JOURNAL OF APPLIED ECONOMETRICS
J. Appl. Econ. **22**: 855–889 (2007)
Published online in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/jae.965

MODEL-FREE EVALUATION OF DIRECTIONAL PREDICTABILITY IN FOREIGN EXCHANGE MARKETS

JAEHUN CHUNG[a] AND YONGMIAO HONG[b]*

[a] *Balance Sheet Measurement, Canadian Imperial Bank of Commerce, Toronto, Ontario, Canada*
[b] *Department of Economics, Cornell University, Ithaca, New York, USA; Wang Yanan Institute for Studies in Economics, Xiamen, China*

SUMMARY

We examine directional predictability in foreign exchange markets using a model-free statistical evaluation procedure. Based on a sample of foreign exchange spot rates and futures prices in six major currencies, we document strong evidence that the directions of foreign exchange returns are predictable not only by the past history of foreign exchange returns, but also the past history of interest rate differentials, suggesting that the latter can be a useful predictor of the directions of future foreign exchange rates. This evidence becomes stronger when the direction of larger changes is considered. We further document that despite the weak conditional mean dynamics of foreign exchange returns, directional predictability can be explained by strong dependence derived from higher-order conditional moments such as the volatility, skewness and kurtosis of past foreign exchange returns. Moreover, the conditional mean dynamics of interest rate differentials contributes significantly to directional predictability. We also examine the co-movements between two foreign exchange rates, particularly the co-movements of joint large changes. There exists strong evidence that the directions of joint changes are predictable using past foreign exchange returns and interest rate differentials. Furthermore, both individual currency returns and interest rate differentials are also useful in predicting the directions of joint changes. Several sources can explain this directional predictability of joint changes, including the level and volatility of underlying currency returns.

Received 6 December 2005; Revised 14 August 2006

1. INTRODUCTION

Since the seminal work of Meese and Rogoff (1983a), the efficiency of foreign exchange markets has been examined extensively. While market efficiency is an ongoing argument, it is widely viewed that it is difficult to beat the martingale model or the random walk model in predicting the conditional mean dynamics of foreign exchange rate changes (e.g., Diebold and Nason, 1990; Hsieh, 1988, 1989, 1993; McCurdy and Morgan, 1987; Meese and Rogoff, 1983a, 1983b; Meese and Rose, 1991). Most existing studies, however, are based on the tests of some forecast models or forecast rules. In other words, these studies examine the efficiency of models rather than data, and as a result their conclusions were model dependent. In addition, as Taylor (1995) has reported, such a model-driven test for the foreign exchange market efficiency seems elusive with the presence of risk premia and expectation errors. Therefore, it is highly desirable to evaluate the efficiency of foreign exchange markets using a model-free econometric procedure. In this paper, we examine

* Correspondence to: Yongmiao Hong, Department of Economics, Cornell University, 424 Uris Hall, Ithaca, NY 14850, USA. E-mail: yh20@cornell.edu
Contract/grant sponsor: Cheung Kong Scholarship of the Chinese Ministry of Education and Xiamen University.
Contract/grant sponsor: National Science Foundation; Contract/grant number: SES-0111769.

directional predictability in foreign exchange markets using a class of new model-free evaluation procedures.

There are several reasons why the directional predictability of foreign exchange returns is important. First, from a statistical point of view, it may be relatively easier to predict the direction of changes. Directional predictability depends on all conditional moments rather than merely the conditional mean of the foreign exchange rate changes (Christoffersen and Diebold, 2002; Hong and Chung, 2006). Thus, the forecasts of the direction of changes may be easier than the forecasts of the conditional mean. Cheung *et al.* (2005) have shown that certain structural models outperform the random walk with statistical significance in foreign exchange markets when evaluated on direction-of-change criteria, although they are less able to forecast the conditional mean dynamics of the foreign exchange rate changes (see also Breen *et al.*, 1989; Engel 1994; Kuan and Liu, 1995; Larsen and Wozniak, 1995; Leitch and Tanner, 1991, 1995; Pesaran and Timmermann, 1995, 2002; Shephard and Rydberg, 2003; Satchell and Timmermann, 1995; for more related discussions).

Second, from an economic point of view, the directional predictability of foreign exchange returns is more relevant to many financial applications than forecasting the conditional mean dynamics. For example, Leitch and Tanner (1991, 1995) showed that the direction-of-change criterion may be better able to capture a utility-based measure of forecasting performance such as economic profits (see Granger and Pesaran, 2000; Pesaran and Skouras, 2001; for further discussion). Market timing, one form of active asset allocation management, is essentially the prediction of turning points in financial markets. There have been a number of tests for market timing ability in the literature (e.g., Henriksson and Merton, 1981; Cumby and Modest, 1987; Pesaran and Timmermann, 1992), although they are intended to evaluate the directional predictability of models or forecasters.

Third, the direction of changes is an important maneuver in foreign exchange rate markets. For instance, the technical trading rules widely used by foreign exchange dealers (Taylor and Allen, 1992) are heavily based on forecasts of direction of changes (e.g., Pring, 1991). Also, central banks under pegged exchange rate systems often use the direction of exchange rate changes as a key instrument to maintain monetary stability. They will intervene in the foreign exchange market when the domestic currency is expected either to appreciate or depreciate beyond a certain, often politically determined threshold. Hence the study on the direction of changes will provide important insights to market practitioners and policy makers.

Finally, the direction of changes can be an alternative instrument for the link between foreign exchange rates and interest rates. Most early studies on this subject have focused on the relationship between the level of (expected) exchange rate changes and interest rate differentials, formally known as 'uncovered interest rate parity (UIP)'. Unfortunately, while the theoretical implication of the UIP−interest rate differentials serve as a useful predictor of the future spot foreign exchange rates is important, its validity has been questioned on various grounds in the literature. This motivates us to look for an alternative relationship, that is, whether interest rate differentials are useful to predict the direction of future foreign exchange rates. This still links foreign exchange rates with interest rates, but relaxes a rather restrictive condition imposed by UIP, under which the expected changes in a foreign exchange rate should exactly counterbalance the difference between domestic and foreign interest rates.

One interesting issue in the foreign exchange markets is currency crisis. There have been a variety of theoretical and empirical studies on currency crisis (see Kaminsky *et al.*, 1998, for an excellent survey). Due to quantifying difficulties, a currency crisis is typically represented by an indicator (binary) function, which is equal to unity if there is a sudden fall of foreign exchange rate beyond a certain threshold, namely, a large negative change. Several recent studies further suggest that some models for binary dependent variables (i.e., the currency crisis indicator) may have descriptive or predictive ability for future currency crises (e.g., Frankel and Rose, 1996a; Berg and Pattillo, 1999; Kumar *et al*., 2003). Perhaps even more interesting is when a currency crisis spreads from one market to another (or they occur simultaneously), which is commonly referred to as 'market contagion'. This growing and pervasive phenomenon suggests that during a crisis period a large adverse price change in one market will be closely followed by a large adverse price change in another market, regardless of market fundamentals (King and Wadhwani, 1990), implying a quite strong positive directional dependence between two markets during the turmoil period.[1] In pursuit of better understanding of directional movement, it is useful to examine the directions of large changes and large joint changes.

Ultimately, it is an empirical issue whether the direction of foreign exchange rate changes is predictable. All technical trading rules are built on a fundamental assumption; i.e., the pattern of the foreign exchange market is regular and can be repeated. Indeed, technically oriented forecasts are generally more accurate in predicting the direction of changes in the exchange rates than economic structural models (e.g., Cumby and Modest, 1987; Somanath, 1986). Considerable evidence in the literature suggests that these rules may generate significant profits in the foreign exchange market. Examples include Dooley and Shaffer (1983), Sweeney (1986), and Levich and Thomas (1993) for the use of filter rules, Lee and Mathur (1996) and LeBaron (1999) for the use of moving average trading rules, and Neely and Weller (1999) for the use of genetic programming. Some speculations suggest that the directions of foreign exchange rate changes are predictable by anticipating monetary policies: the monetary authorities might use foreign exchange market intervention as a means of monetary policies (rather than merely as an instrument for exchange rates stability) to achieve and strengthen major macroeconomic goals, such as high employment, low inflation, economic growth, trade balance, and price stability. In fact, several studies suggest that the monetary authorities may actually intervene to signal future monetary policies (e.g., Carlson *et al*., 1995; Mussa, 1981). Thus, once the speculators realize the expected future stance of monetary policies, they are able to exploit potential gains from the aforementioned intervention by correctly following the direction of the short-run trend (e.g., Baillie and Osterberg, 1997; Bonser-Neal and Tanner, 1996; Dominguez and Frankel, 1993; Ghosh, 1992).

There is a growing consensus that real and nominal exchange rates exhibit mean reversion toward the equilibrium level implied by economic fundamentals (e.g., Abuaf and Jorion, 1990; Frankel and Rose, 1996b; Jorion and Sweeney, 1996; Lothian and Taylor, 1996).[2] More interestingly, the degree of mean reversion is stronger when the deviation of actual exchange rates from the equilibrium is greater (e.g., Taylor and Peel, 2000; Taylor *et al*., 2002). The role of transaction costs has been central to theoretical models of explaining this nonlinearity. For instance, Dumas (1992) and Sercu *et al*. (1995) suggest that transaction costs produce 'a band of inaction' within which international price differentials incur no arbitrage. Similarly, due to friction and political costs, it is natural to expect greater intensity of market intervention when a substantial deviation is observed and expected to continue (Ito and Yabu, 2004). Consequently, the adjustment process

[1] See, for example, Bae *et al*. (2003) for further discussion.
[2] The commonly used benchmark is the level implied by the Purchasing Power Parity. In its relative version, this proposition states that the percentage change in nominal exchange rates should be equal to the inflation differentials (See Bleaney and Mizen, 1995, for a survey).

DOI: 10.1002/jae

takes place only when the perceived misalignment is large enough to cover such costs.[3] An alternative viewpoint can be discerned from the exchange rate behavior postulated by the target zone model (Krugman, 1991). In an exchange rate target zone, the monetary authorities allow exchange rates to float freely within the zone. However, if the rates approach the edge, i.e., upper or lower limits of the zone, they actively intervene in the foreign exchange market. In this framework, the exchange rates follow a bounded process and thereby exhibit mean reversion within the zone (see Anthony and MacDonald, 1998, 1999, for empirical evidence of this implication). Again, these findings may provide another strand of evidence that supports directional predictability in foreign exchange markets. In the presence of (nonlinear) mean reversion of exchange rates, it is intuitively plausible that the direction of foreign exchange rate changes is predictable from monetary fundamentals. That is, when the domestic interest rate is significantly higher than foreign interest rates or when the domestic inflation rate is significantly lower than foreign inflation rates, appreciation of the domestic currency is anticipated because of exogenous realignment pressures (i.e., market intervention) or endogenous realignment pressures (i.e., market forces to bring the rates back to the equilibrium), which are inherited by a mean reversion process. Therefore, we are at least able to predict the direction of future foreign exchange rate changes, even if it is difficult to predict the level of the exchange rate changes using economic fundamentals.

As pointed out earlier, the preceding studies described are model specific. They provide directional predictability of models (rather than data), but cannot explain why there exists such an opportunity to profit in the foreign exchange market from the currency attacks or technical trading rules. In contrast, our model-free evaluation will provide a statistical explanation based upon raw observed data about whether the direction of changes is predictable. In addition, it provides some guidance in constructing forecast models, such as the choice of information sets and conditional variables.

Based on a sample of spot rates and futures prices in six major currencies, our analysis reveals a number of interesting findings. First, we find significant evidence on directional predictability for the majority of both spot and future foreign exchange rates. The directions of foreign exchange returns can be predicted not only by the past history of foreign exchange returns, but also by the past history of interest rate differentials. Directional predictability for larger returns is stronger, owing to the persistent volatility clustering of past foreign exchange rate changes and the time-varying conditional mean dynamics of interest rate differentials. We also find significant evidence on directional predictability of the co-movement between two foreign exchange rates, especially the co-movement of large changes. These results are useful for financial risk management and investment diversification, as they provide useful information for understanding extreme market movements and extreme market co-movements.

Our findings have important implications. First, the evidence of directional predictability provides a solid statistical basis for any successful directional forecast models and technical trading rules. Second, our results suggest that interest rate differentials can be useful instruments in predicting the direction of foreign exchange rate changes. Third, the documented dependencies between the direction of foreign exchange rate changes and two conditioning series—the past exchange rate changes and past interest rate differentials—suggest that both foreign exchange market intervention and interest rate defense can be effective tools in managing foreign exchange

[3] See Kilian and Taylor (2001), Taylor *et al*. (2002) and Taylor and Taylor (2004) for further discussion and other possible sources of this asymmetry.

DOI: 10.1002/jae

markets. Lastly, our evidence of directional predictability of joint changes in two currencies suggests that it is possible to predict simultaneous foreign exchange markets movements.

The paper is organized as follows: Section 2 discusses hypotheses on directional predictability in foreign exchange rate changes, including those large changes and the direction of co-movements in two currencies. Section 3 describes the model-free evaluation methods for directional predictability. Section 4 describes the data and summary statistics, Section 5 presents our empirical findings and discusses their implications, and Section 6 contains concluding remarks and directions for future research.

2. DIRECTIONAL PREDICTABILITY IN FOREIGN EXCHANGE MARKETS

Let Y_t denote the return of the spot foreign exchange rate S_t at time t. We define a direction indicator function

$$Z_t(c) = \mathbf{1}(Y_t > c) \tag{1}$$

where $\mathbf{1}(\cdot)$ denotes the indicator function, taking value 1 when $Y_t > c$ and value zero when $Y_t \leq c$, and c is a threshold constant. This indicator function characterizes the direction of positive price changes. A similar indicator function can be defined for the direction of negative price changes when $Y_t < -c$.

It is important to consider directional predictability of the foreign exchange rate with different threshold values for the following reasons. First, since an asset price may be quoted in minimum price increments (or ticks), marginal investors who determine market prices may be more interested in whether the asset prices rise above or fall below such thresholds. In a similar vein, those investors who are in pursuit of profit may be further interested in the direction of the changes large enough to ensure net profits after transaction costs. Therefore, the provision of a threshold value can be seen as representing practical considerations to help build more successful trading strategies. Next, the deriving forces of small and large changes in asset prices may be different. Maheu and McCurdy (2003), for example, show that the dynamics of returns can consist of two different components: (i) occasional jumps (i.e., large changes),[4] which are driven by important news events, and tend to be clustered together; (ii) (smooth) small changes, which are due to liquidity trading or strategic trading, as information dissimilates over time. At the same time, it has been observed that there is an asymmetry in the dependence structure for small and large changes, as in Longin and Solnik (2001), Ang and Chen (2002), and Hong *et al.* (2007), who found the correlation is stronger between large changes than that between small changes, and even stronger on the downside (i.e., negative large returns). Lastly, investors may have different valuation assessments between small and large changes in the foreign exchange rates. For example, momentum traders, who seek to exploit a short-term trend, may react more strongly to large changes since the direction and strength of the trend become more recognizable at the larger changes. In addition, large changes often contain more valuable information, while small changes display mere noise. Therefore, it is necessary for investors to segment price changes so as to filter out irrelevant information from the observations.[5]

[4] Jorion (1988) points out that there are more jumps in the foreign exchange market than in stock markets.

[5] This is exactly the rationale behind the most popular technical trading rule—filter rules. Filter rules generate a 'buy' signal when a currency rises c% above its most recent trough; a 'sell (short)' signal when it falls by c% from the recent peak. Smaller filters capture turning points better but lead to more frequent trades and higher transaction costs. In contrast, larger filters result in less frequent trades and lower brokerage fees, but they miss the turning points by a larger amount.

DOI: 10.1002/jae

In practice, the choice of threshold c can either be made conditional on data or held fixed at multiple values such as tick sizes or transaction costs. There is no obvious rationale for preferring one or another criterion: a posterior threshold gained from the observations may be more suitable for the purpose of statistical data analysis, while the latter will be of interest to those in pursuit of practical use. Since our study concerns a statistical evaluation of directional predictability, we will use the multiples of the standard deviation $\sigma_Y = \sqrt{\mathrm{var}(Y_t)}$ without loss of generality.[6]

We are interested in testing whether the direction of foreign exchange rate changes with threshold c is predictable using the history of its own past changes. The null hypothesis is

$$\mathbb{H}_0 : E[Z_t(c)|I_{t-1}] = E[Z_t(c)] \text{ almost surely } (a.s.) \tag{2}$$

where $I_{t-1} \equiv \{Y_{t-1}, Y_{t-2}, \ldots\}$ is the information set available at time $t-1$. Note that our null hypothesis $\mathbb{H}_0$ is not the same as the hypothesis of $E(Y_t|I_{t-1}) = \mu$ *a.s.* for some constant μ, where the latter hypothesis checks whether there exists a predictable time-varying conditional mean. It is shown that, irrespective of the existence of a time-varying conditional mean predictability, directional predictability may exist through the interaction between a nonzero unconditional mean μ, volatility dependence, and serial dependence in higher-order conditional moments such as skewness and kurtosis (Christoffersen and Diebold, 2002; Hong and Chung, 2006). This fact, that directional predictability can be derived from such various sources, may explain why it is easier to predict the direction than the level of the change, as many empirical studies document.

While rejecting the null hypothesis $\mathbb{H}_0$ of no directional predictability is evidence against market efficiency, it could be viewed as an alternative way to assess the efficacy of successful exchange market intervention.[7] Note that, under the null hypothesis $\mathbb{H}_0$ of (2), market intervention through a sale/purchase of the foreign (or domestic) currency, has no impact on the direction of exchange rates movements. In other words, for intervention to be effective, it should be able to systematically affect the direction of foreign exchange rates. Since the sequence of direction indicators $\{Z_t(c)\}$ is a Bernoulli process, we have only two possible outcomes: 'up' or 'down'. Thus, the outcomes following the intervention identified as either 'success' or 'failure' might be drawn randomly rather than resulting from the intended effects of the intervention (see, for example, Fatum and Hutchison 2002, 2003, for related discussion based on an event study approach).

A rejection of no directional predictability does not warrant a successful intervention. An intervention might move foreign exchange rates in an unintended direction, since expectations of future foreign exchange rates can be directly or indirectly affected by many other factors. For instance, when the announcement of intervention negatively affects investor sentiment, leading to uncertainty in the market, the effects of the intervention may be mediated or even aggravated (e.g., Dominguez, 1993). Kaminsky and Lewis (1996) also show that when the goal of intervention policies is inconsistent with what subsequent monetary policies aim at, they are sometimes counterproductive (Mussa, 1979). Hence our arguments on efficacy via the direction-of-change approach need be grounded only in the events of successful intervention.

[6] See Linton and Whang (2003) for the use of quantiles as a threshold in their study of directional predictability.
[7] There are several viewpoints about definition and evaluation categories of a successful intervention. For example, the monetary authorities, with a desire to reduce volatility rather than to maximize profit, attempt to smooth out changes in exchange rates and delay the adjustment to underlying fundamental forces by 'leaning against the wind'. In such a circumstance, the success of intervention may be based on the ability to revert the direction of exchange rate movements. On the other hand, when the authorities need to support the current trend of foreign exchange rates, they are likely to focus on whether it helps move the foreign exchange rate in the same direction of the current movements—i.e., to 'lean with the wind' (see Dominguez and Frankel, 1993, for further discussion).

The last, but not least important point of $\mathbb{H}_0$ in (2) is that the existence of directional predictability and/or conditional mean predictability does not necessarily lead to the rejection of the efficient market hypothesis. The market can still be efficient unless a trading strategy based on such predictable patterns yields consistent and sufficient excess-risk adjusted returns (Malkiel, 1992, 2003). Moreover, it is often perceived that the validity of predictability needs to be tested further by out-of-sample evaluation. Indeed, exchange rate predictability has been largely assessed on the basis of out-of-sample evaluation in the literature (e.g., Cheung *et al.*, 2005; Engel, 1994; Mark, 1995; Meese and Rogoff, 1983a, 1983b). Inoue and Kilian (2004) point out, however, that once proper critical values are considered, both in-sample and out-of-sample tests are asymptotically equally reliable under the null of no predictability. They also show that any sample-splitting out-of-sample evaluation can be subject to a loss of information and thus lower power for small samples. In the present context, our evaluation of directional predictability is model free (i.e., we do not use any model), so our results are not subject to potential problems of in-sample overfitting.[8] In fact, Hong and Lee (2003) find that the degree of significance of the generalized spectral tests is positively correlated with the out-of-sample predictive ability of a best-forecast model for foreign exchange rates.

Economic theory suggests that equilibrium exchange rates are determined by factors both inside and outside the currency market. For example, interest rates are one of the most important instrumental variables in financial markets. The link between foreign exchange rates and interest rates is a well-known feature of the foreign exchange market. One commonly cited relationship in the literature is a condition known as uncovered interest rate parity (UIP):

$$E[\ln(S_{t+1}/S_t)|I_{t-1}] = r_t - r_t^*, \tag{3}$$

where r_t and r_t^* denote the domestic and foreign risk-free interest rates, respectively. Under the UIP condition, the interest rate market will lead the currency market as money flows from one country to another: higher (lower) domestic interest rates would increase expectations of a US dollar appreciation (depreciation) with an inflow (outflow) of foreign capital. While theoretically apparent, there has been little solid empirical evidence to support the above claim. A detailed analysis of the causes of its empirical failure is beyond our scope here; we simply note that the existence of a risk premium, the Peso problem, and expectational errors is known to account for the violation of UIP (see Froot and Thaler, 1990; Hodrick, 1987; Lewis, 1995; for a survey). Other explanations include transaction costs (e.g., Frenkel and Levich, 1975, 1977), capital control such as monetary policies (Chinn and Meredith, 2004; Faust and Rogers, 2003), market intervention (Mark and Moh, 2003), delayed overshooting (Eichenbaum and Evans, 1995), and misleading statistical inference problems (e.g., Baillie and Bollerslev, 2000; Maynard and Phillips, 2001; Bekaert and Hodrick, 2001).

Recent works have been more favorable for the validity of the UIP condition: Alexius (2001), Bekaert and Hodrick (2001), and Chinn and Meredith (2004) argue that UIP remains valid at long horizons, while Chaboud and Wright (2005) show that the UIP condition cannot be rejected by high-frequency intra-daily data. In a similar vein, Mark (1995) shows that the forecastability of

[8] Of course, subsamples testing, which is analogous to out-of-sample testing, could provide an interesting extension to our analysis, in view of potential structural changes in the data-generating process of foreign exchanges. We refer the interested reader to Alquist and Chinn (2006) for out-of-sample evaluation of foreign exchange rate modeling.

DOI: 10.1002/jae

exchange rates associated with monetary fundamentals is more pronounced in longer horizons. Further, Kilian and Taylor (2001) demonstrate that, using a (mean-reverting) nonlinear smooth transition autoregressive (STAR) model, exchange rates are forecastable over long horizons but not in short horizons.[9] Besides the horizon-specific findings, Huisman *et al.* (1998), and Flood and Rose (2002) also pointed out that UIP holds better during volatile periods whereas Bansal and Dahlquist (2000) and Bekaert *et al.* (2002) showed that the validity of UIP is more related to currencies (rather than horizons).

These inherent weaknesses in the empirical validity of the UIP condition led us to look for an alternative linkage; we instead focus our attention on the relationship between the direction of foreign exchange rates and interest rate differentials, which yet remains to be investigated thoroughly. Let I_{t-1}^{ID} denote an information set at time $t-1$ available in the interest rate market, which contains lagged interest rate differentials $\{ID_{t-1}, ID_{t-2}, \ldots\}$, where $ID_t \equiv r_t - r_t^*$. Accordingly, our next question is whether interest rate differentials ID_t can be used to predict the direction of foreign exchange rate changes:

$$\mathbb{H}_0 : E[Z_t(c)|I_{t-1}^{ID}] = E[Z_t(c)] \ a.s. \tag{4}$$

Apparently, this hypothesis is more sensible to postulate the link between interest rates and exchange rates, because it does not require a one-to-one relationship between interest rate differentials and expected foreign exchange rate changes in the UIP condition (3). Indeed, recent studies suggest that interest rate differentials are associated with the direction of future foreign exchange rates. Furman and Stiglitz (1998) and Flood and Rose (2002) argue that, despite the violation of UIP (i.e., a discrepancy between expectations of appreciation/depreciation and interest rate differentials), higher domestic interest rates relative to foreign interest rates at least tend to appreciate the domestic currency during a crisis period.

Another way to view a rejection of the null in (4) is similar to what we have discussed previously for $\mathbb{H}_0$ in (2). That is, it should be viewed as a necessary but not sufficient condition for the effectiveness of a successful interest rate defense.[10] Given the rejection of the null hypothesis $\mathbb{H}_0$ in (4), the monetary authorities may affect the direction of foreign exchange rates by raising/lowering domestic interest rates to discourage speculative currency attacks.[11] In this regard, successful interest rate defenses can be attributed to the existence of dependence between the direction of exchange rate changes and interest rate differentials. Further, within this context, a comparison between the effects of past returns and past interest rate differentials on the direction of foreign exchange returns gives valuable information about which instruments are a more effective tool for the monetary authorities to accomplish their objective. Thus the use of other market information I_{t-1}^{ID} can provide further insights on directional predictability of foreign exchange rates.

[9] As such, the findings for the UIP condition and, by inference, the forecastability of exchange rates appear to be sensitive to the forecast horizon. However, we do not explore this issue in this paper, since the sample sizes for long-horizon returns are not be large enough to ensure the comparability of test results across different time horizons. While our generalized cross-spectrum approach detects directional predictability well in finite samples (Hong and Chung, 2006), comparative analysis between the short (daily data with more than 3000 observations) and long (e.g., yearly data with fewer than 20 observations) horizons may lead to misleading inference.

[10] See also Flood and Jeanne (2000) and Flood and Rose (2002) for related discussion in the context of UIP.

[11] A rejection of $\mathbb{H}_0$ in (4) is not necessarily an indication of a successful interest rate defense. Active interest rate defense can be costly under certain conditions, such as when interest rate hikes result in a further depreciation due to increased risk—the perverse effects (e.g., Furman and Stiglitz, 1998).

DOI: 10.1002/jae

It is well known that there exist volatility co-movements (e.g., Hamao *et al.*, 1990). Some authors (Longin and Solnik, 1995; Ramchand and Susmel, 1998) show that correlation between markets may increase during periods of high volatility. If the skewness varies jointly between two markets, this will suggest an increase in the probability of the occurrence of a large event with the same sign on both markets. If the kurtosis varies jointly between two markets, there will be an increase in the probability of the occurrence of a large event on the markets, whatever the direction of the shock is. Jondeau and Rockinger (2003) also show that there is evidence that large events generating skewness tend to occur simultaneously for stock markets. In other words, very large events of a given sign tend to occur jointly. In particular, this result indicates that crashes will tend to happen at the same time. Building on these backgrounds, it will be interesting to examine whether the direction of joint changes in two currencies, particularly the direction of large changes in two markets, is predictable using various moments of market information available.

3. EVALUATION METHOD

As discussed earlier, the dynamics of directional predictability of asset returns is highly nonlinear due to the fact that directional predictability depends on serial dependence in every time-varying conditional moment. We thus use a nonlinear analytic tool, namely the generalized cross-spectrum approach primarily employed in Hong and Chung (2006). The generalized cross-spectrum approach, which extends Hong's (1999) univariate generalized spectrum to a bivariate time series context, is based on the spectrum of the transformed time series via the characteristic function, allowing us to detect both linear and nonlinear cross-dependencies. Formally, for a strictly stationary bivariate process $\{Z_t, Y_t\}$, whose marginal characteristic functions are $\varphi_Z(u) = E(e^{\mathbf{i}uZ_t})$ and $\varphi_Y(u) = E(e^{\mathbf{i}uY_t})$, and whose pairwise joint characteristic function is $\varphi_{ZY,j}(u, v) \equiv E[e^{\mathbf{i}(uZ_t+vY_{t-|j|})}]$ for $u, v \in (-\infty, \infty)$, $\mathbf{i} = \sqrt{-1}$ and $j = 0, \pm 1, \ldots$, the generalized cross-spectrum is defined by

$$f_{ZY}(\omega, u, v) \equiv \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZY,j}(u, v) e^{-\mathbf{i}j\omega}, \quad \omega \in [-\pi, \pi], \tag{5}$$

where ω is the frequency and $\sigma_{ZY,j}(u, v)$ is the generalized cross-covariance function between the transformed series:

$$\sigma_{ZY,j}(u, v) \equiv \operatorname{cov}(e^{\mathbf{i}uZ_t}, e^{\mathbf{i}vY_{t-|j|}}). \tag{6}$$

It is easy to see that $\sigma_{ZY,j}(u, v) = 0$ for all $u, v \in (-\infty, \infty)$ if and only if Z_t and $Y_{t-|j|}$ are independent. Thus it can capture any type of pairwise cross-dependence between $\{Z_t\}$ and $\{Y_{t-j}, j > 0\}$ over various lags (including those with zero autocorrelation). In this spirit, $f_{ZY}(\omega, u, v)$ can capture various linear and nonlinear cross-dependencies.[12] Another important advantage of using the characteristic function is that it requires no moment condition on $\{Z_t\}$ and $\{Y_t\}$, and so it does not suffer from the potential problem when the moment condition fails, which is often found in high-frequency economic and financial time series (e.g., Pagan and Schwert,

[12] A simulation study in Hong and Chung (2006) shows that the proposed generalized cross-spectral test has reasonable size with good power against directional predictability under various plausible linear and nonlinear data-generating processes. Furthermore, in an empirical study, Hong and Lee (2003) find that the changes of most major foreign exchange rates are serially uncorrelated, but the generalized spectral tests significantly reject the null hypothesis of martingale difference sequences, revealing the advantages of a generalized spectral approach over traditional linear models or measures.

1990). Moreover, the generalized spectrum shares a nice feature of the conventional spectral approach—it incorporates information on serial dependence from virtually all lags. This will ensure to capture serial dependence at higher lag orders, and hence enhance good power for tests against the alternatives involving a persistent dependence structure (i.e., serial dependence decays to zero slowly as $j \to \infty$).

3.1. Generalized Cross-Spectral Derivative Tests

It is important to point out that the generalized cross-spectrum $f_{ZY}(\omega, u, v)$ itself is not suitable for testing the null hypotheses $\mathbb{H}_0$ in (2) and (4), because the generalized spectrum $f_{ZY}(\omega, u, v)$ encompasses all pairwise cross-dependencies in various conditional moments of both $\{Z_t\}$ and $\{Y_{t-j}, j > 0\}$. Fortunately, $f_{ZY}(\omega, u, v)$ can be differentiated to reveal possible specific patterns of cross-dependence in various conditional moments, thanks to the use of the characteristic function. In particular, one can use the generalized cross-spectral density derivative

$$f_{ZY}^{(0,m,l)}(\omega, u, v) \equiv \frac{\partial^{m+l}}{\partial u^m \partial v^l} f_{ZY}(\omega, u, v) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZY,j}^{(m,l)}(u, v) e^{-\mathbf{i}j\omega}, \quad m, l \geq 0 \tag{7}$$

By varying the combination of the derivative orders (m, l), the generalized cross-spectral derivative $f_{ZY}^{(0,m,l)}(\omega, u, v)$ can capture various specific aspects of cross-dependence between $\{Z_t\}$ and $\{Y_{t-j}, j > 0\}$. For example, to test the null hypothesis $\mathbb{H}_0$ of (2): $E(Z_t|I_{t-1}) = E(Z_t)$ a.s. (with $Z_t = Z_t(c)$), we can use the (1, 0)th order generalized cross-spectral derivative

$$f_{ZY}^{(0,1,0)}(\omega, 0, v) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZY,j}^{(1,0)}(0, v) e^{-\mathbf{i}j\omega}, \quad \omega \in [-\pi, \pi] \tag{8}$$

where

$$\sigma_{ZY,j}^{(1,0)}(0, v) \equiv \frac{\partial}{\partial u} \sigma_{ZY,j}(u, v)|_{u=0} = \text{cov}(\mathbf{i}Z_t, e^{\mathbf{i}vY_{t-|j|}})$$

The measure $\sigma_{ZY,j}^{(1,0)}(0, v)$ checks correlations between Z_t and all moments of $Y_{t-|j|}$, and is thus suitable for testing whether $E(Z_t|Y_{t-|j|}) = E(Z_t)$ for all j.[13]

As in Hong and Chung (2006), we consider a stepwise procedure for hypothesis testing, which begins by examining directional predictability using $f_{ZY}^{(0,1,0)}(\omega, 0, v)$, then proceeds for separate inferences on various sources such as time-varying conditional mean, volatility clustering and conditional skewness or other higher-order conditional moments. Once directional predictability is detected, this stepwise testing procedure will reveal useful information in making inferences on the nature of directional predictability and thus the modeling of directional forecasts.[14] In

[13] See Bierens (1982) and Stinchcombe and White (1998) for more discussion in a related but different context.

[14] For a modeling exercise of directional forecasts, we refer to Hong and Chung (2006), in which a class of autologistic models is considered for an out-of-sample test. In addition, a moving average technical trading rule is used in Hong and Lee (2003), who find the nonlinearity in conditional mean by applying the generalized spectral tests of Hong (1999). While their research interests are primarily in examining the predictability of exchange rate changes in mean, they also conduct forecasts on the direction of changes as an integral part of forecasting exchange rate changes.

DOI: 10.1002/jae

particular, we use the following higher-order generalized cross-spectral derivative with the choice of $l = 1, 2, 3, 4$ respectively:

$$f_{ZY}^{(0,1,l)}(\omega, 0, 0) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZY,j}^{(1,l)}(0, 0) e^{-\mathbf{i}j\omega}, \quad \omega \in [-\pi, \pi] \tag{9}$$

where

$$\sigma_{ZY,j}^{(1,l)}(0, 0) \equiv \frac{\partial^{1+l}}{\partial u \partial v^l} \sigma_{ZY,j}(u, v)|_{(u,v)=(0,0)} = \mathrm{cov}[\mathbf{i}Z_t, (\mathbf{i}Y_{t-|j|})^l], \qquad l \geq 1$$

As expected, $\sigma_{ZY}^{(1,l)}(0, 0)$ will be proportional to cross-covariance $\mathrm{cov}(Z_t, Y_{t-|j|}^l)$ and, as a consequence, $f_{ZY}^{(0,1,l)}(\omega, 0, 0)$ for $l = 1, 2, 3, 4$ can be used to test whether Z_t is predictable using the level of past changes $\{Y_{t-j}\}$, past volatility $\{Y_{t-j}^2\}$, past skewness $\{Y_{t-j}^3\}$ and past kurtosis $\{Y_{t-j}^4\}$, respectively.

Following Hong (1999, Theorem 1), we can consistently estimate the above generalized cross-spectral density derivative by a smoothed kernel estimator:

$$\hat{f}_{ZY}^{(0,1,l)}(\omega, 0, v) = \frac{1}{2\pi} \sum_{j=1-T}^{T-1} (1 - |j|/T)^{1/2} k(j/p) \hat{\sigma}_{ZY,j}^{(1,l)}(0, v) e^{-\mathbf{i}j\omega}, \quad \omega \in [-\pi, \pi], \tag{10}$$

where $\hat{\sigma}_{ZY,j}^{(1,l)}(u, v) = \frac{\partial^{1+l}}{\partial u \partial v^l} \hat{\sigma}_{ZY,j}(u, v)$, $\hat{\sigma}_{ZY,j}(u, v) = \hat{\varphi}_{ZY}(j, u, v) - \hat{\varphi}_{ZY}(j, u, 0)\hat{\varphi}_{ZY}(j, 0, v)$ is the empirical generalized cross-covariance function between $\{Z_t(c)\}$ and $\{Y_t\}$, and $\hat{\varphi}_{ZY}(j, u, v) = (T - |j|)^{-1} \sum_{t=|j|+1}^{T} e^{\mathbf{i}(uZ_t(c)+vY_{t-|j|})}$ is the empirical joint characteristic function of $\{Z_t(c), Y_{t-|j|}\}$. Here, $k(\cdot)$ is a kernel function, $p \equiv p(T)$ is a bandwidth,[15] and the factor $(1 - |j|/T)^{1/2}$ is a finite sample correction factor for better finite sample performance.

Under the null hypothesis $\mathbb{H}_0$ of no directional predictability, $f_{ZY}^{(0,1,l)}(\omega, 0, v)$ becomes a flat generalized cross-spectrum:

$$f_{ZY,0}^{(0,1,l)}(\omega, 0, v) \equiv \frac{1}{2\pi} \sigma_{ZY,0}^{(1,l)}(0, v), \quad \omega \in [-\pi, \pi] \tag{11}$$

which can be consistently estimated by

$$\hat{f}_{ZY,0}^{(0,1,l)}(\omega, 0, v) \equiv \frac{1}{2\pi} \hat{\sigma}_{ZY,0}(0, v) \tag{12}$$

Thus, any significant difference between $f_{ZY}^{(0,1,l)}(\omega, 0, v)$ and $f_{ZY,0}^{(0,1,l)}(\omega, 0, v)$ will indicate evidence against $\mathbb{H}_0$. Such a discrepancy can be measured by the quadratic norm between the estimators $\hat{f}_{ZY}^{(0,1,l)}(\omega, 0, v)$ and $\hat{f}_{ZY,0}^{(0,1,l)}(\omega, 0, v)$:

$$\hat{Q}(1, l) = \pi T \int \int_{-\pi}^{\pi} |\hat{f}_{ZY}^{(0,1,l)}(\omega, 0, v) - \hat{f}_{ZY,0}^{(0,1,l)}(\omega, 0, v)|^2 \mathrm{d}\omega \mathrm{d}W(v)$$

[15] For the choice of p, Hong (1999, Theorem 2.2) proposes a data-driven method which minimizes an asymptotic integrated mean squared error criterion for the generalized spectral density estimator. It still involves the choice of a preliminary 'pilot' lag order $\overline{p}$, but the impact of choosing $\overline{p}$ is much smaller.

DOI: 10.1002/jae

$$= \sum_{j=1}^{T-1} k^2(j/p)(T-j) \int |\hat{\sigma}_{ZY,j}^{(1,l)}(0, v)|^2 \mathrm{d}W(v) \tag{13}$$

where $W(\cdot)$ is a positive and nondecreasing weighting function, and the unspecified integral is taken over the support of $W(\cdot)$.[16] Then, the resulting test statistic is a standardized version of the cumulative sum of $\hat{Q}(1, l)$:

$$M_{ZY}(1, l) = \left[\hat{Q}(1, l) - \hat{C}_{ZY}(1, l) \sum_{j=1}^{T-1} k^2(j/p)\right] / [\hat{D}_{ZY}(1, l)]^{1/2} \tag{14}$$

where the centering and scaling factors $\hat{C}_{ZY}(1, l)$ and $\hat{D}_{ZY}(1, l)$ are approximately the mean and the variance of the quadratic form $T\hat{Q}$ in (13) and their expressions are given in Hong and Chung (2006). Under $\mathbb{H}_0$, the statistic $\hat{M}_{ZY}(1, l)$ is asymptotically $N(0, 1)$. It generally diverges to positive infinity under the alternatives to $\mathbb{H}_0$, and thus allows us to use upper-tailed $N(0, 1)$ critical values as appropriate critical values (see Hong and Chung, 2006, for details).

The last stage of our stepwise testing procedure is to examine whether the directions of past returns $\{Z_{t-j}, j > 0\}$ can be useful to predict the directions of future returns $\{Z_t\}$. This aims to explore a growing empirical evidence of pattern anomalies in foreign exchange markets, such as over/underreaction (e.g., Larson and Madura, 2001, and references therein) and long swing (Engel and Hamilton, 1990). The former indicates short-term price reversal (or continuation) following large price changes, while the latter presents periodic short-term foreign exchange rate movements in one direction. In a period of time where these pattern anomalies are found, the successive directions of foreign exchange rate movements can be examined as a function of past directions.

To capture serial dependence in the univariate time series $\{Z_t(c)\}$ that consists of past and future directions, we use the generalized spectral density function of Hong (1999):

$$f_{ZZ}(\omega, u, v) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZZ,j}(u, v) e^{-\mathbf{i}j\omega} \tag{15}$$

where the generalized covariance function is

$$\sigma_{ZZ,j}(u, v) = \mathrm{cov}(e^{\mathbf{i}uZ_t(c)}, e^{\mathbf{i}vZ_{t-|j|}(c)}) \tag{16}$$

The associated test statistic $M_{ZZ}(1, 0)$ to test $\mathbb{H}_0 : E(Z_t|Z_{t-|j|}) = E(Z_t)$ a.s. can be derived in a similar manner to the test statistic $M_{ZY}(1, 0)$: we compare a consistent kernel estimator for the (1, 0)th order univariate generalized spectral derivative $f_{ZZ}^{(0,1,0)}(\omega, 0, v)$ and a consistent estimator for the flat spectrum $f_{ZZ,0}^{(0,1,0)}(\omega, u, v)$.[17] Likewise, the $M_{ZZ}(1, 0)$ test has the same $N(0, 1)$ limit distribution as $M_{ZY}(1, l)$ (Hong, 1999).

[16] As different choices of the derivative orders (m, l) yield tests of various hypotheses, different $W(\cdot)$ may be selected depending on which hypothesis is of interest. For the omnibus test $M_{ZY}(1, 0)$, we put $W(\cdot) = W_0(\cdot)$, where $W_0(\cdot)$ is the $N(0, 1)$ CDF. For the separate tests $M_{ZY}(1, l)$ with $l \geq 1$, we put $W'(\cdot) = \delta(\cdot)$, where $\delta(\cdot)$ is the Dirac delta function; namely, $\delta(u) = 0$ for all $u \neq 0$ and $\int_{-\infty}^{\infty} \delta(u)\mathrm{d}u = 1$. For further discussion, see Hong (1999).

[17] Alternatively, one could test directional predictability by testing the i.i.d. property for $\{Z_t(c)\}$. Because the direction indicator $Z_t(c)$ is a Bernoulli random variable taking value 0 or 1, it is independent of I_{t-1} if $Z_t(c)$ is not predictable using I_{t-1}. Thus, if evidence against i.i.d. is found for $\{Z_t(c)\}$, one can conclude that the direction of returns is predictable using the past history of the return directions $\{Z_{t-1}(c), Z_{t-2}(c), \ldots\}$. See Hong and Chung (2006) for further discussion.

DOI: 10.1002/jae

Finally, it is straightforward to test whether interest rate differentials $\{ID_t\}$ are useful in predicting the direction of foreign exchange rate returns $\{Z_t\}$. We will repeat the above evaluation measures, but with change of argument $Y_t = ID_t$. Accordingly, we denote $M_{ZID}(1, 0)$ as an omnibus test for $\mathbb{H}_0$ of (4), and $M_{ZID}(1, l)$ with $l = 1, 2, 3, 4$ and $M_{ZZ_{ID}}(1, 0)$ as separate tests to check whether $\{Z_t\}$ is predictable using the level, volatility, skewness, kurtosis and directions of past interest rate differentials $\{ID_{t-j}\}$, respectively.

3.2. Tests for the Direction of Joint Changes in Two Currencies

Our aim is now to gauge directional predictability of joint changes in two currencies. Intuitively, previous measures $f_{ZY}(\omega, u, v)$ and $f_{ZZ}(\omega, u, v)$ cannot be directly applicable when there are more than two variables involved (as is the case when we explore the directional predictability of joint changes in two currencies using their return series $\{Y_{1t}, Y_{2t}\}$).[18] For this purpose, we will use the multivariate generalized cross-spectral density below.

Suppose we have a strictly stationary time series process $\{Z_t, Y_{1t}, Y_{2t}\}$, and define the generalized cross-covariance function between $\{Z_t\}$ and $\{Y_{1t-j}, Y_{2t-j}, j > 0\}$ as

$$\sigma_{ZY_1Y_2,j}(u, v, \tau) \equiv \mathrm{cov}(e^{\mathbf{i}uZ_t}, e^{\mathbf{i}(vY_{1t-|j|}+\tau Y_{2t-|j|})}), \qquad j = 0, \pm 1, \ldots \tag{17}$$

where $u, v, \tau \in (-\infty, \infty)$, $\mathbf{i} = \sqrt{-1}$. By the Fourier transform of $\sigma_{ZY_1Y_2,j}(u, v, \tau)$, we readily obtain the generalized cross-spectral density between $\{Z_t\}$ and $\{Y_{1t-j}, Y_{2t-j}, j > 0\}$:

$$f_{ZY_1Y_2}(\omega, u, v, \tau) \equiv \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma_{ZY_1Y_2,j}(u, v, \tau) e^{-\mathbf{i}j\omega}, \quad \omega \in [-\pi, \pi] \tag{18}$$

Like $\sigma_{ZY}(u, v)$ and $\sigma_{ZZ}(u, v)$, because $\sigma_{ZY_1Y_2}(u, v, \tau) = 0$ for all $u, v, \tau \in (-\infty, \infty)$ if and only if $\{Z_t\}$ and $\{Y_{1t-j}, Y_{2t-j}\}$ are mutually independent, $\sigma_{ZY_1Y_2}(u, v, \tau)$ can capture any type of pairwise cross-dependence between $\{Z_t\}$ and $\{Y_{1t-j}, Y_{2t-j}\}$, and so is $f_{ZY_1Y_2}(\omega, u, v, \tau)$. As a result, we can use $f_{ZY_1Y_2}(\omega, u, v, \tau)$ to explore how Z_t depends on the entire past history of two currency returns $\{Y_{1t-j}, Y_{2t-j}, j > 0\}$.

When $E|Z_t|^{2m} < \infty$ and $E(|Y_{1t}|^{2l} + |Y_{2t}|^{2l}) < \infty$, we can introduce the generalized cross-spectral density derivative between $\{Z_t\}$ and $\{Y_{1t-j}, Y_{2t-j}, j > 0\}$ by defining

$$f^{(0,m,l,l)}_{ZY_1Y_2}(\omega, u, v, \tau) \equiv \frac{\partial^{m+2l}}{\partial u^m \partial v^l \partial \tau^l} f_{ZY_1Y_2}(\omega, u, v, \tau) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \sigma^{(m,l,l)}_{ZY_1Y_2,j}(u, v, \tau) e^{-\mathbf{i}j\omega}, \quad m, l \geq 0 \tag{19}$$

As before, our test statistics for the direction of joint changes will be based on comparison via the quadratic form between two cross-spectral derivative estimators $\hat{f}^{(0,1,l,l)}_{ZY_1Y_2}(\omega, u, v, \tau)$ and $\hat{f}^{(0,1,l,l)}_{ZY_1Y_2,0}(\omega, u, v, \tau)$, where the latter is implied by the null hypothesis $\mathbb{H}_0$ of no directional predictability:

$$\hat{Q}(1, l, l) = \pi T \int \int \int_{-\pi}^{\pi} |\hat{f}^{(0,1,l,l)}_{ZY_1Y_2}(\omega, 0, v, \tau) - \hat{f}^{(0,1,l,l)}_{ZY_1Y_2,0}(\omega, 0, v, \tau)|^2 \mathrm{d}\omega \mathrm{d}W(v) \mathrm{d}W(\tau)$$

[18] For notational simplicity, we use the same notation Z for the direction indicator of joint changes in this section.

DOI: 10.1002/jae

$$= \sum_{j=1}^{T-1} k^2(j/p)(T-j) \int\int |\hat{\sigma}^{(1,l,l)}_{ZY_1Y_2,j}(0,v,\tau)|^2 \mathrm{d}W(v)\mathrm{d}W(\tau) \tag{20}$$

Accordingly, we have the test statistic

$$M_{ZY_1Y_2}(1,l,l) = \left[\hat{Q}(1,l,l) - \hat{C}_{ZY_1Y_2}(1,l,l)\sum_{j=1}^{T-1} k^2(j/p)\right] / [\hat{D}_{ZY_1Y_2}(1,l,l)]^{1/2} \tag{21}$$

where

$$\hat{C}_{ZY_1Y_2}(1,l,l) = \hat{\lambda}(c)[1-\hat{\lambda}(c)] \int |\hat{\sigma}^{(l,l)}_{Y_1Y_2,0}(v,-v)|^2 \mathrm{d}W(v)$$

$$\hat{D}_{ZY_1Y_2}(1,l,l) = 2\hat{\lambda}^2(c)[1-\hat{\lambda}(c)]^2 \sum_{j=1}^{T-2}\sum_{\tau=1}^{T-2} k^2(j/p)k^2(\tau/p) \int\int |\hat{\sigma}^{(l,l)}_{Y_1Y_2,j-\tau}(u,v)|^2 \mathrm{d}W(u)\mathrm{d}W(v)$$

and $\hat{\sigma}_{Y_1Y_2,j}(u,v) = \hat{\varphi}_{Y_1Y_2,j}(u,v) - \hat{\varphi}_{Y_1Y_2,j}(u,0)\hat{\varphi}_{Y_1Y_2,j}(0,v)$ is the empirical generalized autocovariance function of $\{Y_{1t}, Y_{2t}\}$, $\hat{\lambda}(c) = T^{-1}\sum_{t=1}^{T} Z_t(c)$ is the sample proportion for $\{Y_{1t} > c, Y_{2t} > c\}$. All the $M_{ZY_1Y_2}(1,l,l)$ tests have the same $N(0,1)$ limit distribution as $M_{ZY}(1,l)$.[19]

Once again, we conduct the stepwise testing procedure in a manner analogous to the previous case: we begin with a hypothesis test to check whether $E(Z_t|Y_{1t-|j|}, Y_{2t-|j|}) = E(Z_t)$, $\quad j = 0, \pm 1, \ldots$, using the omnibus test statistic $M_{ZY_1Y_2}(1,0,0)$. We then proceed to use the derivative tests $M_{ZY_1Y_2}(1,l,l)$, for $l = 1,2,3,4$ to search possible sources of directional predictability of joint changes. Finally, we will use the $M_{ZZ_{Y_1}Z_{Y_2}}(1,0,0)$ test to examine whether the directions of past returns can be used to predict the direction of future joint changes.

We further perform the analyses via $f_{ZY_1}(\omega,u,v)$ and $f_{ZY_2}(\omega,u,v)$, which will tell us whether the direction of joint changes in two currencies is predictable, using individual returns $\{Y_{1t-j}\}$ and $\{Y_{2t-j}\}$, respectively. Also, the same test procedures will be repeated for examining the direction of joint changes based on interest rate differentials, using two interest rate differential series $\{ID_{1t-j}, ID_{2t-j}\}$ jointly and individually. With these versatile test sets, we can better characterize the nature of directional predictability of joint changes in foreign exchange markets.

4. DATA

Daily foreign exchange spot rates in currency units per US dollar and daily foreign currency futures prices for the Australia dollar (AD), the Canadian dollar (CD), the British pound (BP), the Japanese yen (JY), the Swiss franc (SF) and the Deutschemark (DM) are employed to examine directional predictability of the foreign exchange market. Foreign exchange spot rates are noon buying rates in New York for cable transfers payable and available from the Board of Governors of the Federal Reserve System (www.federalreserve.gov). Futures prices for the same six currencies, denoted by an F-prefix on each symbol, are daily closing prices traded at the Chicago Mercantile

[19] The proof is a straightforward extension of that given in Hong and Chung (2006).

DOI: 10.1002/jae

Exchange (CME) and obtained from *Datastream*. We compute returns as the percent logarithmic difference

$$Y_t = 100 \ln(S_{t+1}/S_t),$$

where S_t is an exchange spot rate or futures price.[20]

To construct interest rate differentials $r_t - r_t^*$, we use the 3-month London InterBank Offered Rate (LIBOR) for the US dollar (USD) and all six currencies as the domestic risk-free interest rate r_t and the foreign risk-free interest rate r_t^*, respectively. Daily observations on the interest rates come, when available, from *Datastream*.[21] Table I reports descriptive statistics of the sample. The first two panels include some basic statistics for the returns on spot rates and futures prices, which have the same starting date, December 1 1987, but have different ending dates for DM. Upon the introduction of the euro and the irrevocably fixed conversion rates, the DM data stop after December 31 1998 and December 14 2001, respectively, for spot rates and future prices. Total observations in futures prices are slightly more than those in spot rates, due to different trading days in each market.

The sample means of returns are marginally different across currencies and markets (i.e., spot rates and futures prices), but they are all close to zero. CD is most stable for both spot and futures, with a standard deviation that is roughly half the size of other currencies. There is evidence of leptokurticity, but there is no clear evidence of negative skewness (particularly for FJY).[22]

The statistics for interest rate differentials, reported in the last panel in Table I, are computed over the same period to match the ending date of the returns in both spot and futures markets. In general, interest rate differentials have a sizeable non-zero sample mean: the mean interest rate differentials of AD, CD and BP (*vis-à-vis* USD) are negative, which implies risk-free interest rates for AD, CD and BP are, on average, higher than that for USD. In contrast, the mean interest rate differentials of JY, SF and DM (*vis-à-vis* USD) are positive (particularly for JY). Compared to the exchange rate changes, interest rate differentials are much smoother and less volatile. It remains, however, to see whether the relatively tranquil nature of interest rate differentials can be used to forecast the direction of foreign exchange returns. For interest rate differentials, there is evidence of negative skewness, but there is no clear evidence of excess kurtosis (except for AD).

5. EMPIRICAL EVIDENCE

5.1. Directional Predictability of Changes in a Single Currency

We now use the generalized cross-spectral (GCS) tests to examine directional predictability of individual currency returns and its possible sources. We first consider the following direction indicators:

$$Z_t^+(c) = \mathbf{1}(Y_t > c), \text{ and } Z_t^-(c) = \mathbf{1}(Y_t < -c)$$

[20] Note that our definition of returns may be nominal (rather than actual) values to study solely the direction of the changes in the underlying spot (or futures) price: relative rates of return on US dolloars comprise both (nominal) price changes and interest rate differentials.
[21] For the Canadian dolloar, we use the 3-month Treasury Bill rates.
[22] These stylized facts differ from those of the daily returns in stock markets. The returns in stock markets commonly exhibit leptokurtosis, fat tails and negative skewness (see, for example, Fama, 1965). For more discussion on the stylized facts and statistical properties of the daily returns from foreign exchange markets, we refer to Hsieh (1988) and de Vries (1994).

DOI: 10.1002/jae

Table I. Summary statistics for sample data

Symbols	Ending date	Obs.	Mean (%)	SD (%)	Skew.	Kurt.	$\widehat{r^1}(1)$	$\widehat{r^2}(1)$
Spot								
AD	2003/04/30	3875	−0.003	0.612	−0.285	8.487	0.012	0.209
CD	2003/04/30	3875	0.002	0.310	0.018	5.278	0.036	0.128
BP	2003/04/30	3875	−0.003	0.591	−0.265	5.597	0.060	0.142
JY	2003/04/30	3875	−0.003	0.708	−0.477	7.084	0.035	0.209
SF	2003/04/30	3875	0.000	0.721	−0.119	4.499	0.027	0.123
DM	1998/12/31	2787	0.001	0.668	0.038	4.778	0.037	0.152
Futures								
FAD	2003/04/30	3901	−0.003	0.640	−0.256	6.614	−0.010	0.060
FCD	2003/04/30	3901	−0.002	0.325	−0.145	5.391	0.002	0.145
FBP	2003/04/30	3901	−0.003	0.635	−0.220	6.548	0.000	0.078
FJY	2003/04/30	3901	0.003	0.758	0.664	10.451	−0.010	0.100
FSF	2003/04/30	3901	0.000	0.752	0.091	4.811	−0.005	0.097
FDM	2001/12/14	3557	−0.008	0.703	−0.057	5.256	−0.005	0.061
Interest rate differentials								
$r - r^*(AD)$	2003/04/30	3901	−0.023	0.025	−0.925	3.359	0.999	0.999
$r - r^*(CD)$	2003/04/30	3901	−0.008	0.019	−0.188	2.472	0.999	0.997
$r - r^*(BP)$	2003/04/30	3901	−0.024	0.022	−0.774	2.407	0.999	0.998
$r - r^*(JY)$	2003/04/30	3901	0.030	0.024	−0.423	1.866	1.000	0.999
$r - r^*(SF)$	2003/04/30	3901	0.015	0.027	−0.627	2.391	1.000	0.998
$r - r^*(DM)$	1998/12/31	2787	0.003	0.030	−0.655	2.113	0.999	0.999
	2001/12/14	3557	0.000	0.028	−0.883	2.603	0.999	0.999

Notes:

1. Starting date for all spots and futures is December 1 1987.
2. Obs., sample size (T); SD, standard deviation; Skew., skewness; Kurt., kurtosis.
3. $\widehat{r^1}(1)$ and $\widehat{r^2}(1)$ are the first-order sample autocorrelation in returns and squared returns, respectively.
4. r and r^* denote the domestic (US) and foreign risk-free interest rates, respectively.

for $c = 0, 0.5, 1,$ in units of the sample standard deviation of $\{Y_t\}$.[23] Here, two types of indicator function are designed to examine dynamic characteristics of directional movement in up and down markets,[24] while three threshold values are used to capture different magnitudes of changes in returns. In this paper, we mainly focus on pairwise cross-dependencies between $Z_t(c)$ and two key variables: past returns $\{Y_{t-j}\}$ and past interest rate differentials $\{ID_{t-j} = r_{t-j} - r^*_{t-j}\}$, where r_t is the domestic (US) risk-free interest rate and r^*_t is the foreign risk-free interest rate at time t. We further rescale interest rate differentials centered at 0 to synchronize the levels of interest rate differentials across different countries.

We first examine directional predictability using the past history of $\{Y_t\}$. Table II reports the test statistics $M_{ZY}(1, l)$ for $l = 0, 1, 2, 3, 4$ and $M_{ZZ}(1, 0)$ with the preliminary lag order $\overline{p} = 21$

[23] In this study, we do not consider c higher than one; the sample frequency that price changes are higher than one sample standard deviation of $\{Y_t\}$ is relatively low, and so this may reduce the statistical power of the test. The price limits in the futures market make the use of higher threshold values even more undesirable. Brennan (1986) and Kodres (1993), using a sign test, point out that price limits are more likely clustered in the same direction. Therefore, it may lead to spurious findings when we consider the stochastic behavior of directional movements of significantly higher changes.

[24] McQueen *et al.* (1996) find evidence of different autocorrelations in returns between up and down stock markets.

DOI: 10.1002/jae

and the Bartlett kernel.[25] Note, for comparison, that GCS tests are asymptotically one-sided $N(0, 1)$ tests and thus upper-tailed $N(0, 1)$ critical values should be used, which are 1.65 and 2.33 at the 5% and 1% significance levels, respectively.

The first top panel reports the omnibus $M_{ZY}(1, 0)$ statistic, checking whether the directions of each currency return is predictable using its own past returns $\{Y_{t-j}, j > 0\}$. For all individual currency returns in both spot and futures markets, there exists strong evidence of directional predictability. Except for FSF and FDM, the $M_{ZY}(1, 0)$ statistic value becomes larger as threshold c increases, suggesting that the directions of large returns are easier to predict than the directions of small returns using past returns. Comparing the spot and futures markets, we find that the directions of the returns in the futures market are generally easier to predict with zero threshold ($c = 0$). In contrast, when $c = 1$, the evidence is stronger for those in the spot market in most cases. Further, there is no clear evidence that the direction of negative returns is easier to predict than that of positive returns, using past returns. Among other things, the directions of AD, CD and BP in both spot and futures markets (respectively, FAD, FCD and FBP) are considerably easier to predict, especially with large thresholds ($c = 0.5, 1$).

The remaining panels in Table II examine possible sources of the documented directional predictability. We report the test statistics $M_{ZY}(1, l)$ for $l = 1, 2, 3, 4$ and $M_{ZZ}(1, 0)$. These test statistics can tell us to what extent past returns contain useful information for predicting the direction of future returns. Specifically, each test statistic shows whether the direction of negative and positive returns (left to right) can be predicted using the level, volatility, skewness, kurtosis and the direction of past returns (top to bottom), respectively. As shown in $M_{ZY}(1, 1)$, the level of past returns $Y_{t-|j|}$ has not been shown to be very useful in predicting the directions of individual currency returns, because no clear pattern of statistical significance emerges for the $M_{ZY}(1, 1)$ test. In contrast, $M_{ZY}(1, 2)$ shows strong evidence that past volatility is a valuable source of information about directional predictability of individual currency returns, particularly with large thresholds ($c = 0.5, 1$). Like $M_{ZY}(1, 0)$, the test statistic $M_{ZY}(1, 2)$ is monotonically increasing in threshold level c, except for the direction of positive changes in FSF. Moreover, using past volatility, it is generally easier to predict the direction of negative returns than that of positive returns, and the directions of the returns in the spot market than those in the futures market.

Next, $M_{ZY}(1, 3)$ and $M_{ZY}(1, 4)$ display patterns similar to $M_{ZY}(1, 2)$, and these similarities are much clearer for the statistic $M_{ZY}(1, 4)$. There is generally consistent evidence that the direction of large returns ($c = 0.5, 1$) is predictable using past skewness and kurtosis. Greater directional predictability is found in the spot market than in the futures market. However, unlike $M_{ZY}(1, 2)$, there seems no clear evidence that the direction of negative returns is easier to predict than that of positive returns using past skewness and kurtosis of individual currency returns.

Finally, like $M_{ZY}(1, 0)$, the $M_{ZZ}(1, 0)$ test indicates that the directions of future individual currency returns are predictable using the directions of past individual currency returns, and become more predictable with larger thresholds. It is also easier to predict the directions of the returns in spot rates than in futures prices with large thresholds ($c = 0.5, 1$). The $M_{ZZ}(1, 0)$ test further suggests that the direction of negative returns is easier to predict than that of positive returns, using the directions of past returns.

In light of the above results, nonlinear models can be more useful in predicting the foreign exchange dynamics than linear regression models. For example, the significance of the $M_{ZZ}(1, 0)$

[25] For robust results, we also use preliminary lag orders $\overline{p}$ from 11 to 51. The results are very similar, and for reasons of space we only report the results with $\overline{p} = 21$.

DOI: 10.1002/jae

Table II. GCS test statistics for changes in single currency spot and futures ($\overline{p} = 21$): using past returns

	Positive direction			Negative direction		
Currency	$c = 0$	$c = 0.5$	$c = 1.0$	$c = 0$	$c = 0.5$	$c = 1.0$
$M_{ZY}(1, 0)$						
AD	4.93	10.84	15.48	4.96	9.73	16.52
CD	1.80	10.45	10.78	1.22	8.23	17.56
BP	−0.38	6.37	13.97	−0.10	17.47	22.68
JY	0.26	3.05	7.23	0.60	7.39	12.18
SF	1.72	4.10	6.43	1.82	1.90	4.23
DM	−0.16	8.46	13.58	−0.04	1.64	8.41
FAD	6.20	11.22	10.70	5.74	9.66	12.76
FCD	0.39	10.13	13.67	0.01	8.03	8.09
FBP	2.61	6.19	9.95	3.72	15.54	19.38
FJY	0.90	6.20	9.13	0.17	7.97	11.13
FSF	5.11	0.13	3.69	5.51	3.69	4.08
FDM	4.03	0.18	1.29	4.79	4.44	3.39
$M_{ZY}(1, 1)$						
AD	3.69	3.15	2.12	4.21	2.04	3.75
CD	2.07	1.31	2.14	1.86	2.20	0.74
BP	−0.13	1.88	5.48	0.10	3.00	8.12
JY	0.42	−0.02	1.11	0.50	2.15	7.20
SF	0.92	1.43	0.03	1.20	1.23	3.15
DM	−0.56	2.45	0.03	−0.09	0.58	0.82
FAD	7.89	5.04	3.80	5.40	1.60	0.08
FCD	0.42	1.15	0.71	−0.81	0.35	0.55
FBP	2.23	2.31	1.07	1.59	0.46	3.08
FJY	1.71	0.96	4.58	1.22	2.63	5.38
FSF	6.24	−0.71	3.54	6.47	5.17	0.64
FDM	2.76	−0.70	−0.40	3.62	1.68	−0.63
$M_{ZY}(1, 2)$						
AD	0.34	6.36	14.68	0.31	7.98	15.28
CD	−0.06	9.30	16.32	−0.54	9.78	30.76
BP	0.69	10.26	25.90	0.92	27.60	46.19
JY	−1.34	8.40	21.71	−1.34	7.87	26.11
SF	1.21	3.84	16.60	1.26	8.52	12.94
DM	0.58	8.62	28.84	−0.10	7.31	22.00
FAD	−1.09	4.60	12.14	−0.66	7.21	13.43
FCD	−0.98	15.81	21.59	−0.54	7.46	9.17
FBP	1.24	7.18	15.54	1.93	20.51	36.94
FJY	−0.54	6.25	15.81	−0.39	7.79	18.34
FSF	0.12	3.00	1.47	0.15	2.42	12.24
FDM	−0.28	1.97	2.06	−0.04	1.96	6.57
$M_{ZY}(1, 3)$						
AD	−0.21	1.33	3.41	−0.29	−0.72	0.92
CD	0.13	−0.92	0.29	0.08	0.45	1.88
BP	2.79	2.08	7.40	2.68	7.04	18.03
JY	−0.41	0.43	4.01	−0.37	1.61	9.42
SF	1.39	3.45	6.78	1.36	0.99	4.18
DM	1.03	3.48	3.95	1.50	0.79	2.16
FAD	1.32	0.25	−1.01	1.14	2.39	2.45
FCD	−1.42	−0.77	−0.01	−1.50	−1.31	−0.09
FBP	−0.33	−0.28	1.82	−0.36	0.91	2.11
FJY	−0.62	0.38	5.83	−0.57	−0.03	3.04
FSF	2.61	0.13	0.85	2.64	2.70	1.45
FDM	0.15	−0.28	−0.21	0.32	0.09	1.24

DOI: 10.1002/jae

Table II. (*Continued*)

Currency	Positive direction $c = 0$	Positive direction $c = 0.5$	Positive direction $c = 1.0$	Negative direction $c = 0$	Negative direction $c = 0.5$	Negative direction $c = 1.0$
$M_{ZY}(1, 4)$						
AD	1.47	2.74	7.04	1.35	4.84	7.43
CD	−1.19	1.71	5.32	−1.28	1.52	8.86
BP	0.68	2.39	8.37	0.96	12.21	24.22
JY	−0.13	1.03	7.40	−0.07	3.77	16.74
SF	0.53	0.46	8.82	0.59	5.71	9.13
DM	0.51	2.80	14.76	−0.02	4.44	13.58
FAD	−0.53	0.32	5.73	−0.45	1.31	5.03
FCD	−1.32	6.64	9.37	−1.08	1.94	2.97
FBP	0.27	1.69	3.35	0.62	6.58	12.90
FJY	−0.24	2.46	8.69	−0.35	0.43	3.41
FSF	0.26	0.57	−0.56	0.53	1.05	7.25
FDM	−0.28	−0.15	−0.41	−0.31	1.29	2.16
$M_{ZZ}(1, 0)$						
AD	1.65	2.50	0.42	1.98	4.69	13.40
CD	1.92	10.09	9.49	1.52	0.39	9.84
BP	−1.10	0.21	6.11	−1.03	8.08	22.66
JY	−0.63	2.51	5.54	−0.47	7.06	13.32
SF	1.82	−1.07	5.60	1.88	1.33	2.38
DM	−1.16	0.04	7.89	−0.73	0.62	6.74
FAD	5.56	2.21	1.44	3.80	2.02	10.53
FCD	−0.46	1.03	5.16	−1.03	4.67	3.20
FBP	0.29	0.88	2.04	0.03	7.56	18.28
FJY	0.50	5.45	8.58	0.24	2.68	3.84
FSF	2.61	−0.24	3.71	3.65	2.98	2.59
FDM	1.76	−0.03	2.06	2.95	2.02	2.57

Notes:

1. GCS tests are asymptotically one-sided $N(0,1)$ tests and thus upper-tailed asymptotic critical values may also be used, which are 1.65 and 2.33 at the 5% and 1% levels, respectively. $M(1,l)$ represents test statistics on the martingale test, serial correlation test, ARCH-in-mean test, skewness-in-mean test and kurtosis-in-mean test for $l = 0, \ldots 4$, respectively.
2. Currency returns are defined by $100 \ln(S_t/S_{t-1})$ where S_t is an exchange spot rate or futures price.
3. A preliminary bandwidth, $\overline{p}$ is crucial to run GCS tests. We have computed GCS test statistics for $\overline{p} = 11, \ldots, 50$, but reported only for the value of $\overline{p} = 21$ to save space.
4. A threshold value c is introduced to forecast bigger changes. A higher threshold value of c implies a bigger change in rate or price.

test suggests that the past own directions are useful in predicting future directions of exchange rate changes. This might be due to directional clustering, implying that an autologistic model of direction indicators may have some predictive ability for future directions. Nevertheless, the significance of separate inference tests $M_{ZY}(1, l)$ does not necessarily imply that a simple polynomial model in $\{Y_{t-j}\}$ will forecast the direction of exchange rate changes well, particularly in an out-of-sample context (see Hong and Lee, 2006, for an out-of-sample forecasting exercise for foreign exchange rates). A high-order polynomial model may not be robust to outliers in a time series context, and foreign exchange returns may have a more subtle nonlinear dynamics, although the powers of lagged variable Y_{t-j} have predictable ability. For example, a significant

DOI: 10.1002/jae

directional dependence on Y_{t-j}^2 may be due to a bilinear or nonlinear moving average-type structure. Obviously, a comprehensive investigation of modeling and forecasting the nonlinear dynamics in foreign exchange rates is needed, but this is beyond the scope of the present paper.

We now turn to examining whether directional predictability of individual currency returns can be explained by interest rate differentials. Table III reports the test statistics $M_{ZID}(1, l)$ for $l = 0, 1, 2, 3, 4$ and $M_{ZZ_{ID}}(1, 0)$. The omnibus test $M_{ZID}(1, 0)$ checks whether interest rate differentials can be used to forecast the directions of individual currency returns, and various derivative tests $M_{ZID}(1, l)$ for $l = 1, 2, 3, 4$ examine specific types of cross-dependence between Z_t and $\{(ID_{t-j})^l, j > 0\}$. Finally, the $M_{ZZ_{ID}}(1, 0)$ statistic checks whether $E(Z_t|Z_{ID,t-j}) = E(Z_t)$ for all $j > 0$; namely it checks whether the direction of past interest rate differentials can be used to predict the direction of future returns in foreign exchange markets. As indicated in $M_{ZID}(1, 0)$, there exists strong evidence of directional predictability using interest rate differentials, except for the positive direction of FJY and the negative direction of JY. The $M_{ZID}(1, 0)$ test also suggests that the directions of the returns with large thresholds ($c = 0.5, 1$) are much easier to predict than those with zero threshold using interest rate differentials, although the value of $M_{ZID}(1, 0)$ is not monotonically increasing in threshold c. These results provide considerable empirical support for the idea that interest rate differentials are a useful predictor for the directions of future foreign exchange rate changes.

Next, $M_{ZID}(1, 1)$ shows strong evidence that the direction of individual currency returns is predictable using the level of interest rate differentials. Interestingly, in many cases the descriptive pattern of the statistical significance in the $M_{ZID}(1, 1)$ test closely resembles that in the $M_{ZID}(1, 0)$ test. For example, the values of $M_{ZID}(1, 0)$ and $M_{ZID}(1, 1)$ for AD and FAD exhibit a $\cap$-shape function of c for the negative directions. On the other hand, those of FCD exhibit a $\cup$-shape function of c for positive directions, and are monotonically decreasing in threshold c for negative directions. Since this pattern similarity associated with $M_{ZID}(1, 0)$ is not found for the remaining GCS tests, it appears that a deriving source for directional predictability using interest rate differentials may be the time-varying conditional mean of interest rate differentials. This is consistent with Lothian and Wu's (2003) finding that the level of interest rate differentials plays an important role in explaining predictability of exchange rate movements. They point out that large interest rate differentials have much stronger forecasting power of foreign exchange rates than small interest rate differentials (see also Flood and Rose, 2002; Huisman *et al.*, 1998).

Likewise, $M_{ZID}(1, 2)$ indicates that, except for JY and FJY, the direction of individual currency returns is predictable using past volatility of interest rate differentials. However, the evidence is not strong and the overall statistical significance is much weaker than that for the $M_{ZY}(1, 2)$ test—we have seen that the past volatility of the returns is most helpful in predicting the direction of future returns. Taken together, these findings suggest that the smooth and symmetric nature of the volatility of interest rate differentials may result in weaker impact on directional predictability than the volatility of individual currency returns.

Finally, $M_{ZID}(1, 3)$ and $M_{ZID}(1, 4)$ show limited evidence of directional predictability from skewness and kurtosis of past interest rate differentials. In fact, there are many cases where neither skewness nor kurtosis of past interest rate differentials is useful in predicting the direction of individual currency returns (e.g., AD in both spot and futures markets). On the other hand, $M_{ZZ_{ID}}(1, 0)$ shows strong evidence that the direction of past interest rate differentials can be used to predict the direction of future individual currency returns. When compared to $M_{ZZ}(1, 0)$,

DOI: 10.1002/jae

Table III. GCS test statistics for changes in single currency spot and futures ($\overline{p} = 21$): using interest rate differentials

	Positive direction			Negative direction		
Currency	$c = 0$	$c = 0.5$	$c = 1.0$	$c = 0$	$c = 0.5$	$c = 1.0$
$M_{ZID}(1, 0)$						
AD	6.41	3.71	7.14	7.01	21.49	15.65
CD	7.00	7.93	4.23	7.02	0.74	6.76
BP	1.29	24.69	32.28	1.13	6.64	26.84
JY	1.36	3.78	15.39	0.08	−0.75	0.23
SF	4.24	2.69	4.34	3.70	9.09	13.30
DM	0.65	3.58	10.51	0.51	6.28	11.84
FAD	3.21	2.49	2.68	9.04	15.25	14.90
FCD	10.34	1.79	8.29	19.04	7.80	5.73
FBP	0.02	24.01	34.17	2.53	13.11	25.33
FJY	1.92	−0.58	0.83	1.99	11.92	14.31
FSF	3.07	9.63	7.83	5.79	1.51	4.37
FDM	3.61	10.93	5.01	2.02	1.88	3.18
$M_{ZID}(1, 1)$						
AD	3.04	−0.06	0.33	3.01	9.98	2.37
CD	7.05	4.73	1.71	7.08	0.00	−0.56
BP	1.55	25.46	26.40	1.18	2.93	23.73
JY	1.58	3.73	13.76	0.14	−0.64	−0.21
SF	4.38	−0.03	3.45	4.12	13.38	19.62
DM	0.54	2.11	9.16	0.74	7.25	13.51
FAD	2.69	1.49	−0.70	5.98	6.29	2.48
FCD	10.77	1.35	1.97	19.52	8.22	4.25
FBP	0.77	23.63	29.76	3.91	8.58	20.55
FJY	1.48	−0.63	−0.53	1.08	11.38	12.39
FSF	2.01	13.63	12.90	4.59	−0.37	3.87
FDM	4.55	12.93	6.96	2.72	0.88	2.16
$M_{ZID}(1, 2)$						
AD	−0.21	2.35	3.11	0.33	2.11	5.92
CD	0.36	2.11	2.35	0.48	−0.24	5.29
BP	3.24	12.16	7.41	3.17	−0.47	8.44
JY	−0.34	−0.71	0.80	−0.66	−0.21	−0.35
SF	−0.32	3.62	7.41	−0.06	4.20	7.00
DM	−0.67	1.83	8.35	−0.69	−0.21	5.31
FAD	−0.70	3.34	2.45	−0.69	2.08	5.43
FCD	1.12	0.01	6.85	5.23	2.31	1.18
FBP	0.20	10.05	10.63	3.33	0.30	5.76
FJY	−0.70	−0.29	−0.60	−0.60	−0.34	0.37
FSF	−0.70	3.91	6.37	−0.68	2.59	6.67
FDM	0.28	2.07	2.35	0.04	2.38	3.10
$M_{ZID}(1, 3)$						
AD	−0.70	−0.27	−0.32	−0.69	−0.31	−0.69
CD	3.48	0.83	−0.15	3.59	1.53	0.26
BP	3.63	18.74	10.38	3.29	−0.58	12.58
JY	0.54	1.57	5.82	−0.46	−0.71	−0.61
SF	2.92	0.60	5.75	3.28	13.10	17.05
DM	0.63	0.59	6.96	0.94	4.87	10.83
FAD	−0.13	1.58	−0.01	0.02	−0.45	−0.69
FCD	6.35	1.96	−0.28	11.89	5.57	1.51
FBP	1.43	15.20	14.43	6.12	0.94	8.22
FJY	−0.15	−0.69	−0.36	−0.51	5.24	4.43
FSF	1.27	12.92	15.19	2.17	0.45	4.55
FDM	2.70	8.26	5.82	1.69	0.67	1.51

DOI: 10.1002/jae

Table III. (*Continued*)

Currency	Positive direction			Negative direction		
	$c = 0$	$c = 0.5$	$c = 1.0$	$c = 0$	$c = 0.5$	$c = 1.0$
$M_{ZID}(1, 4)$						
AD	−0.26	−0.26	0.68	0.17	−0.39	0.38
CD	1.13	1.52	0.94	1.37	−0.48	0.66
BP	4.10	13.72	5.95	3.84	−0.52	8.37
JY	0.19	−0.37	1.69	−0.51	−0.11	0.46
SF	1.87	0.07	2.82	2.51	9.11	9.00
DM	−0.16	0.27	6.38	0.23	1.52	5.85
FAD	−0.64	1.41	0.36	−0.68	−0.43	0.41
FCD	2.83	−0.68	2.12	5.74	1.22	−0.29
FBP	1.07	11.26	9.60	4.82	−0.04	4.64
FJY	−0.53	−0.16	−0.65	−0.71	0.92	1.16
FSF	0.58	9.04	11.24	0.97	0.09	2.30
FDM	1.26	4.52	3.66	0.89	0.85	1.49
$M_{ZZ_{ID}}(1, 0)$						
AD	4.53	0.94	6.63	4.59	4.80	1.01
CD	8.96	3.12	−0.43	9.13	0.38	4.81
BP	0.33	15.52	1.03	−0.05	5.56	18.09
JY	0.57	9.77	−0.24	−0.45	−0.71	−0.33
SF	4.70	−0.54	−0.67	4.31	5.27	11.57
DM	−0.17	−0.26	−0.58	−0.07	2.51	15.42
FAD	1.80	−0.68	1.89	5.78	3.22	1.06
FCD	13.85	2.77	0.48	20.11	10.58	8.13
FBP	0.42	16.38	1.99	0.96	11.50	16.06
FJY	2.53	−0.67	2.21	2.40	6.36	4.27
FSF	2.89	13.62	1.88	5.76	1.60	15.25
FDM	4.61	20.00	0.97	3.47	2.86	4.23

Notes:

1. GCS tests are asymptotically one-sided $N(0,1)$ tests and thus upper-tailed asymptotic critical values may also be used, which are 1.65 and 2.33 at the 5% and 1% levels, respectively. $M(1, l)$ represents test statistics on the martingale test, serial correlation test, ARCH-in-mean test, skewness-in-mean test and kurtosis-in-mean test for $l = 0, \ldots 4$, respectively.
2. Interest rate differentials are defined by $r_t - r_t^*$ where r_t is the domestic (US) risk-free interest rate and r_t^* is the foreign risk-free interest rate.
3. A preliminary bandwidth $\overline{p}$ is crucial to run GCS tests. We have computed GCS test statistics for $\overline{p} = 11, \ldots, 50$, but reported only for the value of $\overline{p} = 21$ to save space.
4. A threshold value c is introduced to forecast bigger changes. A higher threshold value of c implies a bigger change in rate or price.

the directions of past interest rate differentials are more useful to predict the directions of the returns with zero threshold. Such differences are, however, attenuated with large thresholds ($c = 0.5, 1$).

In summary, the GCS tests $M_{ZY}(1, 0)$ and $M_{ZID}(1, 0)$ show that the directions of the individual returns in spot and futures foreign exchange markets with any threshold are predictable using past history of both returns and interest rate differentials. Moreover, this evidence is generally stronger for greater movements ($c = 0.5, 1$). Our generalized cross-spectral derivative tests show that the level, volatility, skewness, kurtosis and direction of past returns and interest rate differentials are more or less useful in predicting the direction of individual currency returns. In particular, based on past returns, although the generally insignificant statistic $M_{ZY}(1, 1)$ indicates a weak predictive power of conditional mean dynamics for the direction of future returns, we can see from $M_{ZY}(1, l)$ for $l = 2, 3, 4$ and $M_{ZZ}(1, 0)$ that strong dependencies derived from higher order conditional moments and the directions of past returns can attribute to the documented directional predictability. Furthermore, our GCS test results based on interest rate differentials suggest that the conditional mean dynamics of interest rate differentials contribute significantly to directional predictability, which provides an important policy implication—the monetary authorities can have substantial influence on the foreign exchange markets as they can affect the direction of future foreign exchange rates through the domestic (foreign) currency and/or the domestic interest rate. This monetary policy may be more effective with changes in the volatility of foreign exchange returns and/or the level of interest rate differentials.

5.2. Directional Predictability of Joint Changes in Two Currencies

We now examine directional predictability of returns co-movements in foreign exchange rate markets. Specifically, we are interested in the direction of joint changes in two currencies within each spot market and each futures market.[26] Consider individual returns $\{Y_{kt}\}$, $k = 1, 2$, where the subscript k denotes currency k. A new direction indicator of joint changes is then defined as follow:

$$Z_t^+(c) = \mathbf{1}(Y_{1t} > c_1, Y_{2t} > c_2), \qquad c = (c_1, c_2)$$
$$Z_t^-(c) = \mathbf{1}(Y_{1t} < -c_1, Y_{2t} < -c_2), \qquad c = (c_1, c_2)$$

for $c_k = 0, 0.5, 1$, in units of the sample standard deviation of $\{Y_{kt}\}$, $k = 1, 2$. As in the previous section, $Z_t^+(c)$ and $Z_t^-(c)$ can detect upward and downward market comovements, respectively. Further, with nonzero thresholds (i.e., $c_k = 0.5, 1$), these indicators are able to detect greater co-movements between two currency returns.

In applying the GCS tests to directional predictability of joint changes, we use twofold tests: (i) a test of directional predictability using the past returns of two currencies, checking whether $E(Z_t|Y_{1t-j}, Y_{2t-j}) = E(Z_t)$ for all $j > 0$; (ii) a test of directional predictability using past individual returns of each currency, checking whether $E(Z_t|Y_{kt-j}) = E(Z_t)$ for all $j > 0$, and for $k = 1, 2$. Naturally, the latter consists of two sets of GCS tests on the direction of changes in a single currency. Similar to Section 5.1, each of these GCS tests will be conducted with past currency returns and interest rate differentials.

We first report the GCS test results based on past returns in Table IV. For reasons of space, we only present the GCS test statistics for the direction of joint negative changes in the spot market. Overall, the patterns for the direction of joint positive changes are rather similar to those of joint negative changes, though less significant at times. Likewise, the results for the futures market are largely similar to those for the spot market, unless otherwise noted.[27]

Table IV consists of three sections: the first section provides the GCS test statistics using past returns of two currencies jointly (hereafter denoted as 'joint returns'), while the remaining

[26] One may be also interested in the joint changes between spot and futures markets.
[27] All (unreported) results are available upon request from the authors.

DOI: 10.1002/jae

Table IV. GCS test statistics for negative joint changes in two currency spot rates ($\overline{p} = 21$): using past returns

Cc1	Cc2	Joint returns				Returns of Cc 1				of Cc 2		
			$c = 0$	$c = 0.5$	$c = 1$		$c = 0$	$c = 0.5$	$c = 1$	$c = 0$	$c = 0.5$	$c = 1$
AD	CD	$M_{ZY_1Y_2}(1, 0, 0)$	0.87	1.96	4.69	$M_{ZY_k}(1, 0)$	2.67	4.86	6.69	1.60	10.83	7.37
		$M_{ZY_1Y_2}(1, 1, 1)$	0.76	−0.55	2.70	$M_{ZY_k}(1, 1)$	1.22	1.72	−0.20	2.61	2.50	−0.37
		$M_{ZY_1Y_2}(1, 2, 2)$	−0.17	1.35	11.76	$M_{ZY_k}(1, 2)$	0.07	−0.41	2.06	−0.03	12.15	16.84
		$M_{ZY_1Y_2}(1, 3, 3)$	−0.76	1.92	12.38	$M_{ZY_k}(1, 3)$	−0.86	−0.56	−0.05	0.16	2.46	1.60
		$M_{ZY_1Y_2}(1, 4, 4)$	−0.88	1.94	12.14	$M_{ZY_k}(1, 4)$	0.95	−0.80	−0.50	−0.37	5.09	6.09
		$M_{ZZ_1Z_2}(1, 0, 0)$	0.32	−0.86	8.80	$M_{ZZ_k}(1, 0)$	1.23	2.92	3.40	1.44	3.94	3.51
AD	BP	$M_{ZY_1Y_2}(1, 0, 0)$	1.00	8.36	4.14	$M_{ZY_k}(1, 0)$	3.44	4.39	3.90	−1.35	2.97	2.85
		$M_{ZY_1Y_2}(1, 1, 1)$	−0.64	4.73	9.25	$M_{ZY_k}(1, 1)$	2.95	0.63	0.18	−0.88	−0.21	0.95
		$M_{ZY_1Y_2}(1, 2, 2)$	−1.17	3.32	12.17	$M_{ZY_k}(1, 2)$	0.02	0.13	4.05	−0.81	2.68	4.50
		$M_{ZY_1Y_2}(1, 3, 3)$	−0.60	0.03	8.46	$M_{ZY_k}(1, 3)$	0.07	−0.32	−0.36	0.16	0.88	0.88
		$M_{ZY_1Y_2}(1, 4, 4)$	−0.78	−0.35	7.11	$M_{ZY_k}(1, 4)$	0.30	−0.53	0.91	−1.12	−0.45	0.87
		$M_{ZZ_1Z_2}(1, 0, 0)$	0.49	2.78	3.37	$M_{ZZ_k}(1, 0)$	1.84	1.53	−0.72	−1.16	0.34	−0.64
AD	JY	$M_{ZY_1Y_2}(1, 0, 0)$	2.25	7.64	11.38	$M_{ZY_k}(1, 0)$	0.84	6.36	7.59	1.00	3.59	7.22
		$M_{ZY_1Y_2}(1, 1, 1)$	4.40	5.54	8.99	$M_{ZY_k}(1, 1)$	0.85	0.69	1.74	2.95	2.93	−1.20
		$M_{ZY_1Y_2}(1, 2, 2)$	0.26	−1.32	−0.98	$M_{ZY_k}(1, 2)$	−0.43	3.09	4.30	−0.85	3.87	13.07
		$M_{ZY_1Y_2}(1, 3, 3)$	0.56	−1.37	−1.40	$M_{ZY_k}(1, 3)$	0.51	1.04	−0.90	0.02	0.53	0.18
		$M_{ZY_1Y_2}(1, 4, 4)$	0.66	−1.35	−1.44	$M_{ZY_k}(1, 4)$	−0.18	0.17	−1.70	−0.13	−0.77	2.19
		$M_{ZZ_1Z_2}(1, 0, 0)$	1.15	11.28	7.12	$M_{ZZ_k}(1, 0)$	0.76	1.69	1.40	0.14	−0.21	1.74
AD	SF	$M_{ZY_1Y_2}(1, 0, 0)$	2.36	5.84	6.68	$M_{ZY_k}(1, 0)$	0.98	6.01	8.60	2.03	0.45	1.05
		$M_{ZY_1Y_2}(1, 1, 1)$	7.26	15.38	12.05	$M_{ZY_k}(1, 1)$	−0.68	0.84	4.91	2.25	0.04	0.54
		$M_{ZY_1Y_2}(1, 2, 2)$	1.95	−0.40	1.83	$M_{ZY_k}(1, 2)$	−0.40	1.57	3.16	1.82	0.83	0.36
		$M_{ZY_1Y_2}(1, 3, 3)$	0.92	−1.34	−1.26	$M_{ZY_k}(1, 3)$	0.18	2.18	0.34	−0.21	0.39	0.04
		$M_{ZY_1Y_2}(1, 4, 4)$	0.56	−1.38	−1.43	$M_{ZY_k}(1, 4)$	0.37	0.84	−1.03	1.22	−0.56	−0.49
		$M_{ZZ_1Z_2}(1, 0, 0)$	0.83	11.00	11.17	$M_{ZZ_k}(1, 0)$	0.01	3.47	1.17	2.29	−0.49	0.89
AD	DM	$M_{ZY_1Y_2}(1, 0, 0)$	0.42	3.08	7.69	$M_{ZY_k}(1, 0)$	0.42	2.06	6.80	−0.40	0.03	4.24
		$M_{ZY_1Y_2}(1, 1, 1)$	3.09	12.12	18.86	$M_{ZY_k}(1, 1)$	−0.51	0.70	4.55	0.60	−0.42	2.18
		$M_{ZY_1Y_2}(1, 2, 2)$	2.42	2.09	8.02	$M_{ZY_k}(1, 2)$	0.66	2.96	2.36	0.69	4.05	3.07
		$M_{ZY_1Y_2}(1, 3, 3)$	2.33	0.62	6.15	$M_{ZY_k}(1, 3)$	0.93	3.61	0.48	0.41	3.89	1.53
		$M_{ZY_1Y_2}(1, 4, 4)$	2.21	−0.48	3.13	$M_{ZY_k}(1, 4)$	−0.15	0.90	−0.73	0.63	4.64	0.88
		$M_{ZZ_1Z_2}(1, 0, 0)$	−1.04	5.75	9.36	$M_{ZZ_k}(1, 0)$	−0.88	0.87	−0.57	0.60	−1.42	0.18
CD	BP	$M_{ZY_1Y_2}(1, 0, 0)$	0.16	2.67	2.53	$M_{ZY_k}(1, 0)$	2.18	3.06	3.87	−1.04	0.97	−0.08
		$M_{ZY_1Y_2}(1, 1, 1)$	2.18	1.00	2.58	$M_{ZY_k}(1, 1)$	1.31	3.40	1.55	0.61	0.93	2.47
		$M_{ZY_1Y_2}(1, 2, 2)$	−0.54	2.47	1.28	$M_{ZY_k}(1, 2)$	−1.24	1.40	4.04	−1.04	3.14	0.52
		$M_{ZY_1Y_2}(1, 3, 3)$	0.75	0.80	1.02	$M_{ZY_k}(1, 3)$	−1.34	1.26	1.05	2.75	0.84	4.30
		$M_{ZY_1Y_2}(1, 4, 4)$	−1.16	0.42	−0.22	$M_{ZY_k}(1, 4)$	−0.48	1.32	1.88	−1.30	0.26	0.15
		$M_{ZZ_1Z_2}(1, 0, 0)$	0.01	−0.97	1.67	$M_{ZZ_k}(1, 0)$	1.86	−0.73	1.78	−0.89	−0.26	1.67
CD	JY	$M_{ZY_1Y_2}(1, 0, 0)$	0.76	3.40	6.73	$M_{ZY_k}(1, 0)$	0.45	5.18	4.22	0.45	−0.08	5.42
		$M_{ZY_1Y_2}(1, 1, 1)$	0.56	1.94	3.90	$M_{ZY_k}(1, 1)$	1.58	2.53	1.23	0.77	−0.38	1.64
		$M_{ZY_1Y_2}(1, 2, 2)$	0.15	0.83	4.47	$M_{ZY_k}(1, 2)$	−0.63	4.28	9.20	−0.60	0.13	6.97
		$M_{ZY_1Y_2}(1, 3, 3)$	−0.55	0.70	−0.17	$M_{ZY_k}(1, 3)$	1.22	0.41	3.93	0.09	0.53	1.99
		$M_{ZY_1Y_2}(1, 4, 4)$	−0.27	0.29	0.09	$M_{ZY_k}(1, 4)$	−1.08	0.18	6.34	0.02	0.16	1.20
		$M_{ZZ_1Z_2}(1, 0, 0)$	−0.37	4.31	8.07	$M_{ZZ_k}(1, 0)$	0.40	2.45	2.03	−0.22	1.46	5.50
CD	SF	$M_{ZY_1Y_2}(1, 0, 0)$	1.49	4.81	7.06	$M_{ZY_k}(1, 0)$	−0.41	3.41	6.11	2.67	2.17	3.81
		$M_{ZY_1Y_2}(1, 1, 1)$	3.61	2.78	2.74	$M_{ZY_k}(1, 1)$	1.26	0.99	1.59	3.10	0.40	2.24
		$M_{ZY_1Y_2}(1, 2, 2)$	−0.42	−0.58	−0.45	$M_{ZY_k}(1, 2)$	−1.23	3.19	6.73	−0.32	4.14	5.85
		$M_{ZY_1Y_2}(1, 3, 3)$	0.01	−0.97	−1.38	$M_{ZY_k}(1, 3)$	0.00	0.01	0.59	0.96	−0.21	0.13
		$M_{ZY_1Y_2}(1, 4, 4)$	−0.65	−1.34	−1.44	$M_{ZY_k}(1, 4)$	−0.95	1.04	1.31	−1.01	−0.06	1.82
		$M_{ZZ_1Z_2}(1, 0, 0)$	0.56	3.04	1.42	$M_{ZZ_k}(1, 0)$	−0.10	−0.34	2.32	2.17	2.71	2.27
CD	DM	$M_{ZY_1Y_2}(1, 0, 0)$	0.56	2.02	7.85	$M_{ZY_k}(1, 0)$	−0.34	1.47	8.44	1.90	0.95	4.03
		$M_{ZY_1Y_2}(1, 1, 1)$	2.40	3.26	2.15	$M_{ZY_k}(1, 1)$	−0.33	2.40	3.16	3.05	−0.11	0.78
		$M_{ZY_1Y_2}(1, 2, 2)$	−0.62	0.53	4.15	$M_{ZY_k}(1, 2)$	−0.95	2.73	9.37	0.22	3.33	5.27
		$M_{ZY_1Y_2}(1, 3, 3)$	0.01	−0.60	−0.36	$M_{ZY_k}(1, 3)$	−0.48	2.95	0.89	1.68	1.40	−0.74

DOI: 10.1002/jae

Table IV. (*Continued*)

Cc1	Cc2	Joint returns	$c=0$	$c=0.5$	$c=1$	Returns of Cc 1	$c=0$	$c=0.5$	$c=1$	of Cc 2 $c=0$	$c=0.5$	$c=1$
		$M_{ZY_1Y_2}(1,4,4)$	−0.78	−1.33	−1.10	$M_{ZY_k}(1,4)$	−0.89	0.93	3.12	0.25	2.51	2.41
		$M_{ZZ_1Z_2}(1,0,0)$	1.07	0.96	1.59	$M_{ZZ_k}(1,0)$	−0.49	−0.79	−0.30	1.45	0.69	−0.14
BP	JY	$M_{ZY_1Y_2}(1,0,0)$	2.15	3.73	2.75	$M_{ZY_k}(1,0)$	0.25	4.34	3.75	1.00	1.07	1.83
		$M_{ZY_1Y_2}(1,1,1)$	7.05	15.84	13.00	$M_{ZY_k}(1,1)$	0.02	0.11	3.20	−0.26	−0.30	1.84
		$M_{ZY_1Y_2}(1,2,2)$	−0.01	5.00	5.27	$M_{ZY_k}(1,2)$	0.23	9.71	6.61	−0.47	0.98	8.27
		$M_{ZY_1Y_2}(1,3,3)$	−0.31	3.16	2.71	$M_{ZY_k}(1,3)$	0.64	1.74	3.36	0.38	0.02	7.00
		$M_{ZY_1Y_2}(1,4,4)$	−0.38	2.91	2.64	$M_{ZY_k}(1,4)$	−0.51	2.35	1.84	0.22	1.14	9.67
		$M_{ZZ_1Z_2}(1,0,0)$	1.04	3.99	5.43	$M_{ZZ_k}(1,0)$	−0.16	1.35	2.26	0.58	−0.53	1.25
BP	SF	$M_{ZY_1Y_2}(1,0,0)$	−0.16	3.96	7.60	$M_{ZY_k}(1,0)$	−0.11	4.62	8.79	−0.32	2.19	5.00
		$M_{ZY_1Y_2}(1,1,1)$	0.69	14.65	22.69	$M_{ZY_k}(1,1)$	0.13	0.93	3.12	−0.50	−0.11	1.96
		$M_{ZY_1Y_2}(1,2,2)$	−0.63	4.57	9.07	$M_{ZY_k}(1,2)$	−0.44	8.18	19.16	−0.02	6.18	9.40
		$M_{ZY_1Y_2}(1,3,3)$	−0.96	1.89	3.48	$M_{ZY_k}(1,3)$	2.09	0.87	2.60	1.91	0.77	1.66
		$M_{ZY_1Y_2}(1,4,4)$	−0.95	0.84	1.66	$M_{ZY_k}(1,4)$	−0.26	2.59	7.26	−0.18	2.28	3.32
		$M_{ZZ_1Z_2}(1,0,0)$	−0.58	7.38	8.03	$M_{ZZ_k}(1,0)$	−0.16	2.07	5.16	−0.07	2.00	1.96
BP	DM	$M_{ZY_1Y_2}(1,0,0)$	1.01	4.77	12.39	$M_{ZY_k}(1,0)$	0.16	5.56	13.46	0.69	3.81	9.48
		$M_{ZY_1Y_2}(1,1,1)$	0.48	18.11	25.82	$M_{ZY_k}(1,1)$	−0.53	1.66	2.83	−0.52	0.24	1.86
		$M_{ZY_1Y_2}(1,2,2)$	−0.96	7.12	10.10	$M_{ZY_k}(1,2)$	−0.75	9.81	21.84	0.14	10.88	15.31
		$M_{ZY_1Y_2}(1,3,3)$	−1.35	3.55	4.90	$M_{ZY_k}(1,3)$	1.84	2.34	4.41	1.88	2.76	5.03
		$M_{ZY_1Y_2}(1,4,4)$	−1.35	2.24	3.82	$M_{ZY_k}(1,4)$	−0.87	2.74	8.39	0.00	6.87	7.19
		$M_{ZZ_1Z_2}(1,0,0)$	−0.34	6.49	14.48	$M_{ZZ_k}(1,0)$	−0.31	2.83	8.60	−1.14	−0.21	6.83
JY	SF	$M_{ZY_1Y_2}(1,0,0)$	2.57	3.11	3.40	$M_{ZY_k}(1,0)$	1.33	2.44	3.41	1.72	3.19	4.54
		$M_{ZY_1Y_2}(1,1,1)$	6.50	17.45	11.42	$M_{ZY_k}(1,1)$	1.11	1.35	3.60	0.45	1.19	6.00
		$M_{ZY_1Y_2}(1,2,2)$	2.60	12.61	10.33	$M_{ZY_k}(1,2)$	−1.27	4.20	8.66	3.78	13.70	6.81
		$M_{ZY_1Y_2}(1,3,3)$	2.11	10.23	9.63	$M_{ZY_k}(1,3)$	−0.81	1.64	4.87	0.43	5.58	7.25
		$M_{ZY_1Y_2}(1,4,4)$	1.59	8.78	8.96	$M_{ZY_k}(1,4)$	−0.46	2.93	7.70	3.19	11.41	8.64
		$M_{ZZ_1Z_2}(1,0,0)$	1.38	5.24	4.71	$M_{ZZ_k}(1,0)$	0.42	1.24	1.98	1.97	0.82	3.87
JY	DM	$M_{ZY_1Y_2}(1,0,0)$	−0.11	3.62	3.06	$M_{ZY_k}(1,0)$	−0.36	2.13	2.99	0.22	4.42	4.06
		$M_{ZY_1Y_2}(1,1,1)$	3.93	7.55	4.88	$M_{ZY_k}(1,1)$	0.09	1.57	1.29	−0.54	2.57	2.17
		$M_{ZY_1Y_2}(1,2,2)$	1.46	4.06	3.37	$M_{ZY_k}(1,2)$	−0.63	3.13	4.59	2.85	9.45	3.57
		$M_{ZY_1Y_2}(1,3,3)$	0.85	1.97	1.52	$M_{ZY_k}(1,3)$	−0.86	1.34	−0.22	0.64	3.18	1.53
		$M_{ZY_1Y_2}(1,4,4)$	0.41	1.31	0.74	$M_{ZY_k}(1,4)$	−0.28	2.42	1.40	1.85	6.09	1.68
		$M_{ZZ_1Z_2}(1,0,0)$	0.39	4.34	1.76	$M_{ZZ_k}(1,0)$	−0.63	0.34	3.98	−1.06	3.80	−0.38
SF	DM	$M_{ZY_1Y_2}(1,0,0)$	0.26	1.05	3.92	$M_{ZY_k}(1,0)$	0.58	0.98	2.33	0.32	1.68	5.40
		$M_{ZY_1Y_2}(1,1,1)$	2.09	6.42	11.80	$M_{ZY_k}(1,1)$	−0.36	1.19	1.16	−0.68	0.37	1.60
		$M_{ZY_1Y_2}(1,2,2)$	1.65	3.72	7.92	$M_{ZY_k}(1,2)$	1.46	5.51	9.72	1.80	6.63	13.99
		$M_{ZY_1Y_2}(1,3,3)$	0.67	1.76	5.52	$M_{ZY_k}(1,3)$	2.16	2.86	2.00	0.54	1.51	2.63
		$M_{ZY_1Y_2}(1,4,4)$	0.22	0.93	4.47	$M_{ZY_k}(1,4)$	0.94	2.96	5.96	1.47	2.72	8.07
		$M_{ZZ_1Z_2}(1,0,0)$	0.21	2.04	3.23	$M_{ZZ_k}(1,0)$	0.31	0.62	3.27	−0.59	0.59	3.63

Notes:

1. Cc1, currency 1; Cc2, currency 2.
2. GCS tests are asymptotically one-sided $N(0,1)$ tests and thus upper-tailed asymptotic critical values may also be used, which are 1.65 and 2.33 at the 5% and 1% levels, respectively. $M(1,l)$ represents test statistics on the martingale test, serial correlation test, ARCH-in-mean test, skewness-in-mean test and kurtosis-in-mean test for $l = 0, \ldots 4$, respectively.
3. The direction of joint negative changes is defined by $Z_t^-(c) = \mathbf{1}(Y_{1t} < -c_1) \cdot \mathbf{1}(Y_{2t} < -c_2)$, where return of currency k is $Y_{kt} = 100\ln(S_{kt}/S_{kt-1})$ for $k = 1, 2$.
4. A preliminary bandwidth $\overline{p}$ is crucial to run GCS tests. We have computed GCS test statistics for $\overline{p} = 11, \ldots, 50$, but reported only for the value of $\overline{p} = 21$ to save space.

DOI: 10.1002/jae

two sections list the GCS test statistics using past individual returns of each currency (hereafter, 'individual returns'). For each section, we have a total of 15 panels corresponding to 15 sample joint changes (obtained by combination of six different currencies). Subsequently, each panel contains the following GCS tests performed on three different thresholds ($c = 0, 0.5, 1$) respectively:[28] (i) the omnibus test that checks whether the direction of joint changes is predictable using past joint returns, denoted $M_{ZY_1Y_2}(1, 0, 0)$, and using past individual returns, denoted $M_{ZY_k}(1, 0)$, $k = 1, 2$; (ii) the derivative tests that examine whether directional predictability of joint changes can be explained by the level, volatility, skewness and kurtosis of joint returns, denoted $M_{ZY_1Y_2}(1, l, l)$ for $l = 1, 2, 3, 4$, and of individual returns, denoted $M_{ZY_k}(1, l)$ for $l = 1, 2, 3, 4$ and $k = 1, 2$; (iii) the tests that check whether the directions of past joint returns and past individual returns can be used to predict the direction of future joint changes, which are respectively denoted as $M_{ZZ_{Y_1}Z_{Y_2}}(1, 0, 0)$ and $M_{ZZ_{Y_k}}(1, 0)$ for $k = 1, 2$.

First, $M_{ZY_1Y_2}(1, 0, 0)$ shows that, although there is little evidence that the direction of joint negative changes with zero threshold is predictable using past joint returns, there exists strong evidence that the direction of large joint negative changes ($c = 0.5, 1$) is predictable using past joint returns of the two currencies. Likewise, $M_{ZY_1}(1, 0)$ and $M_{ZY_2}(1, 0)$ show equally strong evidence that past individual returns of each currency are useful in predicting the direction of large joint negative changes ($c = 0.5, 1$). Further, the values of these omnibus test statistics $M_{ZY_1Y_2}(1, 0, 0)$, $M_{ZY_1}(1, 0)$ and $M_{ZY_2}(1, 0)$ are generally monotonically increasing in threshold level c, implying that the direction of joint negative changes in the spot market becomes more easily predictable as we consider larger downside co-movements.

It is interesting to note that we have documented significant results whenever joint negative changes are formed by two underlying individual currency returns for which their directional predictability for single negative changes are quite strong.[29] Moreover, they can be predicted (and explained) equally by past joint returns and past individual returns. On the other hand, when only one currency has predictive power for the direction of joint negative changes, the GCS tests based on joint returns of two currencies show somewhat mixed results. Thus, we may argue that directional dependence induced by individual currency returns plays an important role in explaining directional predictability of joint changes.[30]

Turning to the remaining GCS tests in Table IV, we find that the sources of directional predictability of joint changes differ from what we have observed for those of single currency changes. More specifically, we can see from $M_{ZY_1Y_2}(1, l, l)$ for $l = 1, 2, 3, 4$ and $M_{ZZ_{Y_1}Z_{Y_2}}(1, 0, 0)$ that: (i) in general, the levels of joint returns are most useful in predicting the direction of future joint negative changes; (ii) the volatilities and directions of joint returns are very useful in predicting the direction of large joint negative changes ($c = 0.5, 1$); (iii) in the spot market, the skewness and kurtosis of joint returns are useful in predicting the direction of large joint negative changes ($c = 0.5, 1$).[31] Next, $M_{ZY_k}(1, l)$ for $l = 1, 2, 3, 4$ and $M_{ZZ_{Y_k}}(1, 0)$ of currency k, $k = 1, 2$, suggest that: (i) the volatility of past individual returns is most helpful in predicting the direction of joint negative changes (as we observed in the previous single currency study); (ii)

[28] For simplicity, subscript k is ignored in threshold c.
[29] We recall that, as shown in Table II, the negative directions of AD, CD, BP and JY in the spot and futures markets (FAD, FCD, FBP and FJY) are significantly predictable using their past own returns.
[30] This argument is also valid for the case of positive changes.
[31] This finding is not generally documented in the futures market.

DOI: 10.1002/jae

the level, skewness, kurtosis and direction of past individual returns are also useful sometimes, but are insignificant in many cases.[32]

For the remainder of this section we focus on interest rate differentials ID_t. For reasons of space, we only report the results for the directions of joint negative changes in the spot market in Table V.[33] As in to Table IV, the first section of Table V provides the GCS test statistics based on past interest rate differentials of two countries jointly (hereafter, 'joint interest rate differentials'), while the remaining two sections of Table V list the GCS test statistics based on past individual interest rate differentials of each currency (hereafter, 'individual interest rate differentials').

First, our GCS tests $M_{ZID_1ID_2}(1, 0, 0)$ and $M_{ZID_k}(1, 0)$ for $k = 1, 2$ strongly suggest that the directions of joint changes with any threshold can be predicted using past joint and individual interest rate differentials. There is also strong evidence that the directions of greater co-movements ($c = 0.5, 1$) are easier to predict. However, we find no clear descriptive pattern of their statistical significance.

Next, our remaining GCS tests based on interest rate differentials suggest that the level, volatility, skewness, kurtosis and direction of past joint and individual interest rate differentials are useful in predicting directional predictability of joint changes. For example, the directions of joint changes for the pairs BP&SF and BP&DM in both spot and futures markets (not shown here) are easily predictable and become more easily predictable with large threshold ($c = 0.5, 1$). Further, their directional predictability of joint changes can be well explained by the sources considered in this study.

To sum up, we observe that the directions of joint changes in both spot and futures markets are predictable, using joint and/or individual components of currency returns and interest rate differentials. These findings are more striking with greater co-movements ($c = 0.5, 1$). Individual components of dependencies induced by currency returns are indeed important in exploring the direction of joint changes. Documented directional predictability of joint changes can be explained by various sources. In particular, the level of joint returns and the volatility of past individual returns are very helpful in predicting the directions of joint changes. These results can provide valuable information for financial risk management and portfolio diversification, as our study offers a possible link among the co-movement of returns, correlation and variance. For instance, a diversified portfolio is typically constructed among assets with negative or low correlation to each other. And, given a similar degree of correlation, overall risk can be further reduced by selecting assets with low volatility. Hence, when building a diversified portfolio, it seems natural to prefer assets with low volatility and low correlation to assets with greater volatility and/or high correlation. Meanwhile, comparative analytics of our GCS test for joint changes can provide the basis for a choice between assets with low correlation and greater volatility, and assets with high correlation and low volatility. In this regard, our GCS tests for joint changes will be useful in developing an effective composition of a portfolio.

6. CONCLUSION

We have examined directional predictability in foreign exchange markets using a model-free statistical evaluation procedure. This method is developed to test whether the direction of the

[32] In general, the statistical significances of these GCS tests are modestly weaker for the futures market.
[33] We obtain similar results for the directions of joint positive changes, which are available upon request.

DOI: 10.1002/jae

Table V. GCS test statistics for negative joint changes in two currency spot rates ($\overline{p} = 21$): using interest rate differentials

Cc1	Cc2	Joint interest rate differentials				Interest rate differentials of Cc 1				of Cc 2		
			$c=0$	$c=0.5$	$c=1$		$c=0$	$c=0.5$	$c=1$	$c=0$	$c=0.5$	$c=1$
AD	CD	$M_{ZID_1ID_2}(1,0,0)$	6.61	1.63	0.30	$M_{ZID_k}(1,0)$	8.80	1.30	−0.59	6.88	1.94	0.73
		$M_{ZID_1ID_2}(1,1,1)$	−0.67	−0.30	−0.69	$M_{ZID_k}(1,1)$	6.84	−0.41	−0.52	10.35	−0.10	−0.31
		$M_{ZID_1ID_2}(1,2,2)$	−0.29	0.02	−0.69	$M_{ZID_k}(1,2)$	−0.15	0.67	−0.70	−0.58	0.13	−0.47
		$M_{ZID_1ID_2}(1,3,3)$	0.05	0.12	−0.69	$M_{ZID_k}(1,3)$	0.69	−0.58	−0.55	9.83	3.61	2.38
		$M_{ZID_1ID_2}(1,4,4)$	0.19	0.02	−0.67	$M_{ZID_k}(1,4)$	−0.33	−0.58	−0.60	−0.60	−0.61	−0.65
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	7.44	−0.60	−0.63	$M_{ZZ_{ID_k}}(1,0)$	10.26	−0.63	−0.62	6.31	1.84	−0.65
AD	BP	$M_{ZID_1ID_2}(1,0,0)$	6.62	12.90	6.12	$M_{ZID_k}(1,0)$	9.16	17.03	6.27	3.04	7.67	5.14
		$M_{ZID_1ID_2}(1,1,1)$	2.86	5.15	4.20	$M_{ZID_k}(1,1)$	9.83	15.72	6.45	2.93	4.62	2.24
		$M_{ZID_1ID_2}(1,2,2)$	2.95	2.68	1.01	$M_{ZID_k}(1,2)$	1.09	7.29	8.41	1.29	−0.55	−0.14
		$M_{ZID_1ID_2}(1,3,3)$	1.74	0.35	−0.40	$M_{ZID_k}(1,3)$	3.22	6.81	6.40	1.76	0.21	−0.50
		$M_{ZID_1ID_2}(1,4,4)$	0.87	−0.50	−0.71	$M_{ZID_k}(1,4)$	1.06	4.24	6.14	1.72	−0.26	−0.24
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	5.88	11.69	5.33	$M_{ZZ_{ID_k}}(1,0)$	9.35	18.46	9.38	3.65	2.75	0.61
AD	JY	$M_{ZID_1ID_2}(1,0,0)$	7.61	4.00	7.66	$M_{ZID_k}(1,0)$	11.46	4.75	8.93	1.35	1.54	5.37
		$M_{ZID_1ID_2}(1,1,1)$	−0.70	−0.19	0.23	$M_{ZID_k}(1,1)$	3.25	−0.13	0.47	1.77	−0.05	4.47
		$M_{ZID_1ID_2}(1,2,2)$	−0.54	−0.71	−0.63	$M_{ZID_k}(1,2)$	−0.68	0.77	6.25	−0.67	4.06	3.82
		$M_{ZID_1ID_2}(1,3,3)$	−0.47	−0.45	−0.72	$M_{ZID_k}(1,3)$	−0.64	−0.70	0.10	1.57	0.74	2.52
		$M_{ZID_1ID_2}(1,4,4)$	−0.66	−0.22	−0.21	$M_{ZID_k}(1,4)$	−0.39	−0.61	2.56	0.48	1.73	3.89
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	3.45	−0.67	−0.69	$M_{ZZ_{ID_k}}(1,0)$	15.52	4.05	−0.31	−0.38	1.89	3.01
AD	SF	$M_{ZID_1ID_2}(1,0,0)$	6.69	3.69	3.04	$M_{ZID_k}(1,0)$	11.59	6.04	3.65	1.33	1.33	2.36
		$M_{ZID_1ID_2}(1,1,1)$	1.08	0.46	−0.70	$M_{ZID_k}(1,1)$	6.71	4.81	2.47	0.56	−0.68	−0.69
		$M_{ZID_1ID_2}(1,2,2)$	−0.68	−0.70	−0.31	$M_{ZID_k}(1,2)$	−0.70	2.29	8.77	−0.56	4.33	3.95
		$M_{ZID_1ID_2}(1,3,3)$	−0.51	−0.41	−0.58	$M_{ZID_k}(1,3)$	−0.24	1.59	5.35	−0.63	2.47	−0.30
		$M_{ZID_1ID_2}(1,4,4)$	−0.72	−0.72	−0.43	$M_{ZID_k}(1,4)$	−0.70	0.99	6.57	−0.61	4.14	0.89
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	5.70	−0.42	−0.27	$M_{ZZ_{ID_k}}(1,0)$	15.80	3.93	3.09	1.32	0.05	1.09
AD	DM	$M_{ZID_1ID_2}(1,0,0)$	10.64	8.70	10.93	$M_{ZID_k}(1,0)$	15.22	14.77	15.75	1.24	−0.53	0.13
		$M_{ZID_1ID_2}(1,1,1)$	4.06	4.97	9.41	$M_{ZID_k}(1,1)$	12.19	12.43	15.52	0.20	−0.44	−0.14
		$M_{ZID_1ID_2}(1,2,2)$	−0.68	7.68	21.71	$M_{ZID_k}(1,2)$	−0.43	7.01	18.71	2.17	−0.59	−0.64
		$M_{ZID_1ID_2}(1,3,3)$	1.49	4.84	14.12	$M_{ZID_k}(1,3)$	2.48	6.50	15.51	−0.28	0.03	−0.61
		$M_{ZID_1ID_2}(1,4,4)$	−0.32	3.25	13.37	$M_{ZID_k}(1,4)$	0.01	5.76	15.69	1.33	−0.61	−0.70
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	5.40	−0.42	N/A	$M_{ZZ_{ID_k}}(1,0)$	19.52	17.26	16.34	0.71	−0.61	−0.69
CD	BP	$M_{ZID_1ID_2}(1,0,0)$	9.60	11.87	7.46	$M_{ZID_k}(1,0)$	9.72	13.06	9.24	11.01	13.03	6.39
		$M_{ZID_1ID_2}(1,1,1)$	7.60	7.36	2.84	$M_{ZID_k}(1,1)$	11.72	16.95	14.55	11.91	15.43	6.75
		$M_{ZID_1ID_2}(1,2,2)$	9.42	12.78	5.83	$M_{ZID_k}(1,2)$	2.01	4.31	0.81	6.22	4.81	0.86
		$M_{ZID_1ID_2}(1,3,3)$	9.39	14.32	6.92	$M_{ZID_k}(1,3)$	8.80	15.02	14.86	9.67	12.47	3.90
		$M_{ZID_1ID_2}(1,4,4)$	9.40	14.66	7.19	$M_{ZID_k}(1,4)$	4.02	8.25	1.94	7.05	8.29	2.35
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	11.40	10.29	3.33	$M_{ZZ_{ID_k}}(1,0)$	8.99	12.63	7.50	10.06	8.90	2.26
CD	JY	$M_{ZID_1ID_2}(1,0,0)$	6.39	0.38	1.14	$M_{ZID_k}(1,0)$	9.69	0.07	0.75	3.85	−0.15	0.97
		$M_{ZID_1ID_2}(1,1,1)$	−0.14	0.32	1.52	$M_{ZID_k}(1,1)$	10.33	−0.24	−0.55	4.53	−0.68	1.00
		$M_{ZID_1ID_2}(1,2,2)$	1.65	−0.47	1.24	$M_{ZID_k}(1,2)$	−0.55	0.32	0.00	0.49	0.83	3.47
		$M_{ZID_1ID_2}(1,3,3)$	2.25	−0.71	0.54	$M_{ZID_k}(1,3)$	5.19	0.22	−0.56	3.57	−0.35	2.03
		$M_{ZID_1ID_2}(1,4,4)$	2.23	−0.64	−0.02	$M_{ZID_k}(1,4)$	−0.45	−0.55	−0.10	2.92	0.81	4.04
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	4.85	−0.52	0.03	$M_{ZZ_{ID_k}}(1,0)$	12.69	−0.65	−0.36	2.29	−0.71	1.73
CD	SF	$M_{ZID_1ID_2}(1,0,0)$	13.29	7.77	3.16	$M_{ZID_k}(1,0)$	14.47	8.81	3.11	11.07	5.77	3.12
		$M_{ZID_1ID_2}(1,1,1)$	−0.48	−0.71	−0.64	$M_{ZID_k}(1,1)$	14.02	11.75	3.67	10.55	6.63	3.84
		$M_{ZID_1ID_2}(1,2,2)$	0.65	0.46	−0.36	$M_{ZID_k}(1,2)$	−0.32	−0.71	0.08	1.84	0.75	0.07
		$M_{ZID_1ID_2}(1,3,3)$	0.33	1.33	0.90	$M_{ZID_k}(1,3)$	5.76	10.00	2.42	5.04	5.26	3.07
		$M_{ZID_1ID_2}(1,4,4)$	−0.20	1.49	2.09	$M_{ZID_k}(1,4)$	0.13	0.11	−0.48	3.62	3.88	1.86
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	12.39	3.01	−0.61	$M_{ZZ_{ID_k}}(1,0)$	13.57	6.09	−0.28	15.53	0.76	−0.61
CD	DM	$M_{ZID_1ID_2}(1,0,0)$	13.42	10.53	3.01	$M_{ZID_k}(1,0)$	18.85	16.25	5.43	1.85	1.29	0.46
		$M_{ZID_1ID_2}(1,1,1)$	0.99	−0.13	−0.49	$M_{ZID_k}(1,1)$	19.50	18.77	5.30	1.24	1.51	0.69
		$M_{ZID_1ID_2}(1,2,2)$	0.20	−0.64	−0.65	$M_{ZID_k}(1,2)$	−0.69	−0.56	0.78	2.84	2.46	3.48

DOI: 10.1002/jae

Table V. (*Continued*)

Cc1	Cc2	Joint interest rate differentials				Interest rate differentials of Cc 1				of Cc 2		
			$c=0$	$c=0.5$	$c=1$		$c=0$	$c=0.5$	$c=1$	$c=0$	$c=0.5$	$c=1$
		$M_{ZID_1ID_2}(1,3,3)$	0.59	−0.44	−0.34	$M_{ZID_k}(1,3)$	10.65	11.87	2.43	0.91	2.04	2.88
		$M_{ZID_1ID_2}(1,4,4)$	0.54	−0.22	0.26	$M_{ZID_k}(1,4)$	−0.68	−0.44	1.03	3.32	4.15	5.22
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	5.08	0.76	0.70	$M_{ZZ_{ID_k}}(1,0)$	20.52	10.63	0.47	2.22	−0.31	1.86
BP	JY	$M_{ZID_1ID_2}(1,0,0)$	15.34	18.51	9.40	$M_{ZID_k}(1,0)$	13.46	22.65	12.41	14.73	12.94	5.94
		$M_{ZID_1ID_2}(1,1,1)$	0.32	0.09	−0.40	$M_{ZID_k}(1,1)$	13.22	21.27	10.19	16.46	17.32	8.53
		$M_{ZID_1ID_2}(1,2,2)$	4.09	4.60	1.90	$M_{ZID_k}(1,2)$	3.41	2.62	0.26	−0.43	0.51	0.91
		$M_{ZID_1ID_2}(1,3,3)$	4.49	5.55	2.67	$M_{ZID_k}(1,3)$	7.25	9.41	2.59	11.28	16.66	8.70
		$M_{ZID_1ID_2}(1,4,4)$	3.77	4.86	2.71	$M_{ZID_k}(1,4)$	4.18	3.35	−0.08	1.67	3.61	1.80
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	8.22	5.58	6.62	$M_{ZZ_{ID_k}}(1,0)$	16.23	14.54	7.39	10.03	6.30	14.00
BP	SF	$M_{ZID_1ID_2}(1,0,0)$	15.49	35.82	30.07	$M_{ZID_k}(1,0)$	13.65	40.28	37.32	15.88	29.83	22.73
		$M_{ZID_1ID_2}(1,1,1)$	4.59	11.84	16.17	$M_{ZID_k}(1,1)$	15.51	39.61	30.65	18.29	35.43	28.94
		$M_{ZID_1ID_2}(1,2,2)$	10.23	18.19	15.24	$M_{ZID_k}(1,2)$	7.83	16.27	12.18	5.26	15.98	18.95
		$M_{ZID_1ID_2}(1,3,3)$	8.97	15.49	10.62	$M_{ZID_k}(1,3)$	13.23	25.62	14.03	12.92	25.89	24.42
		$M_{ZID_1ID_2}(1,4,4)$	7.48	13.10	7.64	$M_{ZID_k}(1,4)$	9.29	17.81	9.17	9.83	18.79	15.43
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	11.19	27.13	30.38	$M_{ZZID_k}(1,0)$	12.56	32.78	31.03	16.79	27.09	37.03
BP	DM	$M_{ZID_1ID_2}(1,0,0)$	13.84	36.36	31.56	$M_{ZID_k}(1,0)$	14.98	43.49	34.19	10.53	20.69	23.51
		$M_{ZID_1ID_2}(1,1,1)$	1.72	2.24	3.26	$M_{ZID_k}(1,1)$	14.77	41.33	27.89	10.21	20.20	22.20
		$M_{ZID_1ID_2}(1,2,2)$	6.39	7.58	5.93	$M_{ZID_k}(1,2)$	6.71	5.62	−0.05	3.49	9.85	17.21
		$M_{ZID_1ID_2}(1,3,3)$	5.32	6.17	3.63	$M_{ZID_k}(1,3)$	11.32	24.72	10.28	6.02	13.41	17.40
		$M_{ZID_1ID_2}(1,4,4)$	3.75	4.50	1.94	$M_{ZID_k}(1,4)$	7.31	8.07	0.42	5.18	10.14	13.15
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	9.10	22.27	14.50	$M_{ZZ_{ID_k}}(1,0)$	12.35	36.36	6.98	11.49	16.67	33.09
JY	SF	$M_{ZID_1ID_2}(1,0,0)$	8.21	3.74	0.03	$M_{ZID_k}(1,0)$	10.48	4.46	−0.19	3.69	1.36	−0.70
		$M_{ZID_1ID_2}(1,1,1)$	−0.10	−0.66	−0.70	$M_{ZID_k}(1,1)$	12.00	5.76	0.27	5.20	2.20	−0.56
		$M_{ZID_1ID_2}(1,2,2)$	3.78	1.07	−0.43	$M_{ZID_k}(1,2)$	−0.36	−0.44	−0.70	4.01	0.35	−0.70
		$M_{ZID_1ID_2}(1,3,3)$	5.12	1.86	−0.17	$M_{ZID_k}(1,3)$	9.99	5.51	2.01	5.35	2.24	−0.36
		$M_{ZID_1ID_2}(1,4,4)$	4.97	1.92	0.03	$M_{ZID_k}(1,4)$	−0.21	−0.61	−0.52	5.72	1.82	−0.54
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	4.62	−0.69	−0.43	$M_{ZZ_{ID_k}}(1,0)$	5.85	0.53	1.09	3.82	−0.69	−0.67
JY	DM	$M_{ZID_1ID_2}(1,0,0)$	1.61	0.40	−0.41	$M_{ZID_k}(1,0)$	1.82	0.50	−0.53	0.58	−0.61	−0.63
		$M_{ZID_1ID_2}(1,1,1)$	−0.09	−0.71	−0.69	$M_{ZID_k}(1,1)$	2.87	1.22	−0.67	0.60	−0.55	−0.60
		$M_{ZID_1ID_2}(1,2,2)$	1.64	−0.49	−0.71	$M_{ZID_k}(1,2)$	−0.70	−0.71	−0.45	1.37	−0.62	−0.61
		$M_{ZID_1ID_2}(1,3,3)$	2.14	−0.36	−0.68	$M_{ZID_k}(1,3)$	4.16	3.23	−0.01	0.60	−0.69	−0.70
		$M_{ZID_1ID_2}(1,4,4)$	1.93	−0.40	−0.62	$M_{ZID_k}(1,4)$	0.11	0.05	−0.45	1.89	−0.56	−0.71
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	0.96	−0.65	−0.70	$M_{ZZ_{ID_k}}(1,0)$	0.40	−0.71	0.35	0.98	−0.71	−0.70
SF	DM	$M_{ZID_1ID_2}(1,0,0)$	1.80	4.29	9.30	$M_{ZID_k}(1,0)$	1.94	4.97	10.86	1.46	3.90	9.65
		$M_{ZID_1ID_2}(1,1,1)$	1.18	1.32	5.13	$M_{ZID_k}(1,1)$	3.82	7.58	14.76	2.46	5.41	11.63
		$M_{ZID_1ID_2}(1,2,2)$	4.18	4.40	7.01	$M_{ZID_k}(1,2)$	2.33	1.78	4.57	0.25	0.74	5.69
		$M_{ZID_1ID_2}(1,3,3)$	5.13	5.41	6.36	$M_{ZID_k}(1,3)$	6.37	8.67	13.53	2.69	5.06	10.70
		$M_{ZID_1ID_2}(1,4,4)$	5.25	5.58	5.58	$M_{ZID_k}(1,4)$	5.62	5.13	6.35	1.88	2.70	6.82
		$M_{ZZ_{ID_1}Z_{ID_2}}(1,0,0)$	2.12	2.12	11.94	$M_{ZZ_{ID_k}}(1,0)$	1.87	1.27	12.08	2.12	2.10	14.33

Notes:

1. Cc1, currency 1; Cc2, currency 2.
2. GCS tests are asymptotically one-sided $N(0,1)$ tests and thus upper-tailed asymptotic critical values may also be used, which are 1.65 and 2.33 at the 5% and 1% levels, respectively. $M(1,l)$ represents test statistics on the martingale test, serial correlation test, ARCH-in-mean test, skewness-in-mean test and kurtosis-in-mean test for $l = 0, \ldots 4$, respectively.
3. The direction of joint negative changes is defined by $Z_t^-(c) = \mathbf{1}(Y_{1t} < -c_1) \cdot \mathbf{1}(Y_{2t} < -c_2)$, where return of currency k is $Y_{kt} = 100\ln(S_{kt}/S_{kt-1})$ for $k = 1, 2$. Interest rate differential is defined by $r_t - r_t^*$ where r_t is the domestic (US) risk-free interest rate and r_t^* is the foreign risk-free interest rate.
4. A preliminary bandwidth $\overline{p}$ is crucial to run GCS tests. We have computed GCS test statistics for $\overline{p} = 11, \ldots, 50$, but reported only for the value of $\overline{p} = 21$ to save space.

DOI: 10.1002/jae

changes of an economic time series is predictable using the past history of its own changes, and it further provides a class of separate inference procedures to explore possible sources of directional predictability. We have examined directional predictability for both foreign exchange spot rates and futures prices in six major currencies using two widely used and readily available aspects of market information: the past history of foreign exchange returns and interest rate differentials. We have documented strong evidence that the directions of foreign exchange returns can be predicted not only by the past history of foreign exchange returns but also by the past history of interest rate differentials, where the latter suggests that interest rate differentials can be a useful predictor of the direction of future foreign exchange rates. This evidence becomes stronger when we consider the direction of larger changes. Our results based on the separate inference procedures further demonstrate that, despite the weak conditional mean dynamics of foreign exchange returns, directional predictability can be explained by strong dependencies derived from higher-order conditional moments such as the volatility, skewness and kurtosis of past own foreign exchange returns. It is also documented that the conditional mean dynamics of interest rate differentials contributes significantly to directional predictability of foreign exchange rates.

We also examine the co-movements between two foreign exchange rates, especially the co-movements of large changes. There is strong evidence that the directions of joint changes are predictable using past foreign exchange returns and/or interest rate differentials. Several sources can explain this directional predictability of joint changes. Among them, the levels of joint currency returns and the volatilities of past individual returns are remarkably useful in predicting the directions of joint changes.

Our findings have important policy implications. For example, the sources of directional predictability would be of importance to the monetary authorities who look for effective instruments to manage foreign exchange markets. Furthermore, the sources of directional predictability of joint (large) changes can provide useful information for understanding the dynamic characteristics of directional movements in crisis and of (extreme) directional comovements, which are useful in improving proactive risk management. Given various sources of directional predictability, it would be interesting to see how they can be developed into feasible modeling. We leave this for future research.

ACKNOWLEDGEMENTS

The authors are grateful to Warren Bailey, Robert Jarrow, Jaesun Noh and Byung-Sam Yoo for helpful comments and references, and to the Cheung Kong Scholarship of the Chinese Ministry of Education and Xiamen University, and the National Science Foundation for financial support via NSF Grant SES-0111769. We thank Steven Durlauf (Co-editor) and an anonymous referee for many constructive suggestions. Any remaining errors are solely ours. Views and opinions expressed here are those of the authors and do not necessarily reflect those of the Canadian Imperial Bank of Commerce.

REFERENCES

Abuaf N, Jorion P. 1990. Purchasing power parity in the long run. *Journal of Finance* **45**: 157–174.
Alexius A. 2001. Uncovered interest parity revisited. *Review of International Economics* **9**: 505–517.

Alquist R, Chinn MD. 2006. Conventional and unconventional approaches to exchange rate modeling and assessment. Working paper, Department of Economics, University of Michigan, and Department of Economics, University of Wisconsin.
Ang A, Chen J. 2002. Asymmetric correlations of equity portfolios. *Journal of Financial Economics* **63**: 443–494.
Anthony M, MacDonald R. 1998. On the mean-reverting properties of a target-zone exchange rate: some evidence from the ERM. *European Economic Review* **42**: 1493–1523.
Anthony M, MacDonald R. 1999. The width of the band and exchange rate mean-reversion: some further ERM-based results. *Journal of International Money and Finance* **18**: 411–428.
Bae KH, Karolyi GA, Stulz RM. 2003. A new approach to measuring financial contagion. *Review of Financial Studies* **16**: 717–763.
Baillie RT, Bollerslev T. 2000. The forward premium anomaly is not as bad as you think. *Journal of International Money and Finance* **19**: 471–488.
Baillie RT, Osterberg WP. 1997. Central bank intervention and risk in the forward market? *Journal of International Economics* **43**: 483–497.
Bansal R, Dahlquist M. 2000. The forward premium puzzle: different tales from developed and emerging economies. *Journal of International Economics* **51**: 115–144.
Bekaert G, Hodrick RJ. 2001. Expectations hypotheses tests. *Journal of Finance* **56**: 1357–1394.
Bekaert G, Wei M, Xing Y. 2002. Uncovered interest rate parity and the term structure. NBER Working Paper 8795.
Berg A, Pattillo C. 1999. Are currency crises predictable? A test. *International Monetary Fund Staff Papers* **46**: 107–138.
Bierens H. 1982. Consistent model specification tests. *Journal of Econometrics* **20**: 105–134.
Bleaney M, Mizen P. 1995. Empirical tests of mean-reversion in real exchange rates: a survey. *Bulletin of Economic Research* **47**: 171–195.
Bonser-Neal C, Tanner G. 1996. Central bank intervention and the volatility of foreign exchange rates: evidence from the options market. *Journal of International Money and Finance* **15**: 853–878.
Breen W, Glosten L.R, Jagannathan R. 1989. Economic significance of predictable variations in stock index returns. *Journal of Finance* **44**: 1177–1189.
Brennan MJ. 1986. A theory of price limits in futures markets. *Journal of Financial Economics* **16**: 213–233.
Carlson JB, McIntire JM, Thomson JB. 1995. Federal funds futures as an indicator of future monetary policy: a primer. *Federal Reserve Bank of Cleveland Economic Review* **31**: 20–30.
Chaboud A, Wright JH. 2005. Uncovered interest parity: it works, but not for long. *Journal of International Economics* **66**: 349–362.
Cheung Y, Chinn MD, Garcia Pascual A. 2005. Empirical exchange rate models of the nineties: are any fit to survive? *Journal of International Money and Finance* **24**: 1150–1175.
Chinn MD, Meredith G. 2004. Monetary policy and long-horizon uncovered interest rate parity. *International Monetary Fund Staff Papers* **51**: 409–430.
Christoffersen P, Diebold F. 2002. Financial asset returns, market timing, and volatility dynamics. Working paper, Faculty of Management, McGill University, and Department of Economics, University of Pennsylvania.
Cumby R, Modest D. 1987. Testing for market timing ability: a framework for forecast evaluation. *Journal of Financial Economics* **19**: 169–189.
de Vries CG. 1994. Stylized facts of nominal exchange rate returns. In *Handbook of International Macroeconomics*, van der Ploeg F (ed.). Basil Blackwell: Oxford; 506–534.
Diebold FX, Nason J. 1990. Nonparametric exchange rate prediction? *Journal of International Economics* **28**: 315–322.
Dominguez KM. 1993. Does central bank intervention increase the volatility of foreign exchange rates? NBER Working Paper 4532.
Dominguez KM, Frankel AJ. 1993. Does foreign exchange intervention matter? The portfolio effect. *American Economic Review* **83**: 1356–1369.
Dooley MP, Shaffer J. 1983. Analysis of short-run exchange rate behavior: March 1973 to November 1981. In *Exchange Rate and Trade Instability: Causes, Consequences and Remedies*, Bigman D, Taya T (eds). Ballinger: Cambridge, MA; 43–69.

Dumas B. 1992. Dynamic equilibrium and the real exchange rate in a spatially separated world. *Review of Financial Studies* **5**: 153–180.

Eichenbaum M, Evans C. 1995. Some empirical evidence on the effects of shocks to monetary policy on exchange rates. *Quarterly Journal of Economics* **110**: 975–1009.

Engel C. 1994. Can the Markov switching model forecast exchange rates? *Journal of International Economics* **36**: 151–165.

Engel C, Hamilton J. 1990. Long swings in the dollar: are they in the data and do markets know it? *American Economic Review* **80**: 689–713.

Fama EF. 1965. The behavior of stock-market prices. *Journal of Business* **38**: 34–105.

Fatum R, Hutchison MM. 2002. Is foreign exchange market intervention an alternative to monetary policy? Evidence from Japan. Working paper, University of California, Santa Cruz.

Fatum R, Hutchison MM. 2003. Is sterilized foreign exchange intervention effective after all? An event study approach. *Economic Journal* **113**: 390–411.

Faust J, Rogers JH. 2003. Monetary policy's role in exchange rate behavior. *Journal of Monetary Economics* **50**: 1403–1424.

Flood RP, Jeanne O. 2000. An interest rate defense of a fixed exchange rate? International Monetary Fund working paper.

Flood RP, Rose AK. 2002. Uncovered interest parity in crisis. *International Monetary Fund Staff Papers* **49**: 252–266.

Frankel JA, Rose AK. 1996a. Currency crashes in emerging markets: an empirical treatment. *Journal of International Economics* **41**: 351–366.

Frankel JA, Rose AK. 1996b. A panel project on purchasing power parity: mean reversion within and between countries. *Journal of International Economics* **40**: 209–224.

Frenkel JA, Levich RM. 1975. Covered interest arbitrage: unexploited profits? *Journal of Political Economy* **83**: 325–338.

Frenkel JA, Levich RM. 1977. Transaction costs and interest arbitrage: tranquil versus turbulent periods. *Journal of Political Economy* **85**: 1209–1226.

Froot KA, Thaler RH. 1990. Anomalies foreign exchange. *Journal of economic perspectives* **4**: 179–192.

Furman J, Stiglitz JE. 1998. Economic crises: evidence and insights from East Asia. *Brookings Papers on Economic Activity* **2**: 1–135.

Ghosh AR. 1992. Is it signaling? Exchange intervention and the dollar–Deutschemark rate. *Journal of International Economics* **32**: 201–220.

Granger CWJ, Pesaran MH. 2000. A decision theoretic approach to forecast evaluation. In *Statistics and Finance: An Interface*, Chan WS, Lin WK, Tong H (eds). Imperial College Press: London; 261–278.

Hamao Y, Ronald WM, Ng N. 1990. Correlations in price changes and volatility across international stock markets. *Review of Financial Studies* **3**: 281–307.

Henriksson RD, Merton R. 1981. On market timing and investment performance. II: Statistical procedures for evaluating forecasting skills. *Journal of Business* **54**: 513–533.

Hodrick R. 1987. *Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets*. Harwood: Chur, Switzerland.

Hong Y. 1999. Hypothesis testing in time series via the empirical characteristic function: a generalized spectral density approach. *Journal of the American Statistical Association* **84**: 1201–1220.

Hong Y, Chung J. 2006. Are the directions of stock price changes predictable? A generalized cross-spectral approach. Working paper, Department of Economics, Cornell University.

Hong Y, Lee TH. 2003. Inference on predictability of foreign exchange rates via generalized spectrum and nonlinear time series models. *Review of Economics and Statistics* **85**: 1048–1062.

Hong Y, Tu J, Zhou G. 2007. Asymmetries in stock returns: statistical tests and economic evaluation. *Review of Financial Studies* (forthcoming).

Hsieh DA. 1988. The statistical properties of daily foreign exchange rates: 1974–1983. *Journal of International Economics* **24**: 129–145.

Hsieh DA. 1989. Testing for nonlinear dependence in daily foreign exchange rates. *Journal of Business* **62**: 339–368.

Hsieh DA. 1993. Implications of nonlinear dynamics for financial risk management. *Journal of Financial and Quantitative Analysis* **28**: 41–64.

DOI: 10.1002/jae

Huisman R, Koedijk K, Kool C, Nissen F. 1998. Extreme support for uncovered interest parity. *Journal of International Money and Finance* **17**: 211–228.
Inoue A, Kilian L. 2004. In-sample or out-of-sample tests of predictability: which one should we use? *Econometric Reviews* **23**: 1–32.
Ito T, Yabu T. 2004. What prompts Japan to intervene in the Forex market? A new approach to a reaction function. NBER Working Paper 10456.
Jondeau E, Rockinger M. 2003. Conditional volatility, skewness, and kurtosis: existence, persistence, and comovements. *Journal of Economic Dynamics and Control* **27**: 1699–1737.
Jorion P. 1988. On jump processes in the foreign exchange and in the stock markets. *Review of Financial Studies* **1**: 427–445.
Jorion P, Sweeney R. 1996. Mean reversion in real exchange rates: evidence and implications for forecasting. *Journal of International Money and Finance* **15**: 535–550.
Kaminsky GL, Lewis KK. 1996. Does foreign exchange intervention signal future monetary policy? *Journal of Monetary Economics* **37**: 285–312.
Kaminsky GL, Lizondo S, Reinhart C. 1998. Leading indicators of currency crises. *International Monetary Fund Staff Papers* **45**: 1–48.
Kilian L, Taylor MP. 2001. Why is it so difficult to beat the random walk forecast of exchange rates? *Journal of International Economics* **60**: 85–107.
King M, Wadhwani S. 1990. Transmission of volatility between stock markets. *Review of Financial Studies* **3**: 5–33.
Kodres LE. 1993. Tests of unbiasedness in foreign exchange futures markets: an examination of price limits and conditional heteroscedasticity. *Journal of Business* **66**: 463–490.
Krugman P. 1991. Target zones and exchange rate dynamics. *Quarterly Journal of Economics* **56**: 669–682.
Kuan CM, Liu T. 1995. Forecasting exchange rates using feed-forward and recurrent neural Networks. *Journal of Applied Econometrics* **10**: 347–364.
Kumar M, Moorthy U, Perraudin W. 2003. Predicting emerging market currency crashes. *Journal of Empirical Finance* **10**: 427–454.
Larsen GA, Wozniak GD. 1995. Market timing can work in the real world. *Journal of Portfolio Management* **21**: 74–81.
Larson SJ, Madura J. 2001. Overreaction and underreaction in the foreign exchange market. *Global Finance Journal* **12**: 153–177.
LeBaron B. 1999. Technical trading rule profitability and foreign exchange intervention. *Journal of International Economics* **49**: 125–143.
Lee ChI, Mathur I. 1996. Trading rule profits in European currency spot cross-rates. *Journal of Banking and Finance* **20**: 949–962.
Leitch G, Tanner J. 1991. Economic forecast evaluation: profits versus the conventional error measures. *American Economic Review* **81**: 580–590.
Leitch G, Tanner J. 1995. Professional economic forecasts: are they worth their costs? *Journal of Forecasting* **14**: 143–157.
Levich RM, Thomas LR. 1993. The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach. *Journal of International Money and Finance* **12**: 451–474.
Lewis KK. 1995. Puzzles in international financial markets. In *Handbook of International Economics III*, Grossman GM, Rogoff K (eds). North-Holland: Amsterdam; 1913–1971.
Linton O, Whang YJ. 2003. A quantilogram approach to evaluating directional predictability. Working paper, London School of Economics and Political Science.
Longin F, Solnik B. 1995. Is the correlation in international equity returns constant: 1960–1990? *Journal of International Money and Finance* **14**: 3–26.
Longin F, Solnik B. 2001. Extreme correlation of international equity markets. *Journal of Finance* **56**: 649–676.
Lothian JR, Taylor MP. 1996. Real exchange rate behavior: the recent float from the perspective of the past two centuries. *Journal of Political Economy* **104**: 488–509.
Lothian JR, Wu L. 2003. Uncovered interest rate parity over the past two centuries. Working paper, Graduate School of Business, Fordham University.
Maheu JM, McCurdy TH. 2003. News arrival, jump dynamics and volatility components for individual stock returns. Working paper, CIRANO.

DOI: 10.1002/jae

Malkiel BG. 1992. Efficient markets hypothesis. In *The New Palgrave Dictionary of Money and Finance*, Newman P, Milgate M, Eatwell J (eds). Macmillan Press: Basingstoke, UK; 739–744.
Malkiel BG. 2003. The efficient market hypothesis and its critics. *Journal of Economic Perspectives* **17**: 59–82.
Mark NC. 1995. Exchange rates and fundamentals: evidence on long-horizon predictability. *American Economic Review* **85**: 201–218.
Mark NC, Moh Y. 2003. Official interventions and occasional violations of uncovered interest parity in the Dollar–DM market. NBER Working Paper 9948.
Maynard A, Phillips PCB. 2001. Rethinking an old empirical puzzle: econometric evidence on the forward discount anomaly. *Journal of Applied Econometrics* **16**: 671–708.
McCurdy TH, Morgan IG. 1987. Tests of the martingale hypothesis for foreign currency futures with time-varying volatility. *International Journal of Forecasting* **3**: 131–148.
McQueen G, Pinegar M, Thorley S. 1996. Delayed reaction to good news and the cross-autocorrelation of portfolio returns. *Journal of Finance* **51**: 889–919.
Meese RA, Rogoff K. 1983a. Empirical exchange rate models of the seventies: do they fit out of sample? *Journal of International Economics* **14**: 3–24.
Meese RA, Rogoff K. 1983b. The out of sample failure of empirical exchange rate models: sampling error or misspecification? In *Exchange Rates and International Economics*, Frenkel J (ed.). University of Chicago Press: Chicago; 67–105.
Meese RA, Rose AK. 1991. An empirical assessment of non-linearities in models of exchange rate determination. *Review of Economic Studies* **58**: 603–619.
Mussa M. 1979. Empirical regularities in the behavior of exchange rates and theories of the foreign exchange market. *Carnegie–Rochester Conference Series on Public Policy* **11**: 9–57.
Mussa M. 1981. The role of official intervention. In *Occasional Paper* 6. Group of Thirty: New York.
Neely C, Weller P. 1999. Predictability in international asset returns: a reexamination. Working paper, Federal Reserve Bank of St Louis.
Pagan A, Schwert W. 1990. Alternative models for conditional stock volatility. *Journal of Econometrics* **84**: 205–231.
Pesaran MH, Skouras S. 2001. Decision based methods for forecast evaluation. In *Companion to Economic Forecasting*, Clements MP, Hendry DF. (eds). Basil Blackwell: Oxford; 241–267.
Pesaran MH, Timmermann A. 1992. A Simple nonparametric test of predictive performance. *Journal of Business and Economic Statistics* **10**: 461–465.
Pesaran MH, Timmermann A. 1995. Predictability of stock returns: robustness and economic significance. *Journal of Finance* **50**: 1201–1228.
Pesaran MH, Timmermann A. 2002. Market timing and return prediction under model instability. *Journal of Empirical Finance* **9**: 495–510.
Pring MJ. 1991. *Technical Analysis Explained: The Successful Investor's Guide to Spotting Investment Trends and Turning Points*. McGraw-Hill: New York.
Ramchand L, Susmel R. 1998. Volatility and cross correlation across major stock markets. *Journal of Empirical Finance* **5**: 397–416.
Satchell S, Timmermann A. 1995. An assessment of the economic value of non-linear foreign exchange rate forecasts. *Journal of Forecasting* **14**: 477–497.
Sercu P, Uppal R, Van Hulle C. 1995. The exchange rate in the presence of transaction costs: implications for tests of purchasing power parity. *Journal of Finance* **50**: 1309–1319.
Shephard N, Rydberg TH. 2003. Dynamics of trade-by-trade price movements: decomposition and models. *Journal of Financial Econometrics* **1**: 2–25.
Somanath VS. 1986. Efficient exchange rate forecasts: lagged models do better than the random walk. *Journal of International Money and Finance* **5**: 195–200.
Stinchcombe M, White H. 1998. Consistent specification testing with nuisance parameters present only under the alternative. *Econometric Theory* **14**: 295–324.
Sweeney RJ. 1986. Beating the foreign exchange market. *Journal of Finance* **41**: 163–182.
Taylor MP. 1995. The economics of exchange rates. *Journal of Economic Literature* **33**: 13–47.
Taylor MP, Allen H. 1992. The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance* **11**: 304–314.

DOI: 10.1002/jae

Taylor MP, Peel DA. 2000. Nonlinear adjustment, long-run equilibrium and exchange rate fundamentals. *Journal of International Money and Finance* **19**: 33–53.
Taylor MP, Peel DA, Sarno L. 2002. Nonlinear mean-reversion in real exchange rates: toward a solution to the purchasing power parity puzzles. *International Economic Review* **42**: 1015–1042.
Taylor AM, Taylor MP. 2004. The purchasing power parity debate. *Journal of Economic Perspectives* **18**: 135–158.

