Testing for the Markov Property in Time Series

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Abstract

The Markov property is a fundamental property in time series analysis and is often assumed in economic and financial modelling. We develop a test for the Markov property using the conditional characteristic function embedded in a frequency domain approach, which checks the implication of the Markov property in every conditional moment (if exist) and over many lags. The proposed test is applicable to both univariate and multivariate time series with discrete or continuous distributions. Simulation studies show that with the use of a smoothed nonparametric transition density-based bootstrap procedure, the proposed test has reasonable sizes and all-around power against non-Markov alternatives in finite samples. We apply the test to a number of financial time series and find some evidence against the Markov property.

Key words: Markov property, Conditional characteristic function, Generalized cross-spectrum, Smoothed nonparametric bootstrap

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1. INTRODUCTION

The Markov property is a fundamental property in time series analysis and is often a maintained assumption in economic and financial modelling. Testing for the validity of the Markov property has important implications in economics, finance as well as time series analysis. In economics, Markov decision processes (MDP), which are based on the Markov assumption, provide a broad framework for modelling sequential decision making under uncertainty (see Rust 1994 and Ljungqvist and Sargent 2000 for excellent surveys) and have been extensively used in economics, finance and marketing. Applications of MDP include investment under uncertainty (Lucas and Prescott 1971, Sargent 1987), asset pricing (Lucas 1978, Hall 1978, Hansen and Singleton 1983, Mehra and Prescott 1985), economic growth (Uzawa 1965, Romer 1986, 1990, Lucas 1988), optimal taxation (Lucas and Stokey 1983, Zhu 1992), industrial organization (Ericson and Pakes 1995, Weintraub, Benkard and Van Roy 2008), and equilibrium business cycles (Kydland and Prescott 1982). In the MDP framework, an optimal decision rule can be found within the subclass of non-randomized Markovian strategies, where a strategy depends on the past history of the process only via the current state. Obviously, the optimal decision rule may be suboptimal if the foundational assumption of the Markov property is violated. Recently non-Markov decision processes (NMDP) have attracted increasing attention (e.g., Mizutani and Dreyfus 2004, Aviv and Pazgal 2006). The non-Markov nature can arise in many ways. The most direct extension of MDP to NMDP is to deprive the decision maker of perfect information on the state of the environment.

In finance, the Markov property is one of the most popular assumptions among most continuous-time models. It is well known that stochastic integrals yield Markov processes. In modelling interest rate term structure, such popular models as Vasicek (1977), Cox, Ingersoll and Ross (1985), affine term structure models (Duffie and Kan 1996, Dai and Singleton 2000), quadratic term structure models (Ahn, Dittmar and Gallant 2002), and affine jump diffusion models (Duffie, Pan and Singleton 2000) are all Markov processes. They are widely used in pricing and hedging fixed-income or equity derivatives, managing financial risk, and evaluating monetary policy and debt policy. If interest rate processes are not Markov, alternative non-Markov models, such as Heath, Jarrow and Morton's (1992) model may provide a better characterization of the interest rate dynamics. In a discrete-time framework, Duan and Jacobs (2008) find that deviations from the Markovian structure significantly improve the empirical performance of the model for the short-term interest rate. In general, if a process is obtained by discretely sampling a subset of the state variables of a continuous-time process that evolves according to a system of nonlinear stochastic differential equations, it is non-Markov. A leading example is the class of stochastic volatility models (e.g., Anderson and Lund 1997, Gallant, Hsieh and Tauchen 1997).

In the market microstructure literature, an important issue is the price formation mechanism, which determines whether security prices follow a Markov process. Easley and O'Hara (1987) develop a structural model of the effect of asymmetric information on the price-trade size relationship. They show that trade size introduces an adverse selection problem to security trading because informed traders, given their wish to trade, prefer to trade larger amounts at any given price. Hence market makers' pricing strategies must also depend on trade size, and the entire sequence of past trades is informative of the likelihood of an information event and thus price evolution. As a result, prices typically will not follow a Markov process. Easley and O'Hara (1992) further consider a variant of Easley and O'Hara's (1987) model and delineate the link between the existence of information, the timing of trades and the stochastic process of security prices. They show that while trade signals the direction of any new information, the lack of trade signals the existence of any new information. The latter effect can be viewed as event uncertainty and suggests that the interval between trades may be informative and hence time *per se* is not exogenous to the price process. One implication of this model is that either quotes or prices combined with inventory, volume, and clock time are Markov processes. Therefore, rather than using the prices series alone, which itself is non-Markov, it would be preferable to estimate the price process consisting of no trade outcomes, buys and sells. On the other hand, other models also explain market behavior but reach opposite conclusions on the property of prices. For example, Amaro de Matos and Rosario (2000) and Platen and Rebolledo (1996) propose equilibrium models, which assume that market makers can take advantage of their superior information on trade orders and set different bid and ask prices. The presence of market makers prevents the direct interaction between demand and supply sides. By specifying the supply and demand processes, these market makers obtain the equilibrium prices, which may be Markov. By testing the Markov property, one can check which models reflect reality more appropriately.

Our interest in testing the Markov property is also motivated by its wide applications among practitioners. For example, technical analysis has been used widely in financial markets for decades (see, e.g., Edwards and Magee 1966, Blume, Easley and O'Hara 1994, LeBaron 1999). One important category is priced-based technical strategies, which refer to the forecasts based on past prices, often via moving-average rules. However, if the history of prices does not provide additional information, in the sense that the current prices already impound all information, then price-based technical strategies would not be effective. In other words, if prices adjust immediately to information, past prices would be redundant and current prices are the sufficient statistics for forecasting future prices. This actually corresponds to a fundamental issue – namely whether prices follow a Markov process.

In risk management, financial institutions are required to rate assets by their default probability and by their expected loss severity given a default. For this purpose, historical information on the transition of credit exposures is used to estimate various models that describe the probabilistic evolution of credit quality. The simple time-homogeneous Markov model is one of the most popular models (e.g., Jarrow and Turnbull 1995, Jarrow, Lando and Turnbull 1997), specifying the stochastic processes completely by transition probabilities. Under this model, a detailed history of individual assets is not needed. However, whether the Markov specification adequately describes credit rating transitions over time has substantial impact on the effectiveness of credit risk management. In empirical studies, Kavvathas (2001) and Lando and Skϕderberg (2002) document strong non-Markov behaviors such as dependence on previous rating and waiting-time effects in rating transitions. In contrast, Bangia, Diebold, Kronimus, Schagen and Schuermann (2002) and Kiefer and Larson (2004) find that first-order Markov ratings dynamics provide a reasonable practical approximation.

Despite innumerable studies rooted in Markov processes, there are few existing tests for the Markov property in the literature. Ait-Sahalia (1997) first proposes a test for whether the interest rate process is Markov by checking the validity of the Chapman-Kolmogorov equation, where the transition density is estimated nonparametrically. The Chapman-Kolmogorov equation is an important characterization of Markov processes and can detect many non-Markov processes with practical importance, but it is only a necessary condition of the Markov property. Feller (1959), Rosenblatt (1960) and Rosenblatt and Slepian (1962) provide examples of stochastic processes which are not Markov but whose first order transition probabilities nevertheless satisfy the Chapman-Kolmogorov equation. Ait-Sahalia's (1997) test has no power against these non-Markov processes.

Amaro de Matos and Fernandes (2007) test whether discretely recorded observations of a continuous-time process are consistent with the Markov property via a smoothed nonparametric density approach. They test the conditional independence of the underlying data generating process (DGP).[1] Because only a fixed lag order in the past information set is checked, the test may easily overlook the violation of conditional independence from higher order lags. Moreover, the test involves a relatively high-dimensional smoothed nonparametric joint density estimation (see more discussion below).

In this paper, we provide a conditional characteristic function (CCF)-characterization for the Markov property and use it to construct an omnibus test for the Markov property. The characteristic function has been widely used in time series analysis and financial econometrics (e.g., Feuerverger and McDunnough 1981, Epps 1987, 1988, Feuerverger 1990, Hong 1999, Singleton 2001, Jiang and Knight 2002, Knight and Yu 2002, Chacko and Viceira 2003, Carrasco, Chernov, Florens and Ghysels 2007, and Su and White 2007b). The basic idea of the CCF-characterization for the Markov property is that when and only when a stochastic process is Markov, a generalized residual associated with the CCF is a martingale difference sequence (MDS). This characterization has never been used in testing the Markov property. We use a nonparametric regression method to estimate the CCF and use a spectral approach to check whether the generalized residuals are explainable by the entire history of the underlying processes. Our approach has several attractive features:

First, we use a novel generalized cross-spectral approach, which embeds the CCF in a spectral framework, thus enjoying the appealing features of spectral analysis. In particular, our approach can examine a growing number of lags as the sample size increases without suffering from the "curse of dimensionality" problem. This improves upon the existing tests, which can only check a fixed number of lags.

Second, as the Fourier transform of the transition density, the CCF can also capture the full dynamics of the underlying process, but it involves a lower dimensional smoothed nonparametric regression than the nonparametric density approaches in the literature.

Third, because we impose regularity conditions directly on the CCF of a discretely observed random sample, our test is applicable to discrete-time processes and continuous-time processes with discretely observed data. It is also applicable to both univariate and multivariate time series processes. Due to the nonparametric nature of the test, it does not need any parametric specification of the underlying process and thus avoids the misspecification problems.

In Section 2, we describe the hypotheses of interest and propose a novel approach to testing the Markov property. We derive the asymptotic distribution of the proposed test statistic in Section 3, and discuss its asymptotic power in Section 4. In Section 5, we use Horowitz's (2003) smoothed nonpara-

[1] There are other existing tests for conditional independence of continuous variables in the literature. Linton and Gozalo (1997) propose two nonparamtric tests for conditional independence based on a generalization of the empirical distribution function. Su and White (2007a, 2007b) check conditional independence by the Hellinger distance and empirical characteristic function respectively. These tests can be used to test the Markov property. However, they will encounter the "curse of dimensionality" problem because the Markov property implies that conditional independence must hold for an infinite number of lags.

metric transition-based bootstrap procedure to obtain the critical values of the test in finite samples and examine the finite sample performance of the test in comparison with some existing tests. We also apply our test to stock prices, interest rates and foreign exchange rates and document some evidence against the Markov property with all three financial time series. Section 6 concludes. All mathematical proofs are collected in the appendix. A GAUSS code to implement our test is available from the authors upon request. Throughout the paper, we will use C to denote a generic bounded constant, $\|\cdot\|$ for the Euclidean norm, and A^* for the complex conjugate of A.

2. HYPOTHESES OF INTEREST AND TEST STATISTICS

Suppose $\{\mathbf{X}_t\}$ is a strictly stationary d-dimensional time series process, where d is a positive integer. It follows a Markov process if the conditional probability distribution of $\mathbf{X}_{t+1}$ given the information set $\mathcal{I}_t = \{\mathbf{X}_t, \mathbf{X}_{t-1}, ...\}$ is the same as the conditional probability distribution of $\mathbf{X}_{t+1}$ given $\mathbf{X}_t$ only. This can be formally expressed as follows:

$$\mathbb{H}_0 : P(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathcal{I}_t) = P(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathbf{X}_t) \quad \text{almost surely (a.s.) for all } \mathbf{x} \in \mathbb{R}^d \text{ and all } t \geq 1. \tag{2.1}$$

Under $\mathbb{H}_0$, the past information set $\mathcal{I}_{t-1}$ is redundant in the sense that the current state variable or vector $\mathbf{X}_t$ will contain all information about the future behavior of the process that is contained in the current information set $\mathcal{I}_t$. Alternatively, when

$$\mathbb{H}_A : P(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathcal{I}_t) \neq P(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathbf{X}_t) \text{ for some } t \geq 1, \tag{2.2}$$

then $\mathbf{X}_t$ is not a Markov process.[2]

Ait-Sahalia (1997) proposes a nonparametric kernel-based test for $\mathbb{H}_0$ by checking the Chapman-Kolmogorov equation

$$g\left(\mathbf{X}_{t+1}|\mathbf{X}_{t-1}\right) = \int_{R^d} g\left(\mathbf{X}_{t+1}|\mathbf{X}_t = \mathbf{x}\right) g\left(\mathbf{X}_t = \mathbf{x}|\mathbf{X}_{t-1}\right) d\mathbf{x} \text{ for all } t \geq 1,$$

where $g(\cdot|\cdot)$ is the conditional probability density function estimated by the smoothed nonparametric kernel method. The Chapman-Kolmogorov equation is an important characterization of the Markov property and can detect many non-Markov processes with practical importance. However, there exist non-Markov processes whose first order transition probabilities satisfy the Chapman-Kolmogorov Equation (Feller 1959, Rosenblatt 1960, Rosenblatt and Slepian 1962). Ait-Sahalia's (1997) test has no power against these processes.

Amaro de Matos and Fernandes (2007) propose a nonparametric kernel-based test for $\mathbb{H}_0$ by checking the conditional independence between $\mathbf{X}_{t+1}$ and $\mathbf{X}_{t-j}$ given $\mathbf{X}_t$, namely

$$g\left(\mathbf{X}_{t+1}|\mathbf{X}_t\right) = g\left(\mathbf{X}_{t+1}|\mathbf{X}_t, \mathbf{X}_{t-j}\right) \text{ for all } t, j \geq 1,$$

[2] Here, we focus on the Markov property of order 1, which is the main interest of economic and financial modelling. However, our approach can be generalized to test the Markov property of order p : $P\left(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathcal{I}_t\right) = P\left(\mathbf{X}_{t+1} \leq \mathbf{x}|\mathbf{X}_t, \mathbf{X}_{t-1}, ..., \mathbf{X}_{t-p+1}\right)$ for p fixed.

which is implied by $\mathbb{H}_0$. By choosing $j = 1$, Amaro de Matos and Fernandes (2007) check

$$g(\mathbf{X}_{t+1}, \mathbf{X}_t, \mathbf{X}_{t-1}) = g(\mathbf{X}_{t+1}|\mathbf{X}_t)\, g(\mathbf{X}_t, \mathbf{X}_{t-1}) \text{ for all } t \geq 1,$$

in their simulation and empirical studies. This approach requires a $3d$-dimensional smoothed nonparametric joint density estimation for $g(\mathbf{X}_{t+1}, \mathbf{X}_t, \mathbf{X}_{t-1})$.

Both the existing tests essentially check the conditional independence of

$$g(\mathbf{X}_{t+1}|\mathbf{X}_t, \mathbf{X}_{t-1}) = g(\mathbf{X}_{t+1}|\mathbf{X}_t) \text{ for all } t \geq 1,$$

which is implied by $\mathbb{H}_0$ in (2.1) but the converse is not true. The most important feature of $\mathbb{H}_0$ is the necessity of checking the entire currently available information $\mathcal{I}_t$. There will be inevitably information loss if only one lag order is considered. For example, the existing tests may overlook the departure of the Markov property from higher order lags, say, $\mathbf{X}_{t-2}$. Moreover, their tests may suffer from the "curse of dimensionality" problem when the dimension d is relatively large, because the nonparametric density estimators $\hat{g}(\mathbf{X}_{t+1}|\mathbf{X}_t, \mathbf{X}_{t-1})$ and $\hat{g}(\mathbf{X}_{t+1}|\mathbf{X}_t)$ involve $3d$ and $2d$ dimensional smoothing respectively.

We now develop a new test for $\mathbb{H}_0$ using the CCF. As the Fourier transform of the conditional probability density, the CCF can also capture the full dynamics of $\mathbf{X}_{t+1}$. Let $\varphi(u|\mathbf{X}_t)$ be the CCF of $\mathbf{X}_{t+1}$ conditioning on its current state $\mathbf{X}_t$, that is,

$$\varphi(\mathbf{u}|\mathbf{X}_t) = \int_{R^d} e^{i\mathbf{u}'\mathbf{x}} g(\mathbf{x}|\mathbf{X}_t) d\mathbf{x}, \ \mathbf{u} \in \mathbb{R}^d, \ i = \sqrt{-1}. \tag{2.3}$$

Let $\varphi(u|\mathcal{I}_t)$ be the CCF of $\mathbf{X}_{t+1}$ conditioning on the currently available information $\mathcal{I}_t$, that is,

$$\varphi(\mathbf{u}|\mathcal{I}_t) = \int_{R^d} e^{i\mathbf{u}'\mathbf{x}} g(\mathbf{x}|\mathcal{I}_t) d\mathbf{x}, \ \mathbf{u} \in \mathbb{R}^d, \ i = \sqrt{-1}.$$

Given the equivalence between the conditional probability density and the CCF, the hypotheses of interest $\mathbb{H}_0$ in (2.1) versus $\mathbb{H}_A$ in (2.2) can be written as follows:

$$\mathbb{H}_0 : \varphi(\mathbf{u}|\mathbf{X}_t) = \varphi(\mathbf{u}|\mathcal{I}_t) \quad \text{a.s. for all } \mathbf{u} \in \mathbb{R}^d \text{ and all } t \geq 1 \tag{2.4}$$

versus the alternative hypothesis

$$\mathbb{H}_A : \varphi(\mathbf{u}|\mathbf{X}_t) \neq \varphi(\mathbf{u}|\mathcal{I}_t) \text{ for some } t \geq 1. \tag{2.5}$$

There exist other characterizations of the Markov property. For example, Darsow, Nguyen and Olsen (1992) and Ibragimov (2007) provide copula-based characterizations of Markov processes. The CCF-based characterization is intuitively appealing and offers much flexibility. To gain insight into this approach, we define a complex-valued process

$$Z_{t+1}(\mathbf{u}) = e^{(i\mathbf{u}'\mathbf{X}_{t+1})} - \varphi(\mathbf{u}|\mathbf{X}_t), \ \mathbf{u} \in \mathbb{R}^d.$$

Then the Markov property is equivalent to the following MDS characterization

$$E\left[Z_{t+1}(\mathbf{u})|\mathcal{I}_t\right] = 0 \text{ for all } \mathbf{u} \in \mathbb{R}^d \text{ and } t \geq 1. \tag{2.6}$$

The process $\{Z_t(\mathbf{u})\}$ may be viewed as an residual of the following nonparametric regression

$$e^{(i\mathbf{u}'\mathbf{X}_{t+1})} = E[e^{(i\mathbf{u}'\mathbf{X}_{t+1})}|\mathbf{X}_t] + Z_{t+1}(\mathbf{u}) = \varphi(\mathbf{u}|\mathbf{X}_t) + Z_{t+1}(\mathbf{u}).$$

The MDS characterization in (2.6) has implications on all conditional moments on $\{\mathbf{X}_t\}$ when the latter exist. To see this, we consider a Taylor series expansion of (2.6), for the case of $d = 1$, around the origin of $\mathbf{u}$:

$$E\left[Z_{t+1}(\mathbf{u})|\mathcal{I}_t\right] = \sum_{m=0}^{\infty} \frac{(i\mathbf{u})^m}{m!} \{E(\mathbf{X}_{t+1}^m|\mathcal{I}_t) - E(\mathbf{X}_{t+1}^m|\mathbf{X}_t)\} = 0 \text{ for } t \geq 1 \tag{2.7}$$

for all $\mathbf{u}$ near 0.[3] Thus, checking (2.6) is equivalent to checking whether all conditional moments of $\mathbf{X}_{t+1}$ (if exist) are Markov. Nevertheless, the use of (2.6) itself does not require any moment conditions on $\mathbf{X}_{t+1}$.

It is not a trivial task to check (2.6). First, the MDS property in (2.6) must hold for all $\mathbf{u} \in \mathbb{R}^d$, not just a finite number of grid points of $\mathbf{u}$. This is an example of the so-called nuisance parameter problem encountered in the literature (e.g., Davies 1977, 1987 and Hansen 1996). Second, the generalized residual process $Z_{t+1}(\mathbf{u})$ is unknown because the CCF $\varphi(\mathbf{u}|\mathbf{X}_t)$ is unknown, and it has to be estimated nonparametrically to be free of any potential model misspecification. Third, the conditioning information set $\mathcal{I}_t$ in (2.6) has an infinite dimension as $t \to \infty$, so there is a "curse of dimensionality" difficulty associated with testing the Markov property. Finally, $\{Z_t(\mathbf{u})\}$ may display serial dependence in its higher order conditional moments. Any test for (2.6) should be robust to time-varying conditional heteroskedasticity and higher order moments of unknown form in $\{Z_t(\mathbf{u})\}$.

To check the MDS property of $\{Z_t(\mathbf{u})\}$, we extend Hong's (1999) univariate generalized spectrum to a multivariate generalized cross-spectrum.[4] Just as the conventional spectral density is a basic analytic tool for linear time series, the generalized spectrum, which embeds the characteristic function in a spectral framework, is an analytic tool for nonlinear time series. It can capture nonlinear dynamics while maintaining the nice features of spectral analysis, particularly its appealing property to accommodate all lags information. In the present context, it can check departures of the Markov property over many lags in a pairwise manner, avoiding the "curse of dimensionality" difficulty. This is not achievable by the existing tests in the literature. They only check a fixed lag order.

Define the generalized covariance function

$$\Gamma_j(\mathbf{u}, \mathbf{v}) = \text{cov}[Z_t(\mathbf{u}), e^{\left(i\mathbf{v}'\mathbf{X}_{t-|j|}\right)}], \qquad \mathbf{u}, \mathbf{v} \in \mathbb{R}^d. \tag{2.8}$$

Given that the conventional spectral density is defined as the Fourier transform of the autocovariance

[3] A multivariate Taylor series expansion can be obtained when $d > 1$. Since the expression is tedious, we do not present it here.

[4] This is not a trivial extension since we use nonparametric estimation in the first stage.

function, we can define a generalized cross-spectrum

$$F(\omega, \mathbf{u}, \mathbf{v}) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \Gamma_j(\mathbf{u}, \mathbf{v}) e^{-ij\omega}, \qquad \omega \in [-\pi, \pi], \quad \mathbf{u}, \mathbf{v} \in \mathbb{R}^d, \tag{2.9}$$

which is the Fourier transform of the generalized covariance function $\Gamma_j(\mathbf{u}, \mathbf{v})$, where ω is a frequency. This function contains the same information as $\Gamma_j(\mathbf{u}, \mathbf{v})$. No moment conditions on $\{\mathbf{X}_t\}$ are required. This is particularly appealing for economic and financial time series. It has been argued that higher moments of financial time series may not exist (e.g., Pagan and Schwert 1990, Loretan and Phillips 1994). Moreover, the generalized cross spectrum can capture cyclical patterns caused by linear and nonlinear cross dependence, such as volatility clustering and tail clustering of the distribution.

Under $\mathbb{H}_0$, we have $\Gamma_j(\mathbf{u}, \mathbf{v}) = 0$ for all $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ and all $j \neq 0$. Consequently, the generalized cross-spectrum $F(\omega, \mathbf{u}, \mathbf{v})$ becomes a "flat" spectrum as a function of frequency ω:

$$F(\omega, \mathbf{u}, \mathbf{v}) = F_0(\omega, \mathbf{u}, \mathbf{v}) \equiv \frac{1}{2\pi} \Gamma_0(\mathbf{u}, \mathbf{v}), \qquad \omega \in [-\pi, \pi], \quad \mathbf{u}, \mathbf{v} \in \mathbb{R}^d. \tag{2.10}$$

Thus, we can test $\mathbb{H}_0$ by checking whether a consistent estimator for $F(\omega, \mathbf{u}, \mathbf{v})$ is flat with respect to frequency ω. Any significant deviation from a flat generalized cross-spectrum is evidence of the violation of the Markov property.

The hypothesis of $E[Z_t(\mathbf{u})|\mathcal{I}_{t-1}] = 0$ for all $\mathbf{u} \in \mathbb{R}^d$ is different from the hypothesis of $\Gamma_j(\mathbf{u}, \mathbf{v}) = 0$ for all $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ and all $j \neq 0$. The former implies the latter but not vice versa. This is the price we have to pay for dealing with the difficulty of the "curse of dimensionality". From a theoretical point of view, the pairwise approach will miss dependent processes that are pairwise independent. However, such processes do not appear in most empirical applications in economics and finance.

It is rather difficult to formally characterize the gap between $E[Z_t(\mathbf{u})|\mathcal{I}_{t-1}] = 0$ for all $\mathbf{u} \in \mathbb{R}^d$ and $\Gamma_j(\mathbf{u}, \mathbf{v}) = 0$ for all $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ and all $j \neq 0$. However, these two hypotheses coincide under some special cases. One example is when $\{\mathbf{X}_t\}$ follows an additive process: $\mathbf{X}_t = \alpha_0 + \sum_{j=1}^{\infty} g(\mathbf{X}_{t-j}) + \varepsilon_t$, where $g(\cdot)$ is not a zero function at least for some lag $j > 0$. Additive time series processes have attracted considerable interest in the nonparametric literature (e.g., Hastie and Tibshirani 1990, Marsry and Tjøstheim 1997, Kim and Linton 2003).

To reduce the gap between $E[Z_t(\mathbf{u})|\mathcal{I}_{t-1}] = 0$ for all $\mathbf{u} \in \mathbb{R}^d$ and $\Gamma_j(\mathbf{u}, \mathbf{v}) = 0$ for all $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ and all $j \neq 0$, we can extend $F(\omega, \mathbf{u}, \mathbf{v})$ to a generalized bispectrum

$$B(\omega_1, \omega_2, \mathbf{u}, \mathbf{v}, \boldsymbol{\tau}) = \frac{1}{(2\pi)^2} \sum_{j=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} C_{j,l}(\mathbf{u}, \mathbf{v}, \boldsymbol{\tau}) e^{(-ij\omega_1 - il\omega_2)}, \quad \omega_1, \omega_2 \in [-\pi, \pi], \quad \mathbf{u}, \mathbf{v}, \boldsymbol{\tau} \in \mathbb{R}^d,$$

where

$$C_{j,l}(\mathbf{u}, \mathbf{v}, \boldsymbol{\tau}) = Z_t(\mathbf{u}) \left[e^{(i\mathbf{v}'\mathbf{X}_{t-|j|})} - \hat{\varphi}(\mathbf{v}) \right] \left[e^{(i\boldsymbol{\tau}'\mathbf{X}_{t-|l|})} - \hat{\varphi}(\boldsymbol{\tau}) \right], \quad \mathbf{u}, \mathbf{v}, \boldsymbol{\tau} \in \mathbb{R}^d$$

is a generalized third order central cumulant function. This is equivalent to the use of $E[Z_t(\mathbf{u})|\mathbf{X}_{t-j}, \mathbf{X}_{t-l}]$. With $C_{j,l}(\mathbf{u}, \mathbf{v}, \boldsymbol{\tau})$, we can detect a larger class of alternatives to $E[Z_t(\mathbf{u})|\mathcal{I}_{t-1}] = 0$. Note that the nonparametric generalized bispectrum approach can check many pairs of lags (j, l), while still avoiding the "curse of dimensionality". Nevertheless, in this paper, we focus on $\Gamma_j(\mathbf{u}, \mathbf{v})$ for simplicity.

Suppose now we have a discretely observed sample $\{\mathbf{X}_t\}_{t=1}^T$ of size T, and we consider consistent estimation of $F(\omega, \mathbf{u}, \mathbf{v})$ and $F_0(\omega, \mathbf{u}, \mathbf{v})$. Because $Z_t(\mathbf{u})$ is not observable, we have to estimate it first. Then we can estimate the generalized covariance $\Gamma_j(\mathbf{u}, \mathbf{v})$ by its sample analogue

$$\hat{\Gamma}_j(\mathbf{u}, \mathbf{v}) = \frac{1}{T-|j|} \sum_{t=|j|+1}^{T} \hat{Z}_t(\mathbf{u}) \left[e^{\left(i\mathbf{v}'\mathbf{X}_{t-|j|}\right)} - \hat{\varphi}(\mathbf{v}) \right], \quad \mathbf{u}, \mathbf{v} \in \mathbb{R}^d, \tag{2.11}$$

where the estimated generalized residual

$$\hat{Z}_t(\mathbf{u}) = e^{(i\mathbf{u}'\mathbf{X}_t)} - \hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1}),$$

$\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$ is a consistent estimator for $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$ and $\hat{\varphi}(\mathbf{v}) = T^{-1}\sum_{t=1}^T e^{i\mathbf{v}'\mathbf{X}_t}$ is the empirical characteristic function of $\mathbf{X}_t$. We do not parameterize $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$, which would suffer from potential model misspecification. We use nonparametric regression to estimate $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$. Various nonparametric regression methods could be used here. For concreteness, we use local linear regression.

Local linear smoothing is introduced originally by Stone (1977) and subsequently studied by Cleveland (1979), Fan (1992, 1993), Ruppert and Wand (1994), Masry (1996a, 1996b) and Masry and Fan (1997), among many others. Local linear smoothing has significant advantages over the conventional Nadaraya–Watson (NW) kernel estimator on the boundary of design points. Fan and Yao (2003) show that although the NW and local linear estimators share the same asymptotic properties at the interior points, their boundary behaviors are very different, namely, the local linear smoothing can enhance the convergence rate of the asymptotic bias in the boundary regions from $h^{r/2}$ to h^r, although the scale or proportionality is different from that of an interior point.

We consider the following local least squares problem:

$$\min_{\boldsymbol{\beta}\in\mathbb{R}^{d+1}} \sum_{t=2}^{T} \left| e^{(i\mathbf{u}'\mathbf{X}_t)} - \beta_0 - \boldsymbol{\beta}_1' \left(\mathbf{X}_{t-1} - \mathbf{x}\right) \right|^2 \mathbf{K}_h\left(\mathbf{x} - \mathbf{X}_{t-1}\right), \ \mathbf{x} \in\mathbb{R}^d, \tag{2.12}$$

where $\boldsymbol{\beta} = \left(\beta_0, \boldsymbol{\beta}_1'\right)'$ is a $(d+1)\times 1$ parameter vector, $\mathbf{K}_h(\mathbf{x}) = h^{-d}\mathbf{K}(\mathbf{x}/h)$, $\mathbf{K} : \mathbb{R}^d \to \mathbb{R}$ is a kernel function, and h is a bandwidth. An example of $\mathbf{K}(\cdot)$ is a prespecified symmetric probability density function. We obtain the following solution:

$$\hat{\boldsymbol{\beta}} \equiv \hat{\boldsymbol{\beta}}(\mathbf{x}, \mathbf{u}) = \begin{bmatrix} \hat{\beta}_0(\mathbf{x}, \mathbf{u}) \\ \hat{\boldsymbol{\beta}}_1(\mathbf{x}, \mathbf{u}) \end{bmatrix} = [\mathbf{X}'\mathbf{W}\mathbf{X}]^{-1}\mathbf{X}'\mathbf{W}\mathbf{Y}, \ \ \mathbf{x} \in\mathbb{R}^d,$$

where $\mathbf{X}$ is a $d(T-1)\times 2$ matrix with the t to $(t+d-1)th$ rows given by $[\mathbf{1}, \mathbf{X}_t - \mathbf{x}]$, $\mathbf{W} = diag[\mathbf{K}_h(\mathbf{X}_1 - \mathbf{x}), \mathbf{K}_h(\mathbf{X}_2 - \mathbf{x})..., \mathbf{K}_h(\mathbf{X}_{T-1} - \mathbf{x})]$, $\mathbf{Z} = \left[e^{(i\mathbf{u}'\mathbf{X}_2)}, e^{(i\mathbf{u}'\mathbf{X}_3)}, ..., e^{(i\mathbf{u}'\mathbf{X}_T)}\right]'$. Note that $\hat{\boldsymbol{\beta}}$ depends on the location $\mathbf{x}$ and parameter $\mathbf{u}$, but for notional simplicity, we have suppressed its dependence on $\mathbf{x}$ and $\mathbf{u}$.

Under suitable regularity conditions, $\varphi(\mathbf{u}|\mathbf{x})$ can be consistently estimated by the local intercept estimator $\hat{\beta}_0(\mathbf{x}, \mathbf{u})$. Specifically, we have

$$\hat{\varphi}(\mathbf{u}|\mathbf{x}) = \sum_{t=2}^{T} \hat{W}\left(\frac{\mathbf{X}_{t-1} - \mathbf{x}}{h}\right) e^{(i\mathbf{u}'\mathbf{X}_t)},$$

where $\hat{W}(\cdot)$ is an effective kernel, defined as

$$\hat{W}(\mathbf{t}) \equiv \mathbf{e}_1' \mathbf{S}_T^{-1} [\mathbf{1}, \mathbf{t}h, ..., \mathbf{t}h]' \mathbf{K}(\mathbf{t})/h^d,$$

$\mathbf{e}_1 = (1, 0, ..., 0)'$ is a $d \times 1$ unit vector, $\mathbf{S}_T = \mathbf{X}'\mathbf{W}\mathbf{X}$ is a $(d+1) \times (d+1)$ matrix. As established by Hansen (2007) and Hjellvik, Yao and Tjϕstheim (1998), for any compact set $\mathbf{G} \subset \mathbb{R}^d$, one has

$$\mathbf{S}_T^{-1} = g(\mathbf{x})^{-1} \begin{bmatrix} 1 & \mathbf{0}' \\ \mathbf{0} & \mathbf{S}_0 \end{bmatrix}^{-1} + o_P(1) \text{ uniformly for } \mathbf{x} \in \mathbf{G},$$

where $g(\mathbf{x})$ is the true stationary density function of $\mathbf{X}_t$, $\mathbf{0}$ is a $d \times 1$ vector of zeros, and $\mathbf{S}_0$ is the $d \times d$ diagonal matrix whose diagonal element is $\int_{\mathbb{R}^d} \mathbf{u}\mathbf{u}'\mathbf{K}(\mathbf{u})\, d\mathbf{u}$. It follows that the effective kernel

$$\hat{W}(\mathbf{t}) = \frac{1}{Th^d g(\mathbf{x})} \mathbf{K}(\mathbf{t}) [1 + o_P(1)]. \tag{2.13}$$

Eq. (2.13) shows that the local linear estimator works like a kernel regression estimator based on the kernel $\mathbf{K}(\cdot)$ with a known design density. The regression estimator $\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$ only involves a d-dimensional smoothing, thus enjoying some advantages over the existing nonparametric density approaches which involve a $2d$ or $3d$ dimensional smoothing.

With the sample generalized covariance function $\hat{\Gamma}_j(\mathbf{u}, \mathbf{v})$, we can construct a consistent estimator for the flat generalized spectrum $F_0(\omega, \mathbf{u}, \mathbf{v})$

$$\hat{F}_0(\omega, \mathbf{u}, \mathbf{v}) = \frac{1}{2\pi} \hat{\Gamma}_0(\mathbf{u}, \mathbf{v}), \qquad \omega \in [-\pi, \pi], \quad \mathbf{u}, \mathbf{v} \in \mathbb{R}^d.$$

Consistent estimation for $F(\omega, \mathbf{u}, \mathbf{v})$ is more challenging. We use a nonparametric smoothed kernel estimator for $F(\omega, \mathbf{u}, \mathbf{v})$:

$$\hat{F}(\omega, \mathbf{u}, \mathbf{v}) = \frac{1}{2\pi} \sum_{j=1-T}^{T-1} (1 - |j|/T)^{1/2} k(j/p) \hat{\Gamma}_j(\mathbf{u}, \mathbf{v}) e^{-ij\omega}, \ \omega \in [-\pi, \pi], \mathbf{u}, \mathbf{v} \in \mathbb{R}^d, \tag{2.14}$$

where $p = p(T) \to \infty$ is a bandwidth or lag order, and $k : \mathbb{R} \to [-1, 1]$ is a kernel function that assigns weights to various lag orders. Note that $k(\cdot)$ here is different from the kernel $\mathbf{K}(\cdot)$ in (2.12). Most commonly used kernels discount higher order lags. Examples of commonly used $k(z)$ include the Bartlett kernel

$$k(z) = \begin{cases} 1 - |z|, & |z| \leq 1, \\ 0, & \text{otherwise}, \end{cases} \tag{2.15}$$

the Parzen kernel

$$k(z) = \begin{cases} 1 - 6z^2 + 6|z|^3, & |z| \leq 0.5, \\ 2(1 - |z|)^3, & 0.5 < |z| \leq 1, \\ 0, & \text{otherwise}. \end{cases} \tag{2.16}$$

and the Quadratic-Spectral kernel

$$k(z) = \frac{3}{(\pi z)^2}\left[\frac{\sin(\pi z)}{\pi z} - \cos(\pi z)\right], \quad z \in \mathbb{R}. \tag{2.17}$$

In (2.14), the factor $(1 - |j|/T)^{1/2}$ is a finite-sample correction. It could be replaced by unity. Under certain regularity conditions, $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$ and $\hat{F}_0(\omega, \mathbf{u}, \mathbf{v})$ are consistent for $F(\omega, \mathbf{u}, \mathbf{v})$ and $F_0(\omega, \mathbf{u}, \mathbf{v})$ respectively. The estimators $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$ and $\hat{F}_0(\omega, \mathbf{u}, \mathbf{v})$ converge to the same limit under $\mathbb{H}_0$ and generally converge to different limits under $\mathbb{H}_A$. Thus any significant divergence between them is evidence of the violation of the Markov property.

We can measure the distance between $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$ and $\hat{F}_0(\omega, \mathbf{u}, \mathbf{v})$ by the quadratic form

$$\begin{aligned} L^2(\hat{F}, \hat{F}_0) &= \frac{\pi T}{2} \int\int\int_{-\pi}^{\pi} \left|\hat{F}(\omega, \mathbf{u}, \mathbf{v}) - \hat{F}_0(\omega, \mathbf{u}, \mathbf{v})\right|^2 d\omega dW(\mathbf{u})\, dW(\mathbf{v}) \\ &= \sum_{j=1}^{T-1} k^2(j/p)(T-j) \int\int \left|\hat{\Gamma}_j(\mathbf{u}, \mathbf{v})\right|^2 dW(\mathbf{u})\, dW(\mathbf{v}), \end{aligned} \tag{2.18}$$

where the second equality follows by Parseval's identity, and $W : \mathbb{R}^d \to \mathbb{R}^+$ is a nondecreasing weighting function that weighs sets symmetric about the origin equally.[5] An example of $W(\cdot)$ is the multivariate independent $N(\mathbf{0}, \mathbf{I})$ CDF, where $\mathbf{I}$ is a $d \times d$ identity matrix. Throughout unspecified integrals are all taken over the support of $W(\cdot)$. We can compute the integrals over $(\mathbf{u}, \mathbf{v})$ by numerical integration. Alternatively, we can generate random draws of $\mathbf{u}$ and $\mathbf{v}$ from the prespecified distribution $W(\cdot)$, and then use the Monte Carlo simulation to approximate the integrals over $(\mathbf{u}, \mathbf{v})$. This is computationally simple and is applicable even when the dimension d is large. Note that $W(\cdot)$ need not be continuous. They can be nondecreasing step functions. This will lead to a convenient implementation of our test but it may adversely affect the power. See more discussion below.

Our proposed omnibus test statistic for $\mathbb{H}_0$ against $\mathbb{H}_A$ is an appropriately standardized version of (2.18), namely,

$$\hat{M} = \left[\sum_{j=1}^{T-1} k^2(j/p)(T-j) \int\int \left|\hat{\Gamma}_j(\mathbf{u}, \mathbf{v})\right|^2 dW(\mathbf{u})\, dW(\mathbf{v}) - \hat{C}\right] / \sqrt{\hat{D}}, \tag{2.19}$$

where the centering factor

$$\hat{C} = \sum_{j=1}^{T-1} k^2(j/p)(T-j)^{-1} \sum_{t=|j|+1}^{T} \int\int \left|\hat{Z}_t(\mathbf{u})\right|^2 \left|\hat{\psi}_{t-j}(\mathbf{v})\right|^2 dW(\mathbf{u})\, dW(\mathbf{v}),$$

[5] If $W(\mathbf{u})$ is differentiable, then its derivative $(\partial/\partial u_a)W(\mathbf{u})$ is an even function of u_a for $a = 1, 2, ...d$.

and the scaling factor

$$\hat{D} = 2\sum_{j=1}^{T-2}\sum_{l=1}^{T-2} k^2(j/p)k^2(l/p) \int\int\int\int \times \left| \frac{1}{T-\max(j,l)} \sum_{t=\max(j,l)+1}^{T} \hat{Z}_t(\mathbf{u}_1)\hat{Z}_t(\mathbf{u}_2)\hat{\psi}_{t-j}(\mathbf{v}_1)\hat{\psi}_{t-l}(\mathbf{v}_2) \right|^2 \times dW(\mathbf{u}_1)\, dW(\mathbf{u}_2)\, dW(\mathbf{v}_1)\, dW(\mathbf{v}_2).$$

where $\hat{\psi}_t(\mathbf{v}) = e^{i\mathbf{v}'\mathbf{X}_t} - \hat{\varphi}(\mathbf{v})$, and $\hat{\varphi}(\mathbf{v}) = T^{-1}\sum_{t=1}^{T} e^{i\mathbf{v}'\mathbf{X}_t}$ is the ECF of $\{\mathbf{X}_t\}$. The factors $\hat{C}$ and $\hat{D}$ are approximately the mean and variance of the quadratic form in (2.18). They have taken into account the impact of higher order serial dependence in the generalized residual $\{Z_t(\mathbf{u})\}$. As a result, the $\hat{M}$ test is robust to conditional heteroskedasticity and time-varying higher order conditional moments of unknown form in $\{Z_t(\mathbf{u})\}$.

In practice, $\hat{M}$ has to be calculated using numerical integration or approximated by simulation methods. This can be computationally costly when the dimension d of $\mathbf{X}_t$ is large. Alternatively, one can only use a finitely many number of grid points for $\mathbf{u}$ and $\mathbf{v}$. For example, we can generate finitely many numbers of $\mathbf{u}$ and $\mathbf{v}$ from a multivariate standard normal distribution. This will dramatically reduce the computational cost but it may lead to some power loss. We will examine this issue by simulation studies.

We emphasize that although the CCF and the transition density are Fourier transforms of each other, our nonparametric regression-based CCF approach has an advantage over the nonparametric conditional density-based approach, in the sense that our nonparametric regression estimator of CCF only involves $d-$dimensional smoothing but the nonparametric joint density estimators used in the existing tests involves $2d$- and $3d$-dimensional smoothing. We expect that such dimension reduction will give better size and power performance in finite samples.

3. ASYMPTOTIC DISTRIBUTION

To derive the null asymptotic distribution of the test statistic $\hat{M}$, we impose the following regularity conditions.

Assumption A.1: *(i) $\{\mathbf{X}_t\}$ is a strictly stationary β-mixing process with mixing coefficient $\beta(j) = O(j^{-\nu})$ for some constant $\nu > 3$; (ii) the marginal density $g(\mathbf{x})$ of $\mathbf{X}_t$ is bounded away from $\mathbf{0}$ for all $\mathbf{x} \in \mathbf{G}$, where $\mathbf{G}$ is a compact set of $\mathbb{R}^d$. $g(\mathbf{x})$ has at least rth order partial derivatives for some integer $r > 0$.*

Assumption A.2: *For each sufficiently large integer q, there exists a $q-$dependent stationary process $\{\mathbf{X}_{qt}\}$, such that $E\|\mathbf{X}_t - \mathbf{X}_{qt}\|^2 \leq Cq^{-\eta}$ for some constant $\eta \geq \frac{1}{2}$ and all large q. The random vector $\mathbf{X}_{qt}$ is measurable with respect to some sigma field, which may be different from the sigma field generated by $\{\mathbf{X}_t\}$.*

Assumption A.3: *The function $\mathbf{K} : \mathbb{R}^d \to \mathbb{R}^+$ is a product kernel of some univariate kernel K, i.e., $\mathbf{K}(\mathbf{u}) = \prod_{j=1}^{d} K(u_j)$, where $K : \mathbb{R} \to \mathbb{R}^+$ satisfies the Lipschitz condition and is a symmetric, bounded,* *and rth continuously differentiable function with* $\int_{-\infty}^{\infty} K(u)\,du = 1$, $\int_{-\infty}^{\infty} u^a K(u)\,du = 0$, $1 \leq a \leq r-1$ and $\int_{-\infty}^{\infty} u^r K(u)\,du < \infty$, *where r is the same as in Assumption A.1.*

Assumption A.4: *(i)* $k : \mathbb{R} \to [-1,1]$ *is a symmetric function that is continuous at zero and all points in* $\mathbb{R}$ *except for a finite number of points. (ii)* $k(0) = 1$; *(iii)* $k(z) \leq c\,|z|^{-b}$ *for some* $b > \frac{3}{4}$ *as* $z \to \infty$.

Assumption A.5: $W : \mathbb{R}^d \to \mathbb{R}^+$ *is a nondecreasing weighting function that weighs sets symmetric about the origin equally, with* $\int \|\mathbf{u}\|^4 dW(\mathbf{u}) < \infty$.

Assumption A.1 and A.2 are regularity conditions on the DGP of $\{\mathbf{X}_t\}$. Assumption A.1(i) restricts the degree of temporal dependence of $\{\mathbf{X}_t\}$. We say that $\{\mathbf{X}_t\}$ is β-mixing (absolutely regular) if

$$\beta(j) = \sup_{s \geq 1} E\left[\sup_{A \in \mathcal{F}_{s+j}^{\infty}} |P(A|\mathcal{F}_1^s) - P(A)|\right] \to 0,$$

as $j \to \infty$, where $\mathcal{F}_j^s$ is the σ-field generated by $\{\mathbf{X}_\tau : \tau = j, ..., s\}$, with $j \leq s$. Assumption A.1(i) holds for many well-known processes such as linear stationary ARMA processes and a large class of processes implied by numerous nonlinear models, including bilinear, nonlinear AR, and ARCH-type models (Fan and Li, 1999). Ait-Sahalia, Fan and Peng (2006), Amaro de Matos and Fernandes (2007) and Su and White (2007a, 2007b) also impose β-mixing conditions. Our mixing condition is weaker than Amaro de Matos and Fernandes' (2007) and Su and White's (2007b). They assume a β-mixing condition with a geometric decay rate.

Assumption A.1(ii) first appears restrictive as it rules out some most commonly used probability densities, such as $N(\boldsymbol{\mu}, \boldsymbol{\sigma}^2)$. This allows us to focus on the essentials and still maintain a relatively straightforward treatment. To satisfy such an assumption, it is a common practice to exclude data in the tails. This, however, leads to information loss. Tails may be particularly informative and interesting for financial time series.

It is well-known that the Markov property is invariant to any strictly monotonic transformation.[6] One can exploit such a property to ensure that $g(\cdot)$ is bounded away from zero from below. Let $\mathbf{Y}_t$ have the cumulative density function (CDF) $\tilde{G}(\cdot)$ with density $\tilde{g}(\cdot)$ and let $L(\cdot)$ be a prespecified CDF with density $l(\cdot)$. Then $\mathbf{X}_t \equiv L(\mathbf{Y}_t)$ has support on $\mathbb{R}^d$ and the CDF of $\mathbf{X}_t$ is given by $G(\mathbf{x}) = \tilde{G}\left[L^{-1}(\mathbf{x})\right]$, $\mathbf{x} \in \mathbb{R}^d$. It follows that

$$g(\mathbf{x}) \equiv \frac{\partial^d G(\mathbf{x})}{\partial x_1 ... \partial x_d} = \tilde{g}\left[L^{-1}(\mathbf{x})\right] \left|\det J\left[L^{-1}(\mathbf{x})\right]\right|^{-1},$$

where $J(\cdot)$ is the Jacobian matrix. To ensure $\min_{\mathbf{x} \in \mathbb{R}^d} g(\mathbf{x}) \geq c > 0$, it suffices that $|\det J(\mathbf{y})| \leq c^{-1}\tilde{g}(\mathbf{y})$, $\mathbf{y} \in \mathbb{R}^d$.[7] No information would be lost in the transformation. Even though $\tilde{g}(\cdot)$ is typically unknown, we often know or are willing to assume enough about $\tilde{g}(\cdot)$, in particular its tail behavior, to specify a transforming CDF $L(\cdot)$ that satisfies $|\det J(\mathbf{y})| \leq c^{-1}\tilde{g}(\mathbf{y})$ thereby ensuring $g(\mathbf{x}) \geq c$. In fact, the condition that $g(\mathbf{x}) \geq c > 0$ is made for simplicity of the asymptotic analysis. It seems plausible that one could allow $g(\mathbf{x}) \to 0$ at the end points with a sufficiently slow rate, and our theory would continue to hold under strengthened conditions on the bandwidth h used in kernel regression estimation

[6] Rosenblatt (1971, Ch. III) provides conditions under which functions of a Markov process are Markov.

[7] When $d = 1$, it boils down to $l(\mathbf{y}) \leq c^{-1}\tilde{g}(\mathbf{y})$.

of CCF. As the involved technicality would be quite complicated and would detract from our main goal, we do not pursue this here. However, we will use simulation to examine the consequence of allowing $g(\mathbf{x}) \to 0$ at the end points.[8]

The proposed test is applicable to both univariate and multivariate time series with discrete or continuous distributions, or a mix of continuous and discrete data. If $\mathbf{X}_t$ takes on discrete values, we can estimate $\varphi(\mathbf{u}|\mathbf{X}_t)$ via a frequency approach, namely replacing $\mathbf{K}_h(\mathbf{x}-\mathbf{X})$ with $1(\mathbf{x}-\mathbf{X})$, where $1(\cdot)$ is the indicator function. If $\mathbf{X}_t$ is a mix of discrete and continuous variables, e.g., $\mathbf{X}_t = (\mathbf{X}_t^d, \mathbf{X}_t^c)$, where $\mathbf{X}_t^d$ and $\mathbf{X}_t^c$ denote discrete and continuous components respectively, following Li and Racine (2007), we can replace $\mathbf{K}_h(\cdot)$ with

$$W_\gamma(\mathbf{x}, \mathbf{X}_s) = \mathbf{K}_h(\mathbf{x}^c - \mathbf{X}_s^c)\,\mathbf{L}_\lambda\left(\mathbf{x}^d, \mathbf{X}_s^d\right),$$

where $\gamma = (h, \lambda)$. And $\mathbf{L}_\lambda(\cdot)$ is the kernel function for the discrete components defined as

$$\mathbf{L}_\lambda\left(\mathbf{x}^d, \mathbf{X}_s^d\right) = \prod_{a=1}^{d} \lambda_a^{1\left(X_{as}^d \neq x_a^d\right)},$$

where $0 \le \lambda_a \le 1$ is the smoothing parameter for $\mathbf{X}_s^d$. Once we get a consistent estimator for $\varphi(\mathbf{u}|\mathbf{X}_t)$, we can calculate the generalized residual and construct the test statistic. For simplicity, we just focus on the continuous case in our theoretical derivation. Cases with discrete data or mix data will be left for future research.

Assumption A.2 is required only under $\mathbb{H}_0$. It assumes that a Markov process $\{\mathbf{X}_t\}$ can be approximated by a q-dependent process $\{\mathbf{X}_{qt}\}$ arbitrarily well if q is sufficiently large.[9] In fact, a Markov process can be q-dependent. Lévy (1949), Rosenblatt and Slepian (1962), Aaronson, Gilat and Keane (1992), and Matús (1996, 1998) provide examples of a q-dependent Markov process. Ibragimov (2007) provides the conditions that a Markov process is a q-dependent process. In this case, Assumption A.2 holds trivially. Assumption A.2 is not restrictive even when $\mathbf{X}_t$ is not a q-dependent process. To appreciate this, we first consider a simple AR(1) process $\{\mathbf{X}_t\}$:

$$\mathbf{X}_t = \alpha \mathbf{X}_{t-1} + \varepsilon_t, \qquad \{\varepsilon_t\} \sim i.i.d.\,(0,1).$$

Define $\mathbf{X}_{qt} = \sum_{j=0}^{q} \alpha^j \varepsilon_{t-j}$, a q-dependent process. Then we have

$$E(\mathbf{X}_t - \mathbf{X}_{qt})^2 = E\left(\sum_{j=q+1}^{\infty} \alpha^j \varepsilon_{t-j}\right)^2 = \frac{\alpha^{2(q+1)}}{1-a}.$$

[8] Alternatively, we can test $E[Z_{t+1} g(\mathbf{X}_t)|\mathcal{I}_t] = 0$ in stead of (2.6) and relax Assumption A.1(ii). But the trade-off is that the centering and scaling factors C and D will be more complicated and we have to estimate $\hat{g}(\mathbf{X}_t)$ in addition to $\hat{\varphi}(\mathbf{u}|\mathbf{X}_t)$.

[9] The proof strategy depends on Assumption A2. It seems plausible that we may relax assumption A.2 and rely on the more generous central limit theorem for degenerate U-statistics (e.g., Theorem 2.1 of Gao and Hong 2008). Due to its complicatedness, this would be left for future research. On the other hand, Assumptions A.1 and A.2 don't imply each other. For example, consider a long memory process $\mathbf{X}_t = \sum_{j=0}^{\infty} \varphi_j \varepsilon_{t-j}$, where $\{\varepsilon_t\}\tilde{}\, i.i.d.(0,1)$, $\varphi_j = \Gamma(j+d)/[\Gamma(d)\Gamma(j+1)] \approx \Gamma^{-1}(d)\, j^{d-1}$, and $\Gamma(\cdot)$ is the Gamma function. Define $\mathbf{X}_{qt} = \sum_{j=0}^{q} \varphi_j \varepsilon_{t-j}$, a q-dependent process. Then we have $E(\mathbf{X}_t - \mathbf{X}_{qt})^2 \approx \Gamma^{-1}(d)\, q^{-1+2d} \cdot \frac{1}{q}\sum_{j=q+1}^{\infty}\left(\frac{j}{q}\right)^{-2(1-d)} = O\left(q^{-1+2d}\right)$. Hence, Assumption A.2 holds if $0 < d \le \frac{1}{4}$, but Assumption A.1 is violated since $\{\mathbf{X}_t\}$ is not a strictly stationary process.

Hence Assumption A.2 holds if $|\alpha| < 1$.

Another example would be an ARCH(1) process $\{\mathbf{X}_t\}$:

$$\begin{cases} \mathbf{X}_t = h_t^{1/2}\varepsilon_t, \\ h_t = \alpha + \beta \mathbf{X}_{t-1}^2, \\ \varepsilon_t \sim i.i.d.N(0,1). \end{cases}$$

This is a Markov process. By recursive substitution, we have $h_t = \alpha + \alpha \sum_{j=1}^{\infty} \prod_{i=1}^{j} \beta \varepsilon_{t-i}^2$. Define $\mathbf{X}_{qt} \equiv h_{qt}^{1/2}\varepsilon_t$, where $h_{qt} \equiv \alpha + \alpha \sum_{j=1}^{q} \prod_{i=1}^{j} \beta \varepsilon_{t-i}^2$. Then $\mathbf{X}_{qt}$ is a q-dependent process and

$$E\left(\mathbf{X}_t - \mathbf{X}_{qt}\right)^2 = E\left(h_t^{1/2} - h_{qt}^{1/2}\right)^2 \leq E\left(h_t - h_{qt}\right) = \alpha \sum_{j=q+1}^{\infty} \prod_{i=1}^{j} E\left(\beta \varepsilon_{t-i}^2\right) = \frac{\alpha \beta^{q+1}}{1-\beta}.$$

Thus Assumption A.2 holds if $\beta < 1$.

For the third example, we consider a mean-reverting Ornstein-Uhlenbeck process $\mathbf{X}_t$:

$$d\mathbf{X}_t = \kappa\left(\theta - \mathbf{X}_t\right)dt + \sigma dW_t,$$

where W_t is the standard Brownian motion. This is known as Vasicek's (1977) model in the interest rate term structure literature. From the stationarity condition, we have $\mathbf{X}_t \sim N\left(\theta, \frac{\sigma^2}{2\kappa}\right)$. Define $\mathbf{X}_{qt} = \theta + \int_{t-q}^{t} \sigma e^{-\kappa(t-s)} dW_s$, which is a q-dependent process. Then

$$\begin{aligned} E\left(\mathbf{X}_t - \mathbf{X}_{qt}\right)^2 &= E\left[e^{-\kappa t}\left(\mathbf{X}_0 - \theta\right) + \int_0^{t-q} \sigma e^{-\kappa(t-s)} dW_s\right]^2 \\ &= e^{-2\kappa t}\left(\frac{\sigma^2}{2\kappa}\right) + \int_0^{t-q} \sigma^2 e^{-2\kappa(t-s)} ds \\ &= \frac{\sigma^2 e^{-2\kappa q}}{2\kappa} = o\left(q^{-\eta}\right), \text{ for any } \eta > 0. \end{aligned}$$

Thus Assumption A.2 holds.

Assumption A.3 imposes regularity conditions on the kernel function used in local linear regression estimation. We permit but do not require the usage of the higher order kernel. The condition on the boundedness of $K(\cdot)$ is imposed for the brevity of proofs and could be removed at the cost of a more tedious proof.

Assumption A.4 imposes regularity conditions on the kernel function $k(\cdot)$ used for generalized cross-spectral estimation. This kernel is different from the kernel $K(\cdot)$ used in the first stage nonparametric regression estimation of $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$. Here, $k(\cdot)$ provides weighting for various lags, and it is used to estimate the generalized cross-spectrum $F(\omega, \mathbf{u}, \mathbf{v})$. Among other things, the continuity of $k(\cdot)$ at zero and $k(0) = 1$ ensures that the bias of the generalized cross-spectral estimator $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$ vanishes to zero asymptotically as $T \to \infty$. The condition on the tail behavior of $k(\cdot)$ ensures that higher order lags will have little impact on the statistical properties of $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$. Assumption A.4 covers most commonly used kernels. For kernels with bounded support, such as the Bartlett and Parzen kernels, $b = \infty$. For kernels with unbounded support, b is a finite positive real number. For example, $b = 1$

for the Daniell kernel $k(z) = \sin(\pi z)/(\pi z)$, and $b = 2$ for the Quadratic-spectral kernel $k(z) = 3/(\pi z)^2 [\sin(\pi z)/(\pi z) - \cos(\pi z)]$.

Assumption A.5 imposes mild conditions on the prespecified weighting function $W(\cdot)$. Any CDF with finite fourth moments satisfies Assumption A.5. Note that $W(\cdot)$ need not be continuous. This provides a convenient way to implement our tests, because we can avoid relatively high dimensional numerical integrations by using finitely many numbers of grid points for $\mathbf{u}$ and $\mathbf{v}$.

Theorem 1: *Suppose Assumptions A.1−A.5 hold, and* $p = cT^{\lambda}$ *for* $0 < \lambda < (3 + \frac{1}{4b-2})^{-1}$ *and* $0 < c < \infty$, $h = cT^{-\delta}$, $\delta \in \left(\frac{2-\lambda}{4r}, \min(\frac{\lambda\nu}{2d}, \frac{2-\lambda}{2d})\right)$. *Then under* $\mathbb{H}_0$,

$$\hat{M} \rightarrow^d N(0,1) \text{ as } T \rightarrow \infty.$$

As an important feature of $\hat{M}$, the use of the nonparametrically estimated generalized residual $\hat{Z}_t(\mathbf{u})$ in place of the true unobservable residual $Z_t(\mathbf{u})$ has no impact on the limit distribution of $\hat{M}$. One can proceed as if the true CCF $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$ were known and equal to the nonparametric estimator $\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$. The reason is that by choosing suitable bandwidth h and lag order p, the convergence rate of the nonparametric CCF estimator $\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$ is faster than that of the nonparametric estimator $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$ to $F(\omega, \mathbf{u}, \mathbf{v})$. Consequently, the limiting distribution of $\hat{M}$ is solely determined by $\hat{F}(\omega, \mathbf{u}, \mathbf{v})$, and replacing $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$ by $\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$ has no impact on the asymptotic distribution of $\hat{M}$ under $\mathbb{H}_0$. The impact of the first stage estimation comes from two sources: bias and variance and we have to balance them. The dimension d affects the variance but not the bias. For given T and h, the variance increases with the dimension and consequently, a smaller dimension allows for a bigger feasible range of δ. The dimension d has no direct impact on λ, as the frequency domain estimation is used for the one-dimensional generalized spectrum $F(\omega, \mathbf{u}, \mathbf{v})$, no matter how big the dimension of $\mathbf{X}_t$ is. However, since we need to balance the convergence speed of h and p, the dimension d has an indirect impact on p. The smaller the dimension is, the bigger the feasible range of λ would have.

Although the use of $\hat{\varphi}(\mathbf{u}|\mathbf{X}_{t-1})$ has no impact on the limit distribution of the $\hat{M}$ test, it may have substantial impact on its finite sample size performance. To overcome such adverse impact, we will use Horowitz's (2003) nonparametric smoothed transition density-based bootstrap procedure to obtain the critical values of the test in finite samples. See more discussion in Section 5 below.

4. ASYMPTOTIC POWER

Our test is derived without assuming a specific alternative to $\mathbb{H}_0$. To get insights into the nature of the alternatives that our test is able to detect, we now examine the asymptotic behavior of $\hat{M}$ under $\mathbb{H}_A$ in (2.2).

Theorem 2: *Suppose Assumption A.1 and A.3- A.5 hold, and* $p = cT^{\lambda}$ *for* $0 < \lambda < (3 + \frac{1}{4b-2})^{-1}$ *and*

$0 < c < \infty$, $h = cT^{-\delta}$, $\delta \in \left(\frac{2-\lambda}{4r}, \min(\frac{\lambda\nu}{2d}, \frac{1}{d})\right)$. *Then under* $\mathbb{H}_A$, *and as* $T \to \infty$,

$$\begin{aligned}
\frac{p^{\frac{1}{2}}}{T}\hat{M} &\to^{p} \frac{1}{\sqrt{D}}\sum_{j=1}^{\infty}\int\int \left|\Gamma_j(\mathbf{u},\mathbf{v})\right|^2 dW(\mathbf{u})\, dW(\mathbf{v}) \\
&= \frac{1}{\sqrt{D}}\int\int\int_{-\pi}^{\pi}\left|F(\omega,\mathbf{u},\mathbf{v}) - F_0(\omega,\mathbf{u},\mathbf{v})\right|^2 d\omega dW(\mathbf{u})\, dW(\mathbf{v}),
\end{aligned}$$

where

$$\begin{aligned}
D &= 4\pi\int_0^{\infty}k^4(z)\,dz\int\int\left|\Sigma_0(\mathbf{u}_1,\mathbf{u}_2)\right|^2 dW(\mathbf{u}_1)\, dW(\mathbf{u}_2) \\
&\quad \times\int\int\int_{-\pi}^{\pi}\left|L(\omega,\mathbf{v}_1,\mathbf{v}_2)\right|^2 d\omega dW(\mathbf{v}_1)\, dW(\mathbf{v}_2),
\end{aligned}$$

and $L(\omega,\mathbf{u},\mathbf{v}) = (2\pi)^{-1}\sum_{j=-\infty}^{\infty}\Omega_j(\mathbf{u},\mathbf{v})\,e^{-ij\omega}$, $\Omega_j(\mathbf{u},\mathbf{v}) = cov\left(e^{i\mathbf{u}'\mathbf{X}_t}, e^{i\mathbf{v}'\mathbf{X}_{t-|j|}}\right)$ *and* $\Sigma_0(\mathbf{u},\mathbf{v}) = cov\left[Z_t(\mathbf{u}), Z_t(\mathbf{v})\right]$.

The restriction on h in Theorem 2 is weaker than that in Theorem 1, as we allow for slower convergence rate of the first stage nonparametric estimation. The function $L(\omega,\mathbf{u},\mathbf{v})$ is the generalized spectral density of the process $\{\mathbf{X}_t\}$, which is first introduced in Hong (1999) in a univariate context. It captures temporal dependence in $\{\mathbf{X}_t\}$. The dependence of the constant D on $L(\omega,\mathbf{u},\mathbf{v})$ is due to the fact that the conditioning variable $\{e^{\left(i\mathbf{v}'\mathbf{X}_{t-|j|}\right)}\}$ is a time series process. This suggests that if the time series $\{\mathbf{X}_t\}$ is highly persistent, it may be more difficult to detect violation of the Markov property because the constant D will be larger.

Following reasoning analogous to Bierens (1982) and Stinchcombe and White (1998), we have that for $j > 0$, $\Gamma_j(\mathbf{u},\mathbf{v}) = 0$ for all $\mathbf{u},\mathbf{v} \in \mathbb{R}^d$ if and only if $E\left[Z_t(\mathbf{u})|\mathbf{X}_{t-j}\right] = 0$ *a.s.* for all $\mathbf{u} \in \mathbb{R}^d$. Thus, the generalized covariance function $\Gamma_j(u,v)$ can capture various departures from the Markov property in every conditional moment of $\mathbf{X}_t$ in view of the Taylor series expansion in (2.7). Suppose $E\left[Z_t(\mathbf{u})|\mathbf{X}_{t-j}\right] \neq 0$ at some lag $j > 0$. Then we have $\int\int\left|\Gamma_j(\mathbf{u},\mathbf{v})\right|^2 dW(\mathbf{u})\, dW(\mathbf{v}) > 0$ for any weighting function $W(\cdot)$ that is positive, monotonically increasing and continuous, with unbounded support on $\mathbb{R}^d$. As a consequence, $P[\hat{M} > C(T)] \to 1$ for any sequence of constants $\{C(T) = o(T/p^{1/2})\}$. Thus $\hat{M}$ has asymptotic unit power at any given significance level, whenever $E\left[Z_t(\mathbf{u})|\mathbf{X}_{t-j}\right] \neq 0$ at some lag $j > 0$.

Thus, to ensure the consistency property of $\hat{M}$, it is important to integrate $\mathbf{u}$ and $\mathbf{v}$ over the entire domain of $\mathbb{R}^d$. When numerical integration is difficult, as is the case where the dimension d is large, one can use the Monte Carlo simulation to approximate the integrals over $\mathbf{u}$ and $\mathbf{v}$. This can be obtained by using a large number of random draws from the distribution $W(\cdot)$ and then computing the sample average as an approximation to the related integral. Such an approximation will be arbitrarily accurate provided the number of random draws is sufficiently large. Alternatively, we can use a nondecreasing step function $W(\cdot)$. This avoid numerical integration or Monte Carlo simulation, but the power of the test may be affected. In theory, the consistency property will not be preserved if only a finite number of grid points of $\mathbf{u}$ and $\mathbf{v}$ are used and the power of the test may depend on the choice of grid points for $\mathbf{u}$ and $\mathbf{v}$.

As revealed by the Taylor series expansion in (2.7), our test, which is based on the MDS characterization in (2.6), essentially checks departures from the Markov property in every conditional moment. When $\hat{M}$ rejects the Markov property, one may be further interested in what causes the rejection. To gauge possible sources of the violation of the Markov property, we can consider a sequence of tests based on the derivatives of the nonparametric regression residual $Z_t(\mathbf{u})$ at the origin $\mathbf{0}$:

$$\frac{\partial^{|\mathbf{m}|}}{\partial u_1^{m_1} \cdots \partial u_d^{m_d}} E\left[Z_t(\mathbf{u})|\mathcal{I}_{t-1}\right]_{\mathbf{u}=\mathbf{0}} = E(X_{1t}^{m_1} \cdots X_{dt}^{m_d}|\mathcal{I}_{t-1}) - E(X_{1t}^{m_1} \cdots X_{dt}^{m_d}|\mathbf{X}_{t-1}) = 0,$$

where the order of derivatives $|\mathbf{m}| = \Sigma_{a=1}^{d} m_a$, and $\mathbf{m} = (m_1, ..., m_d)'$, and $m_a \geq 0$ for all $a = 1, ..., d$. For the univariate time series, the choices of $\mathbf{m} = 1, 2, 3, 4$ corresponds to tests for departures of the Markov property in the first four conditional moments respectively. For each $\mathbf{m}$, the resulting test statistic is given by:

$$\hat{M}(\mathbf{m}) = \left[\sum_{j=1}^{T-1} k^2(j/p)(T-j) \int \left|\hat{\Gamma}_j^{(\mathbf{m},\mathbf{0})}(\mathbf{0},\mathbf{v})\right|^2 dW(\mathbf{v}) - \hat{C}(\mathbf{m})\right] / \sqrt{\hat{D}(\mathbf{m})}, \tag{4.1}$$

where $\hat{\Gamma}_j^{(\mathbf{m},\mathbf{0})}(\mathbf{0},\mathbf{v})$ is the sample analogue of the derivative of the generalized cross-covariance function

$$\Gamma_j^{(\mathbf{m},\mathbf{0})}(\mathbf{0},\mathbf{v}) = \operatorname{cov}\left\{\prod_{a=1}^{d}(iX_{at})^{m_a} - E\left[\prod_{a=1}^{d}(iX_{at})^{m_a}\middle|\mathbf{X}_{t-1}\right], e^{\left(i\mathbf{v}'\mathbf{X}_{t-|j|}\right)}\right\},$$

the centering and scaling factors

$$\hat{C}(\mathbf{m}) = \sum_{j=1}^{T-1} k^2(j/p) \frac{1}{T-j} \sum_{t=|j|+1}^{T} \int \left|\hat{Z}_t^{(\mathbf{m})}(\mathbf{0})\right|^2 \left|\hat{\psi}_{t-j}(\mathbf{v})\right|^2 dW(\mathbf{v}),$$

$$\begin{aligned}\hat{D}(\mathbf{m}) &= 2\sum_{j=1}^{T-2}\sum_{l=1}^{T-2} k^2(j/p)k^2(l/p) \int\int \\ &\times \left|\frac{1}{T-\max(j,l)} \sum_{t=\max(j,l)+1}^{T} \left|\hat{Z}_t^{(\mathbf{m})}(\mathbf{0})\right|^2 \hat{\psi}_{t-j}(\mathbf{v}_1)\hat{\psi}_{t-j}(\mathbf{v}_2)\right|^2 dW(\mathbf{v}_1)\, dW(\mathbf{v}_2),\end{aligned}$$

and

$$\hat{Z}_t^{(\mathbf{m})}(\mathbf{0}) = \prod_{a=1}^{d}(iX_{at})^{m_a} - E\left[\prod_{a=1}^{d}(iX_{at})^{m_a}|\mathbf{X}_{t-1}\right].$$

These derivative tests may provide additional useful information on the possible sources of the violation of the Markov property. Moreover, some economic theories only have implications for the Markov property in certain moments and our derivative tests are suitable to test these implications. For example, Hall (1978) shows that a rational expectation model of consumption can be characterized by the Euler equation that $E\left[u'\left(C_{t+1}\right)|\mathcal{I}_t\right] = u'\left(C_t\right)$, where $u'(C_t)$ is the marginal utility of consumption C_t. This can be viewed as the Markov property in mean. The derivative test $\hat{M}(1)$ can be used to test this implication.

On the other hand, Theorem 2 implies that the $\hat{M}$ test can check departure from the Markov property at any lag order $j > 0$, as long as the sample size T is sufficiently large. This is achieved because $\hat{M}$ includes an increasing number of lags as the sample size $T \to \infty$. Usually, the use of a large number of lags would lead to the loss of a large number of degrees of freedom. Fortunately this is not the case with the $\hat{M}$ test, thanks to the downward weighting of $k^2(\cdot)$ for higher order lags.

5. NUMERICAL RESULTS

5.1 Monte Carlo simulations

Theorem 1 provides the asymptotic null distribution of $\hat{M}$. Consequently, one can implement our test for $\mathbb{H}_0$ by comparing $\hat{M}$ with a $N(0,1)$ critical value. However, like many other nonparametric tests in the literature, its size in finite samples may differ significantly from the asymptotic significance level. Our analysis suggests that the asymptotic theory may not work well even for relatively large samples, because the asymptotically negligible higher order terms in $\hat{M}$ are close in order of magnitude to the dominant U-statistic, which determines the limit distribution of $\hat{M}$. In particular, the first stage smoothed nonparametric regression estimation for $\varphi(\mathbf{u}|\mathbf{X}_{t-1})$ may have substantial adverse effect on the size of $\hat{M}$ in finite samples. Our simulation study shows that $\hat{M}$ displays severe underrejection under $\mathbb{H}_0$. On the other hand, we examine the finite sample performance of an infeasible $\hat{M}$ test by replacing the estimated generalized residual $\hat{Z}_t(\mathbf{u})$ by the true generalized residual. We find that the size of the infeasible test is reasonable. This experiment suggests that the underrejection of $\hat{M}$ is mainly due to the impact of the first stage nonparametric estimation of CCF, which has a rather slow convergence rate. Similar problems are also documented by Skaug and Tjøstheim (1993, 1996), Hong and White (2005) and Fan *et al.* (2006) in other contexts.

To overcome this problem, we use Horowitz's (2003) smoothed nonparametric conditional density bootstrap procedure to more accurately approximate the finite-sample null distribution of $\hat{M}$.[10] The basic idea is to use a smoothed nonparametric transition density estimator (under $\mathbb{H}_0$) to generate bootstrap samples. Specifically, it involves the following steps:

- Step (i) To obtain a bootstrap sample $\mathcal{X}^b \equiv \{\mathbf{X}_t^b\}_{t=1}^T$, draw $\mathbf{X}_1^b$ from the smoothed unconditional kernel density

$$\hat{g}(\mathbf{x}) = \frac{1}{T}\sum_{s=2}^{T} \mathbf{K}_h(\mathbf{x} - \mathbf{X}_{s-1})$$

  and $\{\mathbf{X}_t^b\}_{t=2}^T$ from the smoothed conditional kernel density

$$\hat{g}(\mathbf{x}|\mathbf{X}_{t-1}^b) = \frac{\frac{1}{T}\sum_{s=2}^{T} \mathbf{K}_h(\mathbf{x} - \mathbf{X}_s)\, \mathbf{K}_h\left(\mathbf{X}_{t-1}^b - \mathbf{X}_{s-1}\right)}{\frac{1}{T}\sum_{s=2}^{T} \mathbf{K}_h\left(\mathbf{X}_{t-1}^b - \mathbf{X}_{s-1}\right)}, \quad (5.1)$$

  where $\mathbf{K}(\cdot)$ and h are the same as those used in $\hat{M}$;[11]

- Step (ii) Compute a bootstrap statistic $\hat{M}^b$ in the same way as $\hat{M}$, with $\mathcal{X}^b$ replacing $\mathcal{X} = \{\mathbf{X}_t\}_{t=1}^T$. The same $\mathbf{K}(\cdot)$ and h are used in $\hat{M}$ and $\hat{M}^b$;

[10] For the application of the bootstrap in econometrics, see (e.g.) Horowitz (2001).

[11] Bootstrap samples can be generated by applying the inverse-distribution method to a fine grid of points.

- Step (iii) Repeat steps (i) and (ii) B times to obtain B bootstrap test statistics $\{\hat{M}_l^b\}_{l=1}^B$;
- Step (iv) Compute the bootstrap p-value $p_b \equiv B^{-1}\sum_{l=1}^B \mathbf{1}(\hat{M}_l^b > \hat{M})$. To obtain accurate bootstrap p-values, B must be sufficiently large.

We suggest using the same kernel $\mathbf{K}(\cdot)$ and the same bandwidth h in computing $\hat{g}(\mathbf{x}|\mathbf{X}_{t-1})$, $\hat{M}$ and $\hat{M}^b$. This is not necessary, but it is expected to give a better finite sample approximation.[12] Smoothed nonparametric bootstraps have been used to improve finite sample performance in hypothesis testing. For example, Su and White (2007a, 2007b) apply Paparoditis and Politis' (2000) procedure in testing for conditional independence. Amaro de Matos and Fernandes (2007) use Horowitz's (2003) Markov conditional bootstrap procedure in testing for the Markov property. Paparoditis and Politis' (2000) procedure is very similar to Horowitz's (2003), except that Paparoditis and Politis (2000) generate bootstrap samples from $\hat{g}(\mathbf{x}|\mathbf{X}_{t-1})$ and Horowitz (2003) generates bootstrap samples from $\hat{g}(\mathbf{x}|\mathbf{X}_{t-1}^b)$. We note that both methods can be applied although Horowitz's (2003) procedure is more computationally expensive.[13] With Paparoditis and Politis' (2000) method, $\{\mathbf{X}_t^b\}_{t=1}^T$ is an *i.i.d.* sequence conditional on the original sample $\mathcal{X}$ and hence it is Markov conditional on $\mathcal{X}$. Following Theorem 4.1 of Su and White (2007b), we can show that conditional on $\mathcal{X}$, $\hat{M}^b \to^d N(0,1)$ as $T \to \infty$. The proof strategy is similar to but simpler than that of Theorem 1 due to the fact that $\{\mathbf{X}_t^b\}_{t=1}^T$ is *i.i.d.* conditional on $\mathcal{X}$. First, we can show that the estimation uncertainty in the first stage nonparametric estimation has no impact asymptotically. Second, by applying Brown's (1971) central limit theorem, we can derive the asymptotic normality of $\hat{M}^b$ conditional on $\mathcal{X}$. We note that although we can derive a simplified version of $\hat{C}^b$ and $\hat{D}^b$, the form in (2.19) is still valid. The proof of the consistency with Horowitz (2003) approach is more involved. We conjecture that following Theorem 3.4 of Paparoditis and Politis (2002), we can show that conditional on $\mathcal{X}$, $\mathbf{X}_t^b$ is a ρ-mixing process with a geometric decay rate. Then by applying the central limit theorem of the degenerate $U-$statistics (see, Theorem 2.1 in Gao and Hong 2008), the asymptotic normality of $\hat{M}^b$ conditional on $\{\mathbf{X}_t\}_{t=1}^T$ may be obtained. The consistency result that conditional on $\mathcal{X}$, $\hat{M}^b \to^d N(0,1)$ as $T \to \infty$ shows that the smoothed bootstrap provides an asymptotically valid approximation to the limit distribution of $\hat{M}$ under $\mathbb{H}_0$. It implies that $\hat{M}^b \to^d N(0,1)$ unconditionally. However, it does not indicate the degree of improvement of the smoothed bootstrap upon the asymptotic distribution. $\hat{M}$ is asymptotically pivotal, so it is plausible that $\hat{M}^b$ can achieve reasonable accuracy in finite samples. We will examine the performance of the smoothed bootstrap in our simulation.

We compare the finite sample performance of our test with Su and White's (2007a, 2007b, *SW*) Hellinger Metric test and CCF based test for conditional independence. To examine the sizes of our test under $\mathbb{H}_0$, we consider two Markov DGPs:

$$\begin{aligned}&\text{DGP S1 [AR(1)]:} && X_t = 0.5X_{t-1} + \varepsilon_t,\\ &\text{DGP S2 [ARCH(1)]:} && \begin{cases} X_t = h_t^{\frac{1}{2}}\varepsilon_t \\ h_t = 0.1 + 0.1X_{t-1}^2, \end{cases}\end{aligned}$$

[12] It is different from Paparoditis and Politis (2000), which requires different bandwidths. The reason why the same bandwidth works in our paper is that we use undersmoothing in the first stage and the bias of the first stage nonparametric estimation vanishes to 0 asymptotically. Therefore, we need not balance two bandwidths to get a good approximation of the asymptotic bias. This idea is shown in Theorem 2.1 i) in Paparoditis and Politis (2000) in a different context.

[13] Our simulation experiments show that results based on these two smoothed bootstrap procedures are close.

where $\varepsilon_t \sim i.i.d.N(0,1)$.

To examine the power of our test with the smoothed bootstrap procedure, we consider the following non-Markovian DGPs:

$$\text{DGP P1 [MA(1)]:} \quad X_t = \varepsilon_t + 0.5\varepsilon_{t-1},$$

$$\text{DGP P2 [GARCH(1,1)]:} \quad \begin{cases} X_t = h_t^{\frac{1}{2}}\varepsilon_t \\ h_t = 0.1 + 0.2X_{t-1}^2 + 0.7h_{t-1}, \end{cases}$$

$$\text{DGP P3 [GARCH-in-Mean]:} \quad \begin{cases} X_t = 0.3 + 0.5h_t + z_t \\ z_t = h_t^{\frac{1}{2}}\varepsilon_t \\ h_t = 0.1 + 0.2X_{t-1}^2 + 0.7h_{t-1}, \end{cases}$$

$$\text{DGP P4 [Markov Regime-Switching]:} \quad X_t = \begin{cases} 0.7X_{t-1} + \varepsilon_t, & \text{if } S_t = 0, \\ -0.3X_{t-1} + \varepsilon_t, & \text{if } S_t = 1, \end{cases}$$

$$\text{DGP P5 [Markov Regime-Switching ARCH]:} \quad \begin{cases} X_t = \begin{cases} \sqrt{h_t}\varepsilon_t, & \text{if } S_t = 0, \\ 3\sqrt{h_t}\varepsilon_t, & \text{if } S_t = 1, \end{cases} \\ h_t = 0.1 + 0.3X_{t-1}^2, \end{cases}$$

where $\varepsilon_t \sim i.i.d.N(0,1)$, and in DGPs P4-5, S_t is a latent state variable that follows a two-state Markov chain with transition probabilities $P(S_t = 1|S_{t-1} = 0) = P(S_t = 0|S_{t-1} = 1) = 0.9$. DGPs P4-5 are Markov Regime-Switching model and Markov Regime-Switching ARCH model proposed by Hamilton (1989) and Hamilton and Susmel (1994) respectively. They can capture the state-dependent behaviors in time series. The introduction of the latent state variable S_t changes the Markov property of AR and ARCH processes. The knowledge of X_{t-1} is not sufficient to summarize all relevant information in $\mathcal{I}_{t-1}$ that is useful to predict the future behavior of X_t. The departure from the Markov property comes from the conditional mean in DGPs P1 and P4 and from the conditional variance in DGPs P2, P3 and P5.

Throughout, we consider three sample sizes: $T = 100, 250, 500$. For each DGP, we first generate $T + 100$ observations and then discard the first 100 to mitigate the impact of the initial values.

To examine the bootstrap sizes and powers of the tests, we generate 500 realizations of the random sample $\{X_t\}_{t=1}^T$, using the GAUSS Windows version random number generator. We use $B = 100$ bootstrap iterations for each simulation iteration. To reduce computational costs of our test, we generate $\mathbf{u}$ and $\mathbf{v}$ from a $N(0,1)$ distribution, with each $\mathbf{u}$ and $\mathbf{v}$ having 30 symmetric grid points in $\mathbb{R}$ respectively.[14] We use the Bartlett kernel in (2.14), which has bounded support and is computationally efficient. Our simulation experience suggests that the choices of $W(\cdot)$ and $k(\cdot)$ have little impact on both the size and power of the tests.[15] Like Hong (1999), we use a data-driven $\hat{p}$ via a plug-in method that minimizes the asymptotic integrated mean squared error of the generalized spectral density estimator $\hat{F}(\omega, \mathbf{x}, \mathbf{y})$, with the Bartlett kernel $k(\cdot)$ used in some preliminary generalized spectral estimators. To examine the sensitivity of the choice of the preliminary bandwidth $\bar{p}$ on the size and power of the tests,

[14] We first generate 15 grid points $\mathbf{u}_0, \mathbf{v}_0$ from $N(0,1)$ and obtain $\mathbf{u} = [\mathbf{u}_0', -\mathbf{u}_0']'$ and $\mathbf{v} = [\mathbf{v}_0', -\mathbf{v}_0']'$ to ensure symmetry. Preliminary experiments with different numbers of grid points show that simulation results are not very sensitive to the choice of numbers. Concerned with the computational cost in the simulation study, we are satisfied with current results with 30 grid points.

[15] We have tried the Parzen kernel for $k(\cdot)$, obtaining similar results (not reported here).

we consider $\bar{p}$ in the range of 5 to 20. We use the Gaussian kernel for $\mathbf{K}(\cdot)$. For simplicity, we choose $h = \hat{S}_X T^{-\frac{1}{4.5}}$, where $\hat{S}_X$ is the sample standard deviation of $\{X_t\}_{t=1}^T$.[16] We compare the proposed test with Su and White's (2007a, 2007b) tests. For Su and White's (2007a, 2007b), we check whether X_t is independent of X_{t-2} conditional on X_{t-1}. Following Su and White (2007a, 2007b), we choose a fourth order kernel $\mathbf{K}(u) = (3 - u^2)\varphi(u)/2$, where $\varphi(\cdot)$ is the normal density function, $h = T^{-\frac{1}{8.5}}$ for the nonparametric estimation of SW_a, $h_1 = h_1^* T^{\frac{1}{10}} T^{-\frac{1}{6}}$ and $h_2 = h_2^* T^{\frac{1}{9}} T^{-\frac{1}{5}}$ for SW_b, where h_1^* and h_2^* are the least-squares cross-validated bandwidths for estimating the conditional expectation of X_t given (X_{t-1}, X_{t-2}) and X_{t-1} respectively, and $b = T^{-\frac{1}{5}}$ for the bootstrap.

Table 1 reports the bootstrap sizes and powers of $\hat{M}$, SW_a and SW_b at the 10% and 5% nominal significance levels under DGPs S1-2 and P1-5. $\hat{M}$ has reasonable sizes under the DGPs S1 and S2 at both 10% and 5% levels. Under DGP S1 (AR(1)), the empirical levels of $\hat{M}$ are very close to the nominal levels, especially at the 5% level. When $T = 100$, $\hat{M}$ tends to overreject a little under DGP S2 (ARCH(1)), but the overrejection is not excessive and it improves as T increases. The sizes of $\hat{M}$ are not very sensitive to the choice of the preliminary lag order $\bar{p}$. The smoothed bootstrap procedure has reasonable sizes in small samples. The rejection rate of SW_a decreases monotonically under DGP S1 and reaches 2.8% at the 5% level when $T = 500$. SW_b has good sizes under both DGPs.

Under DGPs P1-5, X_t is not Markov and our test has reasonable power to detect them. Under DGPs P1 and 4 (MA(1) and Markov chain regime-switching), our test dominates SW_a and SW_b for all sample sizes considered. Interestingly, SW_a and SW_b have nonmonotonic power against DGP P4 and their rejection rates only reach 10.4% and 7.2% respectively at the 5% level when $T = 500$. On the contrary, the power of $\hat{M}$ is around 50% at the 5% level when $T = 500$. Under DGPs P2,3 and 5 (GARCH(1,1), Markov Regime-Switching ARCH and GARCH-in-mean), SW_a and SW_b perform slightly better in small samples, but the power of our test increases more quickly with T and outperforms SW_a and SW_b when $T = 500$, which demonstrates the nice feature of our frequency domain approach. Our test examines a growing number of lags as the sample size increases while SW_a and SW_b just check a fixed number of lags. When the violation of the Markov property also comes from higher order lags, our test is expected to have better power. The relatively ranking between SW_a and SW_b is mixed. SW_b is more powerful under DGPs P1,2 and 3.

In summary, the new test with the smoothed bootstrap procedure delivers reasonable size and omnibus power against various non-Markov alternatives in small samples. It outperforms two existing tests considered.

5.2 Application to financial data

As documented by Hong and Li (2005), such popular spot interest rates continuous-time models as Vasicek (1977), Cox, Ingersoll and Ross (1985), Chan, Karolyi, Longstaff and Sanders (1992), Ait-Sahalia (1996) and Ahn and Gao (1999) are all strongly rejected with real interest rate data. They cannot capture the full dynamics of the spot interest rate processes. Although some works are still going on to add the richness of model specification in terms of jumps and functional forms, the models remain to be a Markov process. In fact, the firm rejection of a continuous-time model could be due to the violation of the Markov property, as speculated by Hong and Li (2005). If this is indeed the case, then

[16] Following Ait-Sahali (1997) and Matos and Fernandes (2007), we use undersmoothing to ensure that the squared bias vanishes to zero faster than the variance.

one should not attempt to look for flexible functional forms within the class of Markov models. On the other hand, as discussed earlier, an important conclusion of the asymmetric information microstructure models (e.g., Easley and O'Hara (1987,1992)) is that the asset price sequence does not follow a Markov process. It is interesting to check whether real stock prices are consistent with such a conjecture.

We apply our test to three important financial time series: stock prices, interest rates and foreign exchange rates, and compare it with SW_a and SW_b. We use the S&P500 series, 7-day Eurodollar rate and Japanese Yen, obtained from Datastream. The data are weekly series from January 1, 1988 to to December 31, 2006. The weekly series are generated by selecting Wednesdays series (if a Wednesday is a holiday then the previous Tuesday is used), which all have 991 observations. The use of weekly data avoids the so-called weekend effect, as well as other biases associated with nontrading, asynchronous rates and so on, which are often present in higher frequency data. To examine the sensitivity of our test to the sample size, we consider two subsamples: January 1, 1988 to December 31, 1997 for a total of 521 observations, and January 1, 1998 to December 31, 2006 for a total of 470 observations. Figures 1-6 provide the time series plots and Table 2 reports some descriptive statistics. The augmented Dickey-Fuller test indicates that there is a unit root in all three level series but not in the first differenced series. Therefore, as is standard, we use S&P500 log returns, 7-day Eurodollar rate changes and Japanese Yen log returns. The Kolmogorov-Smirnov (KS) test for the stability of unconditional distributions[17] (Inoune 2001) shows that we are unable to reject the stability hypothesis for all series in both sample periods at the 5% level and we are only able to reject the stability hypothesis for 7-day Eurodollar rate changes in the full sample at the 10% level.[18] Table 3 reports the test statistics and bootstrap p-values of our test, SW_a and SW_b. The bootstrap $p-$values, based on $B = 500$ bootstrap iterations, are computed as described in Section 5.1. For all sample periods considered, our test statistics are quite robust to the choice of $\bar{p}$. For the whole sample and the subsample of 1998 to 2006, we find strong evidence against the Markov property for S&P500 returns, 7-day Eurodollar rate changes and Japanese Yen returns. For the subsample of 1988 to 1997, we are only able to reject the Markov property of 7-day Eurodollar rate changes.[19] The results of SW_a and SW_b are mixed and there seems no clear pattern of these tests. For example, at the 10% level, SW_a is only able to reject the Markov property of S&P500 returns and 7-day Eurodollar rate changes from 1998 to 2006 and SW_b is only able to reject that of S&P500 returns from 1988 to 2006 and 7-day Eurodollar rate changes from 1988 to 2006 and 1988 to 1997.

These results cast some new thoughts on financial modelling. Although popular stochastic differential equation models exhibit mathematical elegance and tractability, they may not be an adequate representation of the dynamics of the underlying process, due to the Markov assumption. Other mod-

[17] Ideally, the conditional distribution of $\mathbf{X}_t$ given $\mathbf{X}_{t-1}$ should be tested. Unfortunately, to our knowledge, no such test is available in the literature. Compared with some existing tests in the literature, Inoue's (2001) tests are model-free, allow for dependence in the data, and are robust against the heavy-tailed distributions observed in financial markets. Hence, they are most suitable here for preliminary testing. Inoue (2001) proposes both KS and Cramer-Von Mises tests for the stability of unconditional distribution. But the class of the supreme test is more popular, as it can identify possible break dates.

[18] We also tried a simulation with an AR(1) model with structrual break. (Results are availabe upon requests.) This DGP is Markov although structrual break exists. Our test does not overreject the null Markov hypothesis, which suggests that our test may be robust to some forms of structural breaks.

[19] We can use (4.1) to gauge possible sources of the violation of the Markov property. For example, whether the departure of the Markov property comes from the conditional mean, conditional variance or higher moments. This will be left for further research.

elling schemes, which allow for the non-Markov assumption, may be needed to better capture the dynamics of financial time series processes.[20]

6. CONCLUSION

The Markov property is one of most fundamental properties in stochastic processes. Without justification, this property has been taken for granted in many economic and financial models, especially in continuous-time finance models. We propose a conditional characteristic function based test for the Markov property in a spectral framework. The use of the conditional characteristic function, which is consistently estimated nonparametrically, allows us to check departures from the Markov property in all conditional moments and the frequency domain approach, which checks many lags in a pairwise manner, provides a nice solution to tackling the difficulty of the "curse of dimensionality" associated with testing for the Markov property. To overcome the adverse impact of the first stage nonparametric estimation of the conditional characteristic function, we use the smoothed nonparametric transition density-based bootstrap procedure, which provides reasonable sizes and powers for the proposed test in finite samples. We apply our test to three important financial time series. Our results suggest that the Markov assumption may not be suitable for many financial time series.

[20] It is possible that the rejection of Markov property is due to structural break or long memory rather than Markov property. But of course, this feature is not particular to the proposed test here, but relevant to all existing tests for Markov property.

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Table 1: Size and power of the test

	$T=100$					$T=250$					$T=500$				
		$\hat{M}$		SW_a	SW_b		$\hat{M}$		SW_a	SW_b		$\hat{M}$		SW_a	SW_b
lag	10	15	20			10	15	20			10	15	20		
Size															
DGP S1: AR(1)															
10%	.066	.088	.090	.080	.112	.094	.098	.096	.072	.090	.088	.086	.092	.058	.088
5%	.042	.042	.048	.040	.064	.036	.044	.048	.036	.050	.044	.048	.044	.028	.048
DGP S2: ARCH(1)															
10%	.116	.122	.126	.164	.102	.082	.094	.098	.138	.100	.094	.092	.092	.086	.100
5%	.070	.064	.066	.102	.040	.046	.040	.040	.078	.058	.048	.048	.050	.050	.050
Power															
DGP P1: MA(1)															
10%	.278	.262	.236	.128	.138	.444	.424	.390	.156	.260	.718	.674	.616	.252	.360
5%	.156	.144	.136	.076	.072	.328	.300	.256	.098	.166	.622	.552	.508	.158	.264
DGP P2: GARCH(1,1)															
10%	.172	.158	.150	.218	.234	.224	.242	.258	.210	.284	.440	.452	.446	.310	.372
5%	.084	.086	.078	.150	.160	.154	.166	.162	.136	.206	.274	.300	.296	.216	.234
DGP P3: GARCH-in-Mean															
10%	.164	.168	.174	.188	.206	.348	.360	.366	.246	.340	.628	.648	.668	.362	.508
5%	.090	.102	.088	.114	.120	.224	.234	.246	.162	.246	.490	.540	.536	.254	.362
DGP P4: Markov Regime-Switching															
10%	.244	.214	.202	.190	.134	.442	.384	.348	.180	.150	.666	.612	.578	.164	.120
5%	.156	.148	.140	.114	.078	.302	.270	.252	.094	.070	.550	.494	.458	.104	.072
DGP P5: Markov Regime-Switching ARCH															
10%	.174	.152	.154	.100	.188	.328	.320	.298	.364	.288	.626	.594	.590	.560	.388
5%	.098	.086	.082	.042	.112	.204	.202	.198	.262	.162	.496	.478	.456	.448	.240

Notes: (i) $\hat{M}$ is our proposed omnibus test,given in (2.19); SW_a and SW_b are Su and White's (2007a) Hellinger metric test and Su and White's (2007b) characteristic function based test respectively;
(ii) 500 iterations and 100 bootstrap iterations for each simulation iteration

Table 2 Descriptive statistics for S&P 500, interest rate and exchange rate

	01/01/1988 – 12/31/2006			01/01/1988 – 12/31/1997			01/01/1998 – 12/31/2006		
	S&P	Eurodollar	JY	S&P	Eurodollar	JY	S&P	Eurodollar	JY
Sample size	991	991	991	521	521	521	470	470	470
mean	0.0017	−0.0017	−0.0001	0.0025	−0.0025	0.0000	0.0008	−0.0004	−0.0002
std	0.0209	0.3272	0.0145	0.0179	0.4087	0.0146	0.0238	0.2019	0.0145
ADF	−0.58	−1.19	−2.07	2.10	−1.00	−1.19	−1.78	−0.72	−2.42
	(0.8728)	(0.6808)	(0.2550)	(0.9999)	(0.7532)	(0.6786)	(0.3896)	(0.8395)	(0.1362)
KS	0.2828	0.0707	0.3939	0.6364	0.1010	0.1818	0.1818	0.1414	0.2828

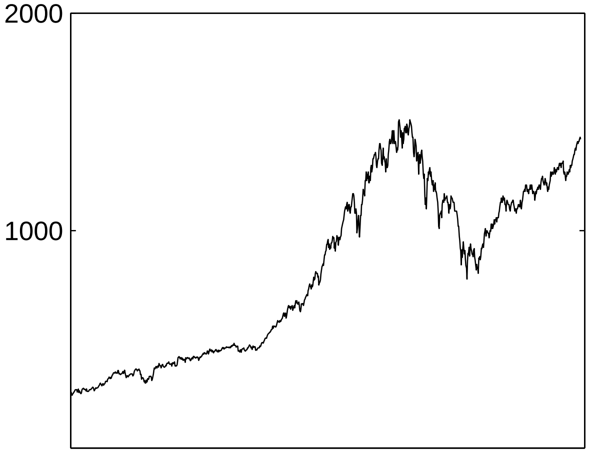
Notes: ADF denotes the augmented Dickey-Fuller test; KS denotes the Kolmogorov-Smirnov test for the stability of unconditional distributions proposed by Inoune (2001).

Table 3 Markov test for S&P 500, interest rate and exchange rate

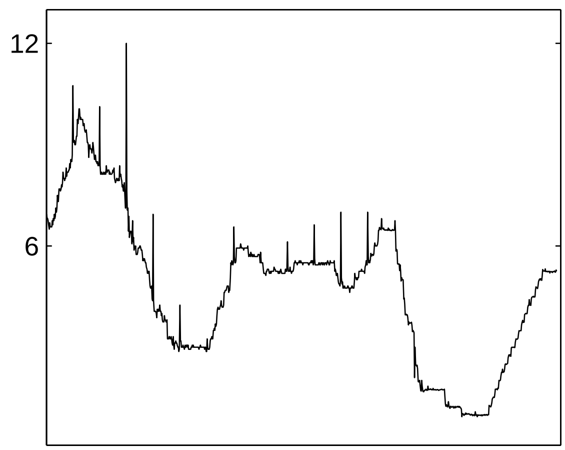
	S&P 500		7-day Eurodollar rate		Japanese Yen	
lag	Statistics	p-values	Statistics	p-values	Statistics	p-values
$\hat{M}$			01/01/1988 – 12/31/2006			
10	0.86	0.0160	0.75	0.0080	1.34	0.0000
11	0.86	0.0160	0.98	0.0040	1.39	0.0000
12	0.89	0.0160	1.16	0.0040	1.52	0.0000
13	0.95	0.0160	1.35	0.0040	1.65	0.0000
14	1.01	0.0160	1.58	0.0020	1.76	0.0000
15	1.05	0.0180	1.79	0.0020	1.85	0.0000
16	1.07	0.0180	1.99	0.0020	1.94	0.0000
17	1.09	0.0200	2.22	0.0020	2.01	0.0000
18	1.11	0.0180	2.48	0.0020	2.08	0.0000
19	1.12	0.0180	2.74	0.0020	2.15	0.0000
20	1.13	0.0180	2.97	0.0000	2.21	0.0000
SW_a	0.79	0.1680	−4.61	0.9920	0.09	0.4600
SW_b	0.36	0.0940	0.21	0.0520	−0.85	0.5700
$\hat{M}$			01/01/1988 – 12/31/1997			
10	−1.39	0.5940	0.25	0.0100	−0.35	0.0980
11	−1.39	0.6120	0.30	0.0100	−0.35	0.1060
12	−1.35	0.6080	0.34	0.0080	−0.27	0.1020
13	−1.30	0.5900	0.38	0.0060	−0.21	0.0980
14	−1.25	0.5840	0.41	0.0080	−0.16	0.0980
15	−1.20	0.5780	0.45	0.0080	−0.12	0.1040
16	−1.15	0.5600	0.49	0.0080	−0.08	0.1040
17	−1.08	0.5260	0.51	0.0080	−0.04	0.1060
18	−1.02	0.5080	0.54	0.0100	−0.01	0.1100
19	−0.96	0.4860	0.57	0.0100	0.03	0.1100
20	−0.91	0.4640	0.62	0.0080	0.06	0.1100
SW_a	−0.36	0.6540	−4.85	0.9900	0.16	0.3640
SW_b	−0.14	0.1680	0.07	0.0700	0.03	0.1100
$\hat{M}$			01/01/1998 – 12/31/2006			
10	1.68	0.0080	0.34	0.0100	0.71	0.0100
11	1.88	0.0060	0.74	0.0040	0.76	0.0120
12	2.06	0.0040	1.08	0.0000	0.82	0.0140
13	2.22	0.0020	1.36	0.0000	0.88	0.0140
14	2.36	0.0020	1.62	0.0000	0.94	0.0140
15	2.48	0.0020	1.87	0.0000	0.98	0.0140
16	2.58	0.0020	2.09	0.0000	1.02	0.0100
17	2.66	0.0000	2.27	0.0000	1.06	0.0100
18	2.74	0.0000	2.44	0.0000	1.09	0.0100
19	2.81	0.0000	2.60	0.0000	1.11	0.0120
20	2.88	0.0000	2.75	0.0000	1.14	0.0120
SW_a	1.12	0.0960	1.50	0.0180	0.63	0.2160
SW_b	−0.07	0.1520	−0.18	0.1740	−1.28	0.8600

Notes: (i) $\hat{M}$ is our proposed omnibus test,given in (2.19); SW_a and SW_b are Su and White's (2007a) Hellingermetric test and Su and White's (2007b) characteristic function based test respectively; (ii) 500 bootstrap iterations.

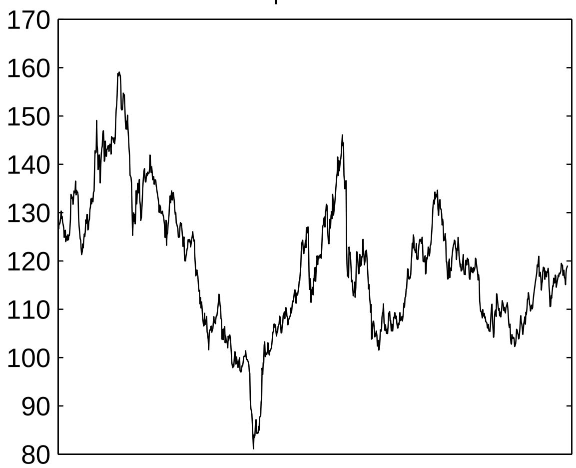
1. S&P500 index



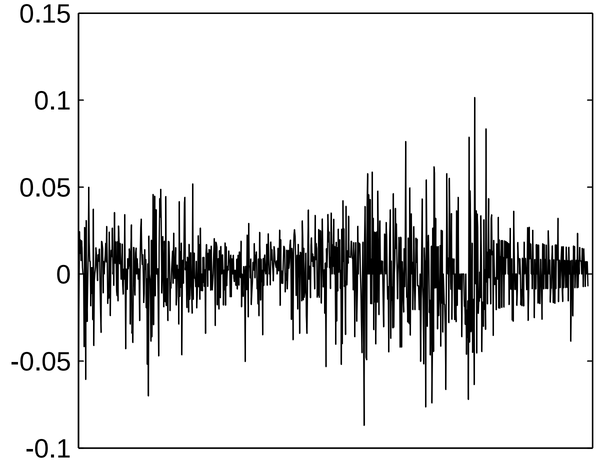
2. 7-day Eurodollar rate



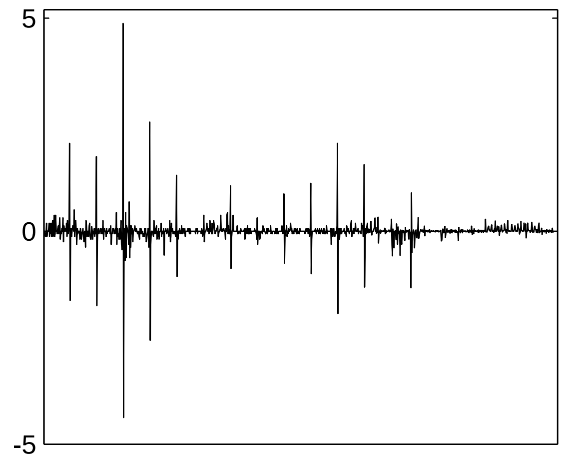
3. Japanese Yen



4. S&P500 return



5. 7-day Eurodollar rate change



6. Japanese Yen return