flexible. Note we have assumed that the first component of X_t is 1. If we further assume that $\beta(z)$ depends on z only in its first component, i.e., $\beta(z) = (\beta_1(z), \beta_{20}, ..., \beta_{p0})'$, where β_{j0} is a constant ($j = 2, ..., p$), then the varying coefficient model reduces to the popular semiparametric partially linear model as considered by Robinson (1988) and others. If one further imposes that $\beta_1(z) = \alpha_0 + z'\alpha_1$, then the partially linear model collapses to the linear model (1). Estimation methods as well as the asymptotic distributions of various kernel-based estimators for varying coefficient models have been considered by Cai, Fan and Yao (2000) and Li et al. (2002), among others.

Even though the varying coefficient model is more flexible than the parametric linear model, it is still possible that the varying coefficient model is misspecified. To guard against this possibility, we will test model adequacy for the varying coefficient model against the following general nonparametric regression model:

$$Y_t = g(X_t, Z_t) + u_t. \tag{4}$$

The fully nonparametric model (4) is robust against functional form misspecifications. However, it also has a major disadvantage, namely, it has the 'curse of dimensionality' problem. We discuss model specification testing in the next section.

3 Model Specification Testing

In applied work it is important to check the adequacy of a given model specification. For example, if a simple linear model is the correct specification, then there is no need in searching for more complex semiparametric/nonparametric specifications. On the other hand, if a given (parametric or semiparametric) model specification is believed to be inadequate, one should search for other more flexible specifications. There exists a rich literature on testing a linear model either against a more flexible semiparametric model or against a fully nonparametric model. However, to the best of our knowledge, there is no formal theoretical work on testing a semiparametric varying coefficient model against a fully nonparametric alternative model. In the next subsection we propose such a test and derive the asymptotic distribution of our proposed test.

3.1 A Test for a Varying Coefficient Model

Testing semiparametric regression models against more general nonparametric alternative models is considered by Fan and Li (1996), Chen and Fan (1999), among others. In this subsection we propose a new test statistic for testing the null model of a varying coefficient model against a general nonparametric alternative model. That is, under H_0 we have $E(Y_t|X_t, Z_t) = X_t'\beta(Z_t)$ almost surely, and the alternative is that $E(Y_t|X_t, Z_t) \neq X_t\beta(Z_t)$ on a set (X_t, Z_t) with positive measure. The null model is therefore given by:

$$Y_t = X_t'\beta(Z_t) + u_t, \tag{5}$$

with $E(u_t|X_t, Z_t) = 0$, where Y_t and u_t are scalars, $X_t \in R^p$ and $Z_t \in R^q$. Replacing the conditional expectation functions in (3) by kernel estimators, we obtain an estimate of $\beta(Z_t)$ given by

$$\hat{\beta}(Z_t) = \left[\frac{1}{na_1 \dots a_q}\sum_{s=1}^{n} X_s X_s' L_{t,s}\right]^{-1} \frac{1}{na_1 \dots a_q}\sum_{s=1}^{n} X_s Y_s L_{t,s},$$

where $L_{t,s} = \prod_{j=1}^{q} l((Z_{tj} - Z_{sj})/a_j)$ is the product kernel function and a_j is the smoothing parameter associated with X_{tj} $(j = 1, ..., q)$ used for estimating the (null model) varying coefficient model. We denote by $\tilde{X}_t$ the $(p-1) \times 1$ vector of X_t obtained by excluding the first component of X_t, i.e., $X_t = (1, \tilde{X}_t')'$. The null hypothesis can also be written as H_0: $E(u_t|W_t) = 0$ a.s., where $W_t = (\tilde{X}_t', Z_t')$. Similar to Fan and Li (1996) and Zheng (1996), we construct our test statistic based on the sample analogue of $J = E\{u_t E[u_t|W_t] f(W_t)\}$. Note that by the law of iterative expectation, we have $J = E\{[E(u_t|W_t)]^2 f(W_t)\} \geq 0$. Further note that $J = 0$ if and only if H_0 is true. Therefore, J provides a sound basis for testing H_0. The sample analogue of J is $J_n = n^{-1} \sum_{t=1}^{n} u_t E(u_t|W_t) f(W_t)$. To obtain a feasible test statistic, we replace u_t by $\hat{u}_t = Y_t - X_t'\hat{\beta}(Z_t)$ and we estimate $E(u_t|W_t)f(W_t)$ by a kernel estimator: $(nh_1 \ldots h_d)^{-1} \sum_{s \neq t}^{n} \hat{u}_s K_{t,s}$, where $K_{t,s} = \prod_{j=1}^{d} K((W_{tj} - W_{sj})/h_j)$, h_j is the smoothing parameter associated with W_{tj} used in estimating the alternative model, and $d = (p-1) + q$ is the dimension of $W_t = (\tilde{X}_t, Z_t)$. Therefore, a feasible statistic is obtained as

$$\tilde{J}_n = (n^2 h_1 \ldots h_d)^{-1} \sum_{t=1}^{n} \sum_{s \neq t}^{n} \hat{u}_t \hat{u}_s K_{t,s}.$$

The random denominator in $\hat{\beta}(Z_t)$ may cause some technical difficulties in deriving the asymptotic distribution of $\tilde{J}_n$. We suggest using a fixed trimming method to avoid this problem.[3] Let M denote a compact set in R^d such that both $f(X_t, Z_t)$ and the determinant of $E(X_t X_t'|Z_t)$ are bounded below by a positive constant for all $(X_t, Z_t) \in M$. Define an indicator function $I_t = 1$ if $(X_t, Z_t) \in M$ and 0 otherwise. Then we replace $\hat{u}_t$ and $\hat{u}_s$ by $\hat{u}_t I_t$ and $\hat{u}_t I_s$ in $\tilde{J}_n$ to obtain a modified statistic

$$\hat{J}_n = \frac{1}{n^2 h_1 \ldots h_d} \sum_{t=1}^{n} \sum_{s \neq t}^{n} \hat{u}_t I_t \hat{u}_s I_s K_{t,s}. \tag{6}$$

To derive the asymptotic distribution of $\hat{J}_n$, the following assumptions will be used, where we also use the definitions of Robinson (1988) for the class of kernel function $\mathcal{K}_\lambda$ and the class of function $\mathcal{G}_\mu^\alpha$, see Robsinson (1988) for details.

We use $f(.)$ to denote the marginal density function of $W_t = (\tilde{X}_t', Z_t')$.

[3]Note that a trimming method is needed mainly for theoretical reasons; in real data applications, trimming methods may not be needed.

(A1) (i) $\{Y_t, X_t, Z_t\}_{t=1}^n$ is a strictly stationary β-mixing process with the mixing coefficient satisfying $\beta(\tau) = O(\rho^\tau)$ for some $0 < \rho < 1$. (ii) $f(W_t)$ and determinant $E(X_t X_t' | Z_t)$ are both bounded below by a positive constant on the compact (trimming) set M, (iii) $f(\cdot) \in \mathcal{G}_\nu^\infty$, $f \in \mathcal{G}_\nu^\infty$ and $\beta(\cdot) \in \mathcal{G}_\nu^{4+\epsilon}$ for some integer $\nu \geq 2$ and some (small) $\epsilon > 0$. (iv) u_t is a martingale difference process, with $E[|u_t^{8+\eta}|] < \infty$, $\sigma_u^2(w) = E(u_t^2 | W_t = w)$, $\mu_4(w) = E(U_t^4 | W_t = w)$, f and each component of β all satisfy some Lipschitz conditions: $|m(u+v) - m(u)| \leq D(u)||v||$, $D(\cdot)$ has finite $(2+\eta')$th moment for some small $\eta' > 0$, where $m(\cdot) = \sigma_u^2(\cdot)$, $\mu_4(\cdot)$, $f(\cdot)$, or $\beta(\cdot)$; and $||\cdot||$ denotes the Euclidean norm of $\cdot$.

(A2) (i) we use product kernel for both $L(\cdot)$ and $K(\cdot)$, let $l(\cdot)$ and $k(\cdot)$ be their corresponding univariate kernel, then $l(\cdot) \in \mathcal{K}_\nu$ and $k(\cdot) \in \mathcal{K}_2$. (ii) Assuming that all h_j's ($j = 1, ..., d$) have the same order as h and that all a_j's ($j = 1, ..., q$) have the same order as a, then $h = O(n^{-\alpha})$ for some $0 < \alpha < (7/8)d$, $a \to 0$, $h^d/a^{2p} \to 0$, $nh^{d/2}a^{2\nu} \to 0$ (all the limits are taken as $n \to \infty$).

The asymptotic distribution of the test statistic $\hat{J}_n$ is given in the next theorem.

THEOREM 3.1 *Assume the conditions (A1) and (A2) hold. Then under H_0,*

$\hat{T}_n \stackrel{def}{=} n(h_1 \dots h_d)^{1/2} \hat{J}_n / \hat{\sigma} \to N(0,1)$ *in distribution,*

where $\hat{\sigma}^2 = 2(n^2 h_1 \dots h_d)^{-1} \sum_{i=1}^n \sum_{j \neq i}^n \hat{u}_t^2 I_t \hat{u}_s^2 I_s K_{t,s}^2$.

The proof of Theorem 3.1 is given in the appendix.

The test statistic $\hat{T}_n$ has an asymptotic standard normal distribution under the null hypothesis. Our simulation results indicate that the normal approximation does not work well for small or moderate samples. Also the test statistic $\hat{T}_n$ depends on two smoothing parameters, a and h. It can be sensitive to different smoothing parameter values. Therefore we propose a bootstrap method as an alternative to approximate the null distribution of $\hat{T}_n$.

A Bootstrap Procedure

We use u_t^* to denote the bootstrap error which is obtained based on the fitted residual based on the null model $\hat{u}_t = Y_t - X_t'\hat{\beta}(Z_t)$. The bootstrap error u_t^* satisfies the following conditions:

$$(i) E^*(u_t^*) = 0, \quad (ii) E^*(u_t^{*2}) = \hat{u}_t^2 \quad \text{and (iii)} \quad E^*(u_t^{*3}) = \hat{u}_t^3, \tag{7}$$

where $E^*(\cdot) = E(\cdot|\mathcal{F}_n)$ and $\mathcal{F}_n = \{(X_t, Z_t, Y_t)\}_{t=1}^n$. For example, the two-point 'wild' bootstrap distribution satisfies (i) - (iii), i.e., $u_t^* = [(1-\sqrt{5})/2]\hat{u}_t$ with probability $r = (1+\sqrt{5})/(2\sqrt{5})$, and $u_t^* = [(1+\sqrt{5})/2]\hat{u}_t$ with probability $1-r$.

We allow for the possibility that $W_t = (\tilde{X}_t', Z_t')$ contains lagged values of Y_t, say, the first component of W_t is Y_{t-1}. We re-write $W_t = (Y_{t-1}, \tilde{W}_t)$, where $\tilde{W}_t$ does not contain lagged value of Y_t. Then the bootstrap test statistic is obtained via the following steps:

Step 1: For $t = 1, ..., n$, generate u_t^* satisfying (7). We fix $W_t^* = W_t \equiv (Y_{t-1}, \tilde{W}_t)$, and generate Y_t^* by $Y_t^* = X_t'\hat{\beta}(Z_t) + u_t^*$. Call $\{Y_t^*, W_t\}_{t=1}^n$ be the bootstrap sample.

Step 2: Obtain the kernel estimator of $\beta(Z_t)$ using the bootstrap sample,

$$\hat{\beta}^*(Z_t) = \left[\sum_{t=1}^n X_t X_t' K_{t,s}\right]^{-1} \sum_{t=1}^n X_t Y_t^* K_{t,s}. \tag{8}$$

Then obtain the estimated bootstrap residual by $\hat{u}_t^* = Y_t^* - X_t'\hat{\beta}^*(Z_t)$.

Step 3: Compute the bootstrap test statistic

$$\hat{J}_n^* = \frac{1}{n^2 h_1 \dots h_d} \sum_{t=1}^n \sum_{s \neq t}^n \hat{u}_t^* I_t \hat{u}_s^* I_s K_{t,s} \tag{9}$$

and the estimated asymptotic variance $\hat{\sigma}^{*2} = 2(n^2 h_1 \dots h_d)^{-1} \sum_{t=1}^n \sum_{s \neq t}^n \hat{u}_t^{*2} I_t \hat{u}_s^{*2} I_s K_{t,s}^2$. The standardized bootstrap statistic is $T_n^* = n(h_1 \dots h_d)^{1/2} J_n^* / \hat{\sigma}^*$.

Step 4: Repeat steps 1-3 a number of times, say B times, and obtain the empirical distribution of the B test statistics of T_n^*. Let $T_{n,\alpha}^*$ denote the α percentile of the bootstrap distribution. We will reject the null hypothesis at significance level α if $T_n > T_{n,\alpha}^*$.

In the above bootstrap procedure, Y_t^* does not depend on Y_{t-1}^*. Therefore, Y_t^* may not follow the same distribution as Y_t. Nevertheless, since $(Y_t^*, Y_{t-1}, \tilde{W}_t)$ is generated by imposing the null hypothesis, so the test statistic based on $(Y_t^*, Y_{t-1}, \tilde{W}_t)$ continue to mimic the null distribution of the original test statistic.[4]

The next theorem shows that the above bootstrap method indeed works.

THEOREM 3.2 *Assuming that the same conditions given in Theorem 3.1 hold, but without imposing the null hypothesis, then we have*

$$\sup_{z \in \mathcal{R}} \left| P\left(\hat{T}_n^* \leq z | \{X_t, Z_t, Y_t\}_{i=1}^n\right) - \Phi(z)\right| = o_p(1), \tag{10}$$

[4]This bootstrap method, as well as the above arguments as why one might expect such a bootstrap procedure works, was generously suggested to us by an anonymous referee.

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable.

A sketch of the proof of Theorem 3.2 is given in the appendix.

3.2 Testing the Adequacy of a Linear Model

If the varying coefficient model (2) cannot be rejected, we further test whether the linear model specification (1) is sufficient for the data. Here the null model is equation (1) and the alternative model is equation (2). For this purpose, we consider the bootstrap version of the Ullah (1985)-type goodness of fit test suggested by Cai, Fan and Yao (2000). This is based on the difference of the sums of squared residuals between the two competing models, which can be understood as a generalization of the likelihood ratio test in linear regressions, and thus we refer to this as GLR:

$$GLR = \frac{\sum_{t=1}^{n} \hat{u}_t^2 - \sum_{t=1}^{n} \tilde{u}_t^2}{\sum_{t=1}^{n} \tilde{u}_t^2}, \tag{11}$$

where $\hat{u}_t$ is the residual from the linear null model, and $\tilde{u}_t$ is the residual from the alternative varying coefficient model. One rejects the null hypothesis of linearity for large values of GLR. Cai, Fan and Yao (2000) suggest using a bootstrap approach to evaluate the p-value of the test. In particular, they bootstrap the centralized residuals from the nonparametric fit instead of the linear fit, because the nonparametric estimate of the residuals is consistent under the both the null and alternative hypotheses.

3.3 Finite Sample Performance for the $\hat{J}_n$ Test

In this subsection we report a small scale simulation result to examine the finite sample performance of the $\hat{J}_n$ test. We consider the following data generating processes.

$$DGP0: \quad y_t = \beta_0(z_t) + \beta_1(z_t)y_{t-1} + u_t,$$

$$DGP1: \quad y_t = 0.1 + 0.1z_t y_{t-1} - 0.6/(0.5 + y_{t-1}^2) + u_t;$$

where z_t is i.i.d. uniform$[-2, 2]$, $\beta_0(z_t) = 0.2z_t + 0.01z_t^2$, $\beta_1(z_t) = 0.4sin(0.5\pi z_t)$ and u_t is i.i.d. $N(0, 0.3^2)$. Note that $DGP0$ is the null model, and $DGP1$ is the alternative model. The number of bootstrap is 400, and the number of replications is 2000. The smoothing parameters are selected via $a = z_{sd}n^{-1/6}$ (for estimating the null model, DGP0), $h_1 = z_{sd}n^{-1/5}$ and $h_2 = y_{-1,sd}n^{-1/5}$, where

z_{sd} and $y_{-1,sd}$ are the sample standard deviation of $\{z_t\}_{t=2}^{n}$ and $\{y_t\}_{t=1}^{n-1}$, respectively. Our selection of smoothing parameters are somewhat ad-hoc, but they satisfy the condition (A2) (with $p = 1$ and $d = 2$) in that $h^d/a^{2p} = h^2/a^2 \to 0$ as $n \to \infty$. The simulation results are reported in Table 1. We observe that the test based on the asymptotic normal critical value is significantly undersized, while the test based on the bootstrap critical values successfully removes the size distortion. Also, the bootstrap test is quite powerful against DGP1.

Table 1: Estimated Size and Power of the J_n Test

Sample Sizes	Bootstrap Test			Asymptotic Test		
	Estimated Size					
	1%	5%	10%	1%	5%	10%
$n = 300$	.010	.058	.130	.000	.000	.001
$n = 600$	.012	.054	.121	.000	.004	.008
	Estimated Power					
$n = 300$	.542	.743	.840	.134	.236	.316
$n = 600$	.963	.993	.998	.680	.810	.868

4 Empirical Results

Monthly data are obtained from Haver Analytics and FRED databases for the following variables: S&P 500 stock price index, U.S. corporate bond Baa yield, 10-year Treasury bond yield, Federal funds rate, industrial production (IP), CPI, and the U.S. government budget deficit (or surplus). The data span from July 1954 to December 2005 (51.5 years) with a total of 618 monthly observations. The starting point is determined by the availability of the federal funds rate. Transformed data are to be used in the empirical specifications below: stock returns (SR_{t-1}), the first differences of corporate bond yield (DCR_{t-1}) and Treasury bond yield (DTR_{t-1}) (all in real terms), the growth in industrial production ($IPG_t = ln(IP_t) - ln(IP_{t-1})$), the first differences of the effective federal fund rate ($DFF_t = FF_t - FF_{t-1}$), and the change in fiscal deficits CFD_t ($CFD_t = FD_t - FD_{t-1}$) normalized by the size of the economy (represented by GDP). For ease of presentation, throughout the paper we denote deficits as positive values of FD and surpluses as negative. Therefore, a positive (negative) CFD_t means either an increase (decrease) in the deficit or a decrease (increase) in the surplus, both of which indicate an expansionary (contractionary) fiscal policy environment.

Note that our methodology will require that the empirical model in this study be parsimonious and include only a few economic variables, as lags of these variables are treated as separate variables in both the nonparametric determination of significant lags and estimation of the semiparametric varying coefficient model. Nevertheless, our model specification below is comparable with many previous studies where industrial production and the federal funds rates (or other short-term interest rates) are included as potentially important predictors of stock returns (e.g., Darrat, 1990; Patelis, 1997; Thorbecke, 1997). Of course, unlike most earlier studies, we also include fiscal deficits. We do not, however, include the inflation rate. While earlier studies focusing on nominal stock returns typically include the inflation rate (e.g., Darrat, 1990; Thorbecke, 1997), motivated perhaps by the Fisher effect, studies using real (or excess) stock returns have not always included inflation as an explanatory variable (e.g., Patelis, 1997). Further, the effect of the inflation rate on real stock returns is implicitly allowed for in our model specification (although with an implicit restriction imposed) when we use nominal interest rates, which can be decomposed into the real interest rate and expected inflation rate components. Hess and Lee (1999) further demonstrate both theoretically and empirically that the (real) stock return-inflation relation can be explained by the supply shock related to output (or industrial production) and the demand shock related to the monetary and fiscal variables, all of which are already included in our model.

Based on the above discussion, we start with the following linear model

$$RET_t = \alpha_0 + \alpha_1 RET_{t-1} + \sum_{i=1}^{m_1} \beta_{1i} IPG_{t-k_{1i}} + \sum_{i=1}^{m_2} \beta_{2i} DFF_{t-k_{2i}} + \sum_{i=1}^{m_3} \beta_{3i} CFD_{t-k_{3i}} + u_t, \quad (12)$$

where RET_t represents one of the three asset return series: SR_{t-1}, DCR_{t-1} and DTR_{t-1}. The corresponding most general nonparametric model has the form

$$RET_t = g(RET_{t-1}, IPG_{t-k_{11}}, ..., IPG_{t-k_{1m_1}}, ..., CFD_{t-k_{31}}, ..., CFD_{t-k_{3m_3}}) + u_t. \quad (13)$$

Nonparametric model specification for time series is an ongoing research topic, and applied researchers have to determine both the values of smoothing parameters and the autoregressive lag orders in nonparametric regressions using time series data. To determine the lag order in model (13), we apply Hurvich, Simonoff and Tsai's (1998) nonparametric version of the corrected Akaike information criterion (AICc) due to its impressive finite-sample properties. Another popular method to select the smoothing parameter and/or the autoregressive lag order is based on the cross-validation method (see Gao and Tong (2004) and the references therein). Given the dimension of the problem, we suggest the following procedure to specify the lag order for each of the three predictor variables in model (13), IPG_t, DFF_t and CFD_t.

Step (i): Treat equation (13) as a model for RET_t with one predictor variable and determine the lag order for that variable. Specifically, first choose k_{11} to minimize AICc for $1 \leq k_{11} \leq K$, where K is the pre-specified maximum lag length. Second, choose k_{11} and k_{12} to minimize AICc for $1 \leq k_{11}$, $k_{12} \leq K$ (here k_{11} may or may not equal the value in the previous search, depending on the dimension of the problem). Conduct a sequence of such searches until the addition of one additional lag no longer improves the model fit.

Step (ii): Given the lag order structure for the first variable, determine the lag structure for the second predictor variable using the same procedure as in step (i). Given the lag structures for the first two variables, specify the lag order for the third variable.

Step (iii): Repeat steps (i)-(ii) for different orderings of the predictor variables.

The above procedure combines and modifies Tjøstheim and Auestad's (1994) directed search procedure for univariate nonparametric model selection and Hsiao's (1981) search procedure in linear models with lagged terms of multiple variables.

When performing a bootstrap test for model adequacy, such as testing the adequacy of the linear regression model, the null model (12) contains lagged terms of both the dependent variable (RET_t) and other explanatory regressors (IPG_t, DFF_t and CFD_t). To implement our proposed bootstrap procedures for testing linearity, we generate random samples by conditioning on the lagged values of the explanatory variables IPG_t, DFF_t and CFD_t.

4.1 Empirical results for U.S. stock returns

We set the maximum lag length $K = 6$. Using the AICc criterion for the stock returns model, we find that $k_{11} = 6$ for IPG_t, $k_{21} = 2$ and $k_{22} = 5$ for DFF_t, and $k_{31} = 5$ for CFD_t. Given this lag structure we first estimate the linear model (12) and obtain the following coefficient estimates:

$$SR_t = 0.18 + 0.24^{**} SR_{t-1} + 0.063 IPG_{t-6} - 0.10^{**} DFF_{t-2} - 0.61^{**} DFF_{t-5} - 0.13 CFD_{t-5}, \qquad (14)$$

where $**$ indicates that the coefficient is significantly different from 0 at the 5% level. The goodness-of-fit R^2 is 0.08. The present value relation theory posits that stock prices equal the expected present value of future cash flows. A contractionary monetary policy shock can exert real effects by decreasing future cash flows or by increasing the discount factors at which those cash flows are capitalized. Consistent with the theory and numerous earlier studies (e.g., Patelis, 1997; Thorbecke, 1997; Bernanke and Kuttner, 2005), we find that a higher federal funds rate is associated with lower stock returns. We also find that growth in industry production has a positive impact on stock returns, and an increase in the deficit (or a decrease in surplus) is associated with lower stock returns. However, the parameter estimates for the latter two variables are statistically insignificant. In particular, the insignificant influence of fiscal deficits on stock returns is consistent with earlier studies using a linear model (e.g., Hess and Lee, 1999).

One possible explanation for the insignificant parameter estimates is neglected nonlinearity. We consider fiscal deficits as a state variable. The use of fiscal deficits as the single state variable is well motivated by Sargent (1999). As suggested by Jensen, Mercer, & Johnson (1996), the pre-existing condition of credit constraints may cause monetary policy to have asymmetric impacts. Hence, federal funds rate changes might be an additional state variable. It should be emphasized that both one and two-state-variable models address the main issue of fiscal deficits as an indicator of constraints on monetary policy actions. Obviously, which model is a better fit is an open question and can only be answered empirically.

We thus turn to various semi/nonparametric model specifications. We start with the following varying coefficient model with two state variables, DFF_{t-5} and CFD_{t-5}:

$$SR_t = (1, SR_{t-1}, IPG_{t-6}, DFF_{t-2})\beta(DFF_{t-5}, CFD_{t-5}) + u_t. \tag{15}$$

The smoothing parameters are selected via $a_j = z_{j,sd}n^{-1/6}$, where $z_{j,sd}$ is the sample standard deviation of $\{z_{jt}\}_{t=7}^n$, and $(z_{1t}, z_{2t}) = (DFF_{t-5}, CFD_{t-5})$. The estimated coefficient functions based on (15) are plotted in Figure 1. The estimation goodness-of-fit R^2 is 0.16 which significantly improves over the linear model R^2 of 0.08. We formally test model (15) against the following fully nonparametric model:

$$SR_t = g(SR_{t-1}, IPG_{t-6}, DFF_{t-2}, DFF_{t-5}, CFD_{t-5}) + u_t. \tag{16}$$

The smoothing parameters are selected via $h_j = x_{j,sd}n^{-1/6}$, where $x_{j,sd}$ the sample standard deviation of $\{x_{jt}\}_{t=7}^{n}$, and $(x_{1t}, ..., x_{5t}) = (SR_{t-1}, IPG_{t-6}, DFF_{t-2}, DFF_{t-5}, CFD_{t-5})$. The J_n test statistic yields a value of -0.555. We conduct 400 bootstrap replications and obtain a p-value of 0.27. Therefore, we fail to reject the varying coefficient model (15) at any conventional level. This suggests that the varying coefficient model can adequately capture the nonlinearity in the data. We further test the adequacy of a simple linear regression model (14) against the semiparametric varying coefficient model (15). Based on 400 bootstrap replications we obtain a p-value of 0.01. Therefore, we reject the linear model at the 5% significance level. As confirming evidence, we also test the linear model (14) directly against the fully nonparametric model (16) using both Li and Wang's (1998) test and Cai, Fan and Yao's (2000) GLR tests. Not surprisingly, the linear model is rejected by both tests at the 1% level.

Figure 1 provide graphs of the four varying coefficient function estimates of model (15) for the intercept term, SR_{t-1}, IPG_{t-6} and DFF_{t-2}. Under different combinations of fiscal and monetary policy conditions, the impacts of these variables on stock returns vary, showing generally nonlinear patterns. An empirically interesting question is whether the combination of the two state variables only affects the coefficients of other variables, but does not affect stock returns directly. This can be tested against model (15) using a partially linear varying coefficient model as the null model, where the intercept does not vary over the state variables (i.e., $\beta_1(DFF_{t-5}, CFD_{t-5}) = \beta_{10}$, a constant). The test result shows that the null model is rejected at the 5% level (with a p-value of 0.01). We also reject the null that none of the slope coefficients in model (15) vary over the state variables at the 5% significance level. All the graphs in Figure 1 show large nonlinearity along the dimension of change in fiscal deficits, while Figure 1b and particularly Figure 1d also show some nonlinearity along the dimension of change in the federal funds rate. Nevertheless, as will be shown shortly, the two-state-variable model is statistically indistinguishable from the one-state-variable at conventional significance levels, implying that the nonlinearity over fiscal deficits is more pronounced than the nonlinearity over the earlier period's credit constraints. Hence, we will reserve the more detailed discussion for the one-state-variable model below.

We now investigate whether a simpler one-state-variable varying coefficient specification is adequate against the two-state-variable varying coefficient model (16). Specifically, the null model is the following one-state variable varying coefficient model:

$$SR_t = (1, SR_{t-1}, IPG_{t-6}, DFF_{t-2}, DFF_{t-5})\beta(CFD_{t-5}) + u_t, \tag{17}$$

where the only state variable is CFD_{t-5}. The $\hat{J}_n$ test and the GLR test of model (17) against the general nonparametric model (16) yields a p-value of 0.260 and 0.157, respectively. Therefore we do not reject the null model (17) at the 5% level. Figure 2 plots the coefficient estimates from model (17) of the intercept, SR_{t-1}, IPG_{t-6}, DFF_{t-2} and DFF_{t-5} as functions of the state variable CFD_{t-5} (along with their 90% confidence bands). For comparison we also plot the linear model estimation results. Under different fiscal conditions, the impacts of these variables on stock returns vary, showing generally nonlinear patterns.

We also consider a partially linear varying coefficient model with one state variable, where the intercept is restrained to be a constant (i.e., $\beta_1(CFD_{t-5}) = \beta_{10}$, a constant). We fail to reject the restrictive null model at the 5% significance level (with a p-value of 0.155 and 0.153 for the $\hat{J}_n$ and the GLR tests, respectively). In contrast, the nonlinearity of the slope coefficients over the state variable is confirmed at the 5% significance level. This result further clarifies the economic content of nonlinearity of the intercept term over the two state variables CFD_{t-5} and DFF_{t-5}, which essentially capture the nonlinearity of $(DFF_{t-5})\beta_5(CFD_{t-5})$ rather than the nonlinearity of $\beta_1(CFD_{t-5})$. Hence, there is evidence that the fiscal deficit is not a (linear or nonlinear) direct information variable for the stock market, but rather serves as a conditioning information variable, one that can indicate the constraints of monetary policy actions.

With the constant intercept imposed, we obtain plots of the varying coefficient estimates for SR_{t-1}, IPG_{t-6}, DFF_{t-2} and DFF_{t-5} on stock returns. These are similar to those in Figure 2 and therefore not reported here.

Figure 2 provides a more clear-cut pattern on how fiscal deficits influence the stock market. Specifically, lagged industrial production growth is a more economically significant predictor for stock returns (as indicated by larger coefficient magnitude) during the periods of fiscal contraction (i.e., when CFD < 0). Its importance decreases when the change in the fiscal surplus gets closer to zero or turns positive. To the extent that economic growth rate generally has a positive impact on the stock market, our result is consistent with the argument that the stock market perceives economic growth to be less sustainable with increasing fiscal deficits. Fatas and Mihov (2003) document that aggressive fiscal policy induces significant macroeconomic instability, which further substantially lowers economic growth rate in the future. Our result is consistent with the idea that the potentially negative impact of fiscal deficits on future economic growth constrains the positive influence of economic growth on the stock market.

It is well known that fiscal deficits may be inflationary, which may or may not be due to government debt monetization (e.g., Canzoneri, Cumby, and Diba, 2001; Catao and Terrones, 2005). In our empirical model, this is most likely to be reflected in the federal funds rate movement as the inflation rate is implicitly a major monetary policy target in the U.S. during much of the sample period. Interestingly, when there is large fiscal contraction, i.e., when CFD < 0, the federal funds rate movement has a larger impact on stock market returns. This influence of the federal funds rate decreases dramatically as the fiscal contraction changes to the fiscal expansion. Thus a tightening of monetary policy in conjunction with a tightening of fiscal policy has a relatively large negative impact on stock returns. A tightening of monetary policy when fiscal policy is loosening does not have this large negative impact. Our results suggest that the impact of monetary policy on stock returns is large and significant only when fiscal policy is loosening. It is a stylized fact that only unanticipated changes in the federal funds rate affect the stock market (e.g., Bernanke and Kuttner, 2005). Our result is consistent with an argument that large increases in the fiscal deficit would lead to higher inflation rates in the future, and therefore to higher future federal funds rate movements, as this would be driven by the consideration of fighting against inflation. This increase in the future federal funds rate is largely anticipated. In contrast, a large increase in the fiscal surplus does not help predict the inflation rate, because the possible reduction in future inflation rates is less certain, as is the response of the federal funds rate. Basically, this is an argument that monetary policy responds asymmetrically to anticipated changes in future inflation. In this case, the funds rate movement could be largely unanticipated by the market, and thus the same amount of federal funds rate movements but with a larger surprise component would have a larger impact on the stock market. In sum, the overall evidence suggests that economic growth and, more importantly, the funds rate, can exert a more pronounced impact on the stock market when there are rate increases accompanied by increases in the fiscal surplus (or decreases in the fiscal deficit) as opposed to rate increases accompanied by increases in fiscal deficits.

4.2 Empirical results for U.S. bond yields

Following much of the literature, we assume that the bond yields contains a unit root and thus focus on the first difference of the yields. However, we also conducted the analysis in levels of both the corporate bond and Treasury bond yields (not reported here), and the basic nonlinearity patterns remain the same.

For the Treasury bond yield, setting the maximum lag length $K = 6$ in the fully nonparametric model (13) and using the AICc criterion, we find that $k_{11} = 6$ for IPG_t, $k_{21} = 2$ for DFF_t, and $k_{31} = 4$ for CFD_t. Given this lag structure we have the OLS estimates of the linear model for the Treasury bond yield (DTR_t) as follows:

$$DTR_t = 0.006 - 0.17^{**} DTR_{t-1} - 0.004 IPG_{t-6} - 0.043^{*} DFF_{t-2} - 0.007 CFD_{t-4}. \tag{18}$$

The R^2 is 0.03. From model (18), we find that the lagged impact of the fiscal policy measure (CFD_t) on Treasury bond returns is not significant at the 5% level. The corresponding fully nonparametric model takes the form:

$$DTR_t = g(DTR_{t-1}, IPG_{t-6}, DFF_{t-2}, CFD_{t-4}) + u_t. \tag{19}$$

We test for the linear null model (18) against the general nonparametric regression model (19). The smoothing parameters are selected via $h_j = x_{j,sd} n^{-1/8}$, where $x_{j,sd}$ is the sample standard deviation of $\{x_{jt}\}_{t=7}^{n}$, and $(x_{1t}, ..., x_{4t}) = (DTR_{t-1}, IPG_{t-6}, DFF_{t-2}, CFD_{t-4})$. We obtain a p-value of 0.003. Hence, we firmly reject the null of a linear model.

Next, we consider a one-state varying coefficient model given by

$$DTR_t = (1, DTR_{t-1}, IPG_{t-6}, DFF_{t-2})\beta(CFD_{t-4}) + u_t. \tag{20}$$

The smoothing parameter is chosen as $a = z_{sd}\, n^{-1/5}$, where z_{sd} is the sample standard deviation of $\{z_t\}_{t=7}^{n}$, and $z_t = CFD_{t-4}$. The estimation goodness-of-fit R^2 is 0.13; comparing this with $R^2 = 0.03$ from the linear regression model suggests that the linear model is misspecified.

To check the adequacy of the varying coefficient model (20), we test the null of a varying coefficient (20) against the nonparametric model (19). The corresponding p-value is 0.08. Therefore, we fail to reject the one-state-variable varying coefficient model (20) at the 5% level.

In Figure 3 we graph the four coefficients of the intercept term, DTR_{t-1}, IPG_{t-6} and DFF_{t-2} as functions of the fiscal policy CFD_{t-4}. Confirming the statistical testing results, most of the coefficient functions appear to be non-constant in the ranges of the state variables.

We further test the null of a partially linear varying coefficient model where the intercept does not vary over the state variables, i.e., $\beta_1(CFD_{t-4}) = \beta_{10}$, a constant. We fail to reject the null model with a p-value of 0.623 and 0.545 for the $\hat{J}_n$ and the GLR tests, respectively. This is similar to our results for stock returns, and suggests that the fiscal deficit is not a (linear or nonlinear) direct information variable in the Treasury bond market. Nevertheless, as shown in Figure 3, the influence of fiscal deficits as a conditioning information variable is clearly present and the nonlinearity of all the slope coefficients over the state variable is confirmed at both the 1% and 5% levels (with a p-value of 0.008). More importantly, there are clearly different patterns over the impact of the funds rate movement on the bond market. Specifically, with large increases in the fiscal deficit, the increase in the funds rate clearly increases Treasury bond yields. As discussed earlier, with a rising deficits and hence rising debt level, agents' expectation of debt monetization may lead to inflationary pressures and to an inflation-bias in discretionary monetary policy. The central bank's action to increase the base interest rate would yield a higher nominal interest rate on outstanding debt and help maintain government fiscal discipline, which may reduce the inflation bias that would otherwise exist in monetary policy and lead to a lower expected inflation rate (e.g., Kutsoati, 2002). On the other hand, with increasing fiscal contraction such a pattern does not appear, so the impact of the funds rate on the Treasury bond market becomes much smaller.

Finally we also conducted similar analysis for the corporate bond yield. Again, we reject a linear specification (with a p-value of 0.003) in favor of a semiparametric varying coefficient model. The detailed results are not reported here to conserve space, but they are available from the authors upon request.

5 Conclusions

This paper examines the role of fiscal policy on the U.S. stock, and Treasury bonds markets. We consider two potential roles: fiscal deficits as a direct information variable, and as a conditioning information variable indicating the impact of constraints on monetary policy actions. Consistent with the earlier literature, linear modeling often leads to the conclusion that there is little significant influence of fiscal policy on asset markets. We show this is misleading due to the neglected nonlinearity problem. Furthermore, compared to a general nonparametric model, a semiparametric varying coefficient model with fiscal deficits as the single variable is found to be adequate to model the nonlinearity for stock returns and treasure bond yields. There is evidence that fiscal deficits is not a direct information variable for the stock and Treasury bond markets. Instead, the influence of fiscal deficits is due to its role as a conditioning information variable, perhaps indicating the constraint on monetary policy actions. In summary, regardless of the type of asset markets under consideration, the results consistently show that the impact of monetary policy on the asset markets varies with the state of fiscal deficits or surpluses.

To our knowledge, this study is among the first to provide positive empirical evidence for the notion of strong interdependence between monetary and fiscal policies, particularly in the context of their impact on financial markets. Due to the traditional isolated consideration of these two policies and the use of linear modeling techniques in previous research, our study calls for reexamining monetary policy issues with proper allowance for the role of fiscal policy and for nonlinear interactions between monetary and fiscal policies.

APPENDIX A: **Proofs of Theorem 3.1** and Theorem 3.2

To simplify the notation we will assume that $a_1 = ... = a_q = a$ and $h_1 = ... = h_d = h$ so that $a_1 \ldots a_q = a^q$ and $h_1 \ldots h_d = h^d$. Denotes $\hat{f}_{w_t} = (nh^d)^{-1} \sum_{s \neq t}^{n} K_{t,s}$, which is a kernel estimator of $f(W_t)$. Using $\hat{u}_t = Y_t - X_t \hat{\beta}_t = X_t'(\beta_t - \hat{\beta}_t) + u_t$, where $\beta_t = \beta(Z_t)$ and $\hat{\beta}_t = \hat{\beta}(Z_t)$, the following expression for $\hat{J}_n$ is immediate from (6):

$$\hat{J}_n = \frac{1}{n^2 h^d} \sum_t \sum_{s \neq t} \{u_t u_s + (\beta_t - \hat{\beta}_t)' X_t X_s' (\beta_s - \hat{\beta}_s) + 2 u_t X_s' (\beta_s - \hat{\beta}_s)\} I_t I_s K_{t,s}$$

$$\stackrel{\text{def}}{=} J_{n1} + J_{n2} + 2 J_{n3}, \tag{A.1}$$

where the definitions of J_{nj} should be apparent. We shall complete the proof of Theorem 3.1 by showing that $nh^{d/2} J_{n1}/\hat{\sigma}_a \to N(0,1)$ in distribution and that $J_{nj} = o_p((nh^{d/2})^{-1})$ for $j = 2, 3$. These results are proved in Lemmas A.1 to A.3 below.

Lemma A.1 $nh^{d/2} J_{n1}/\hat{\sigma} \to N(0,1)$ *in distribution.*

Proof: It follows the same proof as the proof of Lemma A.2 of Li (1999).

Lemma A.2 $J_{n2} = o_p((nh^{d/2})^{-1})$.

PROOF: For notational simplicity we will omit the indicator function I_t (I_s) in the proof below. Note that $K(\cdot)$ is a non-negative function and $\hat{f}_{w_t} = (nh^d)^{-1}\sum_{s\neq t} K_{t,s}$ is a kernel estimator of $f_{w_t} \equiv f(W_t)$, we have (C below denotes a generic constant)

$J_{n2} = (n^2h^d)^{-1}\sum_t\sum_{s\neq t}(\beta_t - \hat{\beta}_t)' X_t X_s' (\beta_s - \hat{\beta}_s) K_{t,s}$

$\leq (1/2)(n^2h^d)^{-1}\sum_t\sum_{s\neq t}[||X_t'(\beta_t - \hat{\beta}_t)||^2 + ||X_s'(\beta_s - \hat{\beta}_s)||^2]K_{t,s}$

$= n^{-1}\sum_t ||X_t'(\beta_t - \hat{\beta}_t)^2||^2 (nh^d)^{-1}\sum_{s\neq t} K_{t,s}$

$= n^{-1}\sum_t ||X_t'(\beta_t - \hat{\beta}_t)||^2 f_{w_t} + n^{-1}\sum_t ||X_t'(\beta_t - \hat{\beta}_t)||^2 (\hat{f}_{w_t} - f_{w_t})$

$\leq Cn^{-1}\sum_t ||X_t'(\beta_t - \hat{\beta}_t)||^2 + sup_{w\in M}|\hat{f}(w) - f(w)|[n^{-1}\sum_t ||X_t'(\beta_t - \hat{\beta}_t)||^2]$

$= [O(1) + o_p(1)]O_p(a^{2\nu} + (na^q)^{-1}) = o((nh^{d/2})^{-1})$

by Lemma A.4 and the fact that $sup_{w\in M}|\hat{f}(w) - f(w)| = o_p(1)$.

Lemma A.3 $J_{n3} = o_p((nh^{d/2})^{-1})$.

PROOF: By following exactly the same arguments as in the proof of Lemma C.5 (i) in Li (1999), and also using the result of Lemma A.4, one can show that

$J_{n3} = (n^2h^d)^{-1}\sum_t\sum_{s\neq t} u_t X_s'(\beta_s - \hat{\beta}_s)K_{t,s} = O_p(n^{-1/2}(nh^d)^{1/2}(a^{2\nu} + (na^q))^{1/2}) = o_p((nh^{d/2})^{-1})$.

Lemma A.4 $n^{-1}\sum_t ||X_t'(\hat{\beta}_t - \beta_t)I_t||^2 = O_p(a^{2\nu} + (na^p)^{-1}) = o_p((nh^{d/2})^{-1})$.

Denote by $m_{1t} = E(X_t X_t'|Z_t)$ and $m_{2t} = E(X_t Y_t|Z_t)$. Then we know that $\beta(Z_t) = m_{1t}^{-1} m_{2t}$. Define $\hat{m}_{1t} = (na^q)^{-1}\sum_{s\neq t}^n X_t X_t' K_{t,s}$ and $\hat{m}_{2t} = (na^q)^{-1}\sum_{s\neq t}^n X_t Y_t K_{t,s}$. Then we have $\hat{\beta}_t - \beta_t = \hat{m}_{1t}^{-1}\hat{m}_{2t} - m_{1t} m_{2t}$. By adding and subtracting terms, we get

$$\begin{aligned}
\hat{\beta}_t - \beta_t &= m_{1t}^{-1}[\hat{m}_{2t} - m_{2t}] + m_{1t}^{-1}[m_{1t} - \hat{m}_{1t}]\hat{m}_{1t}^{-1}\hat{m}_{2t} \\
&= m_{1t}^{-1}[\hat{m}_{2t} - m_{2t}] + m_{1t}^{-1}[m_{1t} - \hat{m}_{1t}]m_{1t}^{-1}m_{2t} + m_{1t}^{-1}[m_{1t} - \hat{m}_{1t}][\hat{m}_{1t}^{-1}\hat{m}_{2t} - m_{1t}^{-1}m_{2t}] \\
&\equiv A_{n,1t} + A_{n,2t} + A_{n,3t}, \qquad \text{(A.2)}
\end{aligned}$$

where $A_{n,1t} = m_{1t}^{-1}[\hat{m}_{2t} - m_{2t}]$, $A_{n,2t} = m_{1t}^{-1}[m_{1t} - \hat{m}_{1t}]m_{1t}^{-1}m_{2t}$ and $A_{n,3t} = m_{1t}^{-1}[m_{1t} - \hat{m}_{1t}][\hat{m}_{1t}^{-1}\hat{m}_{2t} - m_{1t}^{-1}m_{2t}]$. Using (A.2) and the triangle inequality we obtain

$$n^{-1}\sum_t ||X_t'(\hat{\beta}_t - \beta_t)I_t||^2 \leq \frac{3}{n}\sum_t \left[||X_t' A_{n,1t} I_t||^2 + ||X_t' A_{n,2t} I_t||^2 + ||X_t' A_{n,3t} I_t||^2\right] \equiv A_1 + A_2 + A_3,$$

where the definition of A_j $(j = 1, 2, 3)$ should be apparent.

By Lemma A.2 of Fan and Li (1999) we know that for $j = 1, 2$, $A_j = 3n^{-1} \sum_{t=1}^{n} ||X_t' A_{n,jt} I_t||^2 = O_p((na^q)^{-1} + a^{2\nu})$. Finally by the uniform convergence results of Masry (1996), it is easy to show that A_3 has an order smaller than A_1 (or A_2). This completes the proof of Lemma A.4.

Proof of Theorem 3.2

First we introduce a notation. We will write $A_n = O_p^*(1)$ if $E^*[||A_n||] = O_p(1)$, where $E^*(\cdot) = E(\cdot|\{X_t, Z_t, Y_t\}_{t=1}^n)$.[5]

Because the cumulative distribution function for the standard normal random variable is a continuous distribution, by Bhattacharya and Rao (1986), we know that (10) is equivalent to (for a given value of z),

$$\left| P\left(\hat{T}_n^* \le z | \{X_t, Z_t, Y_t\}_{t=1}^n\right) - \Phi(z)\right| = o_p(1). \tag{A.3}$$

From $\hat{u}_t^* = Y_t^* - X_t' \hat{\beta}_t^* = X_t'(\hat{\beta}_t - \hat{\beta}_t^*) + u_t^*$, we get

$$\hat{J}_n^* = \frac{1}{n^2 h^d} \sum_t \sum_{s \neq t} \{u_t^* u_s^* + (\hat{\beta}_t - \hat{\beta}_t^*) X_t X_s{}'(\hat{\beta}_s - \hat{\beta}_s^*) + 2u_t^* X_s'(\hat{\beta}_s - \hat{\beta}_s^*)\} I_t I_s K_{ts,} = J_{n1}^* + J_{n2}^* + J_{n3}^*.$$

It is easy to see that J_{n1}^* is a degenerate U-statistic. The conditional second moment of J_{n1}^* is $E^*(J_{n1}^{*2}) = 2(n^2h^d)^{-2} \sum_t \sum_{s\neq t} E^*(u_t^{*2} u_s^{*2} I_t I_s K_{ts}^2) = 2(n^2h^d)^{-1} \sum_t \sum_{s\neq t} \hat{u}_t^2 \hat{u}_s^2 I_t I_s K_{ts}^2 = (n^2h^d)^{-1}\hat{\sigma}^2$. Therefore, we have that $(n^2h^d)^{1/2} J_{n1}^*/\hat{\sigma} \sim (0, 1)$. It is easy to show that $\hat{\sigma}^* - \hat{\sigma} = o_p(1)$. Thus, $(n^2h^d)^{1/2} J_{n1}^*/\hat{\sigma}$ has conditional mean $o_p(1)$ and conditional variance $1 + o_p(1)$ (conditional on the random sample). Next, it can be shown that J_{n1}^* satisfies the conditions for a degenerate U-Statistics (e.g., de Jong, (1987), Fan and Li (1999), Gao and King (2004)), we know that (A.3) holds true for $(n^2h^d)^{1/2} J_{n1}^*/\hat{\sigma}^*$.

Finally, similar to the proofs of Lemma A.2 and Lemma A.3, one can show that $J_{n2}^* = o_p^*((nh^{d/2})^{-1})$ and $J_{n3}^* = o_p^*((nh^{d/2})^{-1})$. Then (A.3) follows.

References

Bhattacharya, R. N., Rao, R. R., 1986. Normal Approximations and Asymptotic Expansions. R. E. Krieger Publishing Company, Malabar, FL.

Bernanke, B. S., Kuttner, K. N., 2005. What explains the stock market's reaction to federal reserve policy? Journal of Finance 60, 1221-1257.

[5]Here we only give a sufficient condition for $A_n = O_p^*(1)$, which is convenient to use in our context. For a rigorous definition of $A_n = O_p^*(1)$, see Goncalves and White (2004).

Blanchard, O.J., 1981. Output, the stock market, and interest rates. American Economic Review 45, 132-143.

Cai, Z., Fan, J., Yao, Q., 2000. Functional-coefficient regression models for nonlinear time series. Journal of American Statistical Association 95, 941-956.

Canzoneri, M., Cumby, R., Diba, B., 2001. Is the price level determined by the needs of fiscal solvency? American Economic Review 91, 1221-1238.

Catao, L.A.V., Terrones, M.E., 2005. Fiscal deficits and inflation. Journal of Monetary Economics 52, 529-554.

Chen, X., Fan, Y., 1999. Consistent model specification test in semiparametric and nonparametric models for econometric time series. Journal of Econometrics 91, 373-401.

Darrat, A.F., 1990. Stock returns, money and fiscal deficits. Journal of Financial and Quantitative Analysis 25, 387-398.

de Jong, P., 1987. A central limit theorem for generalized quadratic forms. Probability Theory and Related Fields 75, 261-277.

Fan, Y., Li, Q., 1996. Consistent Model Specification Tests: Omitted Variables, Semiparametric Functional Forms, Econometrica 64, 865-890.

Fan, Y., Li, Q., 1999. Central Limit Theorem for Degenerate U-Statistics of Absolute Regular Processes With Applications to Model Specification Testing. Journal of Nonparametric Statistics 10, 245-271.

Fatas, A., Mihov, I., 2003. The case for restricting fiscal policy decision. Quarterly Journal of Economics, 1419-1447.

Gao, J., King, M., 2004. Adaptive Testing in Continuous-Time Diffusion Models. Econometric Theory 20, 844-882.

Gao, J., Tong, H., 2004. Semiparametric non-linear time series model selection. Journal of Royal Society Series B 66, 321-336.

Goncalves, S. and H. White (2004). Maximum likelihood and the bootstrap for nonlinear dynamic model with fixed effects. Journal of Econometrics 119, 199-219.

Hess, P. J., Lee, B. S., 1999. Stock returns and inflation with supply and demand disturbances. Review of Financial Studies 12, 1203-1218.

Hsiao, C., 1981. Autoregressive modelling and money-income causality detection. Journal of Monetary Economics 7: 85-106

Hurvich, C. M., Simonoff, J. S., Tsai, C.L., 1998, Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion. Journal of the Royal Statistical Society Series B 60, 271-293.

Jensen, G., Mercer, J.M., Johnson, R.R., 1996. Business conditions, monetary policy, and expected security returns. Journal of Financial Economics 40, 213-237.

Kutsoati, E., 2002. Debt-contingent inflation contracts and target. Journal of Economic Dynamics & Control 26, 399-421.

Li, Q., 1999. Consistent Model Specification Tests for Time Series Econometric Models. Journal of Econometrics 92, 101-147.

Li, Q., Huang, C., Li, D., Fu, T.T., 2002. Semiparametric Smooth Coefficient Models, Journal of Business and Economic Statistics 20, 412-422.

Li, Q., Wang, S., 1998. A simple consistent bootstrap test for a parametric regression function. Journal of Econometrics 87, 145-165.

Linnemann, L., Schabert, A., 2003. Fiscal policy in the new neoclassical synthesis. Journal of Money Credit and Banking 35, 911-929.

Masry, E., 1996. Multivariate Local Polynomial Regression Estimation for Time Series: Uniform Strong Consistency and Rates. Journal of Time Series Analysis 17, 571-599.

Patelis, A.D., 1997. Stock return predictability and the role of monetary policy. Journal of Finance 52, 1951-1972.

Robinson, P., 1988. Root-N consistent semiparametric regression. Econometrica 56, 931-954.

Sargent, T.J., 1999. A primer on monetary and fiscal policy. Journal of Banking and Finance 23, 1463-1482.

Schabert, A., 2004. Interactions of monetary and fiscal policy via open market operations. Economic Journal 114, C186-C206.

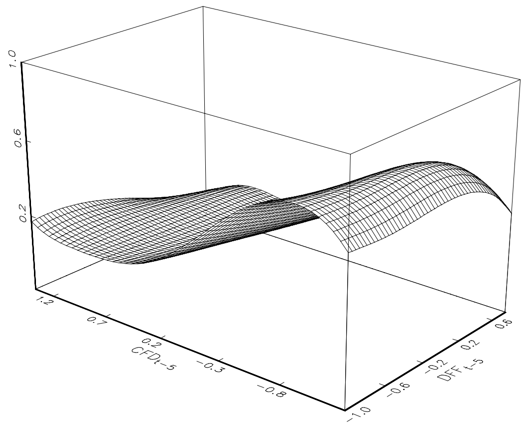
Thorbecke, W., 1997. On stock market returns and monetary policy. Journal of Finance 52, 635-54.

Tjøstheim, D., Auestad, B.H.,, 1994. Nonparametric identification of nonlinear time series: Selecting significant lags. Journal of the American Statistical Association 89, 1410-1419.

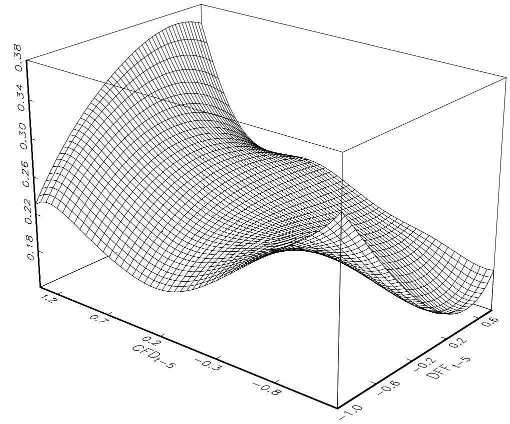
Ullah, A., 1985. Specification analysis of econometric models. Journal of Quantitative Economics 1, 187-209.

Zheng, J.X., 1996. A consistent test for functional form via nonparametric estimation techniques. Journal of Econometrics 75, 263-289.

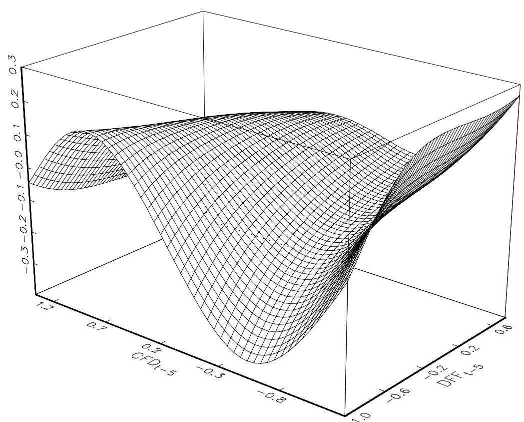
(a) Coefficient on Intercept: $\beta_1(DFF_{t\text{-}5}, CFD_{t\text{-}5})$



(b) Coefficient on $SR_{t\text{-}1}$: $\beta_2(DFF_{t\text{-}5}, CFD_{t\text{-}5})$



(c) Coefficient on $IPG_{t\text{-}6}$: $\beta_3(DFF_{t\text{-}5}, CFD_{t\text{-}5})$



(d) Coefficient on $DFF_{t\text{-}2}$: $\beta_4(DFF_{t\text{-}5}, CFD_{t\text{-}5})$

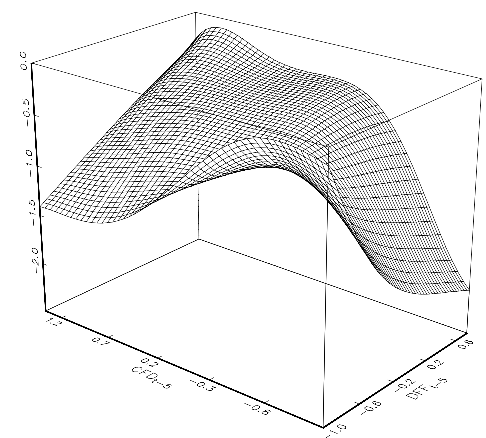
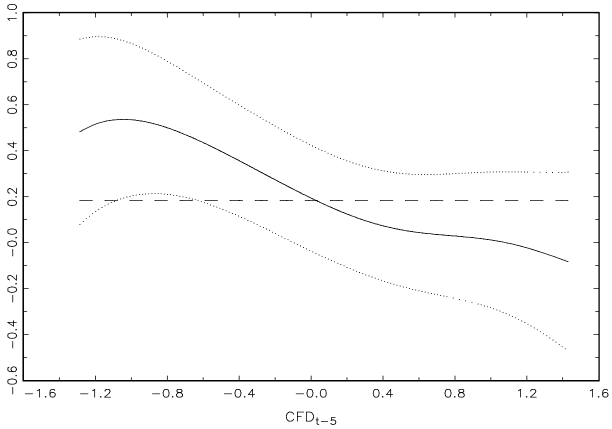
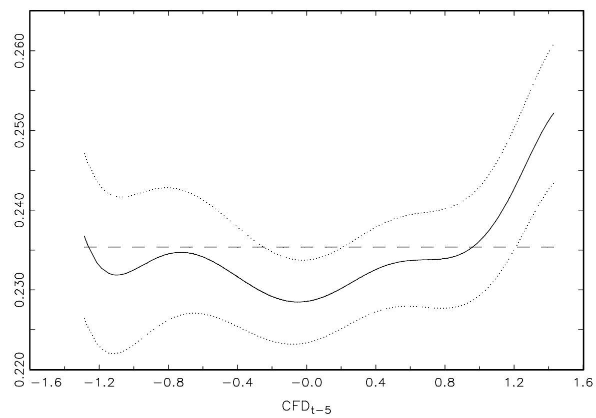


Figure 1. Coefficient estimates of the intercept term, $SR_{t\text{-}1}$, $IPG_{t\text{-}6}$ and $DFF_{t\text{-}2}$ for the two-state-variable smooth coefficient model (14) of stock returns (SR_t)

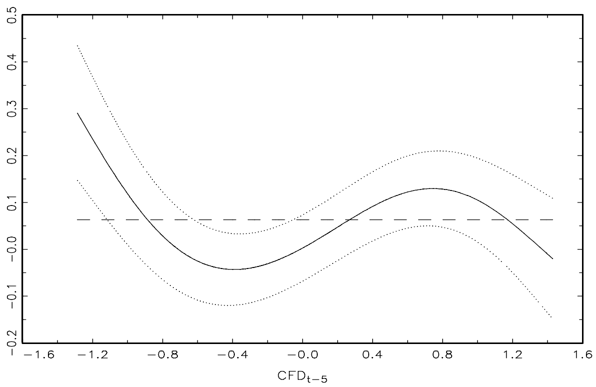
(a) Coefficient on Intercept: $\beta_1(CFD_{t\text{-}5})$



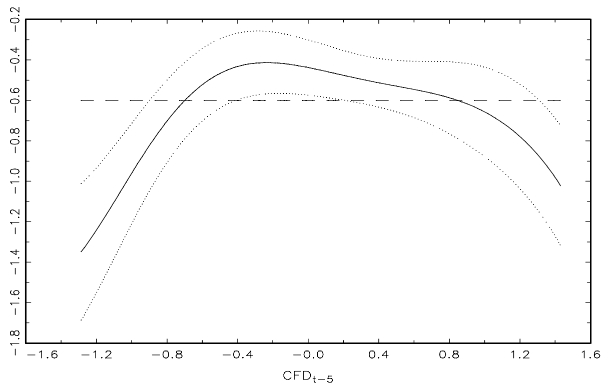
(b) Coefficient on $SR_{t\text{-}1}$: $\beta_2(CFD_{t\text{-}5})$



(c) Coefficient on $IPG_{t\text{-}6}$: $\beta_3(CFD_{t\text{-}5})$



(d) Coefficient on $DFF_{t\text{-}2}$: $\beta_4(CFD_{t\text{-}5})$



(e) Coefficient on $DFF_{t\text{-}5}$: $\beta_5(CFD_{t\text{-}5})$

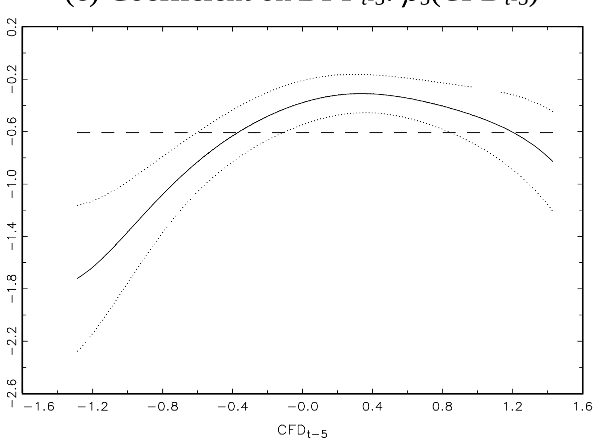


Figure 2. Coefficient estimates of the intercept term, $SR_{t\text{-}1}$, $IPG_{t\text{-}6}$, $DFF_{t\text{-}2}$ and $DFF_{t\text{-}5}$ for the one-state-variable smooth coefficient model (16) of stock returns (SR_t)

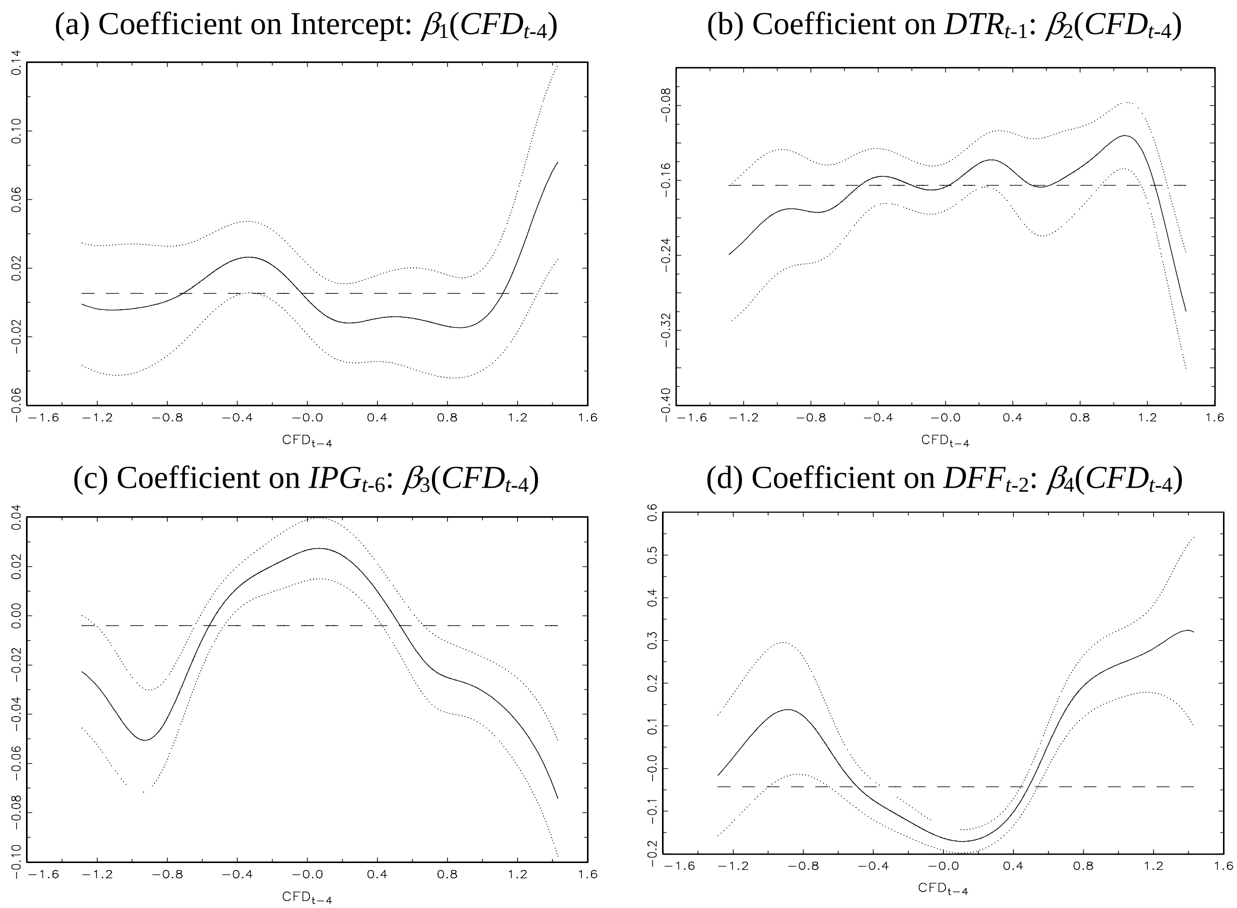


Figure 3. Coefficient estimates of the intercept term, $DTR_{t\text{-}1}$, $IPG_{t\text{-}6}$, and $DFF_{t\text{-}2}$ for the one-state-variable smooth coefficient model (19) of Treasury bond yields (DTR_t)