ESSAYS IN MARKET EFFICIENCY

by

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ABSTRACT

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This dissertation investigates the market inefficiencies of both foreign exchange and equity markets. On the one hand, the efficiency of foreign exchange markets is explored through the measurement of the contribution to price discovery of the spot and futures market, and the its effect on intermarket mispricing. On the other hand, the efficiency of equity markets is tested by examining the martingale behavior of recently popular international stock index ETFs

The first chapter provides a comprehensive analysis of the dynamic intraday price discovery process of the Euro and Japanese Yen exchange rates in three foreign exchange markets based on electronic trading systems: the Chicago Mercantile Exchange (CME) GLOBEX regular futures, E-mini futures, and the EBS interdealer spot market. Contrary to evidence in equity markets and more recent evidence in foreign exchange markets, the spot market is found to consistently lead the price discovery process for both currencies during the sample period. Furthermore, E-mini futures do not contribute more to the price discovery than the electronically traded regular futures.

In the second chapter, we examine the daily return predictability for eighteen international stock index ETFs. Out-of-sample tests are conducted, based on linear and various popular nonlinear models and both statistical and economic criteria for model comparison. The main results show evidence of predictability for six of eighteen ETFs. A simple linear autoregression model, and a nonlinear-in-variance GARCH model, but not several popular nonlinear-in-mean models help outperform the martingale model. The allowance of data-snooping bias also substantially weakens otherwise apparently strong predictability.

The final chapter investigates the relationship between the deviations of prices from their no-arbitrage value and the differences in informational efficiency across foreign exchange markets trading the same underlying asset. This relationship is examined by jointly modeling the dynamics of the futures-cash basis and information share differential across futures and cash markets. Evidence of two-way Granger causality between the no-arbitrage futures-cash basis and the relative speed of adjustment measure is found. Shocks to the no-arbitrage basis predict future differences in the speed of adjustment, and vice versa. The evidence is robust to different currency markets and different degrees of liquidity.

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CHAPTER 1

Introduction

Traditional asset pricing theory assumes that markets are frictionless and that asset prices should follow a martingale process over short-run horizons. In other words, in an efficient market with unpredictable information arrival, short-run deviations of asset prices from their fundamental values should be negligible and unpredictable. However, ample empirical evidence demonstrates the existence of sizable frictions and predictable returns in financial markets. Following this line of research, the goal of this study is twofold. First, we test the theory of instantaneous information diffusion in the presence of frictionless efficient markets. In order to test this hypothesis, we study the contribution to price discovery of two or more markets trading the same underlying asset. Furthermore, we analyze the interrelationship between the price discovery contribution differentials and intermarket mispricing. This hypothesis is tested within foreign exchange markets. Second, we test the efficiency of equity markets by examining the daily return predictability of international stock index exchange-traded funds.

The existence of imperfectly integrated markets or fragmentation in the trading structure of financial markets has emerged as a motivational source for research in financial economics. In chapters two and three, we exploit this market imperfection to determine whether some markets have a more dominant role in the price discovery process – the process of impounding information into prices –, and the implications this may have on the mispricing of fundamentally related assets. A single security trading in multiple markets is expected to reach an identical equilibrium price in all markets assuming a frictionless environment. Information-gathering costs and nonzero skewness in the information distribution among market participants cause securities to trade at prices away from equilibrium in all markets simultaneously. Although, it has been shown that technological advances and market organization can reduce the level of fragmentation in financial markets (Garbade & Silber 1979), differences in markets structures and security designs prevent a complete integration of the markets. More specifically, every market has rules either explicit or implicit that govern the trading mechanism, and these different rules result in discrepancies in the formation and evolution of different market prices for the same security.

Chapter 2 provides a comprehensive analysis of the dynamic price discovery process in the foreign exchange markets with a focus on comparing the role of the spot markets versus derivative markets. Unlike previous research in foreign exchange markets, this chapter includes the spot market as a competing trading structure. This study of price discovery is based on the existence of cointegrating relations among FX products or markets. Three approaches are used to examine the price discovery roles of these markets thoroughly: (1) Information shares, (2) Gonzalo-Granger common factor weights, and (3) Error-correction coefficients. All three approaches assume that an underlying security trading in multiple markets has a common implicit efficient price. An appealing characteristic of a common efficient price is that it supports the economic intuition that, subject to transaction costs, the securities traded in different markets are linked by arbitrage or short-term equilibrium considerations.

Contrary to evidence in equity markets (Chu *et al.* 1999; Hasbrouck 2003; Kurov & Lasser 2004) the FX markets do not allocate the information impounding dominance in derivative instruments. Instead, our data shows that the spot foreign exchange markets lead the price discovery process. We find that regular futures, E-Mini futures, and spot prices are a cointegrated system with one common long-run stochastic trend. However, prices in the three markets do not respond to information simultaneously. While spot prices lead the other two markets in the price discovery process, the regular futures and E-Mini futures markets contribute equally less weight to the long-run common stochastic trend.

Chapter 3 examines the short-run predictability of equity returns using daily observations on eighteen international stock index ETFs. Surprisingly, while many issues such as diversification potentials and herding behaviors on the ETFs have been examined (Pennathur *et al.* 2002; Gleason *et al.* 2004), the important issue of their short-horizon predictability has not yet been investigated. Motivated by recent work using nonlinear models (Hong & Lee 2003), we test the martingale behavior of asset prices. We implement the model selection approach rather than the more traditional hypothesis testing approach since our approach is not affected by model misspecification issues. The efficiency of equity markets is then tested directly by evaluating the out-of sample forecasting performance of several popular models[1].

Having previously found evidence of the informational efficiency of the spot market relative to the foreign exchange futures markets, in chapter 4 we turn our attention to the dynamics of intermarket mispricing. More specifically, we explore the relationship between relative informational inefficiencies across markets and the deviations of asset prices from their no-arbitrage values. Information-based models demonstrate that new information gets impounded into prices as a result of trading by informed traders. If informed traders are more likely to choose one particular market

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[1] We extend the literature by applying a number of nonlinear models that allow for both potential nonlinearity-in-mean and nonlinearity-in-variance

to reveal their private information, prices on this market tend to lead prices on other markets. If the leading market incorporates information first, the slower adjustment of prices to information in the lagging market implies the existence of an intermarket information diffusion channel (Kumar & Seppi 1994). In an attempt to close a gap in the literature, this chapter explores empirically the relationship between arbitrage trading and the degree of relative informational efficiency of financial markets. More specifically, it argues that the behavior of arbitrageurs, measured by the dynamics of the futures-cash basis, is related to the differences in the rate at which markets incorporate common information into prices.

CHAPTER 2

Do Futures Lead Price Discovery in Electronic Foreign Exchange Markets?

2.1 Introduction

Price discovery is the process through which closely related markets attempt to reach the equilibrium price. While price discovery may be considered to be immediate in frictionless Walrasian models of trading behavior which typically assume perfect competition and free entry, such assumption is deemed far from realistic in the market microstructure literature. In fact, it has been one of the most critical questions in market microstructure to investigate how prices are actually determined inside the “black box” of a security market and the process by which prices come to impound new information. In particular, the roles of spot and futures (and other derivative financial instruments) in the price discovery process have received much attention.

In the currency market, the size of the currency futures market is relatively small compared with the over-the-counter spot market. According to the 2007 BIS Triennial survey, average daily volume in exchange-traded currency products totaled 72 billion compared with 2,319 billion in over-the-counter products. Thus, “In FX, however, the futures market is much smaller than the spot market; it is unlikely that a significant share of price determination occurs there.” (Lyons, 2001)

Recent evidence, however, suggests that the currency futures market might play a big role in price discovery compared with the spot market. Using interdealer direct spot transactions market data from the Reuters Dealing 2000-1 system and the futures data from the regular floors trading on the CME for three month in 1996, Rosenberg and Traub (2007) found the currency futures market can have information shares averaging between 80 and 90 percent based on the methodology in Hasbrouck (1995) and Gonzalo and Granger (1995). The currencies they examined are the Deutsche Mark, the British Pound, the Japanese Yen and the Swiss Franc.[2] On the other hand, Tse, Xiang, and Fung (2006), using both the GLOBEX electronic and floor-trading futures data at the CME, and the CMC foreign exchange retail-trading data for three month in 2004, reported that the GLOBEX electronic futures provide the most price discovery in the Euro, and the on-line retail-trading spot market provides the most price discovery in the Japanese Yen. Therefore, the results from Tse, Xiang, and Fung (2006) confirm that of Rosenberg and Traub (2007) in the case of the Euro but not for the Yen. This unsettled issue is particularly important, given the recent dramatic changes in the structure of the foreign exchange market as a whole (Rime 2003).

This chapter provides a comprehensive analysis of the dynamic price discovery process in the electronic foreign exchange markets for two currency pairs, the Euro/$ and the Yen/$. We differ from the existing literature in the following aspects. Firstly, different from previous studies, this study uses the interdealer spot market data from the electronic brokering services (EBS) from April to July of 2005. In the spot market, most of the foreign exchange trading is concentrated in the interdealer market. This EBS dataset has several important advantages. Specifically, the EBS dataset consists of transactable quotes, as opposed to transaction prices from

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[2] In the revised version of the paper, Rosenberg and Traub (2007) augmented their results using the spot market quotes from Bloomberg over a three-month period in 2006. They found that the spot market dominated price discovery.

Reuters D2000-1 system used in previous studies (e.g., Evans, 2002; Rosenberg and Traub, 2007). Furthermore, EBS has become the major trading platform for the two most traded currency pairs, the Yen and the Euro, making the results based on this dataset a true representation of the behavior of global interdealer foreign exchange markets.[3] If the comparison between spot and futures needs to be made, the EBS data should provide the best representation for the spot market with regard to the Euro and the Yen.

Secondly, this chapter examines the price discovery role of electronic-traded foreign exchange spot and futures markets. The allowance for the confounding effect of electronic trading is important as electronic trading has become a major factor in affecting the relative rate of price discovery across different markets. There is substantial empirical evidence showing that the use of electronic trading platforms facilitate price discovery more efficiently than floor trading in equity markets (e.g. Hasbrouck, 2003; Kurov and Lasser, 2004). Recently, Ates and Wang (2006) and Tse, Xiang, and Fung (2006) have demonstrated the informational dominance of the electronically traded regular futures markets over the floor traded regular futures. Nevertheless, no study has compared electronically traded foreign exchange spot and futures markets, with the noticeable exception of Tse, Xiang, and Fung (2006).

Finally, this is the first attempt to investigate the role of E-mini futures in price discovery for the Euro/$ and the Yen/$. The CME introduced E-mini Euro and Yen futures in October 1999. The evidence of the dominant role of E-mini futures in price discovery has been recorded from equity markets (Hasbrouck, 2003; Kurov and Lasser, 2004; Ates and Wang, 2005). However, to the best of our knowledge, no other

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[3] Currently, two electronic brokering systems are used globally for interdealer spot trading, one offered by EBS and the other offered by Reuters Dealing 3000. Euro/$ and yen/$ are traded primarily on EBS while sterling/$ is traded mainly on Reuters (see Chaboud, Chernenko, Howorka, Krishnasami-Lyer, Liu, & Wright, 2004).

study has explored the price discovery role of E-mini futures on foreign exchange markets.

The rest of the chapter is organized as follows: Section 2.2 presents the data. Section 2.3 describes the estimation procedure and presents the results. A brief summary concludes the chapter in Section 2.4.

2.2 Data Description

The dataset consists of intraday tick-by-tick observations (later converted to 5-second intervals in the analysis) covering a four-month period from April 4th, 2005 until July 29th, 2005.[4] Prices are log-transformed and multiplied by a constant number ($p_t^* = \log(p_t) * 10,000$). Data were obtained for three major financial instruments (regular futures, E-mini futures and the interdealer spot market) in two currency markets (Euro/$ and yen/$). Both E-mini futures and the spot market are electronically traded while regular futures have both floor trading and electronic trading at the same time from 7:20 a.m. to 2:00 p.m., but only electronic trading in other times. In this study, however, only data from electronic trading are used.[5]

2.2.1 Futures Market Data

The regular and E-mini futures data are the time and sale data from the Chicago Mercantile Exchange (CME). These futures are the most actively traded FX

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[4] Not all trading days within the four-month sample period have been used in this study. Several days have been excluded from the estimation due to the lack of trading activity in all markets simultaneously. July 4th and July 11th through July 15th have been excluded since not all markets are open to trade on these days, and the econometric techniques rely on having a sufficient number of observations for all instruments for all days.

[5] The regular floor trading data during the sample period were also obtained. However, the floor trading is very infrequent compared with electronic trading (see Table 2.1), thus the floor trading data are not used in the analysis, even though the analysis is restricted to the period of the floor trading hours.

futures in the CME. Table 2.1 provides the summary statistics for the futures contracts used in this chapter. Specifically, for the regular futures contracts, they are not only traded at the CME Globex electronic market but also are traded side-by side with the floor trading using the open outcry system during the regular hours. CME E-mini Japanese Yen futures and E-mini Euro futures began trading in 1999 exclusively on CME Globex. E-mini futures contracts are sized at one-half of the regular futures contracts to make E-mini trading affordable to traders with small margin accounts.

While CME offers a forum for trading the Yen and the Euro in its FX futures markets on both its Globex electronic trading platform as well as on the trading floor, the trading hours differ across these two trading venues (see Table 2.1). This study will only include intraday data for the period of the day when all markets are open (7:20 am to 2:00 pm). These daily samples will make it possible to analyze the price dynamics during information-intensive periods, as the data will also (at least partially) capture any information generated in the floor trading during this period.

For the futures contracts, the nearby contract is the most active contract. Therefore, only the last three full months of the life of nearby contracts are used, and they are rolled over to the next nearby contract the last day of the month prior to the expiration month. Hence, the sample period for the regular futures contracts is constructed using transaction prices from two months (April and May) of the June 2005 contract and two months (June and July) of the September 2005 contract.

The futures volume statistics in Table 2.1 show that the most frequently traded is the Euro/US$ regular futures contract. On the other hand, the Yen/US$ E-mini futures contract is far less traded than any of the other instruments. Day trading on Globex seems to be the most active of all. Night and overnight trading accounts for roughly 25% of the daily volume in all markets. Furthermore, floor trading accounts for a very small percentage of the total daily volume in these derivative markets. The information clearly suggests the attractiveness of the sample data which covers day trading in the electronic markets (GLOBEX).

2.2.2 Spot Market Data

The spot foreign exchange market is much less centralized than the FX futures markets. This market is best described as a decentralized multiple-dealer market. There is no physical location or exchange where dealers meet other traders, nor there is a screen that consolidates all executable quotes in the market. In this way, the spot FX market is very different from most futures markets. Dominated by interbank trading, spot currency transactions occur in the over-the-counter (OTC) markets. Cash currency trading takes place in a number of interconnected markets. On the other hand, private vendors offer electronic trading platforms and market data available for a fee. These retail markets are very accessible to small traders; however, these retail markets are different from the inter-dealer market where large traders account for most of the daily trading volumes in the currency markets. The current market participants are banks, commercial companies, central banks, investments companies, and retail FX brokers. There are 3 main features that distinguish spot FX markets from other markets: a very high trading volume, interdealer trading accounts for most of the volume, and transparency is low.

The spot market data for this study were collected from one of the two leading electronic brokers of interdealer spot foreign exchange market, EBS. Although retail electronic trading in the FX spot markets has been exploding, most of the trading is concentrated in the interbank market. Currently, two electronic brokering systems are used globally for interbank spot trading, one offered by Electronic Broker System

(EBS) and one offered by Reuters (Dealing 3000). The Euro/US$ and Yen/US$ are traded primarily on EBS. Therefore, our data were collected from the leading electronic brokering system in the Euro/US$ and Yen/US$ interbank markets, which comprises most global transactions in these two FX markets. This data provider offers a screen-based anonymous dealing service, operating during global trading hours, which supports trading in all major currencies. Each day 2,000 traders on more than 700 floors globally use this trading platform to trade an average of USD145 billion a day in spot foreign exchange transactions. The data obtained for the spot rates are the bid/ask midpoint. As mentioned in the introduction, the EBS has become the major trading platform for the two most traded currency pairs, the Yen and the Euro.

Table 2.2 reports the summary statistics of all currency markets for both exchange rates. During the 4-month period covered in the sample, trading activity in terms of price quotes is significantly higher in the regular futures and spot markets. For the Euro market, the number of transactions is higher in regular futures than the number of midpoint quotes in the spot market; while for the Yen market, the number of midpoint quotes is higher in the spot market. At the first look, this result on the Euro is surprising given the general notion that the spot market is much larger than the futures market. The result is also consistent with Rosenberg and Traub (2007) who found that there are more futures trades during regular futures trading hours than that in the spot market. Moreover, we only consider regular futures trading hours on the CME Globex (8:20 a.m. to 3:00 p.m. Eastern Time), and this time period does not fully overlap with some of the times of heavy volume in the spot market. On the other hand, in our data, the EBS mid-quotes between bid and ask points are used for the spot market, but actual transaction prices are used for both futures markets. Given that multiple transactions can occur at the same quote, the use of midpoint quote would imply that there are more far more actual transactions in the spot markets than indicated by the number of observations on Table 2.2.

The higher number of daily average trades in the regular futures market does not extend to the E-mini futures market. Trading activity in the E-mini futures markets is significantly lower than either of the other two markets considered here. In particular, the Yen/US$ E-mini futures contract has a relative extreme low trading frequency with 42 trade per day on average over the sample period. Hence, the E-mini Yen futures time series is dropped from the present analysis because of the very low number of observations within a day. This low trading frequency prevents the convergence of our estimation method resulting in considerably unreliable parameter estimates and price discovery measures.

As the correlation coefficient matrix shows, the series are highly correlated. An exception is the correlation between the E-mini contract and the other two instruments in the Yen/US$ market. This correlation is particularly low, due to infrequent trading in the E-mini Yen futures market.

2.3 Methodology and Empirical Results

Based on the standard Augmented Dickey-Fuller unit root test, the null hypothesis of a unit root cannot be rejected for any price series under study. The Johansen (1991) cointegration test results show that the spot exchange rate, the regular futures, and the E-mini futures in the Euro/US$ markets are cointegrated with two cointegration relationships. Similarly, there is one cointegrating vector between regular futures and spot markets for the Yen/US$ series. Hence, the results confirm that prices in the two or three foreign exchange markets share one common stochastic trend or “efficient price.” [6] Given these statistical results, it is appropriate to proceed with the price discovery analysis.

Two standard approaches are used to examine the relative rates of price discovery: (1) Information shares and (2) Gonzalo-Granger common factor weights. Both approaches assume that an underlying security trading in multiple markets has a common implicit efficient price. We also further supplement the analysis with the error correction adjustment approach as used in Eun and Sabherwal (2003). Also note that the chapter’s results reported below remain significant when other time intervals (1 second, 10 seconds, 30 seconds and 1 minute) are considered in the estimation of the model. All the estimations are conducted on daily basis and closely follow that of Hasbrouck (2003).

2.3.1 Information Share (IS) approach

The information share approach proposed by Hasbrouck (1995) decomposes the price series into a random walk component and a stationary component. The random-walk component represents the security’s efficient price which is common to all markets, while the stationary term captures market-specific characteristics. Studying the properties of this common component is the goal of this measure. In particular, Hasbrouck (1995) decomposes the variance of the common efficient price (random walk) innovations. The portion of the variance explained by each market is called the information share of market j. The information share measures the portion of a subset of the market’s information that is impounded into prices by different markets trading the same underlying security. The market with the largest information shares “leads” the other markets by reacting to new information first. If the

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[6] The results are available upon request.

innovations in a market drive the reaction of the other markets, then this market is informationally dominant.

The Stock and Watson (1988) common trends representation of the model is as follows:

$$p_t = p_0 + \psi(\sum_{i=1}^{t} \varepsilon_i)\iota + \Psi(L)\varepsilon_t \tag{2.1}$$

where p_0 is a constant n-vector and $\Psi(L)$ is a matrix polynomial in the lag operator. More specifically, the first term on the right-hand side of equation (2.1) is a vector of initial values that may reflect non-stochastic differences between the price variables. The second term is the product of a scalar random walk and a unit vector, which captures the random walk component that is common to all prices (the "efficient" price). Although this component is unobservable without further identification restrictions, its innovations have the property that they are linear in the disturbances. The third term in equation (2.1) is a zero-mean covariance stationary process.

Define and note that ψ represents the common row vector of $\Psi(1)$. If n = 3, then,

$$\mathrm{var}(\psi\varepsilon_t) = J_1^2\sigma_{11} + J_2^2\sigma_{22} + J_3^2\sigma_{33} \tag{2.2}$$

where J_i are the elements in $\Psi(1)$. Each of these terms represents the contribution to the random-walk innovation from a particular market. The proportion of this for market j (for j = 1, 2, 3) relative to the total variance is defined as the market's j information share:

$$IS_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi'} \quad \text{or} \quad IS_j = \frac{J_j^2 \sigma_{jj}}{J_1^2 \sigma_{11} + J_2^2 \sigma_{22} + J_3^2 \sigma_{33}} \tag{2.3}$$

where Ω is the covariance matrix. The measure in the above equation is too restrictive since price innovations are generally correlated across markets trading the same underlying instrument. If the price innovations are correlated (i.e. $\sigma_{ij} \neq 0$ for $i \neq j$), no unique values may be found for the information shares, and triangularization of the covariance matrix may be used to establish upper and lower bounds.[7]

Therefore, when the covariance matrix Ω is not diagonal, Hasbrouck (1995) defines the information shares of the market j prices as

$$IS_j = \frac{([\psi F]_j)^2}{\psi \Omega \psi'} \tag{2.4}$$

In this equation, F is the Cholesky factorization of Ω, and a lower triangular matrix such that $\Omega = FF'$. The variance attributed to a particular market j is $([\psi F]_j)^2$ and $[\psi F]_j$ is the jth element of the row matrix ψF. The lower triangular factorization maximizes the information shares on the first price. By permuting the order of the market prices, equation (2.4) will provide an upper and lower bound for the information share of each market.

Table 2.3 presents estimates relating to the information shares and the correlations of the price innovations. Due to the presence of nonzero off-diagonal

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[7] Table 2.3 presents the average mean disturbance (price innovation) correlation matrix for the Euro/US$ and the Yen/US$, respectively. The triangularization is implemented since the off-diagonal terms are different from zero.

correlations in the innovations, only upper and lower bounds for the information shares can be established. Care must be exercised in interpreting the lower and upper bounds since they do not provide a single measure of information share. However, following Booth et al. (2002) and many others, the midpoints of lower and upper bounds can be used as a unique measure of the price discovery contribution. The information share statistics reflect the average of all daily estimates. Panel A of Table 2.3 shows that the Euro/US$ spot market contributes the most to price discovery, accounting roughly for over 60% of the information share. The other two prices share the remainder, with the regular futures accounting for 33% and the E-mini futures accounting for comparable shares on average. In the Yen/US$ market, the spot trades lead the price discovery process with roughly 75% of the information share, while the regular futures contributes only about 25% of price discovery.

The findings confirm the recent work of Tse, Xiang and Fung (2006) on Yen as they provide evidence that the Yen spot foreign exchange market dominates the futures markets in price discovery. However, the findings contradict that of Rosenberg and Traub (2007) who find regular futures contribute more to the price discovery in 1996. Also in contrast with the evidence in the equity markets, the results show that the E-mini futures do not dominate the price discovery process in foreign exchange markets. The finding may not be surprising, given relatively low number of trades on the E-mini futures market in Table 2.2. As further pointed out by the referee, although the E-mini currency futures market is a global market, it's rather concentrated among a few banks. Thus, there might not be many informed traders in this market.

Panel A and B in Figure 2.1 present the time series of the daily information shares of the three Euro/US$ instruments and the two Yen/US$ instruments respectively. The information share midpoints are shown. Despite some time variations, it is clear that the spot markets consistently dominate the futures markets over the sample period.[8] These findings hold for both currency markets. It can also be seen that in the Euro/US$ market, there is no information dominance of the E-mini futures market over the regular futures. Overall, these results provide evidence that the spot market is the major contributor to price discovery in foreign exchange markets over time.

2.3.2 Common factor component weight (GG) approach

Let p_t be a (*n* x 1) vector of I(1) price series for the same underlying security in n markets. Even though each individual price series is non-stationary, they are cointegrated with *h* (*h* = *n*-1 in this study) cointegrating relations. The Granger representation theorem shows that the VAR(p) with cointegrated variables can be written in its error-correction form,

$$\Delta p_t = Bz^{*}_{t-1} + \varsigma_1 \Delta p_{t-1} + \varsigma_2 \Delta p_{t-2} + \varsigma_3 \Delta p_{t-3} + ... + \varsigma_{p-1} \Delta p_{t-p+1} + \varepsilon_t \qquad (2.5)$$

Stock and Watson (1988) shows that the price vector can be decomposed into a permanent and a transitory component. Gonzalo and Granger (1995) propose an alternative decomposition of p_t where the permanent component will be a function of the current values of p_t (which differs from the Stock and Watson (1988) representation where the common trend is a function of the current and lagged values

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[8] For a few days during the sample period, the information shares of regular futures market are larger than those in the spot market with increasing transactions for both spot and futures markets. This switch in the relative importance of the information shares on spot and futures markets also sometimes coincides with the days with some identifiable economic news. Nevertheless, the exact reason why such switch occurs is not clear and worthy of pursuing in the future research.

of the disturbances and therefore of p_t).[9] The vector of prices p_t is decomposed as follows,

$$p_t = F_1 f_t + F_2 \tau_t \tag{2.6}$$

where: f_t = common long memory component (vector of common stochastic trends)

τ_t = stationary component

Two conditions are imposed:

(i) f_t is an exact linear function of the current values of p_t

(ii) The transitory component, τ_t , has no permanent effect on p_t

These assumptions or conditions make it possible to identify the common factor and also make the common efficient price f_t observable (a function of the current values of the price vector). In other words, the Gonzalo-Granger approach defines the permanent component of the vector of prices p_t as a linear combination of the current values of the price vector itself, where the linear combination is given by the structure of the A_* . A_* is a matrix orthogonal to the matrix of cointegrating vectors A , and can be estimated as a matrix of (*n* - *h*) eigenvectors using the Johansen (1991) procedure. Given the nature of the Gonzalo-Granger decomposition and the following result:

$$f_t = A_*' p_t \tag{2.7}$$

the A_* matrix (after normalization) becomes a natural measure of the contribution to price discovery of market *i*. The higher the weight, the larger the contribution of the market to the information impounding process is. There is no restriction in the

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[9] De Jong (2002) provides a detailed discussion about the relationship between the Gonzalo-Granger common factor coefficients and the Stock and Watson (1988) decomposition.

decomposition procedure which prevents the factor weights from being negative. Since the size (not the sign) of the weights provide a measure of the market's role in the price discovery process, the weights are normalized so that they come out to be positive and the sum of these weights is equal to one,

$$\omega' = (abs(A_{*}')\iota)^{-1} abs(A_{*}') \tag{2.8}$$

where $abs(.)$ denotes the absolute value of each element in the matrix and ι is (nx1) vector of ones.

Table 2.4 provides the summary statistics of the common factor weights for each market price in the model. The first half of each panel presents the common-factor coefficients obtained by the Gonzalo and Granger (1995) method, and the second half presents the normalized coefficients or weights.[10] In panel A for the Euro, the daily average of the normalized common-factor weights is evidence of a predominant price discovery role of the spot markets. On average, the spot price contributes 60% of the formation of the common-factor component or “efficient price”. The other two prices share the remainder, with the regular futures contributing 23% and the E-mini futures markets contributing 17%. Another interesting observation is that the table under “Min”, both the regular and the E-mini futures prices show no contribution to price discovery in some of the sample days. Panel B shows similar results for the Yen/US$ markets. The common factor weight for the regular futures markets (28%) is much smaller than that of the spot market. Furthermore, compared with the case of the Euro, leaving out the E-mini from the analysis for the Japanese Yen has increased the spot weight by a much larger

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[10] This normalization was necessary to simplify the interpretation of the common-factor coefficients as measures of price discovery. After normalizing, the coefficients are all positive between 0 and 1 and they sum to one.

percentage than the increase in the regular futures weight. This could imply that the spot prices may better capture the price information revealed in the E-mini market than the regular futures market does.

Panel A and B in Figure 2.2 present the time series behavior of the daily estimated Gonzalo-Granger common factor weights over the sample period. The estimate for the spot series is mean reverting around a point higher than 50% in both currency markets. These results are obviously consistent with the results in Table 2.4. In summary, in line with the information share results, the results here support the findings of the dominance of spot market over both the regular and E-mini futures markets and almost equal performance of the regular futures and E-mini futures in the foreign exchange market price discovery.

2.3.3 Error-correction adjustment approach

We further conduct weak exogeneity tests for each exchange rate series based on an error correction model. The idea is that although there is one common stochastic trend for the exchange rates on related spot and future markets, these exchange rates may have temporary deviation from the common trend due to various market frictions. Such exchange rate dynamics across relate markets can be modeled in an error correction model with *n - 1* cointegrating relations (or *n - 1* error correction terms) for *n* exchange rates:

$$\Delta p_t = Bz^*_{t-1} + \varsigma_1 p_{t-1} + \varsigma_2 p_{t-2} + \ldots + \varsigma_{p-1} p_{t-p+1} + \varepsilon_t \qquad (2.9)$$

where B is the (n x (n – 1)) matrix of adjustment coefficients and the error correction terms in z_{t-1}^{*} can be specified using two price differentials involving the spot prices. Specifically, for n = 3,

$$Bz_{t-1}^{*}=\begin{pmatrix} b_{12} & b_{13} \\ b_{22} & b_{23} \\ b_{32} & b_{33} \end{pmatrix}\begin{pmatrix} (p_{1t}-p_{2t})-\mu_2 \\ (p_{1t}-p_{3t})-\mu_3 \end{pmatrix}$$

where μ_i is the average price differential or mean deviation for i = 2, 3. The coefficients for the error correction terms (or so-called adjustment coefficients, given by the B matrix) measure the adjustment speeds by which each variable adjusts itself toward the long-run equilibrium. As pointed out in Eun and Sabherwal (2003), the magnitude of adjustment coefficients can be used to assess the contribution of a particular market to price discovery. A market which has zero (i.e., weakly exogenous) or a smaller (in absolute value) adjustment coefficient than those of other markets is a more dominant source of information in the price discovery process in the long run.

Estimated adjustment coefficients of the error correction models further confirm our results. Table 2.5 provides the estimates and t-statistics of the adjustment coefficients. Panel A provides the adjustment coefficient estimates for the Euro/US$ system of cointegrated series. There are two findings worth noting. First, on average, the coefficient estimates on the spot error-correction terms are not significant at the 0.05 level and thus weakly exogenous, while the estimates on the regular futures and E-mini futures error correction terms are significant at the 0.01 and 0.05 levels, respectively. Second, on average, the absolute values of the adjustment coefficient estimates are higher for the futures markets relative to the spot market. The results suggest that error-correcting adjustments to price differentials occur mainly in the regular futures and E-mini futures markets, which is in line with the leading price discovery role of the spot market. Panel B of Table 2.5 provides very similar results to those in Panel A. The Yen/US$ regular futures markets provide statistically significant adjustment coefficient estimates with a magnitude (in the absolute value) larger than the estimates for the spot market. Therefore, similarly to the Euro/US$ market, error correcting adjustments to price differentials occurs mainly in the futures markets. In summary, these results confirm that the spot market leads the regular futures and E-mini futures markets in the price discovery process.

Panel A and B in Figure 2.3 present the time plots of t-statistics of the adjustment coefficient estimates for both currencies. Consistent with the results in Table 2.5, these graphs reveal that over the majority of trading days, it is primarily the futures markets rather than the spot markets that adjust to price differentials across markets. Hence, the price discovery of the currency markets takes place predominantly in the spot market. The results are also consistent with Kurov and Lasser (2004), which suggest that market j will have a higher information share if other markets tend to have error-correction adjustment to trades initiated in market j.

2.4 Conclusion

Given much recent evidence of the superiority of electronic trading, it is interesting to ask the question: among these markets trading electronically, which one leads the price discovery process? This chapter attempts to answer this question on the foreign exchange market. Using intra-day (tick-by-tick) data, this chapter investigates the contribution to the price discovery on the Japanese Yen and Euro exchange rates of three electronically traded foreign exchange markets: the CME electronically-traded GLOBEX regular futures, electronically-traded small-denomination futures (E-Minis), and the inter-dealer spot market. The results show that transaction prices in the inter-dealer spot foreign exchange market are more informative than the prices in both the regular futures and the E-mini futures markets and thus the spot foreign exchange market leads the price discovery process for both exchange rates during the sample period.

The findings of this study are justifiable by the sheer size of the interdealer spot market compared with the futures markets and the use of EBS interdealer currency spot data as EBS has become the major trading platform for both the Yen and the Euro. However, the results stand in sharp contrast to recent studies that currency futures might lead current spot market in price discovery. In particular, although this study confirms the recent finding of Tse, Xiang and Fung (2006) in favor of the spot markets for the Yen, the finding on the Euro here contradicts that of Tse, Xiang and Fung (2006). Nevertheless, the result of Tse et al. (2006) might not be very surprising given the fact that their spot rate data are from the CMC retail platform, which is unlikely to have informed traders.

The overall findings of this study are also only partially in line with that of Rosenberg and Traub (2007). Interestingly, while Rosenberg and Traub (2007) found currency futures market can lead the spot market in price discovery using the interdealer spot transactions from the Reuters Dealing 2000-1 system from May to August 1996, they also report that the spot market leads futures market using spot market quotes from Bloomberg over the period from March to May 2006. A possible explanation for their result is that “greater transparency is generally associated with more informative prices” (Madhavan, 2000). A market with low transparency is typically associated with lower degree of price discovery. As pointed out by Rime

(2003), the interdealer direct trading platform by Reuters Dealing 2000-1 has a relatively low level of price transparency. However, the spot market might have become more transparent over time. Hence, it might not be surprising that based on the data from 1996, the futures market leads the spot market in price discovery, while using the data from 2006, the spot market leads the futures market as the spot market becomes more transparent. Nevertheless, as discussed earlier, our findings based on the EBS dataset should be most relevant and representative for the two exchange rates under consideration.

Furthermore, we also find *electronically traded* regular futures (on average) contribute (a bit) more than the E-mini futures and the E-mini futures (on average) contribute the least to the price discovery in the Euro/$ and the Yen/$ markets (while the spot market contributes the most). The finding is contradictory to the finding on the role of E-mini futures in the equity markets (e.g., Hasbrouck, 2003; Kurov and Lasser, 2004; Ates and Wang, 2005).

Finally, future research may gain further insight by considering the role of order flow in the price discovery process in foreign exchange markets, as suggested by Evans and Lyons (2002). Given the fact that most studies using high frequency data are limited to sample periods spanning only a few months, it may also be an area of fruitful research to explore potential time variations in contributions of each market to the price discovery process by using a longer period of data.

Tables and Figures

Table 2.1: Trading statistics on CME futures

Symbol	Type	Trading	Globex ADV 7:05am -4:00pm (contracts)	Globex ADV 5:00pm - 7:05pm (contracts)	Globex ADV 5:00pm - 4:00pm (contracts)	Floor ADV 7:20am - 2:00pm (contracts)	Globex “Day” % of Globex Total	Globex % of Total Trading
E7 (Euro)	E-Mini	Globex	2956	526	3482	0	0.83	1.00
EC (Euro)	Regular	Pit & Globex	100675	33704	134379	4788	0.74	0.97
J7 (Yen)	E-Mini	Globex	13	4	17	0	0.73	1.00
JY (Yen)	Regular	Pit & Globex	28169	9593	37762	3307	0.74	0.94

Note: (1) ADV is the Average Daily Volume, (2) "Day" = 7:05am - 4:00pm, (3) Percentages are also period averages, (4) Sample period is from April 4th, 2005 to July 29th, 2005.

Table 2.2: Summary Statistics (daily averages)

Euro

	Spot	Regular futures	E-mini futures
Number of observations	4514	6478	1468
Mean	1.248	1.250	1.250
Standard Deviation	0.002	0.002	0.002
Skewness	-0.027	0.090	0.004
Kurtosis	-0.532	1.428	-0.516

Japanese Yen

	Spot	Regular futures	E-mini futures
Number of observations	3566	2594	42
Mean	0.0092344	0.0092848	0.0092796
Standard Deviation	0.0000094	0.0000096	0.0000095
Skewness	0.037	0.041	-0.108
Kurtosis	-0.644	-0.678	-0.336

Correlation coefficients for the prices (daily averages)

Euro

	Spot	Regular futures	E-mini futures
Spot	1	0.991	0.987
Regular futures		1	0.987
E-mini futures			1

Japanese Yen

	Spot	Regular futures	E-mini futures
Spot	1	0.989	0.690
Regular futures		1	0.692
E-mini futures			1

Note: Sample period is from April 4th, 2005 to July 29th, 2005.

Table 2.3: Information shares

Panel A: Euro

Information Shares

	Spot Trade Price			Regular Contract Price			E-Mini Contract Price		
	Min	Mid	Max	Min	Mid	Max	Min	Mid	Max
Median	0.28	0.61	0.91	0.05	0.33	0.61	0.01	0.23	0.45
Mean	0.31	0.60	0.90	0.06	0.32	0.58	0.03	0.22	0.42
Std. Dev.	0.18	0.11	0.07	0.06	0.12	0.20	0.03	0.10	0.19

Disturbance Correlation Matrix

	Spot Trade Price	Regular Contract Price	E-Mini Contract Price
Spot Trade Price	1	0.576	0.522
Regular Cont. Price		1	0.455
E-Mini Cont. Price			1

Panel B: Japanese Yen

Information Shares

	Spot Trade Price			Regular Contract Price		
	Min	Mid	Max	Min	Mid	Max
Median	0.56	0.75	0.94	0.06	0.25	0.44
Mean	0.55	0.73	0.91	0.09	0.27	0.45
Std. Dev.	0.18	0.13	0.08	0.08	0.13	0.18

Disturbance Correlation Matrix

	Spot Trade Price	Regular Contract Price
Spot Trade Price	1	0.449
Regular Cont. Price		1

Table 2.4: Gonzalo-Granger factor weights

Panel A: Euro

Gonzalo-Granger Common Factor Weights

	Spot	Regular Futures	E-mini futures
Mean	0.85	0.34	0.17
Min	0.38	-0.02	-0.49
Max	1.00	0.89	0.70
Std. Dev.	0.13	0.21	0.26

Gonzalo-Granger Common Factor Weights (Normalized)

	Spot	Regular Futures	E-mini futures
Mean	0.60	0.23	0.17
Min	0.25	0.00	0.00
Max	1.00	0.59	0.44
Std. Dev.	0.15	0.13	0.12

Panel B: Japanese Yen

Gonzalo-Granger Common Factor Weights

	Spot	Regular Futures
Mean	0.90	0.36
Min	0.41	-0.28
Max	1.00	0.91
Std. Dev.	0.11	0.22

Gonzalo-Granger Common Factor Weights (Normalized)

	Spot	Regular Futures
Mean	0.72	0.28
Min	0.31	0.00
Max	1.00	0.69
Std. Dev.	0.14	0.14

Table 2.5: VECM Estimation Results - Adjustment Coefficients

Panel A: Euro

$b_{i,2}$

	Spot	Regular Futures	E-mini futures
Mean	-0.0500	0.1747	-0.0602
	[-1.54]	[5.00]	[-2.20]
Min.	-0.1526	0.0059	-0.1702
	[-3.64]	[1.52]	[-4.91]
Max.	0.0147	0.8063	0.0315
	[0.64]	[11.18]	[1.01]

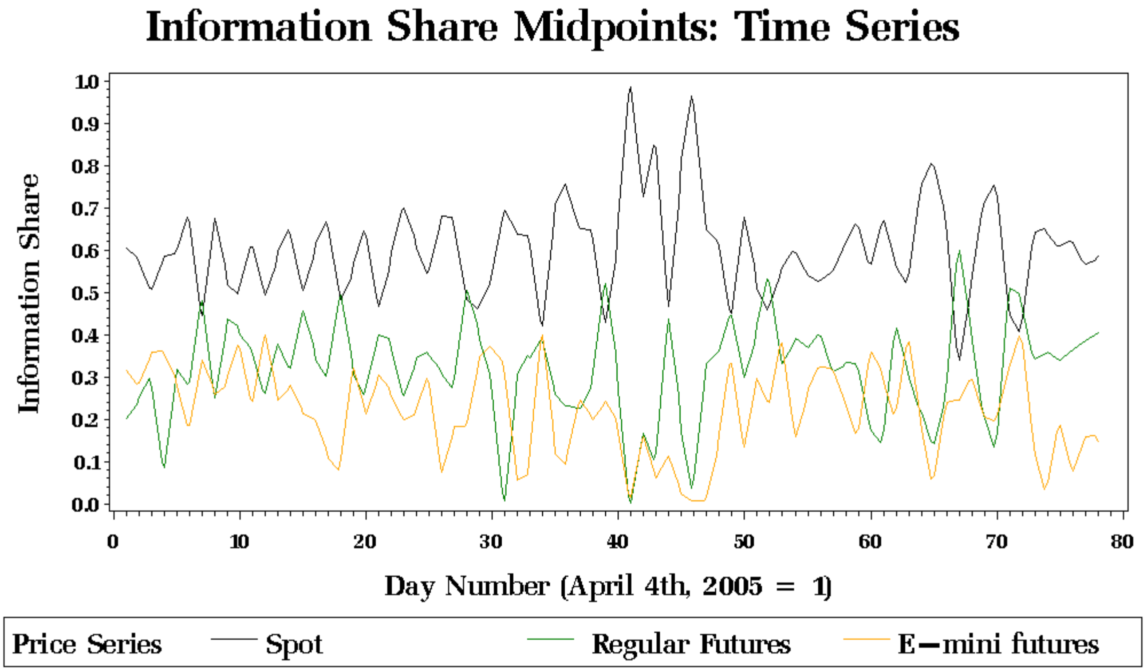
$b_{i,3}$

	Spot	Regular Futures	E-mini futures
Mean	-0.0094	-0.0239	0.0827
	[-0.47]	[-0.82]	[5.17]
Min.	-0.0553	-0.3772	0.0091
	[-2.85]	[-3.71]	[2.47]
Max.	0.0353	0.0305	0.1611
	[2.00]	[1.57]	[8.55]

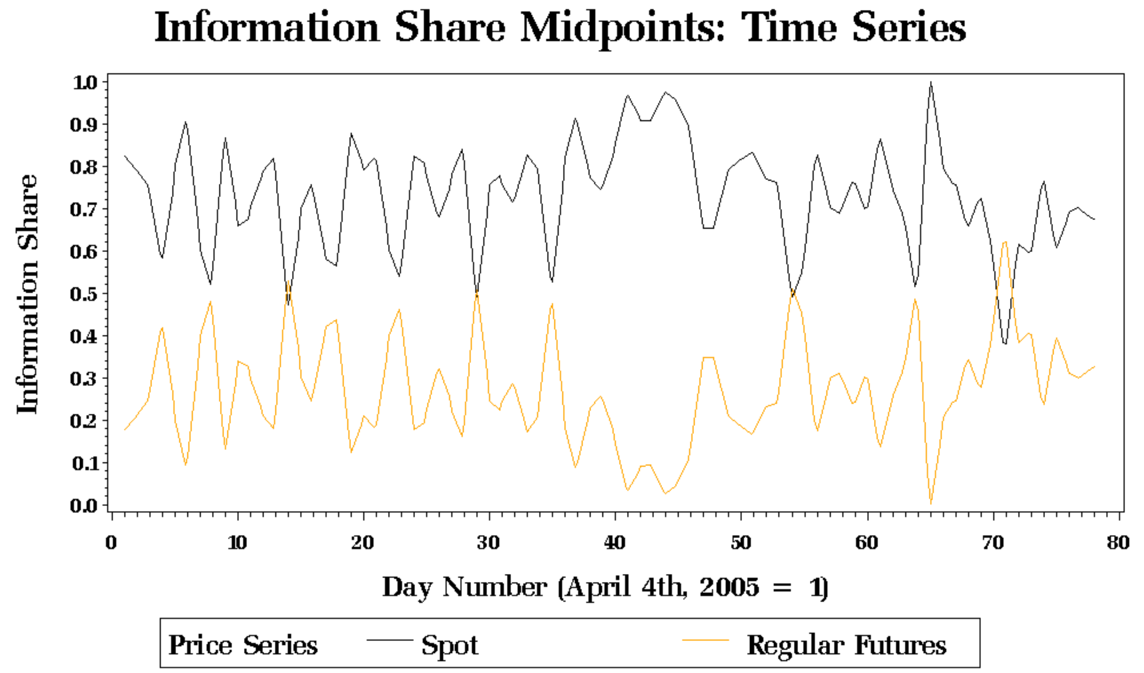
Panel B: Japanese Yen

$b_{i,2}$

	Spot	Regular Futures
Mean	-0.031310	0.077889
	[-1.76]	[5.04]
Min.	-0.138170	0.020805
	[-4.43]	[2.35]
Max.	0.006013	0.177656
	[1.00]	[9.11]

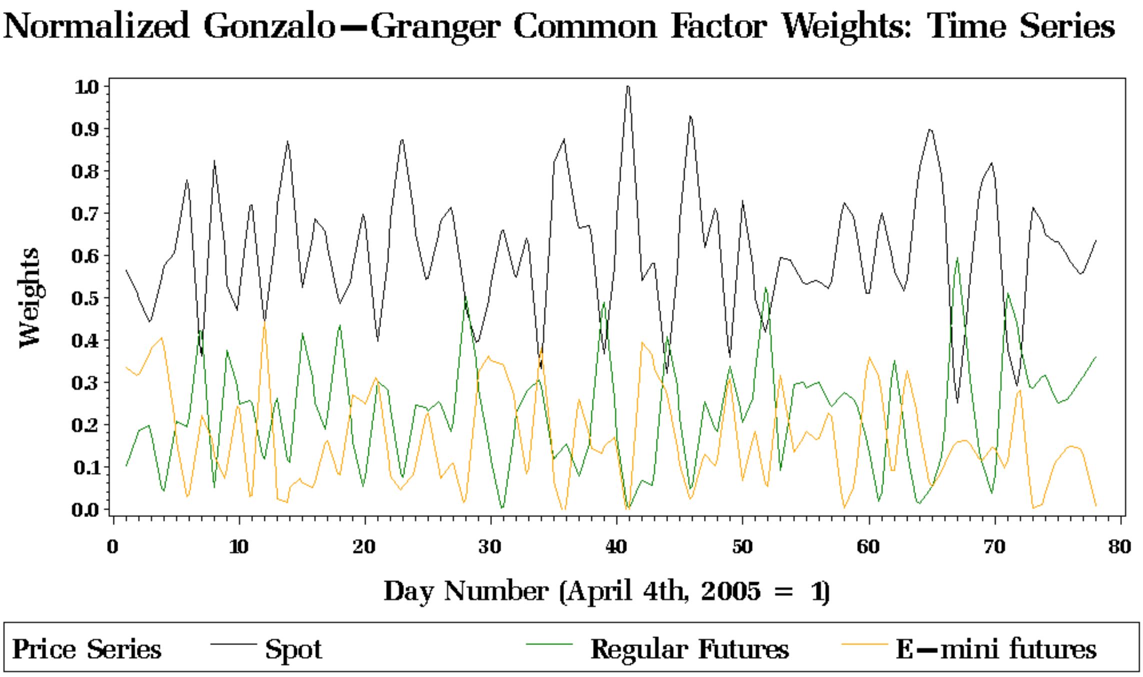


Panel A: Euro/$

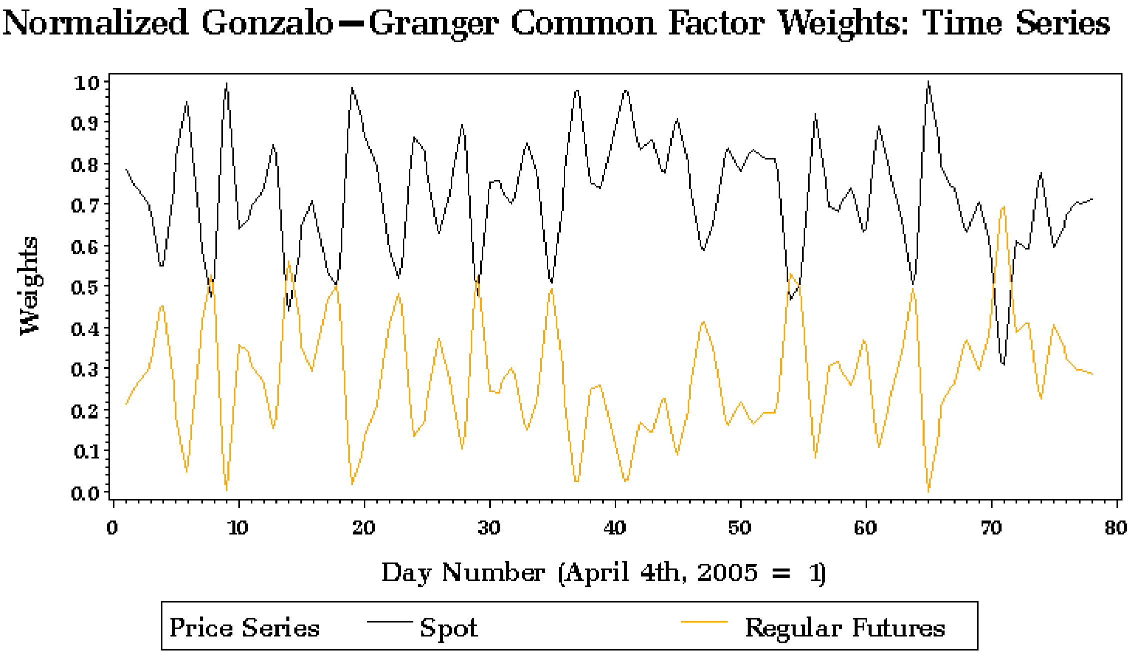


Panel B: Japanese Yen/$

Figure 2.1: Information Shares

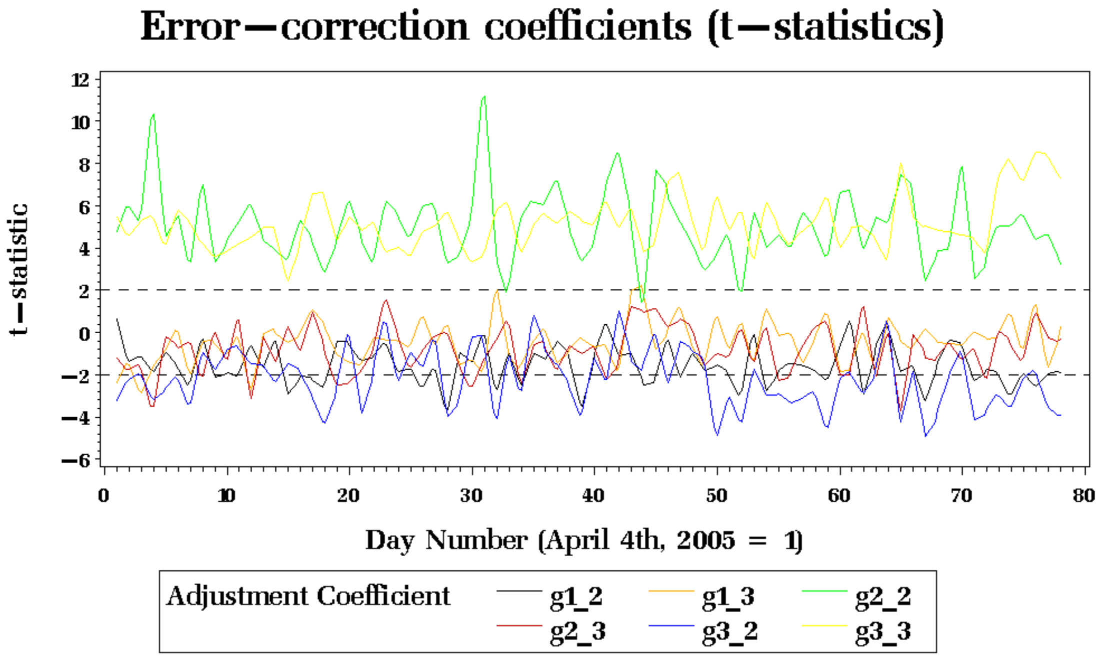


Panel A: Euro/$

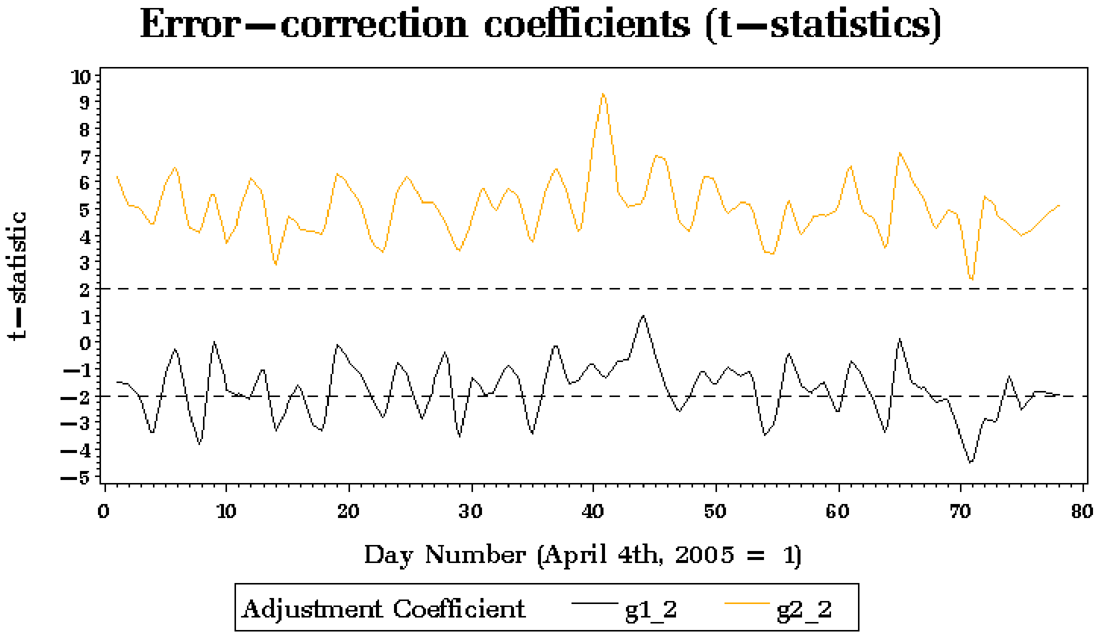


Panel B: Japanese Yen/$

Figure 2.2: Normalized Gonzalo-Granger Factor Weights



Panel A: Euro/$



Panel B: Japanese Yen/$

Figure 2.3: VECM Error-correction Coefficients (t-statistics)

CHAPTER 3

Nonlinearity, Data-Snooping, and Stock Index ETF Return Predictability

3.1 Introduction

Asset return predictability has been one of the most important topics in financial research. The inference on asset return predictability carries important implications to practitioners, for example, for the design of portfolio management strategies. Numerous earlier works have been conducted to examine the short-horizon predictability of stock market returns based on past returns. In this regard, since the variance ratio test was originally developed by Lo and MacKinlay (1988), it has been widely used in testing the random walk hypothesis in international stock market indexes (e.g., Urrutia, 1995; Grieb and Reyes, 1999; Kim and Singal, 2000; Chaudhuri and Wu, 2003; Patro and Wu, 2004).[11]

However, the popular variance ratio test used in the above studies (as well as the traditional autocorrelation test, see, e.g., Chordia, Roll and Subrahmanyam (2005)) assumes linearity and only tests serial uncorrelatedness rather than martingale difference (Hsieh, 1991; McQueen and Thorley, 1991; Hong and Lee, 2003). A nonlinear time series can have zero autocorrelation but a non-zero mean conditional on its past history (i.e., predictable based on the past history). That is, the variance

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[11] The terms “random walk” and “martingale” have been interchangeably used in the efficient capital markets literature. However, it is the martingale property (or unpredictability) of security prices that is of essential interest to this huge body of the literature (Fama, 1991; Granger, 1992). Strictly speaking, the innovations series is independent and identically distributed for “random walk”, while it is a martingale difference sequence for “martingale.”

ratio test may fail to capture predictable nonlinearities in mean (if any) and could yield misleading conclusions in favor of the martingale (or loosely random walk) hypothesis.

This study examines daily return predictability of international stock index exchange-traded funds (ETFs) during the period of 1996-2006. We present the first comprehensive study on the martingale behavior of recently popular international stock index ETFs (loosely in the context of weak-form market efficiency). As one of the most successful financial innovations of all time, there were over 300 ETFs with more than $400 billion of assets as of December 2006. A defining characteristic of ETFs is their ease for intraday active trading and high daily turnover, as it is particularly appealing to investors who demand short-term liquidity and trade in large lots (Poterba and Shoven, 2002). International stock index ETFs presumably provide an attractive investment vehicle for the US investors to explore potential investment opportunities abroad. Surprisingly, while many issues such as diversification potentials and herding behaviors on the ETFs have been examined (e.g., Pennathur, Delcoure and Anderson, 2002; Gleason, Mathur and Peterson, 2004), the important issue of their short-horizon predictability has not yet been investigated. Also noteworthy, daily stock index ETF prices are transaction prices which would not suffer from the notorious non-synchronous trading problem of daily stock market indexes (Ahn et al., 2002), which plagues numerous studies using such data.[12]

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[12] Although international stock index ETFs are designed to track each country stock market index, there may be substantial tracking errors for the ETFs, partly due to their considerable exposure to the U.S. market (e.g., Pennathur, Delcoure and Anderson, 2002). Nevertheless, the predictability of the ETFs as a new financial instrument remains in itself interesting. To extent that the international stock index ETFs track the performance of international stock indexes, the evidence from this study could also shed more light on the short-horizon predictability of international stock market indexes.

We seek to contribute to the literature in the following important aspects. First, we take the model selection approach (e.g., Swanson and White, 1995, 1997), rather than the more traditional hypothesis testing approach as taken in the variance ratio test (or the autocorrelation test). As discussed in Swanson and White (1995, 1997), unlike the traditional hypothesis testing approach, the model selection approach does not require the specification of a correct model for its valid application. By contrast, earlier empirical findings based on variance ratio tests are quite sensitive to potential model misspecification. More important to this study, it allows us to focus directly on the issue of predictability at hand: out-of-sample forecasting performance. Arguably, out-of-sample evidence bears directly on predictability and is important to mitigate the concern of in-sample model overfitting, particularly for nonlinear models. This is also well line with Granger's (1992, p.11) observation that "only out-of-sample evaluation is relevant and, to some extent, avoids these difficulties (due to data mining)." By contrast, all the cited studies above only focus on in-sample evidence (and also typically fail to allow for potential nonlinearity-in-mean).

Further, similar to Swanson and White (1995, 1997), Hong and Lee (2003) and Moreno and Olmeda (2007), this study presents out-of-sample evidence based on both statistical and economic criteria. With the notable exception of Ratner and Leal (1999) and Moreno and Olmeda (2007), few earlier studies on international stock market random walk behavior have considered economic criteria as measured by magnitude of trading returns and particularly the direction of forecasted price changes, which have practical value to investors and other decision-makers.

Second, we extend the literature by applying a number of nonlinear models that allow for both potential nonlinearity-in-mean and nonlinearity-in-variance. As noted earlier, the cited studies above using variance ratio tests (and autocorrelation tests) do not allow for nonlinearity-in-mean. Theoretically, as discussed in McQueen and Thorley (1991), existence of fads or rational speculative bubbles suggests the possibility of nonlinear patterns in stock returns. Or, if the world is governed by a not-too-complex chaotic process, it should have short-term nonlinear predictability (in mean) but not linear predictability (Hsieh, 1991, p.1845). Further, in a survey on the random walk test literature, Granger (1992, p.11) concludes that "benefits can arise…especially from considering non-linear models." Toward this end, this study considers several popular nonlinear models to more comprehensively explore potential nonlinearities in mean, in addition to the more commonly used nonlinear-in-variance models (i.e., GARCH) (see, e.g., Hsieh, 1989, 1991, 1993).[13] In fact, some variants of the popular nonlinear models used in most previous studies (e.g., Hsieh, 1991; Gencay, 1998; Harris and Kucukozmen, 2001; Monoyios and Sarno, 2002; Hong and Lee, 2003; Moreno and Olmeda, 2007) are used in this study.[14]

Finally, model comparisons in this study are improved relative to previous studies by using White's (2000) novel test to address the concern of data-snooping bias (i.e., spuriously superior predicative ability of some complex models due to chance).[15] When several forecast models using the same data are compared, it is crucial to take into account the dependence among these models, which otherwise may result in misleading inference due to data-snooping bias. While the overfitting problem of nonlinear models is well aware in the literature, relatively few earlier

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[13] Note that there is a debate about whether there exists predictable nonlinearity-in-mean in US stock market indexes. For example, although Hsieh (1991) finds little nonlinearity-in-mean in US stock market prices, Gencay (1998) reports nonlinear-in-mean predictability for similar indexes.

[14] Like many earlier studies, a caveat here is that the inference should still be interpreted in light of the limited number of models we examine in this study. In general, martingale means the existence of neither linear nor nonlinear dependence, and we have to test all possible nonlinear dependence to rule out the martingale property of stock returns, which is practically impossible.

[15] As discussed in Campbell et al. (1997, p. 523-524), the problems of overfitting and data snooping are related but different. A typical symptom of overfitting is an excellent in-sample fit but poor out-of-sample performance, while data-snooping refers to excellent but spurious out-of-sample performance.

studies in this line of the literature have addressed the data-snooping issue, which is shown to be nontrivial in this study. The rest of this chapter is organized as follows: Section 3.2 presents econometric methodology; Section 3.3 describes the data; Section 3.4 discusses the empirical results; and finally, Section 3.5 concludes the chapter.

3.2 Econometric Methodology

To forecast ETF daily returns, we use various models for $E(Y_t \mid I_{t-1})$, where Y_t represents the first difference of ETF daily closing prices in logarithm, I_{t-1} is the information set available at time $t-1$. We apply various popular nonlinear models to explore the possibility that daily ETF returns are not a martingale, and have the conditional mean dependence in a complicated form (i.e., nonlinearity-in-mean), and the dependence in (e.g., second (or higher) moments (i.e., nonlinearity-in-variance). We certainly do not assume that the limited number of the nonlinear models can capture all the nonlinearities. However, they do represent some of the most popular nonlinear models widely used in the literature thus far.

The martingale model $Y_t = \mu + \varepsilon_t$ is used as the benchmark for comparison with other models. Table 3.9 lists the various models examined in the chapter, including the autoregressive model (AR(d)), generalized autoregressive conditional heteroskedasticity model (GARCH(p,q)), feedforward artificial neural network (NN(d,q)), functional coefficient model (FC(d,L)), nonparametric regression model (NP(k,m)), and some combinations of these models. The estimation of the AR(d) and GARCH(p,q) models is relatively standard, using the ordinary least squares method and the maximum likelihood method, respectively. We next briefly discuss how to implement more complicated nonlinear models used in this study (i.e., neural network, functional coefficient and nonparametric models).[16]

3.2.1 The Feedforward Artificial Neural Network

Artificial neural networks have proven to be useful in capturing nonlinearity-in-mean in forecasting financial time series. One of the greatest advantages of neural networks over other commonly-used nonlinear time series models is that neural networks can well approximate a large class of functions. The basic structure of neural networks combines many ‘basic’ nonlinear functions via a multilayer structure. Normally there is one intermediate, or hidden, layer between the inputs and output. The intuition is that the explanatory variables simultaneously activate the units in the intermediate layer through some function Ψ and, subsequently, output is produced through some function Φ from the units in the intermediate layer. The following equations summarize this approach:

$$h_{i,t} = \Psi(\gamma_{i0} + \sum_{j=1}^{m} \gamma_{ij} X_{j,t}) \; i = 1,\dots,q \tag{3.1}$$

$$Y_t = \Phi(\beta_0 + \sum_{i=1}^{q} \beta_i h_{i,t}) \tag{3.2}$$

or, more compactly,

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[16] Also note that some of these models are special cases of the others. For example, the AR(1) model is a special case of the NN(1,5) model. Nevertheless, in this study the forecasting results of the NN(1,5) model are systematically worse than the results of the AR(1) model. This, however, may simply indicate rather weak nonlinearity-in-mean in the dataset and thus render more complicated NN(1,5) to perform poorly while the more parsimonious AR(1) perform rather well in the out-of-sample forecasting.

$$Y_t = \Phi\left(\beta_0 + \sum_{i=1}^{q} \beta_i \Psi(\gamma_{i0} + \sum_{j=1}^{m} \gamma_{ij} X_{j,t}) \right) \tag{3.3}$$

where $X_{j,t}$ is the input or an independent variable, $h_{i,t}$ is the node or hidden unit in the intermediate or hidden layer, and Y_t is the output or dependent variable. In this study, the independent variable $X_{j,t}$ coincides with the lagged dependent variable Y_{t-j}. The functions Ψ and Φ can be arbitrarily chosen and still approximate a large class of functions given sufficiently large numbers of units in the intermediate layer.

In this study, we use single layer feedforward neural networks (e.g., Lee, White and Granger, 1993; Gencay, 1998; Hong and Lee, 2003), which is the most basic but perhaps most commonly used neural network in economic and financial applications. In this case, the input variables are connected to multiple nodes (or hidden units), and at each node they are weighted (differently) and transformed by the same activation function Ψ. The output of each node is then weighted again by β_i and summed and transformed by a second activation function Φ.

Following the literature (e.g., Gencay, 1998; Hong and Lee, 2003), we chose the logistic function for the function Ψ and the identity function for the function Φ, which is common practice in the literature. Coefficients for the NN(d,q) model are estimated using nonlinear least squares via the Newton-Raphson algorithm. The final equation we will estimate is as follows:

$$E(Y_t \mid I_{t-1}) = \beta_0 + \sum_{j=1}^{d} \beta_j Y_{t-j} + \sum_{i=1}^{q} \delta_i G(\gamma_{0i} + \sum_{j=1}^{d} \gamma_{ji} Y_{t-j}), \tag{3.4}$$

where $G(z) = (1+e^{-z})^{-1}$ and is a function of Ψ , I_{t-1} is the information set available at $t-1$, and Y_t is the dependent variable (i.e., ETF returns).

3.2.2 The Functional Coefficient Model

The functional coefficient model introduced by Cai et al. (2000) is a new semiparametric nonlinear time series model with time-varying and state-dependent coefficients. It includes threshold autoregression models, smooth transition regression, and many other regime switching models as special cases. The basic model can be expressed as follows:

$$E(Y_t \mid I_{t-1}) = \alpha_0(U_t) + \sum_{j=1}^{d} \alpha_j(U_t) Y_{t-j} \tag{3.5}$$

where $\{(Y_t, U_t)'\}$ is a bivariate stationary process. The smoothing variable U_t may be chosen as a function of explanatory variable vector Y_{t-j} or as a function of other variables. In our forecasts of ETF returns using past returns, U_t is chosen as the difference between the log index price at time $t-1$ (p_{t-1}), and the moving average of the most recent periods L of the log prices at time $t-1$, or:

$$U_t = p_{t-1} - L^{-1} \sum_{j=1}^{L} p_{t-j} \tag{3.6}$$

In this chapter, following the literature (e.g., Gencay, 1998, 1999) and the common practice of technical analysis, we chose L = 200. Traders often use U_t as a buy or sell signal based on its sign, which reveals information on changes in direction, i.e. the moving average rule. Thus, the model might be well suited to forecasting the direction of price movements.

Following Cai et al. (2000), we estimate the term $\{a_j(U_t)\}$ nonparametrically using a local linear estimator. We approximate $a_j(U_t)$ locally (when U_t is close to u) by $a_j(U_t) = a_j + b_j(U_t - u)$. The local linear estimator at point u is $\hat{a}_j(u) = \hat{a}_j$, and $\{(\hat{a}_j, \hat{b}_j)\}$ are chosen by minimizing the sum of locally weighted squares defined as:

$$\sum_{t=1}^{N} [Y_t - a_j - b_j(U_t - u)]^2 K_h(U_t - u) \tag{3.7}$$

where $K_h(.)$ is the kernel function used as weights for points that are included to estimate $\{(\hat{a}_j, \hat{b}_j)\}$. We use the normal distribution as the kernel function, and h is the smoothing parameter or the bandwidth of the window of the kernel function, which is determined by the modified leave-one-out least square cross-validation method proposed in Cai et al. (2000).

3.2.3 The Nonparametric Kernel Regression Model

Because nonlinearities in the conditional means may be complicated and cannot be expressed explicitly, it is desirable to use nonparametric regression to estimate the model without specifying the forms of functions. Again, we use the well-known kernel regression (with some improvements on bandwidth selection to maximize the forecasting power) for estimation and forecasting. In general, a nonparametric regression model can be generally expressed as:

$$E(Y_t \mid I_{t-1}) = g(Y_{t-1}, Y_{t-2}, ..., Y_{t-j}) \tag{3.8}$$

As mentioned above with respect to the nonparametric estimator of $a_j(U_t)$ in the functional coefficient model, $g(.)$ can be estimated by local linear regression. At each point $y_t = \{ y_{t-1}, y_{t-2}, \ldots, y_{t-j} \}$, we can approximate $g(.)$ locally by a linear function $g(Y) = a + (Y - y)'b$. We can also approximate $g(y)$ locally simply by a constant function $g(y) = a$ (i.e., the local constant estimator), which is the approach taken here. The local constant estimator is relatively simple to implement and has been widely used in applied research. Compared to other estimators, it has also drawn most theoretical attention and thus has clear theoretical properties for estimation and inference of nonparametric models. The local constant estimator at point y is given by $g(y) = \hat{a}$, where $\hat{a}$ minimizes the sum of local weighted squares:

$$\sum_{t=1}^{N} [Y_t - a]^2 \prod_{s=1}^{j} K_{hs} \ (Y_{t-s} - y_{t-s}) \tag{3.9}$$

where $\prod_{s=1}^{j} K_{hs} \ (Y_{t-s} - y_{t-s})$ is the product kernel, $K_{h,s}$ is the univariate kernel function, and $h = (h_1, ...h_j)$ is chosen by the leave-one-out cross-validation procedure. The smoothing parameter h is the most important parameter in nonparametric estimation. An inappropriately chosen h will give poor in-sample and out-of-sample prediction. Traditional nonparametric forecasting uses the h that minimizes the in-sample sum square errors to forecast the next-period value based on previous in-sample data. However, while this h is optimal for all in-sample data, it may not be the best h for out-of-sample forecasting. Consequently, we use a modified method to select the smoothing parameter.[17]

Our modified approach consists of finding the best h for out-of-sample forecasting and making forecasts based on this h^*. For example, suppose that we have data points of x_1 to x_{100} and that we want to forecast x_{101}. The traditional approach is to find the best h to minimize the 100 data points' in-sample sum of squared errors (based on x_1 to x_{100}) and then use the h^* and these data points (i.e., x_1 to x_{100}) to forecast x_{101}. We propose the following modified nonparametric forecasting methodology. We use h^* and data points of x_1 to x_{80} to forecast x_{81}, data points of x_2 to x_{81} to forecast x_{82} , …, data points of x_{20} to x_{99} to forecast x_{100}. We find the h^* that minimizes the sum of squared errors of out-of-sample forecast of points x_{81} to x_{100} and use this h^* and data points x_{21} to x_{100} to make our final forecast of x_{101}. In this procedure, we have two parameters to establish: (1) the out-of-sample evaluation length k is set equal to 20 ($\hat{x}_{81}$ to $\hat{x}_{100}$) in the example, and (2) the regression length m is set equal to 80 in the example. Hence, we denote the model as NP(k, m), where the parameters (k, m) are important to the forecasting performance of this modified nonparametric regression model. We thus experiment different evaluation lengths in our study, and it appears that its impact is not substantial in this study. Therefore, in the tables presented below, we only discuss the results based on a particular combination.

Finally, it has also been argued that no single forecasting model performs well for all time periods and under all different criteria, as the pattern of ETF returns can

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[17] We thank Qi Li for making the suggestion.

vary over time and may not follow a simple data generating process. In order to improve the predictability, we closely follow Hong and Lee (2003) and combine several forecasting models. More specifically, we pool forecasts from the AR(1), GARCH(1,1), NN(1,5), FC(1,200), and NP(200,400) models to forecast the conditional mean of price changes.[18]

Denoting these five models as models 1, …, 5, respectively, the combined model is given by:

$$\hat{Y}_t^* \equiv \sum_{k=1}^{5} \omega_{kt} \hat{Y}_{kt} \tag{3.10}$$

where the weight ω_{kt} is determined as follows:

$$\omega_{kt} \equiv \frac{\exp[-\lambda_t \sum_{s=1}^{t-1} (Y_s - \hat{Y}_{ks})^2]}{\sum_{k=1}^{5} \exp[-\lambda_t \sum_{s=1}^{t-1} (Y_s - \hat{Y}_{ks})^2]} \tag{3.11}$$

with $\lambda_t = 1/(2S_t^2)$, S_t^2 is the sample variance of $\{Y_s\}$, s runs from 1 to $t-1$, and Y_{ks} is the out-of-sample prediction by model k. Intuitively, ω_{kt} gives higher weight to the model k if the prediction for model k is better than other models in previous forecasting exercises as measured by the mean squared forecast error (MSFE) criterion.

3.3 Data Description

The dataset consists of daily return observations for eighteen international stock index ETFs from CRSP. These ETFs are traded on the US market and designed

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[18] The Combined II forecasts pool forecasts from all 5 of these models, while the Combined I forecasts exclude the forecast of the GARCH(1,1) model.

to mimic the underlying indices they represent. They are readily available to US investors who want to get access to international stock markets without the involvement of currency exchange. More specifically, we use the daily closing prices on iShares exchange traded funds (ETFs) that track a chosen market index.[19] These markets have been divided into two groups: developed and emerging markets. The developed markets ETFs include Australia, Canada, France, Germany, Italy, Japan, Netherlands, Spain, Switzerland, United Kingdom, and the United States. The emerging markets ETFs include Brazil, Hong Kong, Korea, Malaysia, Mexico, Singapore, and Taiwan. The time period covered for developed market indices spans from April 1, 1996 to August 25, 2006. Among emerging market ETFs, for Hong Kong, Malaysia, Mexico, and Singapore, the starting period is January 4, 1999; for Taiwan, the starting period is June 23, 2000; for South Korea, the starting period is May 12, 2000; and for Brazil, the starting period is July 14, 2000. The use of daily data is appropriate for the purpose of this study and similar to many previous studies (Hsieh, 1991; Gencay, 1998; Monoyios and Sarno, 2002). Unlike higher-frequency intraday data, daily ETF data avoid the microstructure effects which are usually present in intraday dynamics. As thoroughly discussed in Hsieh (1991, p.1848), high-frequency tick by tick data may capture bid-ask bounces and other dependencies which are caused by the micro-market structure. These “artificial” dependencies will be picked up by any good test of nonlinear dynamics. The financial economist must increase the sampling interval in order to average out these “artificial” dependencies. Monoyios and Sarno (2002) also argue that the use of daily data can easily allow for the longer time span of the time series, which is much more important than the

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[19] For the US, the ETF chosen for the S&P 500 index is the SPY because it has a much higher trading volume than the iShares S&P500 ETF index. Also, All ETF returns are already adjusted for dividends.

number of observations per se to model nonlinear dynamics related to lower-frequency properties of the data. In addition, the number of daily observations is large enough to allow efficient in-sample estimation and out-of-sample forecasting evaluation. A limited number of observations tend to produce poor fit and inferior predictability, which could make results biased against rejecting the martingale hypothesis.

3.4 Empirical Results

In order to produce out-of-sample forecasts, we use a rolling regression technique. Suppose there are N observations in the sample, where N = R + P. At time t, we use a rolling sample of size R observations, as estimated using various linear and nonlinear methods, to produce a one-step-ahead forecast, $\hat{Y}_{t+1}$. Therefore, we can generate a sequence of P one-step-ahead forecasts which is used to evaluate each of the models under consideration. Swanson and White (1995, 1997) suggest that the rolling regression technique can further allow for the (potentially nonlinear) relation between the current and past returns to evolve across time.

Applying four forecasting evaluation criteria to the sequence of out-of-sample forecasts, we investigate the forecasting ability of the model relative to the benchmark martingale model. The four evaluation criteria used here are:

$$MSFE = P^{-1}\sum_{t=R}^{N-1}(Y_{t+1} - \hat{Y}_{t+1})^2 \qquad (3.12)$$

$$MAFE = P^{-1}\sum_{t=R}^{N-1}| Y_{t+1} - \hat{Y}_{t+1} | \qquad (3.13)$$

$$MFTR = P^{-1}\sum_{t=R}^{N-1} sign(\hat{Y}_{t+1})Y_{t+1} \tag{3.14}$$

$$MCFD = P^{-1}\sum_{t=R}^{N-1} 1[sign(\hat{Y}_{t+1})sign(Y_{t+1}) > 0] \tag{3.15}$$

where $sign(.)$ denotes $sign(\hat{Y}_{t+1}) = 1$ if $\hat{Y}_{t+1} \geq 0$ and $sign(\hat{Y}_{t+1}) = -1$ if $\hat{Y}_{t+1} < 0$.

Similar to Hong and Lee (2003), the two statistical criteria, mean squared forecast error and mean squared absolute error (MSFE and MAFE) are complemented with two economic criteria, mean forecast trading return and mean correct forecast direction (MFTR and MCFD). Both MFTR and MCFD can be particularly informative to profit-maximizing investors. Because stock returns are volatile, forecast errors can be quite large from period to period, the statistical accuracy of forecasts (as measured by MSFE and MAFE) does not necessarily imply economic accuracy in terms of maximizing investor profits. Investors may base their trading decisions on maximizing profits rather than minimizing forecasting errors. Furthermore, accurate forecasts of the direction of price changes may be equally important or even more important to investors than the magnitude of the changes, as they can be easily translated into profits. Granger (1992) emphasizes that, in this case, it is also desirable to compute economic measures of forecast accuracy, e.g., MFTR and MCFD. Many other authors (e.g., Leitch and Tanner, 1991; Hong and Lee, 2003) have made similar points in the context of forecasting asset prices. Hence, the use of multiple criteria in this study provides a more comprehensive perspective on the predictability of stock returns.

As mentioned above, it is important to have an adequately large number of observations to efficiently estimate the model parameters. In other words, the size of

R must be reasonably large. On the other hand, the size of P must be also large enough to detect the differences in forecasting performance across models. Given the number of observations in our data (N = 2619 and N = 1924 for developed and most emerging markets, respectively), an appropriate or balanced choice for R can be expressed by the ratio R:P = 2:1.[20]

Table 3.1 through Table 3.4 report the results for the developed markets and Table 3.5 through Table 3.8 report the results on the emerging markets. Each table contains one of the forecasting evaluation criteria in the order presented above. For example, Table 3.1 reports the out-of-sample forecast results using the MSFE for the eleven developed countries under consideration. All forecast results are based on an R:P ratio (regression length : total out-of-sample forecasts length) equal to 2:1. Each table also contains the two distinct p-values: P_1 and P_2 based on the White's (2000) Reality Check test. White's (2000) test addresses the dangerous practice of data-snooping or data re-usage for the purpose of inference. He constructs a method for testing the hypothesis that the best model encountered during a specification search has no predictive superiority over the benchmark model. His method, however, permits for data-snooping to be undertaken with some degree of confidence that one will not mistake results generated by chance for genuinely "good" results. For our purpose, P_1 is the bootstrap p-value for comparing a single model to the benchmark model which is the martingale model $Y_t = \mu + \varepsilon_t$. P_2 is the bootstrap reality check p-value for comparing the k models to the benchmark model. The value for P_2 in the table is the bootstrap reality check p-value for the null hypothesis that the best of the first k models has no superior predictive ability over the benchmark model. Of course,

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[20] We also conducted the analysis based on the ratio R:P = 1:1. The results are similar qualitatively and available upon request.

the last P_2 value (in the last row of the table) checks if the best of all the models under consideration has superior predictive ability over the martingale model. The difference between each P_1 and the last P_2 gives an estimate of data-snooping bias. Sullivan, Timmerman and White (1999) and Qi and Wu (2006) used the White's methodology to examine the data-snooping issue in technical trading rules.

Table 3.1 and Table 3.2 report the results for 11 developed markets using statistical criteria MSFE and MAFE. For the benchmark model, the MSFE and MAFE are in levels ($x10^4$ and $x10^2$, respectively). For all other models, they are in ratios relative to that of the benchmark model. For Table 3.1, the results show that except for Spain with the NN(1, 5) model, and Switzerland with the NP(200, 400) model, all MSFE ratios for the three nonlinear-in-mean models (NN(1,5), FC(1,200) and NP(200,400)) are above 1. Therefore, none of the nonlinear-in-mean models outperforms the benchmark. These findings are consistent with previous studies (e.g. Hsieh (1991)) that show a poor forecasting performance of nonlinear-in-mean models relative to the benchmark martingale models in terms of statistical criteria. On the other hand, when evaluated alone, each of the remaining four models (AR(1), GARCH(1,1), and the two combinations) in some cases reveals superior predictive ability than the benchmark. Note that the combined II forecasts pool forecasts from all individual models: AR(1), GARCH(1,1), NN(1,5), FC(1, 200) and NP(200, 400), while the Combined I forecasts exclude the forecast of the GARCH(1,1) model. Based on the MSFE criterion and the P_1 statistics, the AR(1) and the Combined II models show the most forecasting power as they are able to beat the martingale model for four out of the 11 countries. Note that the Combined II forecasts perform better than the Combined I (CI) forecasts. The result is apparently suggestive of the importance of using GARCH models to allow for nonlinearity in volatility. The superiority of these 4 models (albeit moderate) as measured by the MSFE can be more clearly seen in the case of Switzerland. All four models are able to beat the benchmark at the 5% level of significance (except for the GARCH model, which has a P_1 value of 12%). However, with allowance of data-snooping bias, the P_2 in the last row suggests that the best forecasting model among the 7 models is no better than the martingale model, except for Switzerland that AR(1) model clearly beats the benchmark model.

The results obtained using the MAFE as the evaluation criterion (Table 3.2) are very similar to those for the MSFE. The combined II models, when evaluated as a single model, show superior forecasting ability than the benchmark for five countries, which are mostly contributed by either the AR(1), the GARCH(1,1) or both. All three nonlinear-in-mean models fail to outperform the martingale model for all the markets. The GARCH models, however, show a better predictive ability when evaluated by the MAFE relative to the MSFE. Nevertheless, with further allowance of data-snooping bias, the apparent good performance of the Combined II model disappears, again with the only exception of Switzerland, where the AR(1) model as the best model outperforms the benchmark at the 5 percent level (with the P_2 value of 0.04).

Table 3.3 and Table 3.4 report the results using the economic criteria for all developed countries. All results for these two measures are in levels. The meaning of these results is straightforward. The MFTR shows the daily profit (in percentages) generated by the forecasts of the model, and the MCFD shows the percentage of all directional changes correctly predicted by the model. For example, in the case of Switzerland, the AR (1) model generates profit of 0.162% per trading day on average (or equivalently 40.7% per year with 251 trading days) during the out-of-sample period (before allowance for transactions cost) and correctly predicts 55.8% of the directions of changes which is mostly contributed by the superior performance of the AR(1) model. The results based on the MFTR (Table 3.3) suggest some evidence of superior predictive ability for the 3 nonlinear-in-mean models.[21] The NN model generates statistically significant profit (i.e., 0.025% per trading day) in case of the Netherlands. The FC and Nonparametric models are both able to beat the predictive power of the benchmark model in the Swiss stock market. However, for most other countries, the nonlinear-in-mean models do not outperform the benchmark model. On the other hand, for three countries, Germany, Switzerland, and the Netherland, the results reveal that both AR(1) and GARCH(1,1) are able to improve the forecasts of the martingale model. The numbers from the combined forecasts as well as the reality check test statistic P_2 also confirm the superiority of the AR(1) and GARCH(1,1) over the benchmark model for those 3 countries.

The results based on the MCFD criterion are similar to those based on the MFTR in that the 3 nonlinear-in-mean models generally cannot forecast the direction of the changes. Only the NN model is able to outperform the benchmark in the Netherland market, correctly forecasting directional changes in prices 49.1% of the time, 4.8% more often than the martingale model. Again, for the three countries, Germany, Switzerland, and the Netherland, the results reveal that both AR(1) and GARCH(1,1) are able to improve the forecasts of the martingale model. The numbers from the combined forecasts as well as the reality check P_2 in the last row also confirm the result.

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[21] Closely following Fama (1991) and Gencay (1998), we do not explicitly allow for transaction costs in the evaluation of trading rule performance of various models. Although there are surely positive information and trading costs, according to Fama (1991), the researcher instead should focus on the more interesting task of laying out the evidence on the adjustment of prices to various kinds of information (e.g., past returns in this study). Also note that some evidence for nonlinear-in-mean predictability would be even weaker after this consideration of transaction costs, which reinforce the main point of this study.

Overall, there is very limited evidence for predictability based on nonlinear-in-mean models. Among the 11 developed markets, only 3 countries, Germany, Switzerland, and the Netherlands show strong predictability from the AR(1), GARCH(1,1) and combined models based on the 4 statistical and economic criteria. The results based on the statistical criteria for Germany and Netherland, however, are not as strong as that for Switzerland due to the insignificant reality check statistics of P_2 values.

The results for six emerging markets in Table 3.5 through Table 3.8 are largely similar to those of the developed markets. Using statistical evaluation criteria (see Table 3.5 and Table 3.6), our findings suggest that even without allowance for data-snooping bias, nonlinear-in-mean models generally cannot outperform the benchmark, except that the FC model for Malaysia and Singapore outperforms the benchmark based on the MAFE. The models that perform the best are again the AR(1), GARCH(1,1), Combined I, and Combined II (the GARCH model, however, does not outperform the benchmark for any country when measured by the MSFE). Furthermore, using MAFE (instead of the MSFE) as the evaluation criterion provides stronger evidence of predictability in emerging markets. For example, the AR model is able to beat the benchmark in only one market of measured by the MSFE. The predictive ability of this model, however, significantly improves if we use the MAFE to measure forecasting errors. Overall, the statistical evaluation criteria show that without allowance for data-snooping bias, for up to four ETF indices, Hong Kong, Malaysia, Singapore, and perhaps Mexico, the Combined II model based mostly from AR(1) or GARCH(1,1) model predictions is able to outperform the benchmark. Again, the allowance of data-snooping bias substantially changes the picture: the only

P_2 that is in the last row and below 10 percent, is for Malaysia with the MAFE criterion.

The economic evaluation criteria in Table 3.7 and Table 3.8 show, similar to the case of developed countries, that nonlinear-in-mean models do not outperform the benchmark except in a few cases. In the case of Hong Kong, both FC and NP models (as a single model) outperform the benchmark under both the MFTR and MCFD criteria while only FC model outperforms the benchmark under MCFD for Singapore. In this case, we also find some evidence of superior forecasting ability of the FC model over both the AR and GARCH models. Still, the AR and GARCH models outperform the benchmark in some markets. In particular, the AR model outperforms the benchmark for Hong Kong and Singapore based on both MFTR and MCFD, and for Malaysia based on MCFD. When evaluated alone, the GARCH model outperforms the benchmark in 5 out of 7 countries based on MFTR. Overall, based on economic criteria, there remains strong evidence after allowance of data-snooping bias (i.e., based on last row P_2 values) that there is predictability for Hong Kong and Singapore, in addition to Malaysia as suggested by one of the statistical criteria (i.e., MAFE).

3.5 Conclusion

This study investigates the martingale behavior of eighteen stock market index ETFs based on out-of-sample forecasts. In addition to a linear model, this chapter employs several popular nonlinear models to more comprehensively explore potential nonlinearity in asset returns. Using both statistical and economic criteria, we find some evidence against the martingale hypothesis. Among the 18 ETF stock indices, three out of 11 developed markets (Germany, Netherlands, and Switzerland) and three out of seven emerging markets (Hong Kong, Singapore and Malaysia) show predictability in terms of either statistical or economic criteria, or both. However, most of this evidence comes from the linear model and the nonlinear-in-variance GARCH model, while the popular nonlinear-in-mean models (neural network, semiparametric functional coefficient model, nonparametric kernel regression) generally do not help much. This finding confirms the in-sample evidence of Hsieh (1989, 1991, and 1993) and Harris and Kucukozmen (2001) in the out-of-sample context, and it is in line with Moreno and Olmeda (2007) but differs from others (e.g., Gencay, 1998, 1999; Hong and Lee, 2003). Certainly, the differences of financial markets under study might account for such different findings. It is also important to note that the allowance for data-snooping bias using White's Reality Check renders apparent strong predictability on many markets to be tenuous, and particularly undermine otherwise impressive performance of forecast combinations. Hence, the findings of the chapter underscore the importance of allowing for data-snooping in addition to the well-known overfitting problem of nonlinear models.

Finally, our study also contrasts with earlier works (e.g., Patro and Wu, 2004) on the international stock market predictability using the variance ratio test. For example, Patro and Wu (2004) (see their Table 2) show that ten out of the eighteen developed markets exhibit in-sample (linear) daily return predictability. Our results suggest that despite more thorough examination with nonlinear models and multiple evaluation criteria, with the counteracting consideration of data-snooping bias, the predictability of daily international stock market indexes might not be even as widespread as previously thought.

Tables and Figures

Table 3.1: Forecast Evaluation Results for Developed Markets - MSFE

	AU	CA	GE	IT	JP	SW	NE	SP	FR	UK	US
Benchmark	1.175	1.021	1.341	0.933	1.837	1.081	1.086	1.067	0.998	0.844	0.492
AR(1)	1.039	1.017	*0.994*	*0.995*	1.005	*0.973*	1.001	1.000	*0.996*	*0.990*	*0.998*
P_1	1.00	1.00	**0.04**	**0.08**	0.79	**0.00**	0.64	0.46	**0.06**	0.18	0.18
P_2	1.00	0.99	**0.05**	**0.09**	0.78	**0.00**	0.67	0.48	**0.06**	0.16	0.18
GARCH(1,1)	*0.998*	*0.998*	*0.996*	*0.998*	1.000	*0.998*	*0.997*	*0.998*	*0.998*	*0.998*	*0.999*
P_1	0.30	0.23	0.12	0.21	0.35	0.12	**0.08**	0.19	0.21	0.11	0.36
P_2	0.59	0.50	**0.08**	0.11	0.68	**0.00**	0.27	0.45	0.10	0.16	0.35
NN(1,5)	1.007	1.001	1.001	1.018	1.014	1.053	1.004	*0.997*	1.030	1.034	1.052
P_1	0.71	0.53	0.53	0.97	0.97	1.00	0.68	0.32	1.00	0.99	1.00
P_2	0.75	0.72	0.34	0.38	0.85	**0.03**	0.55	0.59	0.42	0.37	0.65
FC(1,200)	1.043	1.012	1.027	1.006	1.010	1.001	1.016	1.017	1.009	1.026	1.006
P_1	1.00	0.96	0.99	0.73	0.84	0.53	0.97	0.97	0.91	0.92	0.91
P_2	0.82	0.79	0.57	0.55	0.90	**0.04**	0.68	0.69	0.56	0.53	0.74
NP(200,400)	1.018	1.006	1.001	1.013	1.008	*0.988*	1.005	1.004	1.008	1.006	1.004
P_1	0.99	0.88	0.62	0.98	0.85	0.14	0.92	0.91	0.98	0.73	0.83
P_2	0.86	0.83	0.59	0.64	0.95	**0.04**	0.70	0.72	0.61	0.56	0.81
Combined I	1.001	*0.998*	*0.990*	*0.998*	*0.999*	*0.978*	*0.998*	*0.997*	1.001	*0.993*	1.002
P_1	0.49	0.31	**0.02**	0.30	0.39	**0.00**	0.29	0.16	0.59	0.22	0.76
P_2	0.86	0.82	0.34	0.64	0.90	**0.04**	0.71	0.63	0.62	0.56	0.81
Combined II	*0.999*	*0.995*	*0.990*	*0.997*	*0.997*	*0.979*	*0.996*	*0.996*	*0.999*	*0.991*	1.000
P_1	0.44	0.11	**0.00**	0.11	0.24	**0.01**	**0.07**	**0.06**	0.33	0.11	0.52
P_2	0.86	0.62	0.33	0.64	0.84	**0.04**	0.65	0.55	0.62	0.56	0.81

Notes: (1) The data are daily data from April 1, 1996 to August 25, 2006. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. For the benchmark model, the MSFEs are in levels (x10^4). For all other models, they are MSFE ratios relative to that of the benchmark model. The smaller MSFE, the better predictive ability of a model.

Table 3.2: Forecast Evaluation Results for Developed Markets - MAFE

	AU	CA	GE	IT	JP	SW	NE	SP	FR	UK	US
						MAFE					
Benchmark	0.838	0.792	0.904	0.764	1.062	0.814	0.799	0.787	0.779	0.708	0.548
AR(1)	1.008	1.006	*0.997*	*0.997*	*0.998*	*0.985*	1.001	*0.999*	*0.999*	*0.991*	1.000
P_1	0.90	0.93	**0.09**	**0.08**	0.28	**0.01**	0.63	0.38	0.19	**0.07**	0.46
P_2	0.89	0.94	**0.10**	**0.08**	0.29	**0.00**	0.64	0.41	0.19	**0.06**	0.46
GARCH(1,1)	*0.996*	*0.996*	*0.997*	*0.999*	1.000	*0.999*	*0.999*	*0.999*	1.000	*0.999*	*0.996*
P_1	**0.02**	**0.01**	**0.04**	0.20	0.33	0.13	0.18	0.38	0.41	0.32	**0.01**
P_2	0.29	0.13	**0.10**	**0.08**	0.29	**0.00**	0.44	0.60	0.33	**0.06**	**0.02**
NN(1,5)	1.003	1.000	1.003	1.014	1.008	1.034	1.004	1.001	1.016	1.020	1.034
P_1	0.63	0.52	0.68	1.00	0.96	1.00	0.78	0.62	1.00	1.00	1.00
P_2	0.47	0.33	0.37	0.31	0.50	**0.02**	0.68	0.77	0.62	0.14	0.35
FC(1,200)	1.014	1.002	1.011	1.004	1.002	*0.995*	1.014	1.008	1.006	1.005	1.001
P_1	0.99	0.66	0.97	0.81	0.66	0.23	1.00	0.96	0.96	0.74	0.71
P_2	0.53	0.42	0.56	0.47	0.65	**0.03**	0.78	0.84	0.72	0.24	0.39
NP(200,400)	1.008	1.004	1.000	1.005	1.003	*0.996*	1.003	1.002	1.006	1.000	1.006
P_1	0.99	0.91	0.54	0.90	0.74	0.27	0.89	0.90	0.98	0.54	0.99
P_2	0.55	0.44	0.60	0.54	0.73	**0.04**	0.83	0.88	0.79	0.25	0.42
Combined I	1.000	1.000	*0.994*	*0.999*	*0.997*	*0.988*	*0.999*	*0.999*	1.001	*0.992*	1.002
P_1	0.51	0.46	**0.02**	0.31	0.19	**0.01**	0.32	0.28	0.76	**0.07**	0.93
P_2	0.55	0.44	0.30	0.54	0.68	**0.04**	0.83	0.81	0.79	0.25	0.42
Combined II	*0.997*	*0.997*	*0.994*	*0.998*	*0.998*	*0.988*	*0.998*	*0.999*	1.000	*0.992*	1.000
P_1	**0.10**	**0.07**	**0.01**	0.12	0.18	**0.01**	0.12	0.20	0.64	**0.05**	0.55
P_2	0.55	0.44	0.29	0.54	0.68	**0.04**	0.72	0.77	0.79	0.25	0.42

Notes: (1) The data are daily data from April 1, 1996 to August 25, 2006. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. For the benchmark model, the MAFEs are in levels (x10^2). For all other models, they are MAFE ratios relative to that of the benchmark model. The smaller MAFE, the better predictive ability of a model.

Table 3.3: Forecast Evaluation Results for Developed Markets - MFTR

	AU	CA	GE	IT	JP	SW	NE	SP	FR	UK	US
Benchmark	0.090	0.094	-0.017	0.075	-0.019	0.019	-0.053	0.086	0.075	0.053	0.026
AR(1)	-0.003	-0.017	0.083	0.087	0.028	0.162	0.012	0.033	0.064	0.055	0.033
P_1	0.98	1.00	**0.04**	0.37	0.21	**0.01**	**0.09**	0.91	0.63	0.50	0.40
P_2	0.98	1.00	**0.03**	0.37	0.23	**0.00**	**0.10**	0.90	0.67	0.47	0.42
GARCH(1,1)	0.090	0.094	0.080	0.075	-0.032	0.073	0.072	0.086	0.075	0.068	0.036
P_1	1.00	1.00	**0.01**	1.00	0.66	**0.01**	**0.02**	1.00	1.00	**0.06**	0.26
P_2	0.50	0.51	**0.04**	0.37	0.29	**0.00**	**0.03**	0.50	0.53	0.40	0.51
NN(1,5)	0.054	0.022	0.003	-0.018	0.001	-0.055	0.025	0.040	-0.011	-0.034	-0.031
P_1	0.77	0.91	0.37	0.95	0.36	0.90	**0.06**	0.89	0.96	0.95	0.93
P_2	0.68	0.69	0.08	0.57	0.42	**0.01**	**0.03**	0.72	0.72	0.57	0.64
FC(1,200)	-0.022	0.042	0.017	0.045	0.037	0.112	-0.026	-0.015	0.012	0.053	0.001
P_1	0.99	0.96	0.22	0.78	0.18	**0.03**	0.26	0.98	0.96	0.47	0.83
P_2	0.75	0.77	**0.09**	0.64	0.42	**0.01**	**0.03**	0.77	0.79	0.61	0.70
NP(200,400)	0.052	0.090	-0.051	-0.008	0.026	0.107	-0.050	0.048	0.029	0.034	-0.017
P_1	0.93	0.57	0.71	0.96	0.25	**0.06**	0.51	0.87	0.80	0.66	0.86
P_2	0.82	0.84	0.11	0.69	0.45	**0.01**	**0.03**	0.82	0.81	0.64	0.74
Combined I	0.025	0.047	0.081	0.044	0.041	0.138	0.011	0.088	0.068	0.066	0.035
P_1	0.96	0.87	**0.04**	0.77	0.17	**0.01**	**0.08**	0.48	0.58	0.39	0.41
P_2	0.84	0.86	0.12	0.70	0.44	**0.02**	**0.04**	0.83	0.83	0.65	0.75
Combined II	0.089	0.086	0.099	0.073	0.038	0.135	0.027	0.069	0.053	0.067	0.034
P_1	0.54	0.62	**0.02**	0.52	0.17	**0.01**	**0.03**	0.71	0.78	0.37	0.37
P_2	0.87	0.88	**0.07**	0.73	0.44	**0.02**	**0.04**	0.85	0.84	0.66	0.76

Notes: (1) The data are daily data from April 1, 1996 to August 25, 2006. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The larger MFTR, the better predictive ability of a model.

Table 3.4: Forecast Evaluation Results for Developed Markets - MCFD

	AU	CA	GE	IT	JP	SW	NE	SP	FR	UK	US
Benchmark	0.552	0.557	0.491	0.523	0.494	0.502	0.443	0.523	0.512	0.497	0.539
AR(1)	0.522	0.497	0.522	0.520	0.513	0.558	0.481	0.507	0.498	0.518	0.519
P_1	0.90	1.00	**0.09**	0.56	0.20	**0.01**	**0.03**	0.78	0.77	0.20	0.79
P_2	0.91	1.00	**0.08**	0.53	0.19	**0.01**	**0.04**	0.77	0.75	0.20	0.81
GARCH(1,1)	0.552	0.557	0.530	0.523	0.492	0.522	0.513	0.523	0.512	0.506	0.549
P_1	1.00	1.00	**0.02**	1.00	0.54	**0.04**	**0.01**	1.00	1.00	**0.09**	0.20
P_2	0.50	0.49	**0.07**	0.48	0.23	**0.01**	**0.01**	0.47	0.49	0.20	0.43
NN(1,5)	0.524	0.499	0.498	0.466	0.483	0.453	0.491	0.498	0.494	0.483	0.470
P_1	0.90	0.99	0.38	0.98	0.66	0.96	**0.02**	0.89	0.74	0.68	1.00
P_2	0.71	0.66	0.11	0.68	0.36	**0.03**	**0.01**	0.69	0.68	0.33	0.56
FC(1,200)	0.507	0.528	0.502	0.507	0.508	0.532	0.453	0.481	0.487	0.511	0.516
P_1	0.98	0.95	0.29	0.76	0.27	0.13	0.32	0.96	0.91	0.29	0.87
P_2	0.76	0.74	0.12	0.73	0.44	**0.04**	**0.01**	0.76	0.75	0.37	0.62
NP(200,400)	0.527	0.540	0.494	0.477	0.501	0.528	0.460	0.508	0.478	0.509	0.452
P_1	0.96	0.86	0.41	0.97	0.42	0.15	0.17	0.78	0.89	0.33	1.00
P_2	0.82	0.81	0.14	0.77	0.47	**0.04**	**0.01**	0.81	0.79	0.40	0.66
Combined I	0.508	0.507	0.532	0.491	0.513	0.540	0.486	0.513	0.498	0.522	0.507
P_1	0.99	0.99	**0.04**	0.91	0.21	**0.05**	**0.02**	0.69	0.74	0.16	0.90
P_2	0.84	0.83	0.14	0.78	0.48	**0.04**	**0.01**	0.82	0.81	0.36	0.67
Combined II	0.549	0.543	0.525	0.511	0.512	0.540	0.493	0.507	0.493	0.522	0.533
P_1	0.58	0.79	**0.05**	0.75	0.22	**0.06**	**0.00**	0.87	0.87	0.15	0.61
P_2	0.87	0.85	0.15	0.80	0.48	**0.04**	**0.01**	0.84	0.83	0.37	0.69

Notes: (1) The data are daily data from April 1, 1996 to August 25, 2006. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The larger MCFD, the better predictive ability of a model.

Table 3.5: Forecast Evaluation Results for Emerging Markets - MSFE

	HK	MA	SI	TW	MX	SK	BR
Benchmark	1.139	0.845	1.228	1.926	2.216	2.433	4.590
AR(1)	*0.985*	*0.991*	*0.989*	1.014	1.006	1.001	1.000
P_1	0.12	**0.07**	0.24	0.89	0.99	0.61	0.48
P_2	**0.09**	**0.07**	0.22	0.92	0.97	0.61	0.47
GARCH(1,1)	*0.998*	1.000	*0.997*	1.001	*0.996*	1.000	*0.998*
P_1	0.17	0.30	0.12	0.78	0.16	0.52	0.31
P_2	**0.09**	**0.07**	0.22	0.90	0.21	0.74	0.53
NN(1,5)	1.012	1.003	1.052	1.050	1.012	1.020	1.023
P_1	0.79	0.64	1.00	0.99	0.89	0.93	0.84
P_2	0.24	0.21	0.45	0.96	0.49	0.88	0.76
FC(1,200)	*0.986*	*0.990*	*0.994*	1.012	1.019	1.002	1.002
P_1	0.19	0.18	0.35	0.91	0.97	0.62	0.58
P_2	0.34	0.32	0.49	0.97	0.67	0.95	0.81
NP(200,400)	1.000	0.990	1.002	1.008	1.002	1.007	1.002
P_1	0.52	**0.10**	0.60	0.82	0.68	0.86	0.64
P_2	0.34	0.34	0.53	0.98	0.72	0.98	0.83
Combined I	*0.977*	*0.987*	*0.987*	1.006	*0.999*	*0.998*	*0.997*
P_1	**0.02**	**0.02**	0.15	0.76	0.33	0.26	0.32
P_2	0.15	0.20	0.47	0.98	0.72	0.90	0.75
Combined II	*0.978*	*0.988*	*0.986*	1.001	*0.997*	*0.998*	*0.995*
P_1	**0.01**	**0.03**	**0.08**	0.56	0.14	0.22	0.18
P_2	0.15	0.20	0.45	0.98	0.72	0.90	0.67

Notes: (1) The data are daily data from January 4, 1999 to August 25, 2006 for most of the emerging markets under consideration. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The smaller MSFE, the better predictive ability of a model.

Table 3.6: Forecast Evaluation Results for Emerging Markets - MAFE

	HK	MA	SI	TW	MX	SK	BR
				MAFE			
Benchmark	0.817	0.710	0.852	1.078	1.122	1.222	1.665
AR(1)	*0.990*	*0.992*	*0.986*	1.011	1.005	1.000	1.002
P_1	**0.09**	**0.02**	**0.04**	0.95	1.00	0.52	0.77
P_2	**0.08**	**0.02**	**0.05**	0.95	0.99	0.49	0.79
GARCH(1,1)	1.001	1.001	*0.997*	1.002	*0.994*	*0.999*	*0.996*
P_1	0.61	0.88	**0.03**	0.90	**0.01**	0.23	**0.06**
P_2	**0.08**	**0.02**	**0.05**	0.95	**0.02**	0.43	**0.10**
NN(1,5)	1.008	1.002	1.028	1.030	1.005	1.014	1.013
P_1	0.80	0.63	0.99	0.99	0.86	0.95	0.93
P_2	0.18	**0.06**	0.19	0.98	0.13	0.68	0.43
FC(1,200)	*0.987*	*0.990*	*0.989*	1.010	1.009	1.001	1.002
P_1	0.11	**0.05**	**0.07**	0.94	0.94	0.67	0.62
P_2	0.16	**0.06**	0.20	0.99	0.27	0.79	0.58
NP(200,400)	1.000	*0.994*	1.002	1.007	*0.999*	1.002	*0.997*
P_1	0.55	0.12	0.61	0.82	0.31	0.78	0.22
P_2	0.16	**0.08**	0.22	0.99	0.28	0.87	0.60
Combined I	*0.986*	*0.991*	*0.990*	1.007	*0.999*	*0.999*	*0.999*
P_1	**0.02**	**0.01**	**0.05**	0.90	0.34	0.37	0.41
P_2	0.14	**0.08**	0.22	0.99	0.28	0.87	0.60
Combined II	*0.987*	*0.992*	*0.990*	1.004	*0.997*	*0.999*	*0.998*
P_1	**0.01**	**0.01**	**0.05**	0.83	**0.07**	0.26	0.22
P_2	0.14	**0.08**	0.22	0.99	0.28	0.87	0.60

Notes: (1) The data are daily data from January 4, 1999 to August 25, 2006 for most of the emerging markets under consideration. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The smaller MAFE, the better predictive ability of a model.

Table 3.7: Forecast Evaluation Results for Emerging Markets - MFTR

	HK	MA	SI	TW	MX	SK	BR
Benchmark	-0.016	0.024	0.018	-0.033	0.147	0.126	0.158
AR(1)	0.068	0.072	0.106	0.016	0.068	0.137	0.183
P_1	**0.07**	0.14	**0.06**	0.28	0.98	0.36	0.33
P_2	**0.05**	0.12	**0.06**	0.28	0.99	0.38	0.32
GARCH(1,1)	0.085	0.052	0.079	0.021	0.147	0.125	0.158
P_1	**0.03**	0.11	**0.07**	**0.09**	**0.00**	0.78	**0.00**
P_2	**0.04**	0.14	**0.07**	0.32	0.49	0.38	0.32
NN(1,5)	-0.009	-0.035	-0.004	-0.076	0.013	0.025	0.046
P_1	0.44	0.88	0.64	0.67	0.97	0.86	0.89
P_2	**0.06**	0.29	0.12	0.46	0.73	0.68	0.57
FC(1,200)	0.094	0.046	0.057	0.034	0.040	0.093	0.141
P_1	**0.01**	0.35	0.25	0.22	0.94	0.71	0.55
P_2	**0.05**	0.32	0.13	0.41	0.82	0.78	0.67
NP(200,400)	0.050	0.063	0.066	-0.084	0.144	0.110	0.158
P_1	**0.10**	0.18	0.22	0.72	0.55	0.81	0.46
P_2	**0.05**	0.36	0.16	0.46	0.89	0.85	0.71
Combined I	0.107	0.059	0.096	-0.004	0.115	0.098	0.218
P_1	**0.02**	0.21	0.11	0.36	0.84	0.81	0.25
P_2	**0.03**	0.37	0.17	0.48	0.92	0.87	0.54
Combined II	0.111	0.072	0.121	-0.034	0.155	0.121	0.172
P_1	**0.01**	0.14	**0.04**	0.49	0.31	0.56	0.40
P_2	**0.02**	0.37	0.11	0.49	0.87	0.89	0.55

Notes: (1) The data are daily data from January 4, 1999 to August 25, 2006 for most of the emerging markets under consideration. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The larger MFTR, the better predictive ability of a model.

Table 3.8: Forecast Evaluation Results for Emerging Markets - MCFD

	HK	MA	SI	TW	MX	SK	BR
Benchmark	0.476	0.479	0.498	0.477	0.561	0.549	0.564
AR(1)	0.523	0.505	0.544	0.474	0.526	0.545	0.557
P_1	**0.03**	**0.09**	**0.03**	0.52	0.99	0.62	0.70
P_2	**0.04**	**0.09**	**0.03**	0.51	0.99	0.62	0.70
GARCH(1,1)	0.498	0.490	0.526	0.481	0.561	0.549	0.564
P_1	0.13	0.13	**0.02**	0.34	1.00	0.32	1.00
P_2	**0.05**	**0.09**	**0.03**	0.58	0.48	0.64	0.49
NN(1,5)	0.477	0.463	0.491	0.459	0.517	0.512	0.515
P_1	0.47	0.68	0.58	0.68	0.99	0.89	1.00
P_2	**0.09**	0.22	**0.07**	0.72	0.69	0.81	0.72
FC(1,200)	0.533	0.505	0.531	0.497	0.510	0.536	0.548
P_1	**0.01**	0.13	**0.06**	0.22	0.98	0.77	0.73
P_2	**0.04**	0.26	**0.08**	0.46	0.80	0.89	0.81
NP(200,400)	0.514	0.498	0.505	0.477	0.557	0.542	0.560
P_1	**0.05**	0.20	0.40	0.49	0.62	0.88	0.71
P_2	**0.05**	0.32	**0.10**	0.51	0.87	0.95	0.86
Combined I	0.533	0.505	0.540	0.479	0.542	0.532	0.564
P_1	**0.02**	0.14	**0.05**	0.46	0.94	0.94	0.50
P_2	**0.05**	0.34	0.11	0.52	0.89	0.96	0.88
Combined II	0.537	0.510	0.551	0.481	0.563	0.545	0.566
P_1	**0.00**	**0.07**	**0.01**	0.42	0.35	0.72	0.38
P_2	**0.04**	0.23	**0.06**	0.53	0.88	0.97	0.84

Notes: (1) The data are daily data from January 4, 1999 to August 25, 2006 for most of the emerging markets under consideration. (2) P_1 is the bootstrap *p*-value for comparing a single model with the martingale model (the benchmark model) using White's (2000) test with 1000 bootstrap replications and a bootstrap smoothing parameter q = 0.75. P_2 is the bootstrap reality check *p*-value for comparing k models with the martingale model, where the null hypothesis is that the best of the first k models has no superior predictive power over the martingale model. (3) AR, NN, FC, NP are various models under considerations. The smaller MFCD, the better predictive ability of a model.

Table 3.9: The Summary of Models

Name	Models for $E(Y_t \mid I_{t-1})$ and $sign[E(Y_t \mid I_{t-1}]$
Benchmark	$E(Y_t \mid I_{t-1}) = \mu$
1. AR(d)	$E(Y_t \mid I_{t-1}) = \beta_0 + \sum_{j=1}^{d} \beta_j Y_{t-j}$
2.GARCH (p,q)	$E(Y_t \mid I_{t-1}) = \mu$ where $\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$
3. NN(d,q)	$E(Y_t \mid I_{t-1}) = \beta_0 + \sum_{j=1}^{d} \beta_j Y_{t-j} + \sum_{i=1}^{q} \delta_i G(\gamma_{0i} + \sum_{j=1}^{d} \gamma_{ji} Y_{t-j}),$ $G(z) = (1 + e^{-z})^{-1}$
4. FC(d,L)	$E(Y_t \mid I_{t-1}) = \alpha_0(U_t) + \sum_{j=1}^{d} \alpha_j(U_t) Y_{t-j}$ where $U_t = Y_{t-1} - L^{-1} \sum_{j=1}^{L} Y_{t-j}$
5. NP(k,m)	$E(Y_t \mid I_{t-1}) = g(Y_{t-1}, Y_{t-2})$
6. Combined I (1, 3, 4, 5)	AR(1), NN(1,5), FC(1,200) and NP(200,400)
7. Combined II (1-5)	AR(1), GARCH(1,1), NN(1,5), FC(1,200) and NP(200,400)

Notes: The benchmark model is the martingale model. AR(d) is the autoregression model. GARCH(p,q) is the generalized autoregressive conditional heteroskedasticity model. NN (d,q) is the neural network model. FC is the functional coefficient model of Cai, Fan and Yao (2000). NP is the nonparametric model estimated by the kernel estimation approach. For NP(*k*,*m*) models the smoothing parameter h is used in nonparametric estimation for minimizing k period out-of-sample.

CHAPTER 4

Arbitrage Trading and Relative Informational Inefficiencies: The Case of Foreign Exchange Markets

4.1 Introduction

The microstructure implications of financial markets have been the focus of a significant amount of research in recent years. It is well documented that market frictions have an impact on the price formation process. While asset pricing theories in the presence of frictionless markets allow for instantaneous diffusion of information, it is clear that trading frictions impede the smooth incorporation of information into prices. Although, in hypothetical frictionless markets, information is impounded into prices instantaneously, there is ample evidence of sizeable frictions which may cause temporary deviations of prices from their no-arbitrage values. As information is generated in the market, prices will adjust to reflect any new information through the trading process. This adjustment process may be delayed, however, by certain microstructure aspects, which in turn will create temporary arbitrage opportunities for market participants.

In a set of two or more assets whose value depends on a common information set, their prices should react and adjust so that not only each price will reflect the new information quickly but also so that creating a portfolio of these assets will not generate arbitrage profits. This hypothesis would only hold in a frictionless world. In reality, however, there are two factors that will prevent the instantaneous adjustment of these prices: (i) the existence of trading frictions, and more importantly, (ii) the fragmentation of financial markets. The latter of these two factors implies not only that financial markets face microstructure frictions, but also that each one of these markets may face different types of frictions or the same type of friction with different intensities. In other words, there are market-specific characteristics that will affect the speed at which the market will incorporate information into prices relative to other markets.[22]

The fragmentation of financial markets and the market-specific frictions give way to another well-documented phenomenon: the lead-lag effect. Lo and Mackinlay (1990) first documented lead-lag patterns in equity markets. They found that the returns of small-cap stocks are correlated with the *lagged* returns of large-cap stocks. Several hypotheses have been offered to explain these findings. Among these explanations are nonsynchronous trading, time-varying risk premia, and differential speeds of adjustment of stocks to economy-wide information shocks. The latter of the three was suggested by Brennan, Jegadeesh and Swaminathan (1993) and it is known as the speed of adjustment hypothesis. The differentials in the speed of adjustment add another dimension to the price formation process through the behavior of arbitrageurs and market makers. If the leading market incorporates information first, the slower adjustment of prices to information in the lagging market implies the existence of an intermarket information diffusion channel (Kumar and Seppi (1994)). Arbitrageurs and market makers are then

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[22] A market is informationally efficient if its prices reflect information instantaneously. Two markets driven by a common information set may incorporate any new information into prices with different speeds. This difference in the speed of adjustment can then be seen as a measure of relative informational inefficiencies.

responsible for eliminating the informational gap through trading and quote-updating, respectively.

Arbitrage trading has a pivotal role in the development of several fundamental financial theories such as the law of one price and market efficiency. In fact, Roll et al. (2007) argues that deviations from no-arbitrage relations should be related to market liquidity, because liquidity facilitates arbitrage. This chapter investigates the relationship between the speed of adjustment hypothesis[23] and arbitrage trading by examining the role of intermarket information diffusion in the price formation process. In an attempt to close a gap in the literature, this chapter explores empirically the relationship between arbitrage trading and the degree of relative informational efficiency of financial markets. More specifically, it argues that the behavior of arbitrageurs, measured by the dynamics of the futures-cash basis, is related to the differences in the rate at which markets incorporate common information into prices. Large differentials in the speed of adjustment of markets to new information may temporarily move prices away from their appropriate level, where the futures-cash basis is zero. At the same time, a wide basis may reveal new information in the form of order flow by triggering arbitrage trading. Extreme order imbalances could create inventory problems for market makers and affect the adjustment speeds across markets. We explore these ideas of bi-directional causality by examining

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[23] The speed of adjustment hypothesis has a prevailing role in explaining the lead-lag effect documented in equity markets. Chordia and Swaminathan (2000) provide evidence that the lead-lag effect arise due to differential speeds of adjustment of stocks to common information shocks. Their results suggest that by examining the relationship between the speed of adjustment hypothesis and arbitrage trading, this study simultaneously argues that the existence of a lead-lag effect makes arbitrage trading possible, and vice versa.

the joint dynamics of the futures-cash basis and the relative information share – a measure of adjustment speed differentials.

Kumar and Seppi (1994) developed an informational model of arbitrage. They argue that arbitrageurs do not generate new information. The informational advantage of the arbitrageur comes “second hand” from his/her ability to use information known in one part of the financial system before it is known in another. Therefore, they argue that the lead-lag effect in fragmented markets and the existence of an intermarket information diffusion channel create arbitrage opportunities for able traders. Arbitrage trading plays a significant role in market efficiency since they are responsible for channeling information already known in the leading markets into the laggings markets.

There are several areas in which this study contributes to the already existing literature. First, it examines the relationship between arbitrage trading and adjustment speed differentials across markets that trade the same underlying asset: futures and cash markets. As documented in Hou (2007), the lead-lag effect is more important economically and it is statistically stronger if we look at stocks within an industry rather than across industries. Therefore, the selection of markets that are very sensitive to a common information set is necessary to guarantee the validity of the results. A large part of the literature explores equity markets across stocks that are not strongly tied to a common information set. Second, we explore intraday dynamics. Chordia et al. (2005) find that equity markets (i.e. NYSE stocks) react to new information very quickly by converging to weak-form market efficiency within 5 to 10 minutes. The measure of the differential speed of adjustment across markets is constructed using transaction (tick-by-tick) data. Third, this study attempts to close the gap between two distinct but related areas in the literature. On the one hand, several studies explore the relationship between market frictions (i.e. (il)liquidity) and the lead-lag effect. On the other hand, research focuses on the interdependence between market frictions and deviations from no-arbitrage relations. In this chapter, the lead-lag effect is directly related to no-arbitrage violations through the lagged adjustment mechanism[24]. In fact, Hou et al. (2005) argue that the information delay[25] can be used as a parsimonious measure of several market frictions. Fourth, this chapter proposes the use of a concrete measure of differentials in the speed of adjustment to information: differences in the share of information across markets introduced by Hasbrouck (1995). Finally, not only can the lead-lag effect be better captured within markets trading the same underlying, but this chapter considers the foreign exchange market which, to my knowledge, has not been explored as of yet.

The rest of the chapter is organized as follows. Section 4.2 presents the data. Section 4.3 explains the construction of the variables in detail. Section 4.4 offers some preliminary evidence. Section 4.5 describes the estimation procedure and presents the results. A brief summary concludes the chapter in Section 4.6.

4.2 Data Description

The dataset consists of intraday tick by tick observations (later converted to 5-second intervals) covering a 4-month period from April 4th, 2005 until July 29th, 2005.[26]

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[24] We follow the recent literature by arguing that differences in the speed of adjustment of markets to new information gives way to the lead-lag effect. Using this well documented cause-effect relationship, we construct a quantitative measure for the adjustment speed differentials – the difference in information shares. By examining the joint dynamics of the futures-cash basis and the information shares differential, we directly investigate the relationship between arbitrage trading and the lead-lag effect.

[25] The information delay presented in Hou (2005) is a used as a single parsimonious measure of market frictions and it quantifies the speed at which prices respond to economy-wide information shocks.

[26] Not all trading days within the four-month sample period have been used in this study. Several days have

Prices are log-transformed and multiplied by a constant number ($p_t^* = \log(p_t) * 10,000$). Data were obtained for three major financial instruments (regular futures, E-mini futures and the interdealer spot market)[27] in two currency markets (Euro/US$ and Yen/US$). Both E-mini futures and the spot market are electronically traded while regular futures have both floor trading and electronic trading at the same time from 7:20 a.m. to 2:00 p.m., but only electronic trading in other times. In this study, however, only data from electronic trading are used.[28]

4.2.1 Futures Market Data

The regular and E-mini futures data are the time and sale data from the Chicago Mercantile Exchange (CME). These futures are the most actively traded FX futures in the CME. Table 4.1 provides the summary statistics for the futures contracts used in this chapter. Specifically, for the regular futures contracts, they are not only traded at the CME Globex electronic market but also are traded side-by side with the floor trading using the open outcry system during the regular hours. CME E-mini Japanese Yen futures and E-mini Euro futures began trading in 1999 exclusively on CME Globex. E-

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been excluded from the estimation due to the lack of trading activity in all markets simultaneously. July 4th and July 11th through July 15th have been excluded since not all markets are open to trade on these days, and the econometric techniques rely on having a sufficient number of observations for all instruments for all days.

[27] The Chicago Mercantile Exchange (CME) is the largest futures market in the U.S. and the second largest in the world (after the Eurex). It offers regular futures contracts on equities, commodities, currencies, interest rates, etc. It also offers E-Mini futures contracts on a selected number of assets. The E-Mini futures contracts are half the size of the regular futures contract and are only traded electronically through the CME Globex trading platform.

[28] The regular floor trading data during the sample period were also obtained. However, the floor trading is very infrequent compared with electronic trading (see Table 4.1), thus the floor trading data are not used in the analysis, even though the analysis is restricted to the period of the floor trading hours.

mini futures contracts are sized at one-half of the regular futures contracts to make E-mini trading affordable to traders with small margin accounts.

While CME offers a forum for trading the Yen and the Euro in its FX futures markets on both its Globex electronic trading platform as well as on the trading floor, the trading hours differ across these two trading venues (see Table 4.1). This study will only include intraday data for the period of the day when all markets are open (7:20 am to 2:00 pm). These daily samples will make it possible to analyze the price dynamics during information-intensive periods, as the data will also (at least partially) capture any information generated in the floor trading during this period.

For the futures contracts, the nearby contract is the most active contract. Therefore, only the last three full months of the life of nearby contracts are used, and they are rolled over to the next nearby contract the last day of the month prior to the expiration month. Hence, the sample period for the regular futures contracts is constructed using transaction prices from two months (April and May) of the June 2005 contract and two months (June and July) of the September 2005 contract.

The futures volume statistics in Table 4.1 show that the most frequently traded is the Euro/US$ regular futures contract. On the other hand, the Yen/US$ E-mini futures contract is far less traded than any of the other instruments. Day trading on Globex seems to be the most active of all. Night and overnight trading accounts for roughly 25% of the daily volume in all markets. Furthermore, floor trading accounts for a very small percentage of the total daily volume in these derivative markets. The information clearly suggests the attractiveness of the sample data which covers day trading in the electronic markets (GLOBEX).

4.2.2 Spot Market Data

The spot foreign exchange market is much less centralized than the FX futures markets. This market is best described as a decentralized multiple-dealer market. There is no physical location or exchange where dealers meet other traders, nor is there a screen that consolidates all executable quotes in the market. In this way, the spot FX market is very different from most futures markets. Dominated by interbank trading, spot currency transactions occur in the over-the-counter (OTC) markets. Cash currency trading takes place in a number of interconnected markets. On the other hand, private vendors offer electronic trading platforms and market data available for a fee. These retail markets are very accessible to small traders; however, these retail markets are different from the inter-dealer market where large traders account for most of the daily trading volumes in the currency markets. The current market participants are banks, commercial companies, central banks, investments companies, and retail FX brokers. There are 3 main features that distinguish spot FX markets from other markets: a very high trading volume, interdealer trading accounts for most of the volume, and transparency is low.

The spot market data for this study were collected from one of the two leading electronic brokers of interdealer spot foreign exchange market, EBS. Although retail electronic trading in the FX spot markets has been exploding, most of the trading is concentrated in the interbank market. Currently, two electronic brokering systems are used globally for interbank spot trading, one offered by Electronic Broker System (EBS) and one offered by Reuters (Dealing 3000). The Euro/US$ and Yen/US$ are traded primarily on EBS. Therefore, our data were collected from the leading electronic brokering system in the Euro/US$ and Yen/US$ interbank markets, which comprises most global transactions in these two FX markets. This data provider offers a screen-based anonymous dealing service, operating during global trading hours, which supports trading in all major currencies. Each day 2,000 traders on more than 700 floors globally use this trading platform to trade an average of USD145 billion a day in spot foreign exchange transactions. The data obtained for the spot rates are the bid/ask midpoint. As mentioned in the introduction, the EBS has become the major trading platform for the two most traded currency pairs, the Yen and the Euro.

Table 4.2 reports the summary statistics of all currency markets for both exchange rates. During the 4-month period covered in the sample, trading activity in terms of price quote is significantly higher in the regular futures and spot markets. For the Euro market, the number of transactions is higher in regular futures than the number of midpoint quotes in the spot market; while for the Yen market, the number of midpoint quotes is higher in the spot market. At the first look, this result on the Euro is surprising given the general notion that the spot market is much larger than the futures market. The result is also consistent with Rosenberg and Traub (2007) who found that there are more futures trades during regular futures trading hours than that in the spot market. Moreover, we only consider regular futures trading hours on the CME Globex (8:20 a.m. to 3:00 p.m. Eastern time), and this time period does not fully overlap with some of the times of heavy volume in the spot market. On the other hand, in our data, the EBS mid-quotes between bid and ask prices are used for the spot market, but actual transaction prices are used for both futures markets. Given that multiple transactions can occur at the same quote, the use of midpoint quote would imply that there are more far more actual transactions in the spot markets than indicated by the number of observations on Table 4.2.

The higher number of daily average trades in the regular futures market does not extend to the E-mini futures market. Trading activity in the E-mini futures markets is significantly lower than either of the other two markets considered here. In particular, the Yen/US$ E-mini futures contract has a relative extreme low trading frequency with 42 trade per day on average over the sample period. Hence, the E-mini Yen futures time series is dropped from the present analysis because of the very low number of observations within a day. This low trading frequency prevents the convergence of our estimation method resulting in considerably unreliable parameter estimates and information share measures.

As the correlation coefficient matrix shows, the series are highly correlated. An exception is the correlation between the E-mini contract and the other two instruments in the Yen/US$ market. This correlation is particularly low, due to infrequent trading in the E-mini Yen futures market.

4.3 Construction of Variables

Using intraday (tick-by-tick) data, daily observations were constructed for two variables: (i) the relative futures-cash basis, and the (i) the information share difference.

4.3.1 Relative Futures-Cash Basis

Two different time series of the bases can be constructed for the US$/Euro market. One of the series is based on the regular futures contract, while the other is based on the smaller E-Mini futures contracts. For the Yen/US$ market, we will examine only one basis time series based on the regular futures contract. Let F be the current futures price, S be the spot exchange rate , r_d the risk-free rate for lending and borrowing in the domestic market, t the time to contract expiration, and r_f the risk-free for lending and borrowing in the foreign market. We define the relative currency futures-cash basis (henceforth, termed the "no-arbitrage basis") as follows,

$$\text{NABAS} = \frac{Fe^{-(r_d - r_f)t} - S}{S} \tag{4.1}$$

In a frictionless world, the no-arbitrage basis should be equal to zero. In practice, however, this quantity exhibits considerable time series variation. These deviations from zero in the no-arbitrage basis will be used as a proxy for relative mispricing which may trigger arbitrage trading.

In order to empirically construct the daily time series for the no-arbitrage basis (equation (4.1)), the following data is used: F is the daily closing price of currency futures contracts traded in the Chicago Mercantile Exchange. There are three time series for the futures contracts as explained in the data section above[29]. S is the spot currency price for the Euro/US$ and the Yen/US$. The riskless domestic and foreign rates are the US$ denominated and the Euro (or Yen) denominated LIBOR, respectively. The yield curve for the LIBOR is extrapolated when necessary.

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[29] Three different time series of the bases have been constructed: (1) Euro/US$ regular futures contract, (2) Euro/US$ E-Mini futures contract and (3) Yen/US$ regular futures contract. The Yen/US$ E-Mini regular futures contract was not used because it is inactively traded (an average number of transactions of 42 per day, see Table 4.2).

Table 4.3 presents the summary statistics for both variables used in this chapter. The mean and median of all three no-arbitrage bases (NABAS) time series are very close to each other. More importantly, when we test that the average no-arbitrage basis is equal to zero, we reject the null hypothesis for all three bases at the 5% level of significance (all three p-values are well below 1%). This shows some preliminary evidence of the significant deviations of the futures-cash currency bases from their no-arbitrage values. These findings are robust across different currency markets (Euro/US$ and Yen/US$) and across markets with different degrees of liquidity (regular and E-Mini futures contracts).

4.3.2 Information Share Differences

In order to quantify the differential speed of adjustment to new information across markets, we construct a statistical measure based on Hasbrouck (1995) information share approach. This newly constructed statistic can be seen as a measure of relative informational inefficiencies across markets. Hasbrouck (1995) proposed the “information share”, which measures the portion of a subset of the market’s information that is impounded into prices by different markets trading the same underlying security. The market with the largest information shares “leads” the other markets by reacting to new information first. If the innovations in a market drive the reaction of the other markets, then this market is informationally dominant[30]. Hasbrouck (1995) decomposes the price series into a random walk component and a stationary component. The random-walk

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[30] In this sense, differences in the information share of two markets trading the same underlying asset can serve as a proxy variable that quantifies their lead-lag relationship. In fact, Hasbrouck (1995) defines the information share as a measure of “who moves first” in the process of price adjustment.

component represents the security’s efficient price which is common to all markets, while the stationary term captures market-specific characteristics. Studying the properties of this common component is the goal of this measure. In particular, this technique decomposes the variance of the common efficient price (random walk) innovations. The portion of the variance explained by each market is called the information share of market j.

The Stock and Watson (1988) common trends representation of the price model is as follows:

$$p_t = p_0 + \psi(\sum_{i=1}^{t} \varepsilon_i)\iota + \Psi(L)\varepsilon_t \qquad (4.2)$$

where p_0 is a constant n-vector and $\Psi(L)$ is a matrix polynomial in the lag operator. More specifically, the first term on the right-hand side of equation (4.2) is a vector of initial values that may reflect non-stochastic differences between the price variables. The second term is the product of a scalar random walk and a unit vector, which captures the random walk component that is common to all prices (the “efficient” price). Although this component is unobservable without further identification restrictions, its innovations have the property that they are linear in the disturbances. The third term in equation (4.2) is a zero-mean covariance stationary process.

Define and note that ψ represents the common row vector of $\Psi(1)$. If n = 3, then,

$$\mathrm{var}(\psi\varepsilon_t) = J_1^2\sigma_{11} + J_2^2\sigma_{22} + J_3^2\sigma_{33} \qquad (4.3)$$

where J_i are the elements in $\Psi(1)$. Each of these terms represents the contribution to the random-walk innovation from a particular market. The proportion of this for market j (for j = 1, 2, 3) relative to the total variance is defined as the market's j information share:

$$IS_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi'} \quad \text{or} \quad IS_j = \frac{J_j^2 \sigma_{jj}}{J_1^2 \sigma_{11} + J_2^2 \sigma_{22} + J_3^2 \sigma_{33}} \tag{4.4}$$

where Ω is the covariance matrix. The measure in the above equation is too restrictive since price innovations are generally correlated across markets trading the same underlying instrument. If the price innovations are correlated (i.e. $\sigma_{ij} \neq 0$ for $i \neq j$), no unique values may be found for the information shares, and triangularization of the covariance matrix may be used to establish upper and lower bounds.[31]

Therefore, when the covariance matrix Ω is not diagonal, Hasbrouck (1995) defines the information shares of the market j prices as,

$$IS_j = \frac{([\psi F]_j)^2}{\psi \Omega \psi'} \tag{4.5}$$

In this equation, F is the Cholesky factorization of Ω, and a lower triangular matrix such that $\Omega = FF'$. The variance attributed to a particular market j is $([\psi F]_j)^2$ and $[\psi F]_j$ is the jth element of the row matrix ψF. The lower triangular factorization maximizes the information shares on the first price. By permuting the order of the market prices, equation (4.5) will provide an upper and lower bound for the information share of each market. The information share of each market is normalized so that they are a number between 0 and 1 and their sum is equal to 1. The total variance of the common efficient price (random walk) innovations is then normalized to 1.

In order to construct a concrete numerical measure of relative informational inefficiency, we take the difference of Hasbrouck's information share for each market. Cabrera, Wang, and Yang (2009) find that the spot market consistently leads the price discovery process relative to the futures (regular and E-Mini) markets for both currencies during this sample period[32]. Their results are based on the comparison of the information share obtained for each market considered in the study. They find that the daily information share for the spot market is consistently higher than that of the regular futures and E-Mini futures markets, for both the Euro/US$ and the Yen/US$. Based on these results, we measure the differential speeds of adjustment as follows:

$$ISDIFF_J = IS_{SPOT} - IS_{FUTURES_J} \qquad (4.6)$$

The IS_{spot} is the information share of the spot currency market. The $IS_{futures}$ is the information share of futures currency market. In the case of the Euro/US$, we construct two time series for the ISDIFF measure, one where the $IS_{futures}$ represents the information share of the regular futures market and one where it represents the information share of the E-Mini futures market. For the Yen/US$ market, there is only one ISDIFF

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[31] Cabrera, Wang, and Yang (2009) present evidence that the average mean disturbance (price innovation) correlation matrix for the Euro/US$ and the Yen/US$ price series. They find that the off-diagonal terms are different from zero; therefore, the triangularization is implemented.

[32] Cabrera, Wang, and Yang (2009) study the same time period examined in this chapter: April 4th, 2005 until July 29th, 2005.

constructed which belongs to the regular futures markets. Altogether, we have three daily time series for the information share differential.

In Table 4.3, the summary statistics of the adjustment speed differential measure is presented. The measure presented is slightly different from the explained above (ISDIFF). Instead of the difference in the information shares, we present the ratio of the information shares (ISRATIO)[33] in order to test the hypothesis that on average the spot market information share is higher than that of the regular futures and E-Mini futures markets. More specifically, we test the null hypothesis that the ISRATIO average is higher than one. The test rejects this hypothesis at the 5% level of significance. These findings are robust across different currency markets (Euro/US$ and Yen/US$) and across markets with different degrees of liquidity (regular and E-Mini futures contracts). Also, these results provide evidence supporting the findings in Cabrera, Wang, and Yang (2009).

4.4 Preliminary Evidence

In order to motivate a more formal statistical analysis of the relationship between arbitrage trading and the relative information inefficiencies in currency markets, we present some preliminary results. The cross-autocorrelation of daily returns between the

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[33] The ratio of the information shares is constructed with the spot market information share always in the numerator:

$$ISRATIO_J = \frac{IS_{SPOT}}{IS_{FUTURES_J}}$$

Using either the ISRATIO or ISDIFF to measure the differences in the speed of adjustment will produce the same qualitative results.

spot and futures markets are obtained in order to shed some light on the existence of a lead-lag effect in foreign exchange markets.

Table 4.4 presents the cross-autocorrelation in daily returns for all five financial instruments examined in this chapter[34]. Lo and Mackinlay (1990) first documented lead-lag patterns in equity markets. They found that the returns of small-cap stocks are correlated with the lagged returns of large-cap stocks. Similarly, Table 4.4 shows the correlation between the returns of spot currency prices and futures currency prices at different lags. This table provides consistent and monotonic evidence of the leading role of the spot currency market in the price discovery process (the lead-lag effect). In Panel A, we find that the correlation coefficients between the today's (lag = 0) Euro/US$ futures (regular and E-Mini) market return and yesterday's (lag = 1) Euro/US$ spot market return are larger than the correlation coefficients between today's (lag = 0) Euro/US$ spot market return and yesterday's (lag = 1) Euro/US$ futures (regular and E-Mini) market return[35]. Similar results are found when we examine the correlation between the Euro/US$ spot market and Euro/US$ futures market across other successive lags. For example, the correlation coefficients between the Euro/US$ futures (regular and E-Mini) market return at lag 1 and Euro/US$ spot market return at lag 2 are larger than the correlation coefficients between Euro/US$ spot market return at lag 1 and Euro/US$ futures (regular and E-Mini) market return at lag 2. In Panel B, we show the results for

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[34] There are three financial instruments studied in the Euro/US$ market and two financial instruments in the Yen/US$ market.

[35] The correlation coefficient between the Euro/US$ spot market return at lag 1 and the Euro/US$ regular futures market return at lag 0 is -0.257. The correlation coefficient between the Euro/US$ spot market return at lag 0 and the Euro/US$ regular futures market return at lag 1 is -0.236. Similar results are shown for the Euro/US$ spot market returns and the Euro/US$ E-Mini futures market return.

the Yen/US$ market. These results are consistent with those of the Euro/US$ market across all lags.

In summary, these cross-autocorrelations provide evidence of the existence of a lead-lag effect in currency markets where the spot market leads the futures market. To explain the cause of this lead-lag phenomenon based on the speed of adjustment hypothesis, we proceed to examine the joint dynamics of the no-arbitrage basis and the information share difference using vector autoregressions.

4.5 Empirical Results

In order to discover any potential bi-directional causality across the variables, we use a vector autoregression framework. More specifically, we adopt bivariate vector autoregressions. Four bivariate VARs are estimated for the Euro/US$ market, pairing each of the two no-arbitrage bases measures (regular futures-cash basis and E-Mini futures-cash basis) with the two information share difference measures (one based on the regular futures and one based on the E-Mini futures contract). Only one bivariate VAR is estimated for the Yen/US$ since we constructed only two variables in this market (the regular futures-cash basis and the information share measure based on the regular futures contract). The number of lags in the VAR is selected on the basis of the Akaike Information Criteria (AIC). The information criteria imply a lag of 3 for five out of the six bivariate regressions[36]. Since the key contribution of this chapter is to examine the direction of the causality between the relative speeds of adjustment across markets and the behavior of arbitrageurs, Table 4.5 presents the pairwise Granger-Causality test. For the null hypothesis that the variable i does not Granger-cause variable j, we test whether the lagged coefficients of i are jointly zero when j is the dependent variable in the VAR. The cell associated with the ith row variable and the jth column variable shows the Chi-square statistic associated with this test (the p-value is shown in brackets below the Chi-square statistic).

In Panel A, the test results for the Euro/US$ market show that there is significant bi-directional causality between the two variables. Six out of eight Chi-square statistics are statistically significant. The no-arbitrage bases in both the regular futures market and E-mini futures market Granger-cause the information share differentials across markets. Reverse causality running from both information share measures to the no-arbitrage bases is found only in futures markets trading regular contracts. The E-Mini information share differential does not Granger-cause the basis or neither regular nor E-mini futures markets. More interestingly, however, is the intermarket causality revealed by these tests. The difference in the speeds of adjustment between the spot currency market and the regular futures markets (measured by the information share differential) Granger-causes the E-Mini futures-cash no-arbitrage basis. The coefficients of the regular futures-cash ISDIFF are jointly different from zero when the E-Mini futures-cash NABAS is used as the dependent variable (Chi-square statistic has a p-value close to 2.2%). Although the same cannot be said about the causality running from the E-mini ISDIFF to the regular futures NABAS, we find much stronger results when we look at the intermarket causality running from the NABAS to the ISDIFF. The statistical results show that the no-arbitrage basis of both markets (regular and E-Mini futures) Granger-cause the information share

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[36] The bivariate VAR pairing the no-arbitrage basis and the information measure constructed based on the

differential of the regular futures and E-Mini futures markets at the 10% and 5% level of significance, respectively. This implies a very close relation between the regular futures and the E-Mini futures markets, where arbitrageurs use information initially revealed in the spot market to trade in both, the more liquid regular futures contracts and the less liquid E-Mini futures contracts. This suggests that liquidity is not the only factor arbitrageurs consider. E-Mini futures contracts have become more popular due to other features such as the smaller contract size which allow smaller investors to participate in the foreign exchange markets.

The results for the Yen/US$ market are presented in Panel B. These results are quantitatively and qualitatively similar to the ones in the Euro/US$ market. For the Yen/US$ market, however, the two variables were constructed using only the regular futures contract. We now estimate the impulse response functions (IRFs) in order to examine the joint dynamics of these variables implied by the full VAR system. An IRF traces the impact of a one standard deviation shock to a specific variable on the current and future values of the endogenous variables. Following Roll et al. (2007), we orthogonalize the impulses.

Figure 4.1 through Figure 4.4 present the responses of the Euro/US$ information and basis measures to a unit standard deviation shock in a particular value traced forward over a 10-day period. Figure 4.5 provides the responses of the Yen/US$ information and basis measures. Two-standard-error bands are also graphed to assess the statistical significance of the results. Period 1 in the impulse response functions represents the contemporaneous response, and the units on the vertical axis are in actual units of the

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E-Mini futures contract is estimated using 2 lags.

response variable (e.g., Euros per US dollar and Yen per US dollar in the case of the no-arbitrage basis). The impulses generally decay over time, which indicates that the variables used in the VARs are stationary.

All figures show that both the information share measure and the no-arbitrage basis are persistent. This can be seen in that shocks to a variable are informative in predicting futures values of the same variable in every instance. For example, the upper left panel of Figure 4.1 shows that a shock to the Euro/US$ ISDIFF has a permanent significant effect on itself. With regard to the cross effects, it can be seen that shocks to the information share measure have a significant positive effect on the no-arbitrage basis (upper right panel on all 5 figures). Similarly, a shock on the no-arbitrage basis has a significant positive effect on the information share measure (lower right panel). These results are robust across both foreign exchange markets considered. Furthermore, the IRFs show that the information measure is informative in forecasting the basis and vice versa, not only within the same futures market (e.g., regular futures NABAS and regular futures ISDIFF) but also across futures markets – a shock to the Euro/US$ E-Mini futures-cash ISDIFF has a permanent positive and significant effect on the Euro/US$ regular futures-cash NABAS (upper right panel in Figure 4.3). In summary, the impulse response functions are consistent with the findings of the Granger-causality tests even after accounting for the persistence of the variables in the system.

Overall, the statistical results obtained from the bivariate VAR and impulse response functions are consistent with the initial hypothesis. On the one hand, the differences in the speed of adjustment across markets are correlated with the intermarket mispricing. On the other hand, arbitrage trading triggered by a wide futures-cash basis (intermarket mispricing) generates larger speed differentials through order flow imbalances.

4.6 Conclusion

The existence of a lead-lag effect in equity markets has been well documented. The same effect was documented here but across foreign exchange markets trading the same underlying currency. This chapter exploits the presence of a lead-lag effect in currency markets to examine the relationship between the difference in the speeds of adjustment of markets to new information and the behavior of arbitrageurs. The central premise of this study is that relative informational inefficiencies across related markets will give way to an intermarket information diffusion channel. Arbitrageurs will then use this channel as a source of arbitrage profits by trading on one “lagging” market based on information already revealed in another “leading” market. This trading will of course close this channel (reestablish informational efficiency) until newer information arrives.

Consistent with the findings of Lo and MacKinlay (1990), we find some evidence of the existence of a lead-lag effect in currency market where we examine the futures and cash markets for the Euro/US$ and the Yen/US$. Using vector autoregressions, we find the there is two-way Granger-causality between the speed at which currency markets adjust to new information and the agents’ opportunities to generate arbitrage profits. These results imply that the ability of a market to process information faster than other markets moves prices away from their no-arbitrage values. In order to capitalize on these market inefficiencies, arbitrageurs could trade on the lagging market based on information already revealed in the faster market. The causality is, however, bi-directional suggesting that the activity of arbitrageurs has a significant effect on the variation of the futures-cash basis around its no-arbitrage value. Using impulse response functions which account for the full dynamics of the VAR and the persistence of the variables used in the system, we find that both variables – the futures-cash no-arbitrage basis and the information share difference – are informative in forecasting each other. Overall both methods (Granger-causality test and impulse response functions) provide similar and consistent results. Furthermore, the chapter results are robust across foreign exchange markets (Euro/US$ and Yen/US$) and across markets with different degrees of liquidity (the E-Mini futures contracts are relatively less liquid instruments than the regular futures contracts).

A possible empirical extension of this chapter would be to consider a more detailed analysis of the role of liquidity on the market's speed of adjustment to new information, and whether the relationship between the speed of adjustment measure and the no-arbitrage basis is significant even after accounting for liquidity. It would also be interesting to consider the basis/information relationship during days of news announcement. Furthermore, a longer sample period could be used.

Tables and Figures

Table 4.1: Trading Statistics on CME Futures

Symbol	Type	Trading	Globex ADV 7:05am -4:00pm (contracts)	Globex ADV 5:00pm - 7:05pm (contracts)	Globex ADV 5:00pm - 4:00pm (contracts)	Floor ADV 7:20am - 2:00pm (contracts)	Globex "Day" % of Globex Total	Globex % of Total Trading
E7 (Euro)	E-Mini	Globex	2956	526	3482	0	0.83	1.00
EC (Euro)	Regular	Pit & Globex	100675	33704	134379	4788	0.74	0.97
J7 (Yen)	E-Mini	Globex	13	4	17	0	0.73	1.00
JY (Yen)	Regular	Pit & Globex	28169	9593	37762	3307	0.74	0.94

Note: (1) ADV is the Average Daily Volume, (2) "Day" = 7:05am - 4:00pm, (3) Percentages are also period averages, (4) Sample period is from April 4th, 2005 to July 29th, 2005.

Table 4.2: Summary Statistics (daily averages)

Euro			
	Spot	Regular futures	E-mini futures
Number of observations	4514	6478	1468
Mean	1.248	1.250	1.250
Standard Deviation	0.002	0.002	0.002
Skewness	-0.027	0.090	0.004
Kurtosis	-0.532	1.428	-0.516

Japanese Yen			
	Spot	Regular futures	E-mini futures
Number of observations	3566	2594	42
Mean	0.0092344	0.0092848	0.0092796
Standard Deviation	0.0000094	0.0000096	0.0000095
Skewness	0.037	0.041	-0.108
Kurtosis	-0.644	-0.678	-0.336

Correlation coefficients for the prices (daily averages)

Euro			
	Spot	Regular futures	E-mini futures
Spot	1	0.991	0.987
Regular futures		1	0.987
E-mini futures			1

Japanese Yen			
	Spot	Regular futures	E-mini futures
Spot	1	0.989	0.690
Regular futures		1	0.692
E-mini futures			1

Note: Sample period is from April 4th, 2005 to July 29th, 2005.

Table 4.3: Summary Statistics for the Future-Cash Bases and Information Shares

Panel A: Euro/US$

					H0: NABAS = 0		H0: ISRATIO = 1	
Asset	Variable	Mean	Median	Std Dev	t-Statistic	p-value	t-Statistic	p-value
Regular	NABAS	-0.00012	-0.00009	0.00022	-4.8658	<.0001		
	ISRATIO	2.69504	1.83144	3.51518			4.176028	<.0001
E-Mini	NABAS	-0.00009	-0.00011	0.00026	-3.07452	0.003		
	ISRATIO	9.04230	2.38489	29.99929			2.321666	0.023

Panel B: Yen/US$

					H0: NABAS = 0		H0: ISRATIO = 1	
Asset	Variable	Mean	Median	Std Dev	t-Statistic	p-value	t-Statistic	p-value
Regular	NABAS	-0.00011	-0.00014	0.000229	-3.97421	0.0002		
	ISRATIO	3.696541	2.66187	5.132817			4.54969	<.0001

Note: Sample period is from April 4th, 2005 to July 29th, 2005.

Table 4.4: Cross-Autocorrelation Coefficients

Panel A: Euro/US$													
		Lag = 0			Lag = 1			Lag = 2			Lag = 3		
		Spot	Regular	E-Mini	Spot	Regular	E-Mini	Spot	Regular	E-Mini	Spot	Regular	E-Mini
Lag = 0	Spot	1.000	0.997	0.997	**-0.240**	**-0.236**	**-0.229**	0.083	0.089	0.085	-0.109	-0.108	-0.109
	Regular		1.000	0.999	**-0.257**	**-0.254**	**-0.247**	0.093	0.098	0.095	-0.119	-0.118	-0.118
	E-Mini			1.000	**-0.273**	**-0.270**	**-0.265**	0.117	0.122	0.119	-0.138	-0.137	-0.137
Lag = 1	Spot				1.000	**0.997**	**0.997**	**-0.241**	**-0.236**	**-0.229**	0.084	0.090	0.086
	Regular					1.000	**0.999**	**-0.258**	**-0.255**	**-0.248**	0.094	0.099	0.096
	E-Mini						1.000	**-0.275**	**-0.271**	**-0.266**	0.117	0.123	0.119
Lag = 2	Spot							1.000	**0.997**	**0.997**	**-0.255**	**-0.251**	**-0.245**
	Regular								1.000	**0.999**	**-0.272**	**-0.269**	**-0.263**
	E-Mini									1.000	**-0.288**	**-0.285**	**-0.281**
Lag = 3	Spot										1.000	**0.997**	**0.997**
	Regular											1.000	**0.999**
	E-Mini												1.000

Panel B: Yen/US$									
		Lag = 0		Lag = 1		Lag = 2		Lag = 3	
		Spot	Regular	Spot	Regular	Spot	Regular	Spot	Regular
Lag = 0	Spot	1.000	0.983	-0.118	-0.090	0.039	0.053	-0.033	-0.014
	Regular		1.000	-0.127	-0.098	0.037	0.046	-0.043	-0.022
Lag = 1	Spot			1.000	0.983	-0.115	-0.088	0.041	0.055
	Regular				1.000	-0.123	-0.095	0.039	0.048
Lag = 2	Spot					1.000	0.983	-0.120	-0.092
	Regular						1.000	-0.128	-0.099
Lag = 3	Spot							1.000	0.983
	Regular								1.000

Note: Correlation coefficients in **bold** are statistically significant at the 5% level of significance

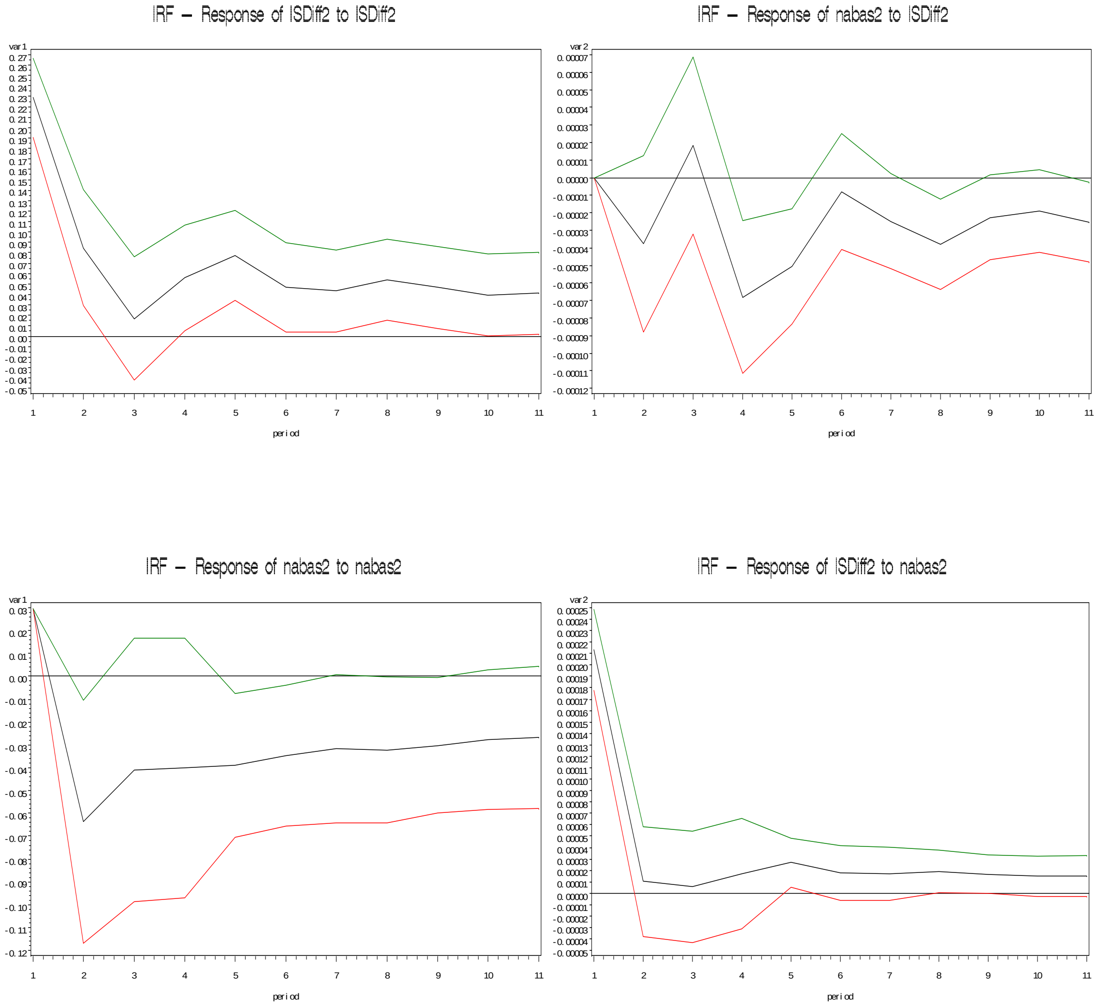
Table 4.5: Vector Autoregression Results: Granger-Causality Tests

(H_0: Row Does Not Granger-Cause Column)

Panel A: Euro/US$					
		NABAS		ISDIFF	
		Regular	E-Mini	Regular	E-Mini
NABAS	Regular			6.77* [0.0796]	4.92** [0.0265]
	E-Mini			6.39* [0.0941]	10.95** [0.0042]
ISDIFF	Regular	10.78** [0.0130]	9.59** [0.0224]		
	E-Mini	0.88 [0.3478]	1.23 [0.5411]		

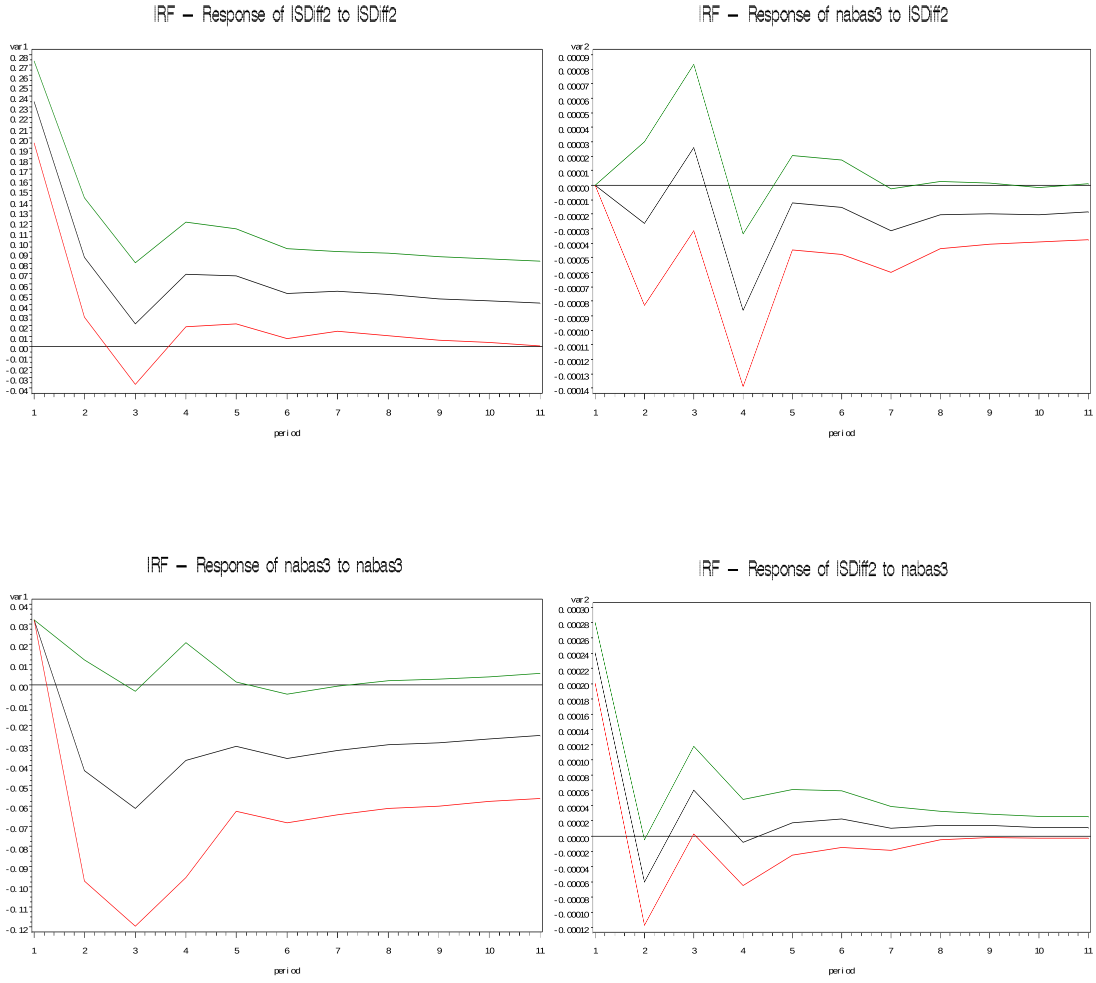
Panel B: Yen/US$					
		NABAS		ISDIFF	
		Regular	E-Mini	Regular	E-Mini
NABAS	Regular			7.91** [0.0478]	
	E-Mini				
ISDIFF	Regular	14.14** [0.0027]			
	E-Mini				

Note: ** The coefficient is significant at the 5% level of significance. * The coefficient is significant at the 10% level of significance.



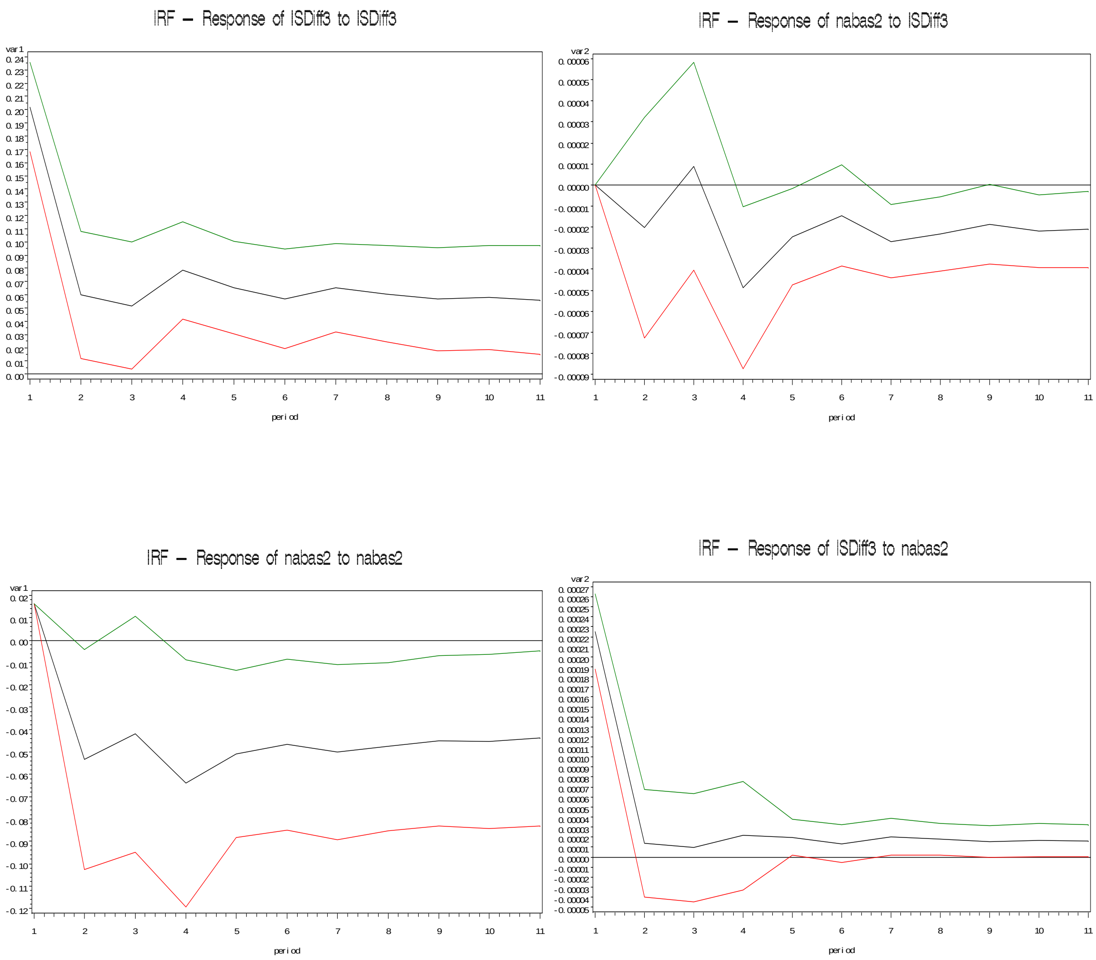
Note: Impulse response function for the bivariate vector autoregression with the Euro/US$ regular futures-cash no-arbitrage basis (NABAS) and the information share differential (ISDIFF).

Figure 4.1: IRF for the Euro/US$ regular futures-cash NABAS and ISDIFF



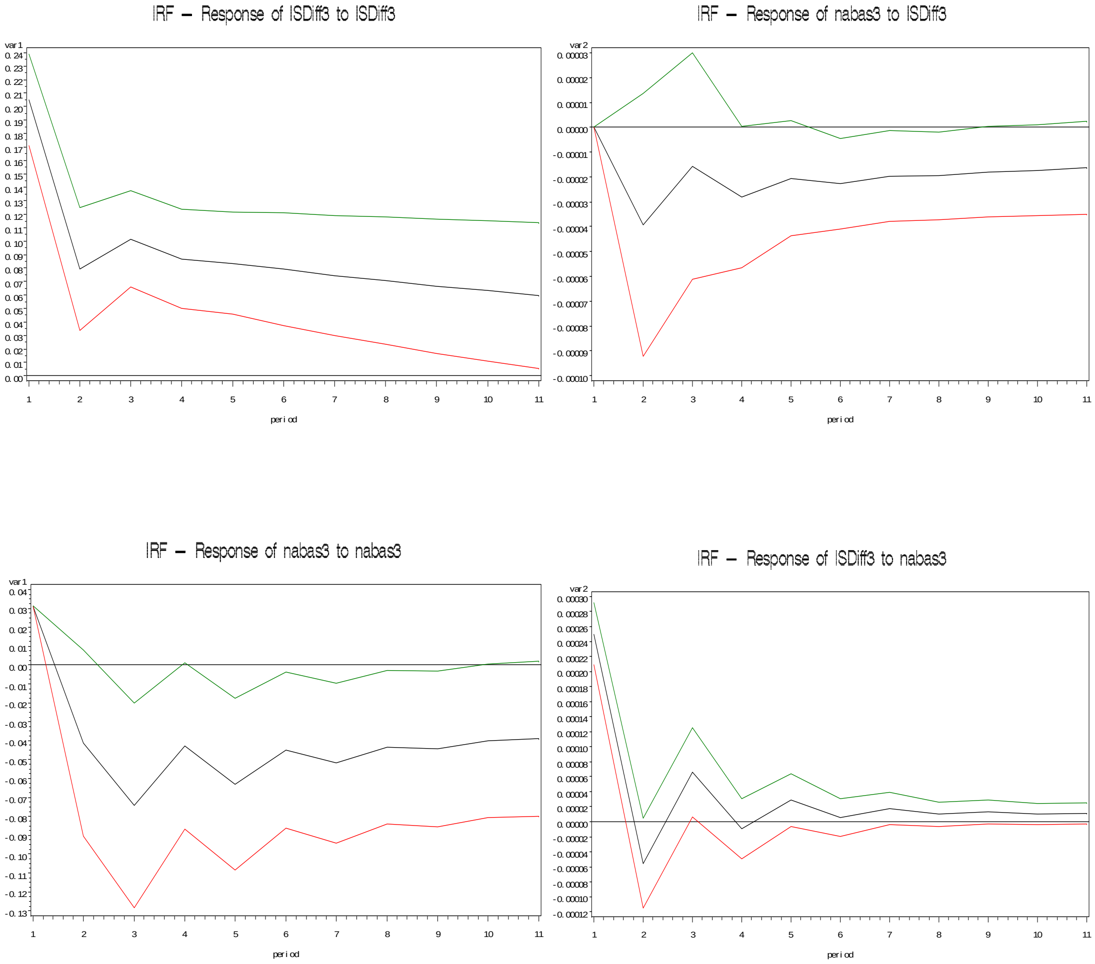
Note: Impulse response function for the bivariate vector autoregression with the Euro/US$ regular futures-cash information share differential (ISDIFF) and the Euro/US$ E-Mini futures-cash no-arbitrage basis (NABAS).

Figure 4.2: IRF for the Euro/US$ regular futures-cash ISDIFF and Euro/US$ E-Mini futures-cash NABAS



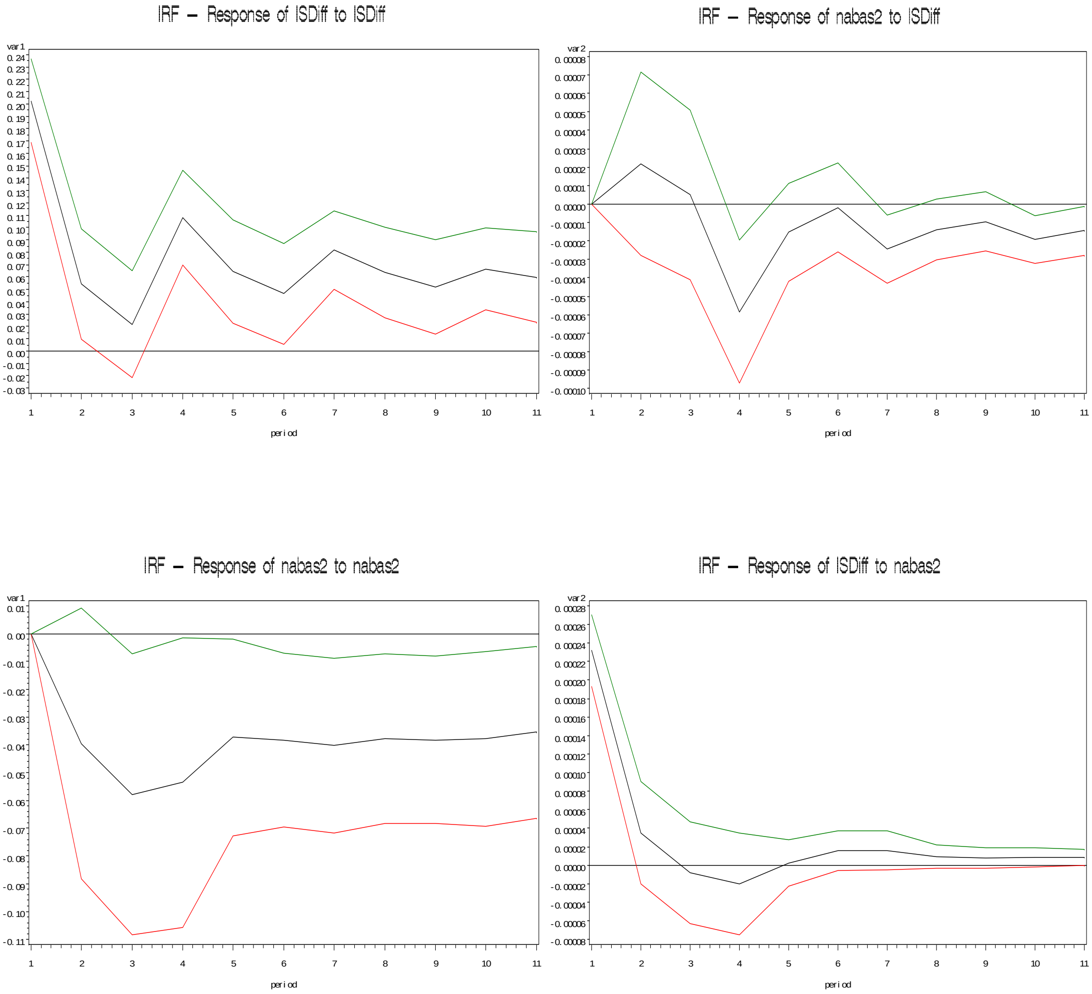
Note: Impulse response function for the bivariate vector autoregression with the Euro/US$ regular futures-cash no-arbitrage basis (NABAS) and the Euro/US$ E-Mini futures-cash information share differential (ISDIFF)

Figure 4.3: IRF for the Euro/US$ regular futures-cash NABAS and Euro/US$ E-Mini futures-cash ISDIFF



Note: Impulse response function for the bivariate vector autoregression with the Euro/US$ E-Mini futures-cash no-arbitrage basis (NABAS) and the information share differential (ISDIFF).

Figure 4.4: IRF for the Euro/US$ E-Mini futures-cash NABAS and ISDIFF



Note: Impulse response function for the bivariate vector autoregression with the Yen/US$ regular futures-cash no-arbitrage basis (NABAS) and the information share differential (ISDIFF).

Figure 4.5: IRF for the Yen/US$ regular futures-cash NABAS and ISDIF

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