Are the Predictive Regression Tests Overrejecting?

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First draft: April 30, 2009

Abstract

This paper presents a source of statistical distortions induced by present value models that may significantly affect statistical inference in the predictive regression both in finite samples and asymptotically. We show both analytically and by simulation that the regression-based tests including optimal robust tests such as Jansson and Moreira's conditional test and Campbell and Yogo's Q-test may suffer from lack of power in the local-to-unity models of the regressor persistence and the discount factor. We also analyze a nonparametric unbiasedness test based on the variance ratio of excess returns that is immune to persistence distortions as well as to some power limitations inherent in regression tests. We provide empirical evidence that supports our assumptions and predictions: (i) the nonparametric unbiasedness test tends to reject more often than the regression-based tests for the unbiased hypothesis of forward exchange rates; (ii) it is not uncommon to observe statistically insignificant negative estimates in the predictive regression when the unbiased hypothesis of foreign exchange rates is not rejected. Then we can conclude that an statistical phenomenon cannot be the main reason for predictable excess returns in foreign exchange markets.

Keywords: variance ratio test, regression-based test, Q-test, JM conditional test, small sample biases, predictability of excess returns.

JEL Classification: C12, C14, F31.

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1 Introduction

The forward premium anomaly, one of the most robust puzzles in international finance, refers to empirical finding that foreign excess returns are predictable. The most popular test of the unbiased hypothesis in foreign exchange markets is based on a predictive regression, in which spot returns are regressed on the forward premium (or equivalently foreign excess returns are regressed on the forward premium). The robust finding of such return regressions is that the estimated slope coefficients are in general negative compared to a null value of one (or zero) and the t-test rejects the hypothesis based on conventional critical values.

However, a doubt on the robustness of previous empirical evidence has been casted, mainly based on the regression tests whose results may be affected by the presence of a very persistent forward premium and other departures of the standard asymptotic inference framework. For example, several studies argue that statistical problems arisen in the regression tests may be at least partially responsible for the deviations from the unbiasedness.[1] Typically, these studies are concerned with the over-rejections of the regression tests based on conventional critical values. The tests for the predictability of excess stock returns also share a common problem of this statistical phenomenon. In response, Jansson and Moreira (2004) and Campbell and Yogo (2006) develop optimal robust tests to the persistence problem based on the assumption of the local-to-unity in the regressor persistence. On the other hand, West (2008) presents another source of statistical distortions based on the typical present value model and shows that the t-test is not consistent as the discount factor approaches asymptotically unity.

The present paper incorporates both assumptions of the local-to-unity in the regressor persistence and in the discount factor, which are taken into account separately in the literature. Based on this framework, we analytically show that the regression-based tests including both Jansson and Moreira's conditional test and Campbell and Yogo's Q-test may suffer from lack of power for testing predictability of excess returns in foreign exchange markets. This arises because the discount factor offsets the faster convergence rate due to (near) nonstationarity and thus biases and/or alternatives are dominated by the corresponding increment in variability implied by the present value model with the local-to-unity regressor persistence and the discount factor. Monte Carlo experiments confirm our analysis in that the regression-based tests have size distortions and produce few additional rejections under local alternatives despite of the nonstationary character of the regression. We also provide

[1] See Baillie and Bollerslev (2000), Maynard and Phillips (2001), Roll and Yan (2000), and Tauchen (2001).

empirical evidence consistent with the predictions of our theory. Using the nonparametric serial dependence test developed in Moon and Velasco (2008) which is robust to these types of statistical distortions, we find that the nonparametric test has more power than the regression-based tests, while the patterns of the rejections of the unbiased hypothesis are quite similar among the latter tests: the serial dependence test agrees with the regression based tests for the rejections of the null hypothesis but it rejects for some currencies even though the latter tests do not.[2]

In addition, the discount factor induces the estimated slope coefficient in the predictive regression to be downward biased. The magnitude of a bias can be large enough to affect the results in the regression and the distribution of the estimated slope coefficient becomes very wide as the discount factor is close to one. So it may not be uncommon to observe statistically insignificant negative estimates of the slope coefficient as long as exchange rates are generated from the present value model with the near unit discount factor, regardless of strong persistence in the regressor. We provide such empirical evidence from foreign exchange markets: the regression-based tests do not reject the null hypothesis in the sample which contains observations in 1975-2007 but excludes them in 1980-87. Nevertheless, most estimates are negative or close to zero.

The organization of the paper follows. Section 2 presents the typical predictive regression. Section 3 presents a simple present value model of exchange rates and investigates the effects of the discount factor on statistical inference on the predictive regression in finite samples. Section 4 shows asymptotic properties of the regression-based tests, while incorporating the assumptions of local-to-unity in the regressor and in the discount factor in an unified framework. Section 5 provides the simulation results of the regression-based tests and the nonparametric serial dependence tests. Section 6 provides empirical results and conclusions follow.

2 Predictive Regressions

Predictive regressions have been widely used for testing hypotheses which state no predictability of excess returns in empirical finance literature. Consider the typical predictive

[2]Maynard (2006) also uses three tests for the unbiased hypothesis that are immune to the persistent behavior of the forward premium. However, he focuses on one particular source of statistical issues in the predictive regression, while we are considering various sources that could potentially generate statistical problems.

regression with observations $t = 1, \cdots, T$,

$$\begin{aligned} y_t &= \alpha + \beta x_{t-1} + u_t \\ x_t &= \gamma + \phi x_{t-1} + v_t, \end{aligned} \tag{1}$$

where u_t is a prediction error and x_0 is fixed and known. For example, y_t is spot return (or foreign excess return), x_{t-1} is the forward premium, and the hypothesis of interest is $\beta = 1$ (or $\beta = 0$) in the regression for testing the unbiased hypothesis of forward exchange rates (or, equivalently, for testing the predictability of foreign excess returns).[3] Or, y_t is an excess stock return on a riskless interest rate, x_{t-1} is a predictor such as dividend yield, short term interest rates, or default spreads, and the hypothesis of interest is $\beta = 0$ in the regression for testing the predictability of excess stock returns.[4] The parameter ϕ measures the degree of persistence in x_t. For example, if $\phi = 1$ then x_t is integrated of order one, denoted by $I(1)$; if $|\phi| < 1$ and constant with sample size T then x_t is integrated of order zero, denoted by $I(0)$.

The covariance matrix of the error terms u_t and v_t in the predictive regression is given by

$$\Sigma = \begin{pmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{pmatrix}. \tag{2}$$

As it is well known, the Gauss-Markov theorem does not apply in the predictive regression if ϕ is equal to one (or not constant) or the contemporaneous covariance between residuals, σ_{uv}, is not zero. For example, Mankiw and Shapiro (1986) show that the conventional t-test based on the standard asymptotic distribution theory may not be reliable in samples of typical size when the regressor is strongly persistent and is not strictly exogenous to innovations to the dependent variable.[5] Following Stambaugh (1999), the bias of the slope coefficient in the regression can be measured by $E[\widehat{\beta} - \beta] = \frac{\sigma_{uv}}{\sigma_v^2} E[\widehat{\phi} - \phi]$, where $E[\widehat{\phi} - \phi]$ is the bias of the estimate of ϕ in the process for x_t. Previous studies typically assume that $(u_t, v_t)'$ is independently distributed $N(0, \Sigma)$ with the normalized variances, $\sigma_u^2 = \sigma_v^2 = 1$, in this canonical problem so that the main source of the bias depends on the distribution of $\widehat{\phi}$. However, West (2008) shows that this assumption on the normalized variances is not innocuous in the predictive regression if the series are generated from the present value model with the near-unit discount factor. The present paper also derives the scale factor $\frac{\sigma_{uv}}{\sigma_v^2}$ from the present value model and shows that it significantly affects the direction and magnitude of biases both in finite samples and asymptotically.

[3] See Engel (1996) and Lewis (1996) for a survey of such tests.

[4] See Campbell and Shiller (1988), Fama and French (1988), and Campbell and Yogo (2006).

[5] See also Bekaert *etal.* (1997) and Campbell and Yogo (2006) and references therein.

3 A Present Value Model of Asset Prices and Potential Biases in the Regression Tests

The present value model of asset prices has been widely used in foreign exchange markets as well as in stock markets. For example, Engel and West (2005) use the model to study the link between fundamentals and the exchange rate, while Campbell and Shiller (1987, 1988) use it for studying the behavior of stock prices and the term structure of interest rates. The present paper confines its attention to foreign exchange markets and provide an example in which the discount factor can potentially induce a statistical distortion in the predictive return regression.

3.1 A Present Value Model of Exchange Rates

In a simple present value model of exchange rates, the spot exchange rate s_t is expressed as a discounted sum of current and future fundamentals,

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i E_t w_{t+i}, \tag{3}$$

where $0 < b < 1$ represents the discount factor and w_t represents the linear combination of logs of fundamental variables such as money and output.[6] This relation between the exchange rate and the fundamentals can be obtained from the typical monetary model of exchange rates, while assuming that no bubbles exist and uncovered interest parity (UIP) holds. Under the assumptions of rational expectations and risk neutrality, UIP is equivalent to the unbiased hypothesis of forward exchange rates which is denoted by $f_{t|k} = E_t(s_{t+k})$ for any maturity k, where s_{t+k} denotes the log of the domestic currency price of foreign currency at time $t+k$, $f_{t|k}$ denotes the log of the k-period ahead forward exchange rate, the domestic currency price at time t of foreign currency delivered at $t+k$, and $E_t(\cdot)$ is a mathematical expectation conditional on a time t information set.

Following Engel and West (2005), the fundamental process for w_t is assumed to follow

$$\Delta w_t = \phi \Delta w_{t-1} + \eta_t, \tag{4}$$

where $0 < \phi < 1$ and η_t represents stochastic disturbances.[7] Both the foreign excess return

[6] See, Engel and West (2005) for a more general framework.

[7] Based on their variance ratio tests, Lo and MacKinlay (1988b) also provide empirical evidence that the process of the log stock prices is better supported by the integrated AR(1) process such as equation (4) than by the stationary AR(1) model in short return horizons. Although it is not the main focus of our paper, we find that the process for spot exchange rates is better supported by equation (4) in both short and long return horizons.

and the forward premium under the unbiased hypothesis are derived from equations (3)-(4)

$$s_{t+1} - f_{t|1} = \frac{1}{1-b\phi}\eta_{t+1},$$
$$f_{t|1} - s_t = E_t s_{t+1} - s_t = \frac{\phi(1-b)}{1-b\phi}\Delta w_t, \tag{5}$$

where the persistence of the forward premium is governed by the parameter ϕ in Δw_t.[8] In the predictive regression, $f_{t|1} - s_t$ is the regressor, $s_{t+1} - f_{t|1}$ is the error term under the unbiased hypothesis, the dependent variable $s_{t+1} - s_t$ is the sum of the two terms, and the hypothesis of interest is $\beta = 1$.

3.2 Near Unity Discount Factor and Downward Biases

We now investigate how the discount factor causes statistical problems in regression (1). The least squares estimator of β_1 in the predictive regression is defined by

$$\widehat{\beta}_1 = \frac{\widehat{Cov}(s_{t+1} - s_t, f_{t|1} - s_t)}{\widehat{Var}(f_{t|1} - s_t)} = 1 + \frac{\widehat{Cov}(s_{t+1} - E_t[s_{t+1}], f_{t|1} - s_t)}{\widehat{Var}(f_{t|1} - s_t)}, \tag{6}$$

where the mean values of both the forward premium and spot return are ignored since their effects are negligible. Using equation (5), the sampling variation of the slope coefficient β can be defined by

$$\widehat{\beta}_1 - 1 = \frac{1}{\phi(1-b)} \frac{\widehat{Cov}(\eta_{t+1}, \Delta w_t)}{\widehat{Var}(\Delta w_t)},$$

i.e. the scale factor $\frac{1}{\phi(1-b)}$ times the sampling variations of $\widehat{\phi}$ about its true value in equation (4). Based on the analysis of Kendall (1954, Eq.(20)), the expected value of the sampling error of the slope coefficient under normality is calculated by

$$E[\widehat{\beta}_1 - 1] = \frac{1}{\phi(1-b)}\theta_1, \tag{7}$$

where $\theta_1 \approx -\frac{1+3\phi}{T}$ denotes the bias of the OLS estimate of ϕ in equation (4) (see, also, Stambaugh (1999)).

Equation (7) shows that the discount factor significantly affects both the direction and magnitude of the bias: since the scale factor is positive but θ_1 is always negative, the estimate of the slope coefficient is on average downward-biased. As b is close to 1, $\frac{1}{\phi(1-b)}$ becomes very large so that it amplifies even a small sampling error θ_1. So, the empirically relevant values of the discount factor b can significantly affect magnitudes of

[8] In the next section, we modify the process for w_t in equation (4) by adding one more shock to avoid singularity in the predictive regression. However, the qualitative results obtained in this section will remain unchanged with this modification.

the biases. For example, Engel and West provide a reasonable range of b with 0.97-0.99 for the quarterly exchange rate data, based on both empirical evidence and implied values in a theoretical model. Converting these numbers into the values of annualized monthly discount factor gives us a higher and tighter range: 0.989-0.994. They also provide evidence that estimates of ϕ range between 0.13 and 0.41, using quarterly data of money supplies, consumer prices, GDP, and interest rates in G7 countries.[9] Based on these values, one can see how importantly the discount factor contributes to the magnitude of biases in regression (1): for $\phi = 0.3$ and $T = 414$, $E[\widehat{\beta}_1 - \beta_1]$ are -1.53 for $b = 0.99$, -0.76 for $b = 0.98$, and -0.51 for $b = 0.97$. There still exist a sizable amount of biases even if we increase sample size to $T = 1000$, which is twice greater than the currently available monthly sample size in foreign exchange markets: $E[\widehat{\beta}_1 - \beta_1]$ are -0.63 for $b = 0.99$, -0.32 for $b = 0.98$, and -0.21 for $b = 0.97$. Further, the distribution of the estimated slope coefficient becomes very wide as the discount factor is close to one. Note that the asymptotic variance of $\widehat{\beta}$ is $\frac{(1-\phi)^2}{\phi^2(1-b)^2}$. These results suggest that it is not uncommon to observe often *statistically insignificant negative estimates* in regression (1).

Interestingly, both the scale factor and the definition of the variance of the estimated slope coefficient indicate the opposite prediction of previous studies on the effects of persistence in the regressor on the estimated slope coefficient in the predictive regression. That is, biases can be even more amplified when $\widehat{\phi} - \phi$ is closely normally distributed in finite samples. For example, for a currently available monthly sample of $T = 414$, $E[\widehat{\beta}_1 - \beta_1] = -0.25/(1-b)$ for $\phi = 0.01$, while $E[\widehat{\beta}_1 - \beta_1] = -0.01/(1-b)$ for $\phi = 0.99$. The magnitude of the biases are 25 times larger for $\phi = 0.01$ where the asymptotic approximation is quite accurate than for $\phi = 0.99$ where the accuracy of the asymptotic approximation is likely suspected. Of course, it may not be valid to rely solely on the magnitude of $E[\widehat{\beta}_1 - \beta_1]$ when ϕ is close to one because the distribution of $\widehat{\phi} - \phi$ may be highly skewed [Kendall (1954) and Bekaert *etal.* (1997)]. However, our Monte Carlo experiments provide evidence that $E[\widehat{\beta}_1 - \beta_1]$ is close to zero even for a value of $\phi = 0.99$ and $T = 414$ when we eliminate the effects of the discount factor by setting $b = 0$.[10] Further, the distribution of the estimated slope coefficient becomes wider as ϕ is closer to zero. This is in contrast with the common view that $\widehat{\beta}_1$ will be biased downward only as ϕ is close to unity.

[9] They report that those statistics are in general not statistically significant. Moon and Velasco (2008), however, provide evidence that the process for Δw_t is better fitted in the ARMA (1,1) model using an extended data. Further the sum of the coefficients for AR(1) and MA (1) components is always positive for G7 countries, which is a necessary condition for generating the same result as in equation (9).

[10] As shown in the Monte Carlo simulations, this result remains unchanged in a general setting.

3.3 Discussion

One of the well-known stylized facts in the exchange rate literature is the near-random walk behavior of exchange rates first established by Meese and Rogoff (1983). Engel and West show analytically and provide evidence that this apparent no-relation between fundamental variables and changes in exchange rates may be reconciled with a present value model with the near-unit discount factor and a unit root process for fundamentals such as equation (4). We showed that the same conditions in Engel and West can generate a significant amount of downward biases in regression (1), providing ground to regard the strong deviations from the unbiased hypothesis just as an statistical phenomenon. However, both alternatives against the unbiased hypothesis and the downward biases under the null lead to observationally equivalent in-sample results. Therefore, methods which are robust to the presence of these types of bias are warranted. We provide one of such tests in this paper, a nonparametric serial dependence test, to investigate these issues.

Suppose that exchange rates are determined from equations (3) and (4), which is the same framework of Engel and West. Then, it is not surprising that we consistently observe negative values of the slope coefficient in regression (1) or estimates close to zero even if the unbiased hypothesis holds, given that bias can be strong in the presence of the near-unit discount factor, despite persistency in the forward premium. Note that the discount factor crucially affects not only the magnitude and sign of the bias but also the width of the distribution of the estimates for a given sample size. Interestingly, these effects on the sampling properties of return regressions have been ignored in the reduced form model where the process for the regressor is exogenously given.

4 Asymptotics in the Model with the Local-To-Unity Regressor and Discount Factor

The biases identified in the previous section, of course, would eventually disappear as the sample size becomes sufficiently large. However, in this section, we show that statistical problems could still exist even asymptotically under a generalized setting which incorporates the assumptions of local-to-unity in the regressor and in the discount factor. We also show that the regression-based tests including optimal robust tests to the persistence problem may be lack of power in this framework and provide a nonparametric serial dependence test which is robust to statistical distortions arisen in the regression-based tests.

4.1 Asymptotic Optimality Theory in Models of Local-To-Unity in the Regressor and the Discount Factor

In this subsection, we present asymptotic optimality theory in the framework where both the regressor and the discount factor approaches to unity with sample size. To avoid singularity in the predictive regression, we now introduce another shock and assume that the process for Δw_t in equation (4) follows

$$\Delta w_t = \phi \Delta w_{t-1} + \eta_{2,t} + \eta_{1,t-1} + \tau \eta_{1,t-2}, \tag{8}$$

for some $\tau > 0$, so that

$$\begin{aligned} u_t &= \frac{1}{1-b\phi}\left(b\left(1+\tau\right)\eta_{1,t} + \eta_{2,t}\right) \\ x_t &= \frac{1-b}{1-b\phi}\left(\eta_{1,t} + \tau\eta_{1,t-1} + \phi\Delta w_t\right) = \frac{1-b}{1-b\phi}\frac{\eta_{1,t} + \tau\eta_{1,t-1} + \phi\eta_{2,t}}{1-\phi L}. \end{aligned}$$

Note that the qualitative results obtained in the previous section remain unchanged in this modified process for Δw_t. We assume that $(\eta_{1t}, \eta_{2t})'$ is an homoskedastic martingale difference process with finite fourth moment and that $\mathrm{E}x_0^2 < \infty$. Denote by $(W_u(s), W_v(s))'$ a two-dimensional Wiener process with correlation γ_0, by $J_c(s)$ the diffusion process defined in $[0,1]$ by $\mathrm{d}J_c(s) = cJ_c(s)\mathrm{d}s + \mathrm{d}W_v(s)$ and $J_c(0) = 0$ and by $\bar{J}_c(s)$ the corresponding demeaned process.

Then the covariance matrix $\Sigma = \Sigma(b)$ of the error terms u_t and v_t of the return regression model (1) has elements given by

$$\begin{aligned} \sigma_{uv}(b) &= \frac{1-b}{(1-b\phi)^2} Cov\left(b\left(1+\tau\right)\eta_{1,t} + \eta_{2,t}, \eta_{1,t} + \tau\eta_{1,t-1} + \phi\eta_{2,t}\right) \\ &= \frac{1-b}{(1-b\phi)^2}\left(b\left(1+\tau\right)\sigma_1^2 + \phi\sigma_2^2\right) \end{aligned}$$

and similarly

$$\sigma_u^2(b) = \frac{1}{(1-b\phi)^2}\left(b^2\left(1+\tau\right)^2\sigma_1^2 + \sigma_2^2\right); \quad \sigma_v^2(b) = \frac{(1-b)^2}{(1-b\phi)^2}\left(\left(1+\tau^2\right)\sigma_1^2 + \phi^2\sigma_2^2\right),$$

with

$$\rho = \frac{\sigma_{uv}}{\sigma_v\sigma_v} = \frac{b\left(1+\tau\right)\sigma_1^2 + \phi\sigma_2^2}{\left(b^2\left(1+\tau\right)^2\sigma_1^2 + \sigma_2^2\right)^{1/2}\left(\left(1+\tau^2\right)\sigma_1^2 + \phi^2\sigma_2^2\right)^{1/2}}.$$

Finally the long run variance of the error v_t is then

$$\omega^2 = \frac{(1-b)^2}{(1-b\phi)^2}\left(\left(1+\tau\right)^2\sigma_1^2 + \phi\sigma_2^2\right)$$

which in general differs from σ_v^2 if $\tau \neq 0$.

We first introduce an assumption on the asymptotic behaviour of the discount factor b used in West (2008),

$$b = 1 - \frac{\delta}{T^{1/2}}, \tag{9}$$

with $\delta > 0$. This specifies that b converges to unity with sample size T at a particular rate, reflecting a high discount factor in the present value model. Under this assumption we can check that the forward premium defined in (5) has a variance that collapses to zero at the T^{-1} rate for any $|\phi| < 1$.

This implies that the OLS coefficient of the return regression (1) is not consistent under the null and its behaviour can be approximated by

$$\widehat{\beta} - 1 \sim_a N(0, V), \tag{10}$$

where $V = \delta^{-2}(1-\phi^2)\left((1+\tau)^2\sigma_1^2 + \sigma_2^2\right) / \left((1+\tau)\sigma_1^2 + \phi^2\sigma_2^2\right)$. In the asymptotic approximation (10) the OLS coefficient is still centered in its true value but the corresponding t tests are not consistent to detect departures from unbiasedness. The results on the downward bias of the slope coefficient extend also to this context, but now the bias is of order $T^{-1/2}$ under (9),

$$\begin{aligned} E\left[\widehat{\beta} - 1\right] &\approx -\frac{1}{1-b}\frac{b(1+\tau)\sigma_1^2 + \phi\sigma_2^2}{(1+\tau^2)\sigma_1^2 + \phi^2\sigma_2^2}\frac{1+3\phi}{T} \\ &\sim -\frac{1}{\delta}\frac{(1+\tau)\sigma_1^2 + \phi\sigma_2^2}{(1+\tau^2)\sigma_1^2 + \phi^2\sigma_2^2}\frac{1+3\phi}{T^{1/2}}. \end{aligned}$$

On the other hand, $V \to 0$ as $\phi \to 1$, suggesting that consistency could be recovered for persistent w_t.

To investigate this last possibility we introduce the following assumption on the autoregressive parameter ϕ in (4) used by Elliott and Stock (1994) in predictive regressions,

$$\phi = 1 - \frac{c}{T}, \tag{11}$$

with $c > 0$. Local-to-unity assumptions on the roots of autoregressive polynomials in regressor dynamics affect the convergence rate of estimates of predictive regressions but have not been used together with conditions like (9) in the analysis of return regressions and related to econometric tools.

By substituting (11) in (5), we obtain that the one-period ahead foreign excess return and the forward premium under the unbiased hypothesis are now

$$\begin{aligned} s_{t+1} - f_{t|1} &\approx \frac{1}{1-b}\left((1+\tau)\eta_{1,t+1} + \eta_{2,t+1}\right), \\ f_{t|1} - s_t &\approx \eta_{1,t} + \eta_{1,t-1} + \Delta w_t = \frac{\eta_{1,t} + \tau\eta_{1,t-1} + \phi\eta_{2,t}}{1-\phi L}, \end{aligned} \tag{12}$$

so the error term u_t in the return regression (1) has a variance that diverges as T goes infinity under (9), while the near integrated forward premium is not affected by scaling but its variance also increases as T due to (near) nonstationarity. This corresponds to a parametrization of Σ that is also consistent with the findings of Amihud and Hurvich (2004) on the variance ratio $\sigma_u^2(b)/\sigma_v^2(b)$.

Note now that the multiplicative factor $(1-b)^{-1}$ in the bias equation (7) diverges with sample size under (9) as $T^{1/2}/\delta$, while the bias of the OLS estimate $\hat{\phi}$ of ϕ depends on the initial conditions and on the parameter c under (11). Given the skewness of the asymptotic distribution of $\hat{\phi}$, this bias is negative and of the T^{-1} order, as in the stationary case $|\phi|<1$. This renders the bias of $\hat{\beta}$ of the same $T^{-1/2}$ order as its convergence rate under (9) and (11), with the near unity discount factor offsetting the faster convergence rate due to (near) nonstationarity.

It is also well known (Elliot and Stock (1994)) that the null asymptotic distribution of the corresponding t-statistic for $\hat{\beta}$ under local-to-unity assumptions on ϕ has two independent components, one normal and a further one depending on c and Brownian motion stochastic integrals, since under (9) and (11) we have that

$$\lim_{T\to\infty}\rho^2=\rho_0^2=\frac{\left((1+\tau)\,\sigma_1^2+\sigma_2^2\right)^2}{\left((1+\tau)^2\,\sigma_1^2+\sigma_2^2\right)\left((1+\tau^2)\,\sigma_1^2+\sigma_2^2\right)}<1.$$

Then we obtain that

$$\mathrm{t}\sim_a\left(1-\rho_0^2\right)^{1/2}Z+\rho_0\frac{\tau_c}{\kappa_c},$$

where $\kappa_c=\left(\int\bar{J}_c^2(s)\,ds\right)^{1/2}$, $\tau_c=\int\bar{J}_c(s)\,dW_u$ and Z is a standard normal random variable independent of the functionals of $J_c(s)$ that leads to standard asymptotics when there is no endogeneity between error terms in different equations.

This results leads to usual asymptotic t-tests being inappropriate both if c is fixed, since they are not asymptotic pivotal, or if $c\to\infty$ with T, because in the later case the tests may lose consistency, cf. (10). Therefore, asymptotic left-hand-side t-tests using normal quantiles can severely overreject the null of $\beta=1$ for moderate values of c. However, in power terms, when $b\to 1$ with T these regression tests might produce few additional rejections under local alternatives despite the nonstationary character of the regression.

4.2 Optimal Robust Tests

Given the analysis of the previous section, developing new procedures that are robust to such biases and slow convergence rates under (9) and (11) is warranted. Maynard (2006) uses three different tests to overcome problems derived from the regressor persistence: the sign test developed by Campbell and Dufour (1995), the covariance-based test developed by Maynard and Shimotsu (2009), and the optimal conditional test developed by Jansson and Moreira (2004). We also consider the Q test of Campbell and Yogo (2006).

As we now illustrate, however, these methods are not immune to the other type of distortion that may plague the predictive regressions. The near-unit discount factor leads to slower rate of convergence of standard OLS regressions, and can also reduce the class of alternatives that these specific tests can detect consistently and therefore their actual power in empirical applications.

The Q statistic of Campbell and Yogo (2006) to test for $H_0 : \beta = \beta_0$ when ϕ is known is

$$Q(\beta_0, \phi) = \frac{\sum_{t=1}^{T}(x_{t-1} - \bar{x})(y_t - \beta_0 x_t - b_{uv}(x_t - \phi x_{t-1})) + \frac{T}{2} b_{uv}(\omega^2 - \sigma_v^2)}{\sigma_u (1-\rho^2)^{1/2} \left(\sum_{t=1}^{T}(x_{t-1} - \bar{x})^2\right)^{1/2}},$$

so that within the class of invariant tests, the tests based on Q are UMP under normality conditional on the ancillary statistic $\sum_{t=1}^{T}(x_{t-1} - \bar{x})^2$, with $b_{uv} = \sigma_{uv}/(\sigma_v \omega)$, $\bar{x}$ is the sample mean of x_t and the last term in the numerator is added to obtain an asymptotically pivotal statistic since in (**??**) the innovation has some autocorrelation. Apart form this correction, the statistic results from regressing $y_t - b_{uv}(x_t - \phi x_{t-1})$ onto a constant and x_t, assuming that ϕ is known (as the elements of Σ, but these can be replaced by consistent estimates). Noting that we can also write

$$Q(\beta_0, \phi) = \frac{\hat{\beta} - \beta_0 - b_{uv}\left(\hat{\phi} - \phi\right) + \frac{T}{2} b_{uv}(\omega^2 - \sigma_v^2)}{\sigma_u (1-\rho^2)^{1/2} \left(\sum_{t=1}^{T}(x_{t-1} - \bar{x})^2\right)^{-1/2}},$$

we observe that Q corrects the bias and side effects from estimation of $\hat{\phi}$ but its standardization under (12) implies that $\sigma_u \sim T^{1/2}\left((1+\tau)^2 \sigma_1^2 + \sigma_2^2\right)^{1/2}/\delta$, so it can detect only alternatives that are $T^{-1/2}$ local to the null β_0, compared to the usual T rate of convergence of $\hat{\beta}$ under (11) and constant b.

For that, consider the following class of T^{-1}-local alternatives in the parameter β indexed by ζ used in Jansson and Moreira (2004),

$$H_{A,T}(\zeta) : \beta = \beta_T(\zeta) = \beta_0 + \zeta T^{-1}\left(\frac{\sigma_{u.v}^2}{\sigma_v^2}\right)^{1/2},$$

where $\sigma_{u.v}^2 = \sigma_u^2(1-\rho^2)$. However in our framework σ_u^2 is diverging with T under (9), so that these alternatives are no longer T^{-1} local to the null $H_0 : \beta = \beta_0$ (i.e. $\zeta = 0$) but only $T^{-1/2}$-local,

$$\beta_T(\zeta) \approx \beta_0 + \zeta \frac{T^{-1/2}}{\delta}\left(\varkappa(1-\rho_0^2)\right)^{1/2},$$

where $\varkappa = \left[(1+\tau)^2 \sigma_1^2 + \sigma_2^2\right] / \left[\left(1+\tau^2\right) \sigma_1^2 + \sigma_2^2\right]$. Then we obtain the following result, cf. Appendix B in Campbell and Yogo (2006).

Proposition 1. Under $H_{A,T}(\zeta)$ the t test statistic behaves as

$$\mathrm{t} \sim_a \zeta \frac{\bar{\omega}}{\bar{\sigma}_v} \left(1-\rho_0^2\right)^{1/2} \kappa_c + \rho_0 \frac{\tau_c}{\kappa_c} + \left(1-\rho_0^2\right)^{1/2} Z,$$

while the Q statistic behaves as

$$Q(\beta_0, \phi) \sim_a \zeta \frac{\bar{\omega}}{\bar{\sigma}_v} \kappa_c + Z,$$

where $\bar{\omega}^2 = \lim_{T\to\infty} \omega^2 = \left(1+\tau^2\right) \sigma_1^2 + \sigma_2^2$ and $\bar{\sigma}_v^2 = \lim_{T\to\infty} \sigma_v^2 = (1+\tau)^2 \sigma_1^2 + \sigma_2^2$.

Jansson and Moreira (2004) consider the framework of Campbell and Yogo (2004) and developed optimal unbiased tests conditional on ancillary statistics. Similarly, their optimal tests can be showed to have nontrivial power against $H_{A,T}(\zeta)$ under (9), as the Q test, but this can be limited for moderate sample sizes even if using correct asymptotic critical values. Further, the implementation of these tests require intensive numerical methods, while, since in practice ϕ is unknown, Campbell and Yogo propose a Bonferroni type of test Q to account for the estimation of ϕ.

With the covariance-based orthogonality tests of Maynard and Shimotsu (2009), a similar effect arises. For example, the covariance estimate they propose is no longer $(T/m)^{1/2}$-consistent under the null of unbiasedness and (9), but diverges with the bandwidth parameter m, that grows with T at most as $T^{1/2}$. In fact, the class of local alternatives that their t-test can detect under (9) is at most $T^{-1/4}$-local to this null for feasible choices of the bandwidths. Finally, the sign tests of Campbell and Dufour (1995) have standard asymptotics and usual $T^{1/2}$ rate of convergence under the null assuming a mediangale type of condition for the error term, irrespective of the dynamic properties of the regressor. However, under (9), the sign test only has power against fixed alternatives and cannot detect local alternatives converging to the null with sample size. The reason for that asymptotic behaviour is that the random error term dominates the sign operator in our framework, explaining the low power of sign tests in applications compared with other methods, *cf.* Maynard (2006).

4.3 The Variance Ratio Test

The nonparametric serial dependence test employed in this paper is based on the variance ratio test developed by Lo and Mckinlay (1988). The variance ratio tests are attractive in the current context since they do not face problems of inference arisen in the regression as shown below.

Tests for the hypothesis of $\beta = 1$ in the predictive regression with the dependent variable of $s_{t+1} - s_t$ and the regressor of $f_{t|1} - s_t$ is equivalent to the tests of the unbiased hypothesis of forward exchange rates stated by $f_{t|1} = E_t[s_{t+1}]$ under the assumption of rational expectations and risk neutrality. Equivalently, one can test for the hypothesis of $\beta = 0$ in the predictive regression with the dependent variable of foreign excess return $s_{t+1} - f_{t|1}$ and the predictor of anything in the time t information set such as $f_{t|1} - s_t$. In particular, this hypothesis implies that foreign excess return should not predictable by anything in the time t information set if expectations are rational. So, under the unbiased hypothesis, the variance of the sum of q consecutive excess returns should be q times greater than that of one period excess return:

$$VR(q) = \frac{Var(\sum_{i=1}^{q} \xi_{t+i})}{qVar(\xi_{t+1})} = 1 + 2\sum_{i=1}^{q-1}\left(1 - \frac{i}{q}\right)\gamma(i) \tag{13}$$

where $\xi_{t+1} = s_{t+1} - f_{t|1}$ denotes foreign excess return and $\gamma(i) = Cov(\xi_{t+1}, \xi_{t+1+i})/Var(\xi_{t+1})$ denotes the autocorrelation of excess return between time $t+1$ and $t+1+i$. $VR(q)$ should be equal to one under the unbiased hypothesis since $\gamma(i)$ is zero for all $i \in (1, q-1)$. If the variance ratio is greater than one, the returns are positively correlated; if the variance ratio is less than one, the returns are negatively correlated. In this sense, the variance ratio tests capture the restriction of uncorrelated excess returns.

One can easily show why the variance ratio test for no predictability of excess return is robust to statistical distortions inherent in the regression test. For example, suppose that exchange rates are generated from equations (3)-(4). Then, by substituting the definition of foreign excess return in equation (5) into equation (13), one can easily see that parameters of b and ϕ are canceled out, while calculating the variance ratio for each q. This holds true even in the general setting where both the discount factor and the regressor are modeled as local-to-unity, and for the empirical counterpart test statistic defined by

$$T(q) = T^{1/2}\frac{\widehat{VR}(q) - 1}{\Omega(q)^{1/2}}$$

where $\Omega(q) = 2(2q-1)(q-1)/\left(3q^2\right)$ and

$$\widehat{VR}(q) = \frac{\widehat{Var}(\sum_{i=1}^{q} \xi_{t+i})}{q\widehat{Var}(\xi_{t+1})}$$

and $\widehat{Var}$ denotes usual sample variances. Then under the previous conditions on the innovations and under the null we have that

$$T(q) \sim_a N(0,1),$$

for both fixed and local-to-unity b and ϕ.

For our empirical study, we consider an alternative variance ratio test using ranks developed by Wright (2000) because the rank-based variance ratio test has better size and power properties than the conventional variance ratio tests when the distribution of excess returns is non-normal. Let $r(\xi_t)$ be the rank of ξ_t among $\xi_1, \ldots, \xi_T$. Then, a simple linear transformation of the ranks $r(\xi_t)$ is defined by

$$r_t = \left(r(\xi_t) - \frac{T+1}{2}\right) \div \sqrt{\frac{(T-5)(T+1)}{12}},$$

where r_t is standardized with sample mean 0 and sample variance 1.

5 Monte Carlo Experiments

Monte Carlo experiments are conducted to evaluate the finite sample accuracy of the asymptotic approximations. In particular, we compare the size and the power of the tests under the framework which incorporates local-to-unity models of both the regressor and the discount factor in the previous section. Those tests include the Q-test, the JM test, the t-test, and the rank-based variance ratio test.[11] The former three tests are called the regression-based tests. The model is calibrated at the monthly frequency.

We use the same data generating process for Δw_t as West (2008):

$$\begin{aligned} \Delta w_t &= \Delta w_{1,t} + \eta_{3,t-1} \\ \Delta w_{1,t} &= \phi \Delta w_{1,t} + \eta_{2,t} + \eta_{1,t-1} + \eta_{1,t-2} \\ e_t &\equiv (\eta_{1,t}, \eta_{2,t}, \eta_{3,t})' \text{ i.i.d.} N(0, diag(\sigma_1^2, \sigma_2^2, \sigma_3^2,)), \end{aligned} \quad (14)$$

where three shocks are used to avoid singularity in the return regression and to generate the persistent behavior of the forward premium in the data. Accordingly, the parameterization closely follows West: $(\sigma_1^2, \sigma_2^2, \sigma_3^2,) = (1, 1, 50)$ are set for all simulations. We largely consider three cases under the null hypothesis of $\beta = 1$ or equivalently $f_{t-1} = E_{t-1}[s_t]$: The first case assumes the discount factor b is zero, that is $\delta = \sqrt{T}$ and includes Models 1-3 with respect to $c = 4$, 8, and 16. The second case assumes that the regressor does not exhibit any persistency, that is $c = T$ and includes Models 4-6 with respect to $\delta = 0.5$, 1, and 2. The third case incorporates the local-to-unity models of the discount factor and the regressor and includes Models 7-15 with respect to a combination of values of (δ, c). We also consider the corresponding 15 models against the following alternative: $\beta = 1 - \frac{d}{T}$, where $d > 0$. Under

[11] The algorithms for CY's Q-test are obtained from Yogo's webpage, while those for JM's conditional test are obtained from Polk's webpage.

this alternative, $f_{t-1|1} = \frac{1}{\beta}E_{t-1}[s_t]+(1-\frac{1}{\beta})s_t$ so that $x_{t-1} = f_{t-1|1}-s_{t-1} = \frac{1}{\beta}(E_{t-1}[s_t]-s_t)$. Table 2 displays parameter values used for these models. For each model, sample sizes of $T = 100$, 400, and 1600 are generated. For example, the implied values of ϕ are 0.96, 0.99, 0.9975 for the three values of T when $c = 4$, while the implied values of b are 0.95, 0.975, and 0.9875 for the corresponding values of T when $\delta = 0.5$.

5.1 The Size of the Tests

Tables 3 and 4 provide simulation results that are based on 10000 repetitions. Table 3a reports the size of the three regression-based tests, while Table 3b reports the results from the rank-based variance ratio test for comparison. All tests reported below are for both right-tail and left-tail one-sided and two-sided alternatives and conducted for 1, 5, 10% significant levels. To conserve the space, we only report the tests results at the 5% significant level.[12] In general, we find that the discount factor significantly affect statistical inference in the regression-based tests such a way as our theory predicts.

We begin with the conventional t-test. Consistent with the results from West, the t-test is not consistent when the discount factor approaches to unity with sample size. For example, the empirical sizes of the 5% two-sided t-test are 12.5, 13.4, and 13.2% for T =100, 400, and 1600, respectively in Model 7 where $\delta = 0.5$ and $c = 4$. The similar pattern of the rejections is found among Models 7-15 where the discount factor is modeled as local-to-unity but with different parameter values of δ. Quantitatively, however, the test tends to more severely over-reject the null as both the discount factor and ϕ are close to unity. The sizes of the 5% two-sided t-test are 5.8, 7.3, and 7.5% in Model 15 where $\delta = 2$ and $c = 16$ so that the implies values for (b, ϕ) are (0.8, 0.84) and (0.9, 0.96) for T=100 and 400. Further, the t-test significantly overrejects against the left-tail alternative, while it underrejects against the right-tail alternative. For example, the empirical sizes of the 5% left-tail test are 20.5, 22.1, 21.7% for the corresponding sample sizes in Model 7, while the rejection rates of the 5% right-tail test are 0.37, 0.39, and 0.32, respectively. So the rejections in the two-sided tests are mainly due to those in the left-tail tests. This downward bias is mainly induced by the near unit discount factor as shown in Sections 3 and 4.

In order to see more clearly the impacts of the discount factor, we set $b = 0$ while setting $c = 4$, 8, and 16 in Models 1-3. Interestingly, the empirical size of the two-sided t-test is close to its nominal value, despite of strong persistence in the regressor. Further, the estimated slope coefficients are centered at the null value of one and the distribution of the estimates is very narrow. So, it is unlikely to observe negative values of the estimated

[12] Other results are available upon request.

slope coefficient under the null hypothesis when the exchange rates are generated from the framework where the regressor is very persistent but the discount factor is close to zero. We now set $\phi = 0$ but allow the discount factor to vary with sample size by setting δ =0.5, 1, and 2 in Models 4-6. The sizes of both the one-sided and two-sided t-tests are now close to their nominal values. For example, the empirical sizes of the 5% two-sided t-test are 5.0, 4.7, and 4.8% for T =100, 400, and 1600, respectively in Model 4, while those of the left-tail test are 5.9, 5.3, and 5.2%. However, the distribution of the estimated slope coefficients becomes very wide so that it is likely to observe negative estimates in this framework: the estimates at the 5% quantile are -2.39, -2.34, and -2.37 for the corresponding sample sizes in Model 4, while those are -1.66, -1.64, and -1.69 at the 10% quantile. This implies that it is not uncommon to observe the insignificant negative estimates in the predictive regression if exchange rates are generated from the framework with the near-unity discount factor.

We now discuss the results from the optimal robust tests to the persistence problem: the Q-test and the conditional test. In general, the size of the conditional test is close to its nominal value, while the Q-test suffers from size distortions for some cases. In particular, the size of the right-tail Q-test is not reliable and similar to the t-test. For example, the empirical sizes of the right-tail conditional test are 5.6, 7.0, and 7.4% for the corresponding sample sizes in Model 7, while those of the right-tail Q-test are 0.3, 0.2, and 0.1. These rejection patterns are quite similar in Models 7-15. When the regressor is not persistent, both t-test and conditional test report comparable size as reported in Models 4-6 in Table 3a, while the Bonferroni Q-test is not reliable. In sum, of the three regression-based tests, the conditional test seems to perform well in terms of size in all the three cases considered for Monte Carlo experiments.

The results from the rank-based variance ratio tests on Models 1-15 are reported in Table 3b. The range of aggregation values is set in a way that the maximum value of q is 5 years for each sample size T and includes $2, 6, 12, 18, 24, 30, 36, 48$, and 60 months. Following Moon and Velasco (2009a), we use a residual-based bootstrap method for calculating critical values to improve finite sample properties of the variance ratio test, in particular, for large q's.[13] In general, the results are quite similar in all the models considered. Therefore, we only report the results from Models 1,4,7,10, and 15 for brevity.[14] Overall, we find that the size of the one-sided and two-sided rank-based variance ratio tests is close to nominal values regardless of assumptions on the discount factor and ϕ for all aggregation values considered in this paper. This suggests that the variance ratio test is robust to potential

[13]Following Wright (2000), one can obtain the exact sampling distribution of the rank-based variance ratios under the null.

[14]The results from other models are available upon request.

biases inherent in the regression test and suitable for investigating the effects of statistical phenomenon.

5.2 The Power of the Tests

Table 4a reports the power of the three regression-based tests. In general, the results from the Monte Carlo experiments confirm the prediction of our analysis in that the regression-based tests do not yield additional power under the local alternative when both the discount factor and the regressor are modeled as local-to-unity. For example, the rejection rates of the 5% two-sided conditional test are 7.6 4.7 and 5.0% for the corresponding sample sizes in Model 7a with $\delta = 0.5$ and $c = 4$, while the power of the Q-test is 18.8, 8.6, and 6.5%. So, there is not much difference between the size and the power of the tests, compared to their sizes in Model 7. These patterns of the rejection rates of the two tests are comparable in Models 7-15 under the local alternative specified above. The main reason for these results is that the discount factor reduces the convergence rate so that the estimate slope coefficient stops being super-consistent even if the regressor is (near) nonstationary. This can be confirmed from the following experiments by setting the discount factor $b = 0$ but varying the persistence in the regressor with sample size as in Models 1-3 under the local alternative. Interestingly, the rejection rates of the Q-test and conditional test are 100% for all specifications. On the other hand, when we shut off the effects of persistence by setting $\phi = 0$ but allow the discount factor to vary in Models 4-6 under the local alternative, the conditional test does not yield additional power. As mentioned before, the Q-test is not reliable in this case.

The power of the optimal robust tests tends to significantly decrease with sample size under the local alternative. This is mainly due to the assumption on the local alternative where the convergence rate is T. Table 4c reports the power of the tests against the following local alternative: $\beta = 1 - \frac{d}{\sqrt{T}}$ keeping the same value for d. Although the rejection patterns are similar between the two local alternatives, the power of the optimal robust tests tends to be more stable with sample size under the square root local alternative.

The power of the rank-based variance ratio test against the same local alternative is very small for all aggregation values, regardless of assumptions on the discount factor and the regressor persistence as reported in Table 4b. The main reason why the variance ratio test does not have power under this alternative is that there is a very strong feedback effect between the forecasting error and the deviation under the alternative in the frameworks considered in this paper. Note that the foreign excess return is defined by $s_t - f_{t-1|1}$ and can be decomposed by

$$s_t - E_{t-1}s_t + E_{t-1}s_t - f_{t-1|1} = s_t - E_{t-1}s_t + (1 - \frac{1}{\beta})(E_{t-1}s_t - s_{t-1}) \quad (15)$$

where the first term in the right-hand, $s_t - E_{t-1}s_t$, is a forecasting error and $(E_{t-1}s_t - s_{t-1})$ is the expected depreciation. Note that $(1 - \frac{1}{\beta})$ is negative by construction under the local alternative, while the correlation between $s_t - E_{t-1}s_t$ and $(E_t s_{t+1} - s_t)$ is positive. This feedback effect cancels out the effects of the own deviation so that the power of the variance ratio test becomes very small.

6 Empirical Results on the Tests of the Predictability of Foreign Excess Returns

The data are simultaneously collected from London close bid and ask prices and obtained from the database of Global Insight. Our sample includes the spot prices of the US dollar against the German deutschmark (GDM), the British pound (BRP), the Japanese yen (JPY), the Canadian dollar (CAD), the Swiss franc (SWF), the Danish krone (DAK), the Swedish krona (SWK), the Norwegian kroner (NWK), the French franc (FRF), the Italian lira (ITL), the Belgian franc (BEF), and the Dutch guilder (DUG) as well as the one-, three-, and six-month prices (forward exchange rates) of the US dollar. The mid prices are used for our empirical study.[15]

We perform the conventional t-test, the Q test, the conditional test, and the rank-based variance ratio test on the predictability of one-, three-, and six-month excess returns against the US dollar from 1975:1 to 2007:12. The regression-based tests use non-overlapping monthly, quarterly, and by-yearly observations for the one-month, three-month, and six-month return horizons, respectively, since algorithms for the optimal robust tests are developed based on nonoverlapping observations.[16] On the other hand, the rank-based variance ratio test uses weekly observations to yield efficiency gains following Moon and Velasco (2009a).[17] Accordingly, the log of the foreign excess return $s_t - f_{t-k|k}$ is measured over a return horizon of k weeks, which includes 4 weeks for the one-month return horizon, 13 weeks for the three-month, and 26 weeks for the six-month return horizon. All log excess returns are annualized in the following way: $(5200/k)\,(s_t - f_{t-k|k})$. Logs of spot returns and forward premiums are also measured accordingly.

[15]The sample period for each currency is provided in Table 1.

[16]The closing price at the end of each month is selected.

[17]Wednesday's closing price is selected for forming our weekly sample. If the following Wednesday is missing, then Thursday's price is used (or Tuesday's if Thursday's is missing). If both days' price is missing then next Wednesday's closing price is selected.

Our empirical study has three goals. The first objective is to compare the performance of the tests proposed in the previous sections. Those tests include the conventional t-test, the Q-test, the JM conditional test, and the rank-based variance ratio test. Another is to analyze if potential statistical distortions in the predictive regression are the main reason for the predictable excess returns in foreign exchange markets. The other is to investigate if our assumptions on local-to-unity in the regressor persistence and the discount factor as well as on the process for fundamentals.

6.1 The Regression-Based Tests

The tests are reported for a two-sided alternative and conducted at a five percent significant level. Table 5 reports the estimates of the slope coefficient in regression (1), $\widehat{\beta}$, the lower and upper bounds of a 95% confidence interval for $\beta = 1$, and t-statistics from the Q-test, the JM's conditional test, and the t-test. y_t is defined by $y_t = s_t - s_{t-k}$ and x_{t-k} is defined by $x_{t-k} = f_{t-k|k} - s_{t-k}$ in regression (1).[18] Tables 5a, 5b, and 5c report the results for one-, three-, and six-month return horizons, respectively. Panel A of each table reports the results using the entire sample observations and Panel B reports the results in the sample that excludes observations in 80-87, following Moon and Velasco (2009b). Over all, we find that the regression-based tests produce parallel results although the t-test rejects a little more often than the others. This holds true for all return horizons considered in this paper. Further, the width of the confidence interval for the slope coefficient is quite similar between the conditional and Q-tests, while it is a bit wider in the t-test. The detailed discussion of the results is as follows.

For the one-month return horizon in Panel A of Table 5a, the Bonferroni confidence interval for β from the Q-test lies below unity for all currencies except for SWK, NWK, FRF, and ITL. This suggests that there is considerable evidence in foreign exchange markets that the unbiased hypothesis of $\beta = 1$ is rejected against the alternative $\beta \neq 1$ at the 5% level.[19] The confidence interval from JM's conditional test also lies below unity and its width and bounds are comparable to those from the Q-test. Although the confidence interval constructed by the conventional critical value is a bit farther away to the left than those from the other two tests, the rejections and non-rejections of the t-test agree with

[18]Equivalently, one can define $y_t = s_t - f_{t-k|k}$ and $x_t = f_{t-k|k} - s_{t-k}$ and consider the hypothesis of $\beta = 0$ for testing the predictability of excess returns. We follow the definitions in the main text to provide an explicit comparison with the previous studies.

[19]Strictly speaking, the test of the unbiased hypothesis (equivalently, the test of no predictable excess returns) in regression (1) means $\alpha = 0$ and $\beta = 1$. However, we skip the results from the joint hypothesis test since our main focus is to study the behavior of the estimate of β.

them.[20] These results are consistent with the findings of previous studies on predictability of excess returns: estimates of β are negative for most major currencies and t-tests reject the hypothesis ($\beta = 1$) based on the conventional asymptotic critical values. In sum, both robust tests to the persistent problem and the conventional t-test produce the same results on the rejections against the unbiased hypothesis, which implies that statistical distortions due to the presence of the strong persistent regressor may not be so severe to overturn the evidence on predictable excess returns.[21]

As documented in Moon and Velasco (2009b), however, the evidence on the rejections of the unbiased hypothesis significantly weakened in the sample that exclude observations in 80-87 as shown in Panel B. All three tests do not reject the null hypothesis for all currencies except for BGF. The only disagreement between the t-test and the robust tests is detected for CAD. The t-test reject the null hypothesis, while both the conditional and Q tests do not. However, the difference among these tests appears to be small even in this case in that the upper bounds from the two robust tests are close to the null value of one: the upper bound on the 95% confidence interval from the Q-test is 1.01, while that from the conditional test is 1.02.

For the three-month return horizon in Panel A of Table 5b, there appear a bit more disagreements between the robust tests and the t-test than in the case of one-month excess return. Nevertheless, the overall results on the predictability of excess returns are analogous to those for the one-month return horizon. The confidence intervals from the three tests lie below the null value of one for most currencies, which provides considerable evidence on predictable excess returns. There are three currencies that the tests do not agree with the rejections. The t-test rejects the null for DAK and BGF, while the robust tests do not. On the other hand, the t-test does not reject it for FRF, while the others do. Consistent with the results for the one-month return horizon, the evidence against the predictability of excess returns is significantly weakened in the subsample as reported in Panel B. All three tests do not reject the null hypothesis for all currencies.

Due to the availability of the data, we mainly focus on studying the predictable excess returns for five major US bilateral rates such as GDM, BRP, JPY, CAD, and SWF for six-month return horizon in Panel A of Table 5c. In contrast to the cases of one- and three-month excess returns, the confidence intervals from the three tests contain the null value. However, these results should be interpreted cautiously in that the tests may not have power due to small sample size. In fact, the t-test rejects the null for all these five bilateral rates using nonoverlapping observations.

[20] We also find similar results from the t-test while using non-overlapping observations.

[21] Maynard (2006) also find quite similar results along this dimension using the conditional test.

6.2 The Rank-Based Variance Ratio Test

The analysis on the local-to-unity models of the regressor persistence and the discount factor in Section 4 implies that both the optimal robust tests and the t-test may suffer from a particular statistical distortion caused by the near-unit discount factor in the present value models. Further, the Monte Carlo experiments based on several variations of the local-to-unit models confirmed our analysis. In this subsection, we provide the results from the rank-based variance ratio test which is robust to these statistical distortions.

Table 6 reports the variance ratios using ranks and p-values obtained from the the residual-based bootstrap method for one- three- and six-month foreign excess returns following Moon and Velasco (2009a). Table 6a reports results for the one-month (k=4) return horizon, Table 6b reports results for the three-month (k=13) return horizon, and Table 6c reports results for the six-month (k=26) return horizon, respectively. Panel A in each table provides the results using the entire sample, while Panel B provides the results using the sample which excludes observations in 80-87. For comparison, Table 7 reports the results using monthly observations. We find that the variance ratio tests using weekly observations are more powerful than using monthly observations in particular for three- and six-month return horizons, while they have quite similar power for one-month return horizon. Below, we only discuss the results using weekly observations.

For one-month return horizon, we use aggregation values q of 2, 12, 24, 36, 48, and 60 months, while we use aggregation values q of 2, 4, 8, 12, 16, and 20 quarters for three-month return horizon and 2, 4, 6, 8, and 10 bi-years for six-month return horizon. We set the range of aggregation values for each return horizon in a way that the maximum value of q is 5 years. Statistics under each q can be compared between return horizons: for example, $q = 12$ months in the one-month return horizon correspond to $q = 4$ quarters in the three-month return horizon.

The variance ratio test rejects the null hypothesis of unpredictability of one-month foreign excess returns for all currencies except for NWK and SWK in Panel A of Table 6a. In general, the rejections occur for most aggregation values q ranged from 2 to 60 months. For example, for GDM, the two-sided p-values associated with the aggregation values $q =$ 2, 12, 24, 36, 48, and 60 are 0.4, 0.2, 0.2, 0.2, 0.6, and 0.8%, respectively. All six p-values indicate that the variance ratios are significantly different from one at the 1% significant level. For NWK, the rejections never occur for all the aggregation values that we have considered. And the rejections for SWK are weak in that they occur marginally for smaller values q and do not reject the null hypothesis for larger aggregation values: for example, the p-values associated with the aggregation values $q = 2$, 12, 24, 36, 48, and 60 are 2.0, 11.8, 6.0, 8.6, 10.0, and 12.0%. As in the case of the regression-based tests, the evidence against the unbiased hypothesis becomes quite weak in the sample that exclude observations in 80-87 as shown in Panel B. The variance ratio test does not reject it for all currencies except for JPY, CAD, and DAK. And it rejects for GDM at the 10% level.

The variance ratio test results on the predictability of one-month foreign excess returns can be compared with those of the regression-based tests for $\beta = 1$ in equation (1). In general, the results from the variance ratio test are consistent with those of the regression-based tests. Both tests decisively reject the hypothesis of no predictability of one-month excess returns for GDM, JYP, CAD, SWF, DNK, BEF, and DUG, while they do not reject it for SWK and NWK. However, the variance ratio test produces different results for some currencies such as FRF and ITL. For example, the variance ratio test rejects it for both FRF and ITL, while the regression-based test do not reject for these currencies. In the subsample, both the nonparametric serial dependence and the regression-based tests provide coinciding results on the rejections and non-rejections of the null although the variance ratio test tends to reject slightly more than others. For example, the variance ratio test rejects the null for JPY, CAD, and DAK, while the optimal robust tests do not reject it for those currencies. On the other hand, the former test does not reject it for BGF, while the latter tests reject it. Overall, the evidence on one-month excess returns suggests that potential statistical distortions in regression (1) due to the reasons analyzed in Section 4 cannot be a main cause for the deviation from unbiasedness of the forward exchange rates.

The disagreements between the variance ratio test and the regression based tests appear more strongly in three- and six-month return horizons. For the three-month return horizon, the variance ratio test does not reject the hypothesis for two out of twelve currencies in Panel A in Table 6b: those include SWK and NWK. On the other hand, the regression-based tests do not reject 5 out of 12 currencies in the sample: those currencies include DAK, SWK, NWK, FRF, and ITL. But all tests agree with the rejections in the subsample as shown in Panel B in Table 6b and in Table 5b. For the six-month return horizon, the regression-based tests do not reject the null at all, while the variance ratio test reject it for all major currencies except for BRP in Panel C of Table 6c. Again, all test agree with the rejections in the subsample.

The significant difference in terms of the rejections of the null hypothesis between the two samples further confirm that the persistence problem may not be critical. One might suspect statistical inference that is so sensitive to a drop of 32 observations from a sample for the three-month return horizon or 16 observations from a sample for the six-month return horizon. That is, its sample moments can change dramatically with a drop of a few data points when a predictor variable is persistent. However, the results on the subsample are robust to this problem in that both the variance ratio test and the robust regression-based tests, which take into account this persistence, provide the similar results as the t-test.[22]

6.3 Empirical Evidence on the Assumptions

The coinciding patterns of the rejections between the variance ratio test and the regression-based tests suggest that statistical phenomenon may not be the main cause for the predictability of foreign excess returns documented in the previous subsections and previous studies. However, the disagreement between the variance ratio and the regression-based tests for some currencies deserves further investigation. Interestingly, it suggests that the variance ratio test has more power than the regression-based tests. This is opposite to the prediction of the usual statistical phenomenon arguments that the regression test may over-reject the null hypothesis. Further, the fact that the variance ratio test has more power than the optimal robust tests to the persistence problem suggests that the reverse option of lack of power of the regression-based tests under alternatives can be possible if biases and/or alternatives are dominated by the corresponding increment in variability implied by a present value model with the local-to-unity regressor and discount factor.

Further, the estimated slope coefficients are negative or close to zero for many currencies in the subsample even if the null hypothesis is not or marginally rejected. Those currencies includes GDM, JPY, CAD, SWF, DAK, FRF, and DUG for the one-month return horizon, GDM, JPY, CAD, SWF, DAK, NWK, FRF, BGF, and DUG for the three-month return horizon. For example, the estimated slope coefficient for JPY is -0.9 for the one-month return horizon, while the upper bounds on the 95% confidence interval from the Q-test and the conditional test are 1.31 and 1.43, respectively. One possible explanation is that the near-unit discount factor in the present value model may reinforce the possible downward biases of the estimates of the slope coefficient in regression (1). At the same time, the distribution of the estimated slope coefficient becomes wider as the discount factor is closer to one, despite the possible persistence of the forward premium. Therefore, insignificant negative values might not be uncommon even under the null as long as exchange rates are determined from equations (3) and (4) with the near-unit discount factor.

The assumption on the persistent growth of the fundamentals implies a positive correlation between the two innovations in predictive regression (1) under the null hypothesis [e.g. see the derivation of the spot return and the forward premium in equation (12).]. Table 8 presents the estimates of $\frac{\sigma_{uv}}{\sigma_u \sigma_v}$ for the return horizons considered above. The first row in

[22] Moon and Velasco (2009b) also conduct a robustness check on the parameter stability based on 8-year rolling regressions.

each panel presents the estimates obtained using the entire sample observations, while the second row presents them using the sample which excludes observations in 80-87. We find that the sign of the estimates of the correlation coefficient changes between the two samples for major currencies in foreign exchange markets. That is, the estimates are negative in the entire sample where the unbiased hypothesis was decisively rejected but become positive in the subsample where the hypothesis tends to hold. On the other hand, those estimates in general are small and close to zero.

7 Conclusion

This paper presents a particular source of statistical distortions induced by present value models with the near-unit discount factor that may significantly affect the estimated slope coefficient in the predictive regression. It shows both analytically and by simulation that the regression-based tests including optimal robust tests may suffer from lack of power in the local-to-unity models of the regressor persistence and the discount factor. It also provides empirical evidence that supports the assumptions in this paper: (i) the three regression-based tests appear to be lack of power as the theory predicted; (ii) most estimates are negative or close to zero even if the unbiased hypothesis is not rejected. Using the nonparametric unbiasedness test that is immune to the presence of biases, to persistence distortions as well as to some power limitations inherent in regression tests, we further show that statistical phenomenon cannot be the main reason for the rejections of the unbiased hypothesis in foreign exchange markets.

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Table 1. Sample Periods

	Starting Date	Ending Date
GDM	January 2, 1975	December 31, 2007
BRP	January 2, 1975	December 31, 2007
JPY	January 2, 1975	December 31, 2007
CAD	January 2, 1975	December 31, 2007
SWF	January 2, 1975	December 31, 2007
DAK	July 6, 1979	December 31, 2007
SWK	April 21, 1987	December 31, 2007
NWK	April 21, 1987	December 31, 2007
FRF	January 2, 1980	December 31, 1998
ITL	January 2, 1980	December 31, 1998
BEF	January 2, 1975	December 31, 1998
DUG	January 2, 1980	December 31, 1998

Table 2a. Results of one-month (k=4) return regression (1) using weekly observations:1975:1-2007:12

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$\widehat{\beta}_k$	-0.67	-1.09	-1.54	-0.56	-1.22	-0.27	0.49	0.57	0.45	0.72	-0.16	-1.37
s.e.	0.63	0.65	0.63	0.38	0.60	0.44	0.63	0.66	0.56	0.75	0.33	0.76
adj R^2	0.00	0.01	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01
T	1714	1712	1714	1714	1713	1477	1073	1073	985	981	1242	983
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$\widehat{\beta}_k$	-0.16	0.56	-0.48	-0.38	-0.15	0.08	0.49	0.68	-0.13	2.43	-0.18	-0.55
s.e.	0.73	0.77	0.91	0.49	0.80	0.50	0.63	0.68	0.97	1.50	0.37	1.03
adj R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00
T	1297	1296	1297	1297	1297	1060	1036	1036	568	565	825	567

Table 2b. Results of three-month ($k = 13$) return regression (1) using weekly observations:1975:1-2007:12

Panel A. The whole sample: 1975:1-2007:12												
$\widehat{\beta}_k$	-0.76	-1.10	-2.30	-0.31	-0.99	-0.37	0.77	0.15	0.24	1.35	0.07	-1.27
s.e.	0.65	0.83	0.58	0.46	0.65	0.57	1.34	0.85	0.82	0.83	0.37	0.88
adj R^2	0.01	0.02	0.07	0.00	0.02	0.00	0.01	0.00	0.00	0.03	0.00	0.02
T	1705	1703	1705	1705	1704	1468	1064	1064	976	972	1233	974
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$\widehat{\beta}_k$	-0.26	0.64	-0.65	-0.29	0.17	0.01	0.78	0.29	-0.01	2.80	-0.03	-0.54
s.e.	0.72	0.91	1.37	0.57	0.85	0.68	1.34	0.93	0.98	1.49	0.37	1.03
adj R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.10	0.00	0.00
T	1288	1287	1288	1288	1288	1051	1027	1027	559	556	816	558

Table 2c. Results of six-month ($k = 26$) return regression (1) using weekly observations:1975:1-2007:12

Panel A. The whole sample: 1975:1-2007:12												
β_6	-0.90	-0.97	-2.49	-0.11	-0.99	-0.09	0.50	-0.04	0.22	1.76	0.13	-1.24
s.e.	0.66	0.87	0.52	0.53	0.56	0.69	1.27	0.79	0.93	0.71	0.32	0.79
adj R^2	0.02	0.02	0.13	0.00	0.03	0.00	0.01	0.00	0.00	0.08	0.00	0.04
T	1692	1690	1692	1692	1691	1455	1051	1051	963	959	1220	961
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
β_6	-0.35	0.76	-1.18	0.04	0.12	0.01	0.53	0.13	-0.07	2.37	0.06	-0.68
s.e.	0.67	0.93	1.10	0.61	0.67	0.87	1.26	0.87	0.99	1.24	0.32	0.91
adj R^2	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.13	0.00	0.01
T	1275	1274	1275	1275	1275	1038	1014	1014	546	543	803	545

Note: Newey and West (1987) standard errors are computed based on the lag length of $2(k-1)$.

Table 2. Parameterization for Monte Carlo Experiments

	δ	c	d
Model 1	$\sqrt{T}$	4	
Model 2	$\sqrt{T}$	8	
Model 3	$\sqrt{T}$	16	
Model 4	0.5	T	
Model 5	1	T	
Model 6	2	T	
Model 7	0.5	4	
Model 8	0.5	8	
Model 9	0.5	16	
Model 10	1	4	
Model 11	1	8	
Model 12	1	16	
Model 13	2	4	
Model 14	2	8	
Model 15	2	16	
Model 1a	$\sqrt{T}$	4	40
Model 2a	$\sqrt{T}$	8	40
Model 3a	$\sqrt{T}$	16	40
Model 4a	0.5	T	40
Model 5a	1	T	40
Model 6a	2	T	40
Model 7a	0.5	4	40
Model 8a	0.5	8	40
Model 9a	0.5	16	40
Model 10a	1	4	40
Model 11a	1	8	40
Model 12a	1	16	40
Model 13a	2	4	40
Model 14a	2	8	40
Model 15a	2	16	40

Table 3a. The size of the regression-based tests

	T	$\widehat{\beta}$ 5%	50%	95%	Q-test 5L	2	5R	JM test 5L	2	5R	t-test 5L	2	5R
Model 1	100	0.98	1.00	1.02	8.7	6.3	2.7	7.2	5.2	3.2	8.0	5.7	3.2
	400	0.99	1.00	1.00	6.0	4.8	3.0	8.1	5.7	2.5	8.5	5.9	2.4
	1600	1.00	1.00	1.00	4.7	3.8	3.1	9.5	6.1	2.1	9.7	6.3	2.0
Model 2	100	0.98	1.00	1.02	10.4	7.5	2.5	6.3	5.0	3.9	6.8	5.4	4.0
	400	0.99	1.00	1.01	5.9	4.6	3.2	7.2	5.3	3.1	7.3	5.4	3.1
	1600	1.00	1.00	1.00	4.0	3.9	3.6	7.9	5.7	2.6	7.8	5.7	2.7
Model 3	100	0.98	1.00	1.02	12.5	9.3	2.5	5.4	5.0	4.4	5.9	5.3	4.5
	400	0.99	1.00	1.01	6.0	4.8	3.3	6.5	5.1	3.6	6.5	5.2	3.8
	1600	1.00	1.00	1.00	3.1	4.1	5.0	7.3	5.2	3.0	7.1	5.3	3.2
Model 4	100	-2.39	0.80	3.98	92.3	91.7	0.0	4.8	4.9	5.1	5.9	5.0	4.0
	400	-2.34	0.90	4.17	45.7	43.7	0.3	4.4	4.5	4.9	5.3	4.7	4.4
	1600	-2.37	0.92	4.29	0.0	100.0	100.0	4.2	4.8	5.5	5.2	4.8	4.8
Model 5	100	-0.60	0.90	2.41	92.4	91.8	0.0	4.8	4.9	5.1	5.9	4.9	4.0
	400	-0.63	0.95	2.54	46.6	44.6	0.3	4.4	4.5	4.9	5.3	4.7	4.4
	1600	-0.66	0.96	2.63	0.0	100.0	100.0	4.2	4.8	5.4	5.2	4.7	4.8
Model 6	100	0.29	0.96	1.63	92.4	91.9	0.0	4.8	4.9	5.1	5.8	4.9	4.0
	400	0.23	0.98	1.73	46.3	44.3	0.3	4.5	4.5	4.9	5.2	4.7	4.4
	1600	0.19	0.98	1.79	0.0	100.0	100.0	4.1	4.7	5.4	5.2	4.7	4.8
Model 7	100	-1.72	0.30	1.32	7.8	5.7	0.3	5.4	5.8	5.6	20.5	12.5	0.4
	400	-0.44	0.64	1.15	8.3	6.0	0.2	4.8	5.9	7.0	22.1	13.4	0.4
	1600	0.28	0.82	1.08	7.8	5.4	0.1	4.3	6.1	7.4	21.7	13.2	0.3
Model 8	100	-1.92	0.35	1.66	7.0	4.9	0.6	6.2	5.2	3.9	14.9	8.8	0.8
	400	-0.53	0.66	1.28	6.9	4.9	0.4	4.8	5.3	5.7	16.6	9.9	0.7
	1600	0.24	0.83	1.15	6.4	4.4	0.3	4.2	5.6	6.4	16.3	9.6	0.7
Modle 9	100	-2.22	0.42	2.29	8.8	6.8	0.7	6.2	5.1	3.5	10.2	6.3	1.6
	400	-0.71	0.68	1.53	6.0	4.4	0.5	5.3	5.0	4.6	12.4	7.7	1.4
	1600	0.15	0.84	1.26	5.5	3.7	0.7	4.5	4.7	5.4	12.1	7.5	1.5
Model 10	100	-0.31	0.67	1.18	7.4	5.2	0.4	6.5	5.8	4.5	19.5	12.0	0.4
	400	0.29	0.82	1.08	8.1	5.7	0.2	5.1	5.9	6.4	21.7	13.2	0.3
	1600	0.65	0.91	1.04	7.7	5.3	0.1	4.5	6.1	7.3	21.6	13.1	0.3
Model 11	100	-0.40	0.69	1.35	6.7	5.1	0.7	6.8	5.3	3.4	14.0	8.1	0.9
	400	0.25	0.83	1.14	6.8	4.9	0.4	5.2	5.3	5.3	16.1	9.7	0.7
	1600	0.63	0.92	1.07	6.3	4.3	0.3	4.3	5.5	6.3	16.3	9.5	0.7
Model 12	100	-0.55	0.73	1.66	9.9	7.8	0.8	6.3	5.0	3.4	9.8	6.1	1.7
	400	0.16	0.84	1.27	5.9	4.2	0.6	5.6	5.0	4.5	12.0	7.5	1.5
	1600	0.58	0.92	1.13	5.4	3.8	0.7	4.5	4.8	5.3	12.0	7.5	1.5
model 13	100	0.39	0.85	1.11	6.3	4.9	1.0	8.4	6.1	3.0	17.0	10.4	0.5
	400	0.66	0.92	1.04	7.3	5.0	0.3	6.0	5.6	5.2	20.9	12.4	0.3
	1600	0.83	0.96	1.02	7.5	5.1	0.1	4.7	5.9	7.0	21.5	13.1	0.3
model 14	100	0.37	0.87	1.20	7.3	5.8	1.0	7.1	5.3	3.1	12.6	7.2	1.2
	400	0.63	0.92	1.08	6.2	4.4	0.6	6.1	5.2	4.2	15.3	9.3	0.7
	1600	0.82	0.96	1.04	6.1	4.2	0.4	4.6	5.4	5.8	16.4	9.4	0.7
model 15	100	0.31	0.89	1.34	14.0	11.3	0.7	6.1	4.9	3.6	9.3	5.8	1.9
	400	0.58	0.93	1.14	5.5	3.9	0.6	6.2	5.4	4.1	11.8	7.3	1.5
	1600	0.79	0.96	1.07	5.4	3.6	0.7	4.8	4.8	5.1	12.1	7.5	1.6

Table 3b. The size of the variance ratio tests

T	q	Model 1			Model 4			Model 7			Model 10			Model 15		
		5L	2	5R	5L	2	5R	5L	2	5R	5L	2	5R	5L	2	5R
100	2	4.8	4.9	5.7	4.6	5.1	5.1	5.5	5.5	5.4	6.3	5.4	4.7	5.9	5.1	4.4
	6	4.4	4.5	4.9	4.6	4.5	5.0	5.5	5.0	4.4	5.2	5.1	4.9	5.3	4.9	4.7
	12	4.9	4.4	4.0	5.1	5.1	5.2	4.7	4.7	4.3	5.1	5.2	4.9	5.1	5.3	5.1
	18	5.2	5.0	5.1	4.9	5.0	5.2	5.0	5.0	4.7	5.2	5.4	4.7	5.1	5.2	4.9
	24	4.9	4.8	4.7	4.6	4.8	5.1	5.1	4.9	4.4	5.1	5.1	5.1	5.1	4.9	4.8
	30	5.0	4.6	4.7	5.3	5.5	5.3	5.0	4.8	4.5	5.1	5.1	4.2	5.5	4.8	4.7
	36	4.6	4.9	4.9	4.7	5.3	5.2	5.7	5.0	4.5	5.5	5.3	4.9	5.0	5.0	4.9
	48	4.4	4.3	4.8	4.6	4.5	4.9	5.3	5.4	5.0	5.6	4.9	4.5	5.4	5.2	4.5
	60	5.3	5.4	5.0	4.8	4.7	5.0	4.7	4.7	5.0	4.9	5.4	5.0	5.0	5.1	4.9
400	2	5.1	5.4	6.1	4.3	4.7	5.2	4.9	4.6	4.7	5.2	5.1	4.9	5.0	5.3	5.1
	6	5.1	5.1	5.2	5.1	4.8	4.7	5.1	5.2	5.1	4.7	4.9	5.1	5.1	4.8	4.8
	12	5.2	5.0	4.8	4.6	4.8	4.9	5.1	5.0	5.3	4.9	4.7	5.0	5.0	4.6	4.8
	18	5.4	5.1	5.2	4.7	5.1	4.8	5.1	4.8	4.9	5.4	4.9	4.9	5.1	5.0	4.9
	24	4.9	4.7	4.7	4.1	4.3	4.6	4.8	5.2	4.9	4.5	4.8	4.8	4.8	4.5	4.8
	30	5.0	5.6	5.5	4.6	4.4	4.8	5.2	5.0	4.9	5.1	4.8	4.9	4.8	4.8	4.8
	36	4.6	4.8	4.9	4.7	4.7	4.7	4.7	5.2	5.6	5.1	5.0	4.9	5.1	4.5	4.8
	48	5.6	5.1	5.1	4.3	4.3	4.7	5.3	5.2	4.8	5.0	4.8	5.3	4.6	4.8	5.0
	60	5.0	5.1	5.8	4.7	4.6	4.6	5.1	5.2	5.1	5.3	5.3	5.1	4.8	5.0	5.1
1600	2	5.1	4.6	4.9	5.1	5.1	5.4	5.1	5.2	5.8	4.8	5.0	5.3	4.6	4.8	5.3
	6	4.6	4.8	5.0	4.7	5.1	5.5	5.3	5.5	5.3	5.2	5.4	5.0	5.1	5.5	4.8
	12	4.4	4.3	5.2	4.4	5.3	5.6	5.2	4.8	4.7	5.2	5.2	4.7	5.1	5.1	4.7
	18	5.1	5.0	4.9	4.8	5.2	5.2	4.9	4.7	5.2	5.0	5.0	5.2	4.7	5.1	5.0
	24	5.1	4.6	4.9	5.1	5.3	5.1	5.0	5.2	5.1	5.1	5.0	4.8	5.1	5.3	4.9
	30	5.0	5.3	5.3	5.1	5.5	5.1	5.1	5.2	4.9	4.8	5.1	5.2	4.9	5.0	5.3
	36	5.3	5.2	5.1	4.8	5.4	5.7	4.9	5.1	5.0	4.7	5.2	5.4	4.6	5.0	5.5
	48	4.8	4.9	5.2	5.3	5.3	4.8	4.7	5.1	4.9	4.8	5.1	5.0	4.8	5.1	5.0
	60	4.9	4.9	5.0	5.3	4.9	4.8	4.7	5.0	5.3	4.9	5.3	5.2	5.0	5.3	5.2

Table 4a. The power of the regression-based tests

	T	$\widehat{\beta}$ 5%	50%	95%	Q-test 5L	2	5R	JM test 5L	2	5R	t-test 5L	2	5R
Model 1a	100	0.59	0.60	0.61	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	400	0.89	0.90	0.90	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	1600	0.97	0.97	0.98	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Model 2a	100	0.59	0.60	0.61	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	400	0.89	0.90	0.91	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	1600	0.97	0.97	0.98	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Model 3a	100	0.59	0.60	0.61	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	400	0.89	0.90	0.91	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
	1600	0.97	0.97	0.98	100.0	100.0	0.0	100.0	100.0	0.0	100.0	100.0	0.0
Model 4a	100	-1.43	0.48	2.39	94.7	94.2	0.0	9.1	6.2	2.4	10.8	7.0	1.9
	400	-2.10	0.81	3.75	47.7	45.6	0.2	5.0	4.5	4.5	6.0	4.9	3.9
	1600	-2.31	0.90	4.19	0.0	100.0	100.0	4.3	4.7	5.3	5.4	4.7	4.6
Model 5a	100	-0.36	0.54	1.45	96.5	96.1	0.0	16.7	10.4	1.0	20.1	12.4	0.7
	400	-0.57	0.86	2.29	50.2	47.9	0.1	5.6	4.7	3.9	6.7	5.0	3.4
	1600	-0.64	0.94	2.56	0.0	100.0	100.0	4.4	4.7	5.2	5.5	4.8	4.4
Model 6a	100	0.17	0.58	0.98	98.9	98.7	0.0	45.9	33.9	0.1	51.8	38.9	0.1
	400	0.21	0.88	1.56	54.1	51.5	0.1	7.1	5.0	3.1	8.4	5.7	2.6
	1600	0.19	0.96	1.75	0.0	100.0	100.0	4.7	4.7	4.9	5.9	4.8	4.2
Model 7a	100	-1.03	0.18	0.79	26.0	18.8	0.0	13.3	7.6	0.3	58.0	40.4	0.0
	400	-0.39	0.57	1.03	12.2	8.6	0.0	6.3	4.7	3.1	31.6	19.5	0.0
	1600	0.27	0.80	1.05	9.3	6.5	0.1	5.0	5.0	5.7	25.8	15.4	0.1
Model 8a	100	-1.15	0.21	1.00	18.4	12.8	0.0	13.8	7.9	0.3	36.3	23.3	0.0
	400	-0.48	0.59	1.16	9.6	6.7	0.1	6.5	4.8	3.0	22.2	13.2	0.2
	1600	0.24	0.81	1.12	7.6	5.1	0.2	4.9	5.0	5.0	18.9	11.1	0.4
Modle 9a	100	-1.33	0.25	1.37	16.8	12.4	0.1	13.3	7.7	0.7	21.6	12.9	0.2
	400	-0.64	0.61	1.38	7.9	5.5	0.3	6.7	4.8	2.8	15.9	9.6	0.7
	1600	0.15	0.82	1.23	6.4	4.3	0.5	5.2	4.5	4.3	13.4	8.2	1.1
Model 10a	100	-0.19	0.40	0.71	73.1	60.2	0.0	39.4	24.5	0.0	94.7	87.1	0.0
	400	0.26	0.74	0.97	18.1	12.6	0.0	9.1	5.3	0.9	44.0	29.1	0.0
	1600	0.63	0.89	1.01	11.1	7.8	0.0	5.8	4.3	3.9	30.2	18.6	0.1
Model 11a	100	-0.24	0.42	0.81	44.2	34.0	0.0	34.8	22.2	0.0	69.1	52.8	0.0
	400	0.22	0.75	1.03	13.4	8.9	0.0	9.0	5.4	1.2	29.6	18.3	0.0
	1600	0.61	0.89	1.05	9.1	5.9	0.1	5.7	4.3	4.0	21.6	12.8	0.2
Model 12a	100	-0.33	0.44	1.00	33.7	26.3	0.0	27.4	17.2	0.0	39.8	26.6	0.0
	400	0.14	0.76	1.14	10.3	7.0	0.1	9.2	5.5	1.5	19.9	11.9	0.3
	1600	0.57	0.90	1.10	7.3	4.8	0.3	5.8	4.3	3.6	15.2	9.2	0.8
Model 13a	100	0.24	0.51	0.67	78.2	76.5	0.4	57.5	44.1	0.0	64.0	51.5	0.0
	400	0.59	0.82	0.94	6.0	18.5	16.8	16.8	9.9	0.7	21.2	12.9	0.4
	1600	0.81	0.93	0.99	6.0	5.9	3.3	14.1	8.4	0.7	23.0	14.2	0.2
Model 14a	100	0.22	0.52	0.72	93.4	89.2	0.0	93.4	84.7	0.0	99.3	97.7	0.0
	400	0.57	0.83	0.97	25.7	18.1	0.0	18.8	10.8	0.1	50.0	34.1	0.0
	1600	0.80	0.94	1.01	12.4	8.4	0.0	7.8	4.6	1.8	28.4	17.7	0.1
Model 15a	100	0.19	0.53	0.81	78.6	72.0	0.0	73.6	60.7	0.0	84.6	73.4	0.0
	400	0.53	0.83	1.03	16.9	11.4	0.0	16.7	9.9	0.3	31.0	19.3	0.0
	1600	0.77	0.94	1.04	9.3	6.3	0.1	8.0	4.8	1.9	19.3	11.4	0.4

Table 5a. Results of the regression-based tests for one-month (m=1) return:1975:1-2007:12

		The whole sample (75-07)					The sample excluding observations in 80-87				
		$\widehat{\beta}$	95L	95U	t-stat	T	$\widehat{\beta}$	95L	95U	t-stat	T
GDM	Q test	-0.92	-2.20	0.32	-3.04	395	-0.22	-1.63	1.19	-1.70	299
	JM test	-0.92	-2.18	0.28	-3.04	395	-0.22	-1.63	1.17	-1.70	299
	t test	-0.92	-2.37	0.54	-2.58	395	-0.22	-1.71	1.26	-1.62	299
BRP	Q test	-1.22	-2.55	0.02	-3.44	395	0.51	-1.11	2.19	-0.58	299
	JM test	-1.22	-2.51	0.01	-3.44	395	0.51	-1.12	2.15	-0.58	299
	t test	-1.22	-2.88	0.43	-2.64	395	0.51	-1.25	2.28	-0.54	299
JPY	Q test	-2.10	-3.46	-0.80	-4.60	395	-0.90	-3.53	1.31	-1.56	299
	JM test	-2.10	-3.44	-0.80	-4.60	395	-0.90	-3.32	1.43	-1.56	299
	t test	-2.10	-3.31	-0.90	-5.07	395	-0.90	-3.19	1.39	-1.63	299
CAD	Q test	-0.68	-1.74	0.41	-3.09	395	-0.41	-1.78	1.01	-2.09	299
	JM test	-0.68	-1.72	0.41	-3.09	395	-0.41	-1.66	1.02	-2.09	299
	t test	-0.68	-1.63	0.27	-3.47	395	-0.41	-1.59	0.77	-2.35	299
SWF	Q test	-1.36	-2.56	-0.17	-3.87	395	-0.31	-1.80	1.26	-1.72	299
	JM test	-1.36	-2.55	-0.18	-3.87	395	-0.31	-1.75	1.27	-1.72	299
	t test	-1.36	-2.67	-0.04	-3.53	395	-0.31	-1.96	1.34	-1.56	299
DAK	Q test	-0.46	-1.61	0.67	-2.56	341	0.14	-1.14	1.42	-1.33	245
	JM test	-0.46	-1.61	0.64	-2.57	341	0.14	-1.17	1.38	-1.33	245
	t test	-0.46	-1.71	0.79	-2.30	341	0.14	-1.05	1.32	-1.44	245
SWK	Q test	0.83	-0.61	2.28	-0.23	248	0.84	-0.60	2.32	-0.22	239
	JM test	0.83	-0.62	2.17	-0.23	248	0.84	-0.63	2.19	-0.22	239
	t test	0.83	-1.84	3.51	-0.12	248	0.84	-1.82	3.51	-0.12	239
NWK	Q test	0.47	-0.83	1.75	-0.80	248	0.63	-0.74	1.99	-0.54	239
	JM test	0.47	-0.84	1.73	-0.80	248	0.63	-0.77	1.96	-0.54	239
	t test	0.47	-1.87	2.81	-0.44	248	0.63	-1.83	3.08	-0.30	239
FRF	Q test	-0.13	-1.57	1.24	-1.67	227	0.13	-1.92	2.21	-0.85	131
	JM test	-0.13	-1.50	1.17	-1.67	227	0.13	-2.02	2.03	-0.86	131
	t test	-0.13	-1.79	1.54	-1.33	227	0.13	-2.05	2.31	-0.79	131
ITL	Q test	0.53	-1.01	1.58	-0.72	227	2.46	0.17	4.55	1.33	131
	JM test	0.53	-0.78	1.78	-0.72	227	2.46	0.17	4.00	1.34	131
	t test	0.53	-0.96	2.02	-0.62	227	2.46	-0.66	5.59	0.93	131
BGF	Q test	-0.14	-0.87	0.83	-2.76	287	-0.09	-0.90	0.98	-2.37	191
	JM test	-0.14	-0.94	0.68	-2.77	287	-0.09	-1.00	0.81	-2.37	191
	t test	-0.14	-0.69	0.41	-4.08	287	-0.09	-0.61	0.43	-4.13	191
DUG	Q test	-1.55	-3.21	0.19	-3.11	227	-0.63	-2.84	1.66	-1.47	131
	JM test	-1.55	-3.29	0.00	-3.12	227	-0.63	-3.38	1.43	-1.48	131
	t test	-1.55	-3.44	0.35	-2.65	227	-0.63	-2.74	1.47	-1.53	131

Note: 'Q test' denotes the Q-test developed by Campbell and Yogo and
'JM test' denotes the conditional test developed by Jansson and Moreira.
'95L' and '95U' denote the lower and upper bounds of a 95% confidence interval.

Table 5b. Results of the regression-based tests for three-month ($m = 3$) return:1975:1-2007:12

		The whole sample (75-07)					The sample excluding observations in 80-87				
		$\widehat{\beta}$	95L	95U	t-stat	T	$\widehat{\beta}$	95L	95U	t-stat	T
GDM	Q test	-0.93	-2.23	0.38	-2.90	131	-0.30	-1.83	1.21	-1.69	99
	JM test	-0.93	-2.20	0.36	-2.91	131	-0.30	-1.77	1.26	-1.70	99
	t test	-0.93	-2.31	0.46	-2.75	131	-0.30	-1.67	1.08	-1.88	99
BRP	Q test	-1.19	-2.59	0.30	-3.03	131	0.47	-1.15	2.28	-0.63	99
	JM test	-1.19	-2.61	0.26	-3.04	131	0.47	-1.17	2.16	-0.63	99
	t test	-1.19	-3.30	0.91	-2.06	131	0.47	-1.23	2.17	-0.62	99
JPY	Q test	-2.79	-4.21	-1.09	-4.84	131	-0.35	-3.65	2.08	-0.96	99
	JM test	-2.79	-4.30	-1.22	-4.86	131	-0.35	-3.61	2.22	-0.96	99
	t test	-2.79	-4.09	-1.49	-5.79	131	-0.35	-3.61	2.91	-0.82	99
CAD	Q test	-0.39	-1.59	0.85	-2.30	131	-0.24	-1.70	1.22	-1.72	99
	JM test	-0.39	-1.56	0.83	-2.30	131	-0.24	-1.61	1.24	-1.73	99
	t test	-0.39	-1.67	0.89	-2.15	131	-0.24	-1.78	1.30	-1.60	99
SWF	Q test	-1.12	-2.38	0.18	-3.25	131	0.15	-1.45	1.75	-1.05	99
	JM test	-1.12	-2.39	0.14	-3.26	131	0.15	-1.44	1.70	-1.05	99
	t test	-1.12	-2.22	-0.02	-3.81	131	0.15	-1.26	1.55	-1.20	99
DAK	Q test	-0.34	-1.79	1.11	-1.85	113	-0.10	-1.83	1.65	-1.26	81
	JM test	-0.34	-1.80	1.08	-1.85	113	-0.10	-1.81	1.59	-1.27	81
	t test	-0.34	-1.50	0.81	-2.31	113	-0.10	-1.52	1.31	-1.56	81
SWK	Q test	0.38	-1.27	2.23	-0.77	82	0.42	-1.21	2.36	-0.72	79
	JM test	0.38	-1.98	1.64	-0.78	82	0.42	-1.99	1.69	-0.72	79
	t test	0.38	-1.94	2.70	-0.53	82	0.42	-1.85	2.69	-0.51	79
NWK	Q test	-0.18	-1.63	1.97	-1.46	82	0.13	-1.43	2.46	-0.98	79
	JM test	-0.18	-2.06	1.35	-1.47	82	0.13	-1.85	1.81	-0.99	79
	t test	-0.18	-1.88	1.51	-1.39	82	0.13	-1.87	2.14	-0.86	79
FRF	Q test	-0.76	-2.47	0.92	-2.09	75	-0.08	-2.45	2.32	-0.92	43
	JM test	-0.76	-2.44	0.88	-2.10	75	-0.08	-2.71	2.05	-0.93	43
	t test	-0.76	-2.69	1.17	-1.82	75	-0.08	-1.69	1.52	-1.36	43
ITL	Q test	1.34	-0.48	3.03	0.38	75	2.98	0.23	5.73	1.52	43
	JM test	1.34	-0.44	3.10	0.38	75	2.98	-0.92	4.00	1.54	43
	t test	1.34	-0.61	3.29	0.35	75	2.98	0.42	5.53	1.57	43
BGF	Q test	-0.77	-2.71	1.39	-1.81	95	-0.66	-2.92	1.81	-1.47	63
	JM test	-0.77	-2.79	1.09	-1.82	95	-0.66	-3.08	1.45	-1.48	63
	t test	-0.77	-2.45	0.90	-2.10	95	-0.66	-2.42	1.10	-1.89	63
DUG	Q test	-1.39	-3.21	0.53	-2.63	75	-0.53	-3.03	2.15	-1.23	43
	JM test	-1.39	-3.32	0.33	-2.65	75	-0.53	-3.77	1.68	-1.25	43
	t test	-1.39	-3.26	0.48	-2.55	75	-0.53	-2.39	1.32	-1.67	43

See note in Table 5a.

Table 5c. Results of the regression-based tests for six-month ($m = 6$) return:1975:1-2007:12

		The whole sample (75-07)					The sample excluding observations in 80-87				
		$\widehat{\beta}$	95L	95U	t-stat	T	$\widehat{\beta}$	95L	95U	t-stat	T
GDM	Q test	-1.25	-4.03	1.55	-1.62	65	-0.15	-3.17	2.87	-0.75	49
	JM test	-1.25	-4.02	1.41	-1.63	65	-0.15	-3.06	2.88	-0.76	49
	t test	-1.25	-4.18	1.69	-1.53	65	-0.15	-3.34	3.04	-0.73	49
BRP	Q test	-2.08	-5.28	1.04	-1.92	65	2.70	-1.44	6.59	0.87	49
	JM test	-2.08	-5.19	1.09	-1.94	65	2.70	-1.43	4.00	0.88	49
	t test	-2.08	-7.14	2.98	-1.22	65	2.70	-0.56	5.95	1.05	49
JPY	Q test	-4.71	-7.95	-1.62	-3.55	65	-2.77	-8.21	2.57	-1.37	49
	JM test	-4.71	-7.82	-1.51	-3.58	65	-2.77	-7.91	2.63	-1.39	49
	t test	-4.71	-6.73	-2.68	-5.63	65	-2.77	-6.47	0.92	-2.05	49
CAD	Q test	-0.90	-3.26	1.50	-1.64	65	-0.11	-2.86	2.65	-0.80	49
	JM test	-0.90	-3.12	1.47	-1.65	65	-0.11	-2.75	2.62	-0.81	49
	t test	-0.90	-3.40	1.60	-1.52	65	-0.11	-2.64	2.42	-0.88	49
SWF	Q test	-1.22	-4.12	1.35	-1.64	65	0.94	-2.33	4.14	-0.04	49
	JM test	-1.22	-4.01	1.35	-1.65	65	0.94	-2.29	4.00	-0.04	49
	t test	-1.22	-3.46	1.02	-1.99	65	0.94	-1.90	3.78	-0.04	49
DAK	Q test	0.05	-2.82	3.32	-0.64	56	-0.24	-3.30	2.89	-0.80	40
	JM test	0.05	-2.91	2.94	-0.65	56	-0.24	-3.28	2.72	-0.81	40
	t test	0.05	-2.36	2.47	-0.78	56	-0.24	-3.23	2.75	-0.84	40
SWK	Q test	0.67	-2.68	4.39	-0.21	41	0.92	-2.73	4.96	-0.05	39
	JM test	0.67	-4.23	3.05	-0.21	41	0.92	-4.17	3.73	-0.05	39
	t test	0.67	-3.81	5.15	-0.15	41	0.92	-4.50	6.34	-0.03	39
NWK	Q test	-0.54	-3.24	3.47	-1.02	41	-0.21	-3.93	3.70	-0.64	39
	JM test	-0.54	-4.01	2.25	-1.04	41	-0.21	-4.27	3.24	-0.65	39
	t test	-0.54	-3.70	2.63	-0.98	41	-0.21	-5.24	4.82	-0.49	39
FRF	Q test	-1.05	-4.83	2.80	-1.11	37	0.58	-4.09	5.32	-0.18	21
	JM test	-1.05	-4.75	2.51	-1.13	37	0.58	-5.39	4.00	-0.19	21
	t test	-1.05	-4.49	2.38	-1.21	37	0.58	-3.62	4.78	-0.21	21
ITL	Q test	3.06	-0.77	6.86	1.06	37	6.52	-0.08	12.08	1.88	21
	JM test	3.06	-0.54	4.00	1.07	37	6.52	-2.06	4.00	1.93	21
	t test	3.06	-1.06	7.18	1.02	37	6.52	-0.76	13.80	1.59	21
BGF	Q test	-1.86	-5.95	2.84	-1.34	47	-1.35	-6.02	3.40	-0.99	31
	JM test	-1.86	-6.09	2.33	-1.35	47	-1.35	-6.04	3.09	-1.01	31
	t test	-1.86	-5.13	1.42	-1.76	47	-1.35	-5.01	2.32	-1.31	31
DUG	Q test	-2.07	-6.30	2.18	-1.51	37	-0.09	-5.27	5.52	-0.43	21
	JM test	-2.07	-6.74	1.60	-1.53	37	-0.09	-7.14	3.95	-0.44	21
	t test	-2.07	-5.81	1.67	-1.67	37	-0.09	-4.41	4.23	-0.53	21

See note in Table 5a.

Table 6a. Results of the rank-based variance ratio test for one-month (k=4) return:1975:1-2007:12

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.11	1.11	1.11	1.05	1.11	1.14	1.12	1.07	1.12	1.17	1.14	1.15
pvalue	0.4	1.2	1.2	26.6	0.6	0.0	2.0	28.6	3.2	0.2	0.0	0.8
$R_k(12)$	1.60	1.44	1.60	1.38	1.51	1.68	1.35	1.15	1.73	1.68	1.78	1.86
pvalue	0.2	1.4	0.4	3.4	0.6	0.2	11.8	39.2	0.6	0.6	0.0	0.2
$R_k(24)$	2.07	1.69	2.03	1.86	1.86	2.19	1.59	1.24	2.01	1.84	2.23	2.27
pvalue	0.2	1.2	0.2	0.4	0.4	0.0	6.0	32.0	0.6	3.0	0.0	0.4
$R_k(36)$	2.23	1.90	2.13	2.17	1.98	2.30	1.70	1.37	1.96	1.79	2.34	2.33
pvalue	0.2	0.6	0.2	0.4	0.4	0.2	8.6	20.4	3.0	4.8	0.4	1.0
$R_k(48)$	2.25	1.96	2.05	2.39	1.89	2.31	1.60	1.45	1.90	1.61	2.21	2.21
pvalue	0.6	1.4	1.4	0.6	2.2	1.4	10.0	17.0	3.2	11.6	1.0	2.0
$R_k(60)$	2.27	1.83	1.84	2.56	1.85	2.31	1.61	1.48	1.90	1.58	2.11	2.14
pvalue	0.8	3.8	4.2	0.2	3.4	0.6	12.0	18.2	4.8	13.0	3.8	4.2
T	1712	1712	1712	1712	1712	1476	1072	1072	984	980	1240	980
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.09	1.05	1.09	1.05	1.09	1.14	1.12	1.07	1.12	1.18	1.12	1.14
pvalue	6.6	35.2	10.2	38.4	7.2	2.2	1.8	27.4	19.2	1.2	8.6	11.8
$R_k(12)$	1.25	1.03	1.46	1.33	1.27	1.47	1.38	1.15	1.26	1.05	1.41	1.26
pvalue	20.0	74.4	2.6	11.6	16.4	2.2	10.0	39.8	28.4	62.8	7.8	29.0
$R_k(24)$	1.51	0.95	1.95	1.75	1.47	1.76	1.63	1.26	1.22	0.73	1.49	1.28
pvalue	8.2	87.4	0.4	2.6	11.8	2.4	6.6	30.8	33.2	93.2	12.0	29.4
$R_k(36)$	1.64	0.85	2.06	1.96	1.52	1.87	1.74	1.37	1.14	0.64	1.35	1.25
pvalue	8.2	97.6	1.0	1.6	9.6	4.6	8.6	22.2	32.8	90.8	23.4	29.0
$R_k(48)$	1.68	0.71	1.85	2.03	1.40	2.01	1.62	1.43	1.00	0.35	0.95	1.08
pvalue	7.2	77.2	4.0	2.8	23.2	4.6	9.6	18.0	36.0	56.8	54.2	34.0
$R_k(60)$	1.70	0.58	1.57	2.02	1.33	2.08	1.61	1.43	0.93	0.21	0.62	0.96
pvalue	9.6	73.4	10.8	4.2	26.8	5.0	13.6	16.6	34.6	26.0	98.8	31.6
T	1296	1296	1296	1296	1296	1060	1036	1036	568	564	824	564

Note: the two-sided p-values are calculated based on 2000 bootstrap samples generated for each q.

Table 6b. Results of the rank-based variance ratio test for three-month (k=13) return:1975:1-2007:12

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.15	1.14	1.23	1.12	1.14	1.17	1.12	1.02	1.26	1.25	1.24	1.27
pvalue	0.6	0.2	0.0	18.0	2.0	0.0	38.8	80.4	1.4	0.0	1.6	2.8
$R_k(4)$	1.39	1.30	1.43	1.26	1.34	1.45	1.30	1.07	1.53	1.41	1.54	1.55
pvalue	0.0	0.8	0.0	15.2	0.0	0.0	14.8	80.8	1.8	0.4	0.4	1.6
$R_k(8)$	1.76	1.44	1.67	1.64	1.61	1.79	1.51	1.18	1.80	1.54	1.95	1.82
pvalue	0.0	0.6	0.0	1.6	0.2	0.0	12.2	38.8	3.8	3.0	0.6	1.4
$R_k(12)$	1.84	1.54	1.68	1.86	1.65	1.85	1.54	1.33	1.78	1.46	2.04	1.79
pvalue	0.0	0.8	0.6	2.4	0.4	0.0	16.0	29.8	6.6	4.4	1.4	6.2
$R_k(16)$	1.79	1.46	1.49	2.00	1.54	1.79	1.38	1.34	1.63	1.30	1.87	1.55
pvalue	0.2	4.6	5.4	0.8	2.2	0.0	26.0	28.4	12.4	18.2	6.2	15.2
$R_k(20)$	1.77	1.23	1.29	2.09	1.54	1.72	1.37	1.40	1.51	1.23	1.76	1.36
pvalue	0.6	22.8	18.8	3.0	4.2	0.6	25.6	21.8	15.6	22.6	8.6	21.2
T	1703	1703	1703	1703	1703	1456	1053	1053	975	962	1222	962
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.05	1.06	1.17	1.12	1.03	1.09	1.13	1.01	1.16	1.09	1.16	1.08
pvalue	82.0	72.8	9.0	26.6	98.0	64.4	35.2	76.2	58.0	96.0	32.8	98.0
$R_k(4)$	1.14	1.09	1.32	1.18	1.09	1.26	1.34	1.08	1.21	0.93	1.29	1.14
pvalue	50.0	57.8	9.6	30.6	68.8	18.8	11.0	68.2	50.0	81.6	25.2	58.6
$R_k(8)$	1.31	0.97	1.62	1.46	1.12	1.40	1.54	1.20	1.08	0.66	1.34	1.11
pvalue	21.4	89.0	3.8	12.0	53.4	21.2	11.2	44.0	63.0	63.8	23.6	52.4
$R_k(12)$	1.39	0.81	1.64	1.54	1.15	1.48	1.56	1.31	0.97	0.52	1.14	1.01
pvalue	22.4	83.2	8.6	10.6	40.8	14.0	14.4	32.0	59.6	65.6	44.6	51.0
$R_k(16)$	1.37	0.63	1.34	1.49	1.00	1.51	1.40	1.32	0.72	0.29	0.66	0.73
pvalue	25.2	62.0	25.4	16.2	61.8	13.8	19.2	28.4	72.8	31.6	92.2	73.0
$R_k(20)$	1.42	0.53	1.14	1.39	1.02	1.56	1.35	1.33	0.71	0.24	0.48	0.71
pvalue	18.6	48.0	39.0	22.2	52.4	15.6	26.8	24.2	61.0	33.8	77.6	64.6
T	1287	1287	1287	1287	1287	1040	1027	1027	559	546	806	546

Note: the same as in Table 6a.

Table 6c. Results of the rank-based variance ratio test for six-month (k=26) return:1975:1-2007:12

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.29	1.26	1.21	1.26	1.23	1.34	1.31	1.16	1.39	1.25	1.41	1.35
pvalue	2.6	5.8	0.2	4.2	0.0	0.4	10.8	60.0	0.0	7.2	0.8	0.2
$R_k(4)$	1.61	1.42	1.38	1.70	1.43	1.61	1.51	1.23	1.62	1.35	1.78	1.59
pvalue	2.4	8.0	0.2	0.8	0.0	1.2	13.8	50.4	0.2	4.8	1.6	0.2
$R_k(6)$	1.69	1.52	1.34	1.93	1.42	1.63	1.53	1.38	1.60	1.31	1.86	1.55
pvalue	3.4	8.8	1.4	0.8	0.8	2.0	18.4	29.6	0.8	10.4	4.6	2.6
$R_k(8)$	1.64	1.44	1.15	2.04	1.28	1.57	1.38	1.39	1.47	1.17	1.70	1.32
pvalue	8.8	20.0	23.2	1.8	5.4	6.4	33.6	28.6	5.0	29.4	10.0	13.4
$R_k(10)$	1.62	1.21	0.96	2.09	1.26	1.48	1.38	1.42	1.39	1.10	1.60	1.11
pvalue	9.8	39.8	75.0	3.0	15.8	15.8	27.8	21.6	8.8	29.8	13.6	30.4
T	1690	1690	1690	1690	1690	1430	1040	1040	962	936	1196	936
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.18	1.16	1.15	1.20	1.14	1.30	1.35	1.19	1.34	1.14	1.39	1.33
pvalue	37.6	43.8	49.8	27.0	46.4	16.4	7.0	48.4	46.6	82.8	11.2	57.0
$R_k(4)$	1.29	1.06	1.36	1.54	1.15	1.39	1.54	1.26	1.15	0.83	1.45	1.25
pvalue	34.4	88.2	22.0	6.8	52.2	22.2	8.6	44.2	79.4	68.6	24.4	51.2
$R_k(6)$	1.33	0.88	1.34	1.66	1.18	1.48	1.56	1.39	1.03	0.68	1.17	1.13
pvalue	30.2	88.2	28.0	7.0	47.4	17.2	14.0	23.4	68.2	79.8	49.2	56.4
$R_k(8)$	1.28	0.71	1.08	1.60	1.03	1.49	1.41	1.41	0.75	0.36	0.65	0.76
pvalue	32.2	66.4	59.4	12.8	66.8	20.6	22.6	25.6	86.2	34.0	79.4	77.2
$R_k(10)$	1.31	0.60	0.93	1.46	1.05	1.53	1.38	1.41	0.74	0.34	0.47	0.72
pvalue	31.0	60.2	75.2	23.8	51.4	17.4	26.2	23.8	67.4	48.2	52.6	67.4
T	1248	1248	1248	1248	1248	1014	1014	1014	520	520	780	520

Note: the same as in Table 6a.

Table 7a. Results of the rank-based variance ratio test for one-month (m=1) return using monthly series

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.13	1.09	1.12	1.06	1.11	1.18	1.14	1.09	1.14	1.19	1.13	1.17
pvalue	1.30	9.10	2.30	35.60	3.20	0.10	4.60	22.80	7.00	1.20	3.40	1.80
$R_k(12)$	1.70	1.51	1.71	1.44	1.53	1.83	1.28	1.10	1.89	1.83	1.85	1.92
pvalue	0.10	1.20	0.10	2.90	0.60	0.30	19.50	50.80	0.50	0.50	0.20	0.10
$R_k(24)$	2.22	1.76	2.17	2.00	1.87	2.37	1.47	1.23	2.28	2.02	2.41	2.36
pvalue	0.00	1.30	0.30	0.40	0.70	0.00	12.60	31.80	0.90	2.00	0.20	0.20
$R_k(36)$	2.39	1.97	2.28	2.37	1.95	2.51	1.54	1.41	2.30	1.93	2.56	2.41
pvalue	0.20	2.00	0.10	0.20	1.20	0.10	14.60	19.60	1.30	5.10	0.70	1.10
$R_k(48)$	2.40	1.96	2.11	2.64	1.83	2.50	1.45	1.46	2.20	1.75	2.48	2.26
pvalue	0.20	3.40	2.00	0.10	5.50	0.40	17.50	19.60	4.00	9.90	1.00	2.80
$R_k(60)$	2.44	1.72	1.83	2.74	1.81	2.47	1.50	1.52	2.07	1.63	2.46	2.14
pvalue	1.20	7.40	5.60	0.60	5.70	0.70	17.20	14.30	4.40	13.00	2.20	3.90
T	1712	1712	1712	1712	1712	1476	1072	1072	984	980	1240	980
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.10	1.03	1.13	1.06	1.11	1.18	1.15	1.09	1.12	1.18	1.10	1.16
pvalue	9.80	72.10	3.80	45.30	8.70	1.10	4.70	24.40	29.10	8.10	24.20	9.50
$R_k(12)$	1.23	1.01	1.54	1.38	1.28	1.54	1.33	1.10	1.21	1.02	1.36	1.23
pvalue	25.30	81.30	2.30	9.70	18.60	3.80	15.20	54.50	37.30	68.20	16.10	35.70
$R_k(24)$	1.46	0.90	2.07	1.93	1.41	1.77	1.53	1.26	1.19	0.70	1.47	1.28
pvalue	10.80	98.90	0.40	1.00	15.50	3.70	10.60	29.70	38.60	90.00	18.60	30.10
$R_k(36)$	1.56	0.81	2.16	2.23	1.39	1.90	1.59	1.40	1.13	0.56	1.31	1.20
pvalue	11.10	89.70	1.40	1.20	21.20	4.20	11.10	21.30	37.30	87.40	26.80	32.10
$R_k(48)$	1.55	0.64	1.84	2.35	1.23	1.99	1.50	1.45	0.95	0.28	0.93	0.96
pvalue	12.20	74.50	7.30	1.60	35.00	4.60	14.40	19.80	38.70	44.80	56.20	41.70
$R_k(60)$	1.59	0.50	1.61	2.34	1.25	2.07	1.50	1.46	0.92	0.19	0.72	0.95
pvalue	15.30	54.00	11.80	2.00	27.10	4.10	16.70	17.00	31.90	33.10	72.70	31.00
T	1296	1296	1296	1296	1296	1060	1036	1036	568	564	824	564

Note: the same as in Table 6a.

Table 7b. Results of the rank-based variance ratio test for three-month (m=3) return using monthly series

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.15	1.13	1.25	1.09	1.15	1.18	1.12	1.01	1.28	1.24	1.25	1.26
pvalue	10.20	16.00	0.20	33.90	8.90	4.30	38.00	78.10	2.30	4.80	1.10	3.10
$R_k(4)$	1.37	1.28	1.44	1.20	1.32	1.44	1.29	1.07	1.52	1.37	1.54	1.54
pvalue	1.20	10.00	0.90	21.40	6.90	2.10	19.30	72.60	2.80	7.70	1.30	2.00
$R_k(8)$	1.73	1.43	1.70	1.52	1.57	1.82	1.52	1.17	1.78	1.49	1.97	1.80
pvalue	0.70	10.30	1.70	5.40	3.80	1.30	11.10	46.50	3.90	13.30	0.50	3.20
$R_k(12)$	1.81	1.54	1.71	1.67	1.61	1.88	1.56	1.30	1.74	1.40	2.09	1.77
pvalue	2.10	9.50	2.60	4.40	7.00	2.70	13.60	30.90	7.50	24.90	0.70	6.10
$R_k(16)$	1.76	1.47	1.53	1.78	1.50	1.81	1.42	1.32	1.57	1.27	1.96	1.57
pvalue	5.10	16.00	11.80	4.20	13.90	5.30	21.70	29.10	14.60	33.70	3.30	14.00
$R_k(20)$	1.74	1.25	1.33	1.88	1.51	1.75	1.41	1.38	1.43	1.23	1.86	1.43
pvalue	7.20	32.00	27.50	3.90	16.70	9.10	23.40	25.40	19.60	31.80	5.40	17.60
T	1703	1703	1703	1703	1703	1456	1053	1053	975	962	1222	962
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.05	1.05	1.19	1.10	1.02	1.12	1.13	0.99	1.16	1.08	1.19	1.13
pvalue	84.10	83.50	6.70	43.20	93.00	40.00	33.60	59.40	58.30	97.20	20.20	74.20
$R_k(4)$	1.13	1.08	1.35	1.13	1.08	1.31	1.32	1.07	1.20	0.87	1.32	1.17
pvalue	48.00	69.80	7.90	48.90	69.30	18.30	12.50	73.70	53.00	63.70	17.30	54.60
$R_k(8)$	1.30	0.99	1.69	1.35	1.10	1.46	1.55	1.19	1.11	0.62	1.43	1.08
pvalue	24.00	87.80	3.90	21.40	57.70	14.10	10.30	44.20	50.90	55.00	17.90	64.60
$R_k(12)$	1.36	0.86	1.72	1.38	1.13	1.48	1.59	1.29	0.99	0.49	1.26	0.95
pvalue	21.10	99.70	6.50	23.50	52.50	16.30	12.40	29.70	55.30	57.90	30.10	59.50
$R_k(16)$	1.33	0.71	1.42	1.30	0.98	1.50	1.45	1.30	0.72	0.28	0.84	0.67
pvalue	25.30	77.40	20.10	28.50	70.50	15.90	20.60	29.10	72.50	27.30	71.30	83.80
$R_k(20)$	1.37	0.60	1.22	1.22	1.01	1.54	1.40	1.32	0.71	0.22	0.66	0.67
pvalue	24.80	68.10	34.60	32.90	56.60	17.10	21.30	26.80	61.50	28.40	85.60	68.60
T	1287	1287	1287	1287	1287	1040	1027	1027	559	546	806	546

Note: the same as in Table 6a.

Table 7c. Results of the rank-based variance ratio test for six-month (m=6) return using monthly series

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. The whole sample: 1975:1-2007:12												
$R_k(2)$	1.28	1.24	1.20	1.23	1.22	1.31	1.30	1.16	1.38	1.26	1.35	1.37
pvalue	3.70	8.80	15.30	9.10	14.30	3.30	14.30	61.50	5.70	28.90	3.00	5.50
$R_k(4)$	1.61	1.38	1.38	1.65	1.42	1.63	1.49	1.26	1.64	1.37	1.71	1.64
pvalue	1.50	12.80	11.50	1.50	9.30	2.40	12.90	38.50	6.20	28.90	2.10	6.60
$R_k(6)$	1.71	1.49	1.33	1.85	1.41	1.70	1.54	1.42	1.65	1.35	1.84	1.66
pvalue	3.70	12.30	25.40	1.10	17.00	5.50	15.60	26.20	15.00	31.40	3.60	10.70
$R_k(8)$	1.68	1.43	1.14	1.94	1.27	1.66	1.41	1.45	1.51	1.25	1.72	1.49
pvalue	6.90	18.20	50.20	2.60	34.00	9.40	24.70	22.30	21.60	36.00	9.20	22.30
$R_k(10)$	1.67	1.20	0.96	1.98	1.25	1.60	1.42	1.49	1.40	1.23	1.63	1.36
pvalue	11.70	42.40	76.10	3.50	34.50	14.40	24.30	20.80	26.00	36.50	13.20	28.20
T	1690	1690	1690	1690	1690	1430	1040	1040	962	936	1196	936
Panel B. Sample period: 1975:1-2007:12 except for 1980:1-1987:12												
$R_k(2)$	1.18	1.15	1.15	1.18	1.15	1.29	1.34	1.20	1.36	1.10	1.31	1.31
pvalue	40.30	48.10	50.60	36.90	54.20	16.40	7.40	44.60	43.30	71.20	22.00	59.70
$R_k(4)$	1.31	1.06	1.33	1.50	1.16	1.38	1.53	1.30	1.21	0.75	1.33	1.19
pvalue	30.60	86.90	24.20	7.90	55.50	21.70	11.10	29.50	63.10	49.20	36.00	64.70
$R_k(6)$	1.37	0.92	1.31	1.60	1.20	1.40	1.58	1.45	1.07	0.62	1.11	1.13
pvalue	29.20	99.50	31.50	8.90	46.40	28.10	14.60	21.70	62.20	62.50	62.10	54.60
$R_k(8)$	1.33	0.77	1.04	1.52	1.05	1.42	1.45	1.49	0.77	0.35	0.68	0.84
pvalue	30.70	77.20	64.90	18.20	64.80	23.20	22.40	19.80	81.10	28.90	83.40	72.30
$R_k(10)$	1.37	0.66	0.91	1.38	1.08	1.45	1.43	1.49	0.74	0.28	0.51	0.82
pvalue	27.20	68.00	81.30	27.80	54.60	22.10	23.40	18.70	71.30	33.00	66.50	61.60
T	1248	1248	1248	1248	1248	1014	1014	1014	520	520	780	520

Note: the same as in Table 6a.

Table 8. Estimates of $\frac{\sigma_{uv}}{\sigma_u \sigma_v}$

	GDM	BRP	JPY	CAD	SWF	DAK	SWK	NWK	FRF	ITL	BEF	DUG
Panel A. One-month return horizon												
Whole	-0.10	-0.06	-0.02	0.05	-0.01	-0.09	-0.16	-0.03	-0.21	-0.12	-0.15	-0.21
Subsample	0.09	0.14	-0.09	0.22	0.12	0.00			-0.15	-0.09	-0.08	-0.08
Panel B. Three-month return horizon												
Whole	-0.21	-0.14	-0.08	-0.01	-0.12	-0.23	-0.46	-0.33	-0.23	-0.14	-0.29	-0.29
Subsample	-0.01	0.05	-0.09	0.12	0.08	-0.17			-0.50	-0.34	-0.19	-0.26
Panel C. Six-month return horizon												
Whole	-0.03	-0.10	-0.04	-0.11	0.02	-0.23	-0.54	-0.44	-0.15	-0.07	-0.30	-0.24
Subsample	0.05	0.03	0.05	0.00	0.18	-0.20			-0.44	-0.35	-0.33	-0.25