

Speculation and Hedging in the Currency Futures Markets: Are They Informative to the Spot Exchange Rates

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Abstract

This paper presents an empirical analysis investigating the relationship between the futures trading activities of speculators and hedgers and the potential movements of major spot exchange rates. A set of trader position measures are employed as regression predictors, including the level and change of net positions, an investor sentiment index, extremely bullish/bearish sentiments, and the peak/trough indicators. We find that the peaks and troughs of net positions are generally useful predictors to the evolution of spot exchange rates but other trader position measures are less correlated with future market movements. In addition, speculative position measures usually forecast price-continuations in spot rates while hedging position measures forecast price-reversals in these markets.

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1. Introduction

The advent of futures markets enables farmers and producers to transfer commodity price risk using hedging strategies on the one hand, and facilitates other market participants, particularly speculators, to exploit information of futures trading to forecast the prices of underlying commodity or assets, often in an attempt to reap excessive profits, on the other. Little controversy has been raised regarding the markets' function of transferring commodity price risk. However, empirical evidence upon whether futures trading activities are informative to market prices appears to be far from unanimous. Houthakker (1957), for example, found that large speculators showed evidence of strong forecasting skill and were consistently profitable. In contrast, Hartzmark (1987, 1991), who investigated the relationship between settlement prices and daily commitments for larger futures traders for nine markets, concluded that these traders are generally incapable of forecasting market price dynamics effectively. Subsequent studies, nevertheless, reconfirmed the information roles of futures traders in affecting price movements. Among them, Leuthold et al. (1994) found that speculators enjoyed a significant forecasting advantage in predicting the direction of price changes in the frozen pork bellies futures market; De Roon et al. (2000) and Tien (2001) showed that hedge pressure was able to account for a large amount of price variation; and Wang (2001) analyzed the usefulness of trader sentiment indexes in forecasting prices in six major agricultural futures markets and confirmed that both large speculators and larger hedgers are both valuable timing indicators, with the former predicting price continuations and the latter predicting price reversals. More recently, Klitgaard and Weir (2004) examined the short-term exchange rate movements and the net positions of speculators in the respective futures market. Their analysis revealed that speculators' trading activities could correctly track 75 percent of weekly exchange rate direction changes, but trader positions were not informative to future exchange rate movements.

Parallel to this burgeoning research on futures trading activities, the recent microstructure literature has gained growing popularity in explicating exchange rate dynamics, against the backdrop of the traditional macro models' failure over several decades.¹ Evans and Lyons have pioneered this line of study. In their influential paper, Evans and Lyons (2002) offered both theoretical motivation and empirical evidence on the close link between short-run exchange rate movements and interdealer order

¹ Meese and Rogoff (1983a, b) first documented the devastating results that fundamental variables, such as interest rates, inflation rates, money supply, real income, and trade balances, fail to present explanatory powers in describing future exchange rate movements over relatively short horizons. Subsequent studies further proved that the Meese and Rogoff finding has an enduring effect on the profession (e.g., Frankel and Rose, 1995; Flood and Taylor, 1996; Cheung et al., 2005).

flow.² Particularly, they found that order flow can account for up to 63 percent of daily exchange rate variation, a sharp contrast to standard fundamentals-based models in which the coefficients of determination are often less than 5 percent. Evans and Lyons' results were further bolstered by their own and other subsequent literature (e.g. Payne, 2003; Evans and Lyons, 2005, 2006; Killeen et al., 2006). The finding that order flow has strong explanatory power for exchange rate behavior sheds light on the fact that trading activities may contain important information about asset prices. In fact, Payne (2003) explicitly measured the information role of order flow, and concluded that 40 percent of currency price variation is due to transaction-related information.

In this paper, we present an empirical investigation of whether speculative and hedging activities in the currency futures markets are informative to future spot exchange rate movements. This attempt, naturally, fuels concern over to what extent transactions in the futures market are important enough to affect spot exchange rate developments given the relatively small size of the futures market compared to that of the global foreign exchange market.³ However, the difference in magnitude between futures trading and global currency market transactions does not preclude the possibility that these markets may still be closely linked through arbitrage (Lyons, 2001). Dominant traders in futures markets, commercial banks, multinational corporations, commercial dealers, and hedge funds, are typically also major players in spot foreign exchange transactions. As such, their trading activities in different markets tend to be intrinsically intercorrelated as the trading strategies in futures markets and those in spot markets are likely rooted in same information.

While this analysis complements the microstructure finance literature from another perspective, understanding the interconnection between currency futures trading activities and the price movements of underlying assets is also of great interest to both market participants and policymakers. Currency traders and other investors, for example, may combine the publicly available information upon speculative and hedging positions with their proprietary information about market prospects to identify profitable trading opportunities if futures trading activities prove to be informative to future price developments. In an increasingly globalized world, exchange rates have become progressively wedded to internal and external economic policies. As trade, investment, and other cross-border businesses are all profoundly influenced by these policies, monetary authorities often respond to exchange rate changes in order to ensure the

² According to Lyons (2001), order flow is a measure of net buying pressure defined as the net of buyer-initiated and seller-initiated orders in the currency market.

³ It is reported that the average daily volume of currency futures transactions accounts for about 7 percent of the total foreign exchange market volume (The Wall Street Journal Europe, May 5, 2006, p20).

effectiveness of their policies on inflation and economic growth. Thus, if the relationship between futures trading activities and spot exchange rate movements is well identified, futures market position data can be used as indicators by policymakers in assessing the potential evolution of asset markets and entire economy.

Our analysis utilizes the data made uniquely available by the CFTC's (Commodity Futures Trading Commission) Commitments of Traders (COT) report. It provides a decomposition of futures positions by type of traders - large speculators, larger hedgers, and small (nonreporting) traders. The COT data have been studied closely by market practitioners and academia in a variety of contexts such as predictability of traders (e.g., Hartzmark, 1991; Leuthold et al., 1997; Wang, 2001; Sanders et al., 2004), profitability of trading strategies (e.g., Kearns and Manners, 2004), risk premia (e.g. Chatrath et al., 1997), hedging pressure effect (e.g. Bessembinder, 1992; De Roon et al., 2000), and futures market volatility (e.g., Wang, 2001). While these studies primarily focus on the behaviors of futures markets, our work attempts to answer the question as to whether trader positions in currency futures markets play an important informational role in linking to the potential evolution of spot exchange rates. In this vein, our analysis is similar in spirit to that of Klitgaard and Weir (2004) who examined the connection between spot exchange rate changes and speculative net positions in future markets, but provides a more comprehensive inspection of this issue in a series of econometric settings. Specifically, we seek empirical evidence of the predictive power of trader positions, measured in several dimensions including the level and change of net positions, sentiment index constructed on actual positions, extremely bullish/bearish sentiments, and the peak/trough indicators of net positions.

Foreign currencies of three advanced economies and one emerging country - the British pound, euro, Japanese yen, and Mexican peso - are considered. We find that peaks and troughs of net positions for both types of traders are generally valuable indicators for potential spot rate movements. Particularly, the speculative peaks and hedging troughs forecast price continuations while the speculative troughs and hedging peaks forecast price reversals over short horizons up to 20 weeks. In contrast, there is no convincing evidence that trader positions, when measured in other forms, are useful for predicting future spot rate changes in the currency markets. One notable exception is the euro. Our results show that the net positions and sentiments of both speculators and hedgers are strongly informative to future euro changes, with the speculative positions and sentiment forecasting price continuation and the hedging ones forecasting price reversal. It is also noteworthy that contrary to the common belief that extremely bullish/bearish sentiments are often important signals to future price movements (e.g., Wang, 2001, 2004), the current analysis does not identify substantial connection between futures traders' extreme sentiments and cash market price developments. Our results also suggest that both speculative and hedging positions,

in all versions of measurement, covary with spot rate changes contemporaneously across all currencies, a result consistent with Klitgaard and Weir (2004).

The remainder of this paper is organized as follows. Section 2 presents empirical model specifications as well as the designs for a sentiment index as well as a dating algorithm identifying peaks and troughs of net positions. Section 3 provides a data description and preliminary analysis while Section 4 presents empirical results. Section 5 concludes.

2. Methodological Specifications

A. Level/Change of Net Positions.

The first issue we would like to investigate is how speculators and hedgers' current positions, or changes from previous positions, could aggregately impinge on the spot rates' movements. The regression form can be summarized as follows:

$$\Delta e_{t+k} = \alpha + \beta \Delta NP_{t,j} + \varepsilon_t \quad (1)$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period (week)-ahead change in log of exchange rate and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rate. $\Delta NP_{t,j} = NP_t - NP_{t-j}$ is the change (in level) over previous j periods' net position and $j = 0, 1, 2, \dots$ ⁴ For $j = 0$, $\Delta NP_{t,0} = NP_t$ is simply the current net positions.

The net of traders' total long positions versus their total short ones is normally viewed as a natural measure of speculative/hedging activities in the futures markets. The net positions held by hedgers are often termed as "hedging pressure" or "hedging demand". Various studies have documented the hedging pressure effects on the market prices. Bessembinder (1992), for example, concluded that hedging pressure variables are important determinants of expected futures returns. His empirical analysis showed that hedging pressure effects are significant in affecting futures returns for mineral and currency markets but appear to be relatively trivial for interest rate index futures. Along the same line, De Roon et al. (2000) studied hedging pressure effects in a set of 20 futures markets, covering financial,

⁴ Net positions are measured respectively according to the trade types, namely speculators and hedgers. For notional simplicity, we use the same notation for both types of traders.

agricultural, mineral, and currency futures. They found that hedging pressure variables have a significant effect on futures returns after controlling for market risk and price pressure effects. Tien (2002) presented similar evidence upon the effects of hedging activities but focused on spot currency price dynamics. He showed that adding a hedging demand variable to the uncovered interest parity regression significantly improves the model fit, with the regression coefficients of determination increased from a trivial 0.01 to a remarkable 0.48. The literature has no lack of evidence documenting the link of speculative trading activities and market movements. A recent study by Klitgaard and Weir (2004), for example, found a strong and stable connection between changes in speculators' positions and spot exchange rates, with net positions accounting for up to 45 percent of weekly variation in major currencies.

The present exercise, along the same line with Tien (2002) and Klitgaard and Weir (2004), looks into the covariation between trading activities and spot currency prices. The connection reported in their studies, however, is limited to be contemporaneous.⁵ The documented instantaneous covariation per se highlights important insights on understanding the financial market behaviors though, market participants and policymakers may be more interested in how and where the markets will move. Commercial firms, for example, often rely on their foresights to position long or short hedging portfolios in the attempt to smooth their business activities, while funds traders seek excessive profitable opportunities by exploiting sophisticated forecasting techniques to predict future price movement. Clues toward the future dynamics of exchange rates are also critically important for policymakers especially monetary authorities whose policies usually have profound and extensive repercussions over the economy. In this regard, we are intrigued enough to cast further exercises in examining whether traders' positions contain useful information in predicting future spot currency prices.

B. Sentiment Index

Investor sentiment, defined broadly as a measure of investors' beliefs about future asset prices and investment risks, is utilized widely in investment practice and financial analysis. In general, researchers construct sentiment indexes using surveyed data such as the forecasts of investment newsletter writers (e.g. Solt and Statman, 1988; Clarke and Statman, 1998), the sentiment of Wall Street strategists (e.g.

⁵ Klitgaard and Weir (2004) indicated that net positions are not useful in forecasting nominal exchange rates for the following week according to Granger causality tests.

Fisher and Statman, 2000), the Consensus index of bullish market opinion (e.g. Wang, 2003), and the Consumer Confidence index (e.g. Qui and Welch, 2004). They also been known to use sentiment indexes based on particular market trading measures, such as trading volume, net positions of open interest, mutual fund flows, closed-end fund discounts, option implied volatility, and insider trading information (see a recent survey by Baker and Wurgler, 2007).

In this study, we use an investment sentiment index following Wang (2001), which is based on net positions of respective type of traders, to investigate the relationship between the spot exchange rates and futures trading activities in the currency futures markets. Particularly, we examine the following regression forms:

$$\Delta e_{t+k} = \alpha + \beta_1 SI_t(l) + \varepsilon_t \quad (2)$$

and

$$\Delta e_{t+k} = \alpha + \beta_1 \Delta SI_t(l) + \beta_2 SI_t^{hi}(l) + \beta_3 SI_t^{lo}(l) + \varepsilon_t \quad (3)$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period (week)-ahead change in log of exchange rate and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rate. $SI_t(l)$ is sentiment index with l lookback periods, defined as

$$SI_t(l) = \frac{NP_t - NP_{t,l}^{min}}{NP_{t,l}^{max} - NP_{t,l}^{min}} \quad (4)$$

where $NP_{t,l}^{max} = \max\{NP_{t-l}, NP_{t-l+1}, \dots, NP_t\}$ and $NP_{t,l}^{min} = \min\{NP_{t-l}, NP_{t-l+1}, \dots, NP_t\}$ are the maximum and minimum net positions over the most recent l periods prior to the current observation. A conventional pick for the lookback periods is a 3-year span which roughly suggests $l = 156$ on the weekly basis. In this exercise, we add flexibility and try different values of the lookback periods. $\Delta SI_t(l) = SI_t(l) - SI_{t-1}(l)$ is the change of investor sentiment at t . The indicator variables, $SI_t^{hi}(l)$ and $SI_t^{lo}(l)$, further indicate whether the current net position is in the upper or lower percentile according to certain cutoff values. For example, we set 0.9 as an extremely high cutoff and 0.1 as an extremely low cutoff such that $SI_t^{hi}(l) = 1$ if $SI_t(l) \geq 0.9$ and $SI_t^{hi}(l) = 0$ otherwise, and $SI_t^{lo}(l) = 1$ if $SI_t(l) \leq 0.1$ and $SI_t^{lo}(l) = 0$ otherwise.

Compared to net positions, which are essentially measured by the number of net long or net short contracts and vary drastically in magnitude across futures markets due to market nature and size, investor

sentiment presents a relative rank of the current net position within the context of the historical range and is not affected by the magnitudes of net positions. Thus, sentiment index facilitates comparisons across markets for the relevant trading activities in forecasting future market price movements. In addition, a relative rank of the current net position may convey more intuitive information regarding the degree of bullishness or bearishness of the markets, which is typically not easy to perceive through traders' net positions as futures trading is a zero-sum game. Particularly, when the current net position is ranked as historically high or low, investors often see signals of important trend changes in the markets and may undertake proper buying or selling strategies. Therefore, extreme sentiment index readings may be effectively linked to the future currency returns. For this matter, we are motivated to examine the predictive power of both the level of sentiment index and extreme ranks of sentiment index.

Some empirical studies have shown that investor sentiment measures are useful to predict the future development of stock returns. Lee et al. (1991), for example, found that changes in individual investor sentiment can lead to fluctuations in discounts of closed-end funds. Qui and Welch (2004) argued that the consumer confidence can be validated as a proxy for investor sentiment and correlates with the excess rate of return on small firms. Based on retail investors' trading activities, Kumar and Lee (2006) recently documented a significant incremental ability of investor sentiment to explain return comovements for stocks with high retail concentrations. Similarly, Baker and Wurgler (2006) showed that investor sentiment index is negatively correlated with cross-section returns for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. In contrast, Solt and Statman (1988) and Clarke and Statman (1998) found no statistically significant relationship between the sentiment of newsletter writers and stock index returns.

Several other researchers have investigated the link between investor sentiment and future market returns based on futures trader position information. Among them, Stephen Brieese pioneered the profession in utilizing the COT report to trace profit opportunities in the futures markets. In his illuminative article, Brieese (1990) showed that the COT data can be used to construct a sentiment indicator which is a reliable guide to important trend changes in the sugar market. Wang (2001) systematically studied the return predictability of investor sentiment by type of traders in six actively traded agricultural futures markets. He confirmed that large speculator sentiment is a price-continuation indicator while hedger sentiment is a price-reversal indicator. Subsequently, Wang (2004) examined the relevant relationship in the currency futures markets. He found that the correlation between the level of sentiment and futures returns is fairly weak but extremely bullish and bearish sentiments are more useful predictors of market returns. Following Wang's specification, Sanders et al. (2004), nevertheless, could not find pervasive evidence that trader positions are predictive to energy futures returns. As a result, they

concluded that “the empirical results using COT data in one industry do not imply similar in other markets” (p. 442). In this regard, our analysis is worthwhile to disentangle the relationship between futures traders’ sentiment and the dynamics of future spot exchange rates.

C. Peaks and Troughs of Net Positions

Market prices never go up and down in straight lines, but move in zigzag patterns instead. Along this zigzag process, peaks and troughs alternate within upward and downward trends which are usually highly persistent over a sustained period of time. This feature of price movements has popularized the peak-and-trough analysis among practitioners in the finance world, which is arguably the most important building block of technical analysis. In the meanwhile, a casual inspection over the time series of the futures trading net positions makes it clear that trading activities follow similar trended zigzag patterns. It is thus particularly intriguing to know if peaks and troughs in the series of net positions help shed light on future movement of spot rates. To this end, we design a dating algorithm to identify peaks and troughs in net positions and consider the following regression relationship:

$$\Delta e_{t+k} = \alpha + \beta_1 \Delta NP_t + \beta_2 NP_t^{max} + \beta_3 NP_t^{min} + \varepsilon_t \quad (5)$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period (week)-ahead change in log of exchange rate and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rate. $\Delta NP_t = NP_t - NP_{t-1}$ is the change of net position at t , and NP_t^{max} and NP_t^{min} are dummy variables such that $NP_t^{max} = 1$ if current net position stays at a peak area, 0 otherwise; $NP_t^{min} = 1$ if current net position stays at a trough area, 0 otherwise. Peaks and troughs are identified based on the following dating algorithm:

1. Peak Area

(1) Use a l -lookback-period window to locate a series of local maxima, which is defined as

$$MAX_t = \max \{ NP_t, NP_{t-1}, \dots, NP_{t-l} \}$$

(2) Define a lower bound for the corresponding local maximum

$$LoBd_t = \begin{cases} MAX_t - m \cdot \sigma_t & \text{if } MAX_t \neq MAX_{t-1} \\ LoBd_{t-1} & \text{if } MAX_t = MAX_{t-1} \end{cases}$$

where σ_t is the standard deviation of net positions over p periods prior to the current observation and m is a scalar which decides the distance of the lower bound from the local maximum.

(3) Record a series of pairs of time points (t_1, t_2)

$$t_1 = \inf \{t: NP_t > MAX_{t-1}\} \text{ and } t_2 = \inf \{t: NP_t < LoBd_t\}$$

(4) Identify the peak area of net positions

Let t_{max} be the time period in which net position reaches the highest during t_1 through t_2 . The times for entering and exiting the peak area are defined as

$$t_{enter}^{peak} = \inf \{t: NP_t \geq LoBd_{t_{max}}\} \text{ and } t_{exit}^{peak} = \sup \{t: NP_t \geq LoBd_{t_{max}}\}$$

$$Peak \ Area = \{NP_t: t_{enter}^{peak} \leq t \leq t_{exit}^{peak}\}$$

2. Trough Area

(1) Use a l -lookback-period window to locate a series of local minima, which is defined as

$$MIN_t = \min \{NP_t, NP_{t-1}, \dots, NP_{t-l}\}$$

(2) Define an upper bound for the corresponding local minimum

$$UpBd_t = \begin{cases} MIN_t + m \cdot \sigma_t & \text{if } MIN_t \neq MIN_{t-1} \\ UpBd_{t-1} & \text{if } MIN_t = MIN_{t-1} \end{cases}$$

where σ_t is the standard deviation of net positions over p periods prior to the current observation and m is a scalar which decides the distance of the lower bound from the local minimum.

(3) Record a series of pairs of time points (t_1, t_2)

$$t_1 = \inf \{t: NP_t < MIN_{t-1}\} \text{ and } t_2 = \inf \{t: NP_t > UpBd_t\}$$

(4) Identify the peak area of net positions

Let t_{min} be the time period in which net position reaches the lowest during t_1 through t_2 . The times for entering and exiting the trough area are defined as

$$t_{enter}^{trough} = \inf \left\{ t : NP_t \leq UpBd_{t_{max}} \right\} \text{ and } t_{exit}^{trough} = \sup \left\{ t : NP_t \leq UpBd_{t_{max}} \right\}$$

$$Trough Area = \left\{ NP_t : t_{enter}^{trough} \leq t \leq t_{exit}^{trough} \right\}$$

This dating algorithm is repeated until the last data point. Since the data series are highly volatile, to avoid the distortion by blips, we apply this algorithm to a slightly smoothed series based on the Hodrick-Prescott filter with a small λ , the HP-filter smoothing parameter.⁶

Note that the time span (t_1, t_2) identified in step (3) roughly defines the peak/trough area of net positions. However, it is highly left-skewed when there is a sustained period of upward/downward movements. Step (4) thus redefines the peak/trough area to correct this issue. This treatment is important in the sense that it captures *de facto* extreme positions on the top or in the bottom without including observations along the trends. In contrast, the extremely bullish sentiment ($SI_t = 1$) or bearish sentiment ($SI_t = 0$) generally represents both peaks/troughs and trends. This mixing may in fact undermine the ability of investor sentiment to address useful information in accounting for future market movements. More importantly, our simple dating mechanism produces real-time selling or buying signals in the light of timing of exit. In particular, the timing of exit from a peak area signals a selling strategy while the timing of exit from a trough area signals a buying strategy.

3. Data and Preliminary Analysis

The currency futures trader positions data used for our analysis are extracted from the Commitments of Traders (COT) reports distributed by the Commodity Futures Trading Commission (CFTC). The COT reports, currently published every Friday, provide a decomposition of positions by categorized traders at the close of the preceding business Tuesday. We collect weekly data for four major foreign currencies, the British pound (GBP), the euro (EUR), the Japanese yen (JPY), and the Mexican peso (MXN), from March 1995 to December 2008 based on the COT options-and-futures-combined report.⁷ We also collect

⁶ We use $\lambda = 10$ for this analysis. The results are robust to both slightly smaller and larger values.

⁷ The CFTC publishes three versions of trader positions separately: the futures-only, the options-and-futures-combined, and the supplemental report. The futures-only report has the longest history but the weekly data are not available until 13 October 1992. Our sample is based on the options-and-futures-combined report which presumably provides more comprehensive information regarding the trader positions than the future only report, although it has a slightly shorter history.

weekly spot exchange rates on Tuesdays through the Federal Reserve Bank of St. Louis. All foreign exchange rates are U.S. dollar priced, i.e. dollars of per unit of foreign currency.⁸ We select these currencies because the first three are the most actively traded currencies in both futures and cash markets while the Mexican peso is an important floating rate in emerging markets and has been extensively studied in the literature.

Futures trading activities are reported according to different types of traders. To ensure that the markets are free from price manipulation, the CFTC regulates futures and options trading through a market surveillance program which requires traders who control positions exceeding the reporting threshold to divulge their actual positions on a daily basis. Reporting levels are adjusted periodically by the CFTC on the basis of trading volume, open interest, and the number and position sizes of individual traders for each market such that about 70 to 90 percent of the open interest in each market is under effective market surveillance.⁹ As a result, traders are divided into reporting and nonreporting traders. The former (large traders) are further categorized as either commercial or noncommercial. The CFTC generally describes commercials as hedgers who have fundamental exposure to market risk and thus use futures contracts to hedge their business operations. Noncommercial traders are commonly referred to as speculators who take futures positions for reasons other than hedging fundamental exposure. Our analysis primarily focuses on the trading activities of hedgers and speculators as they are the most influential players in the futures markets and their positions represent the overwhelming majority of the open interest in these markets.

Descriptive statistics for the spot rate changes and net positions by type of traders are reported in Table 1. Panel A of Table 1 presents the summary of weekly changes of logarithmic Tuesdays' spot exchange rates over the sample period. The average weekly changes are -0.013 percent for the British pound, 0.034 percent for the euro, -0.002 percent for the Japanese yen, and -0.117 percent for the Mexican peso, among which only the last is statistically significant at conventional test levels. A significant negative mean change suggests a sustained period of downward movements in the Mexican peso, which in fact roughly delineates the peso's depreciation over the recent decades. The statistics for other currencies, nevertheless, are less suggestive as they are apparently sample-sensitive. The pound and the euro, for instance, experienced a sharp rise since 2002 until the acceleration of the global financial

⁸ For comparability, the JPY is scaled up by multiplying 100 and the MXN is scaled up by multiplying 10.

⁹ The reporting level for major currency futures is 400 contracts and the reporting level for other currency futures is 100 contracts. Major foreign currency means the currencies and cross-rates between the currencies of Japan, the United Kingdom, Canada, Australia, Switzerland, Sweden and the European Monetary Union.

crisis in September 2008 and plummeted during the financial turmoil as the market switched to the safe haven currencies - the US dollar and the Japanese yen. As for the volatility of the spot rates, no significant variation is exhibited across these four currencies, ranging from 1.209 to 1.498 percent, which is comparable to the results reported by Klitgaard and Weir (2004).

Panel B of Table 1 summarizes the net positions held by speculators and hedgers. On average, speculators are net long in the pound and the yen and net short in the euro and the peso over the period. Not surprisingly, hedgers take opposite positions with net long in the euro and the peso and with net short in the pound and the yen. The results indicate that neither speculators nor hedgers are consistently net buyers or net sellers in the currency futures markets. This is in contrast to results reported by Sanders et al. (2004) for energy markets where large commercials are net short and noncommercials are net long across all energy futures contracts examined. In terms of magnitude, both speculators and hedgers hold the largest net position in the euro futures with average weekly positions of 19,940 contracts and 35,280 contracts, respectively. It is also noticeable that, unlike other currency futures where net positions held by speculators and those held by hedgers roughly offset each other, the euro market has a large gap in net positions between speculators and hedgers, with the latter's net positions almost doubled. The relatively smaller net short position by speculators indicates that small traders may be a more important neutralizing force in the euro futures market than those in other currency markets. Turning to the changes in net positions, it appears that the average weekly changes by both types of traders are largely negligible for all currency futures. This, however, in no way means that net positions are less volatile. Instead, net positions vary extensively from week to week with a minimum absolute mean change of 4,620 contracts and an average standard deviation of over 30,000 contracts across all markets.

Panel B of Table 1 also presents the Augmented Dickey-Fuller (ADF) test statistics concerning the stationarity of net position series. It is well known that exchange rates follow persistent trends and have proved to be $I(1)$ process. As shown in Fig. 1 and Fig. 2, net positions exhibit similar persistence with apparent clustering. However, contrary to visual inspection, the standard unit root test strongly suggests that they are stationary. The stationarity of currency futures net positions thus justifies our modeling the level of net positions as a predictor in the regression analysis without being called into question over spurious regressions.

Panel C of Table 1 reports summary statistics for the sentiment index constructed in Eq. (4) with a lookback period of 3 years. On average, speculators have higher sentiment levels relative to hedgers in all currency futures markets except for the British pound market, where the sentiment indexes by both traders are roughly no different in magnitude. Panel C also shows the proportion of extremely bullish net

positions ($SI \geq 0.9$) and that of extremely bearish net positions ($SI \leq 0.1$). As expected, the high- and low-sentiments each take approximately 10 percent of the entire series, though considerably more extremely bullish positions are held by speculators in the euro and the peso futures while more extremely bearish positions are taken by hedgers in the peso market. This implies that for speculators' net positions in the euro and the peso markets, there are more sustained uptrends relative to downward movements, while for hedgers' net positions in the peso market, there are more persistent downtrends relative to upward movements.

Figures 1 and 2 display the plot of speculative and hedging net positions along with underlying exchange rates, respectively. At a quick glance, we can see positive net long speculative positions are generally associated with upward movements in the spot exchange rates while positive net long hedging positions are often associated with downward movements in the spot exchange rates. Another salient feature is that net positions of both types of traders, in absolute terms, have obtained a substantial increase in recent years for all currencies.

4. Empirical Results

This section presents the results from estimating the series of models specified in Section 2. Table 2 reports the connection between current net positions (NP_t) and the changes of spot rates (Δe_{t+k}). The first two rows show the contemporaneous relation of these two series. The estimated slope coefficients for speculators are uniformly positive and significant at conventional significance levels while the slope coefficients for hedgers are significantly negative. Particularly, an increase of 10,000 contracts in speculators' net long positions is associated with 0.11 percent weekly increase in current exchange rate for the British pound, 0.09 percent for the euro, 0.07 percent for the Japanese yen, and 0.05 percent for the Mexican peso, respectively. In contrast, an increase of 10,000 contracts in hedgers' net long positions is associated with opposite change in current spot rates with roughly the same magnitude for each currency. The estimated results are consistent with our visual inspection of Figures 1 and 2 in which upward movements of spot rates are associated with positive net long positions for speculators and negative long positions for hedgers. This finding confirms Klitgaard and Weir's (2004) conclusion that net positions and exchange rates move together in a reliable and stable fashion.

The evidence of the predictive power of the level of net positions, however, is fairly weak for all currencies except the euro. The estimated slope coefficients are usually insignificant at the 10% level although their significance appears to be enhanced as forecast horizons increase in light of the t -statistics.

In a sharp contrast, net positions by both types of traders in euro futures are consistent predictors of future changes of the spot rate over horizons from 1 week through 20 weeks.¹⁰ The speculators' net positions, for example, predict an approximate 0.04 percent (weekly), 0.16 percent (monthly), and 0.45 percent (quarterly) euro appreciation given an increase of 10,000 net long contracts while the increase of the same amount of hedgers' net long positions predicts commensurate euro depreciation over the relevant horizons. In addition, it is seen that the estimated intercepts for future exchange rate changes are generally insignificant with the exception of the Mexican peso, a result confirming our earlier discussion.

Table 3 presents regression results pertaining to the relationship between changes in net positions and exchange rate movements. We consider both current weekly changes ($j=1$) and accumulated changes ($j=4,8,12$) in net positions. In general, changes in net positions are not quite as informative to future exchange rate movements, notwithstanding the strong contemporaneous connection for all currencies - a conclusion indicated by Klitgaard and Weir (2004) in their Granger causality test results. There are, nevertheless, a few exceptions in the British pound. For example, it appears that both current and accumulated changes over prior 4 weeks in net positions can mildly forecast future pound changes in the period of 8 weeks ahead, and accumulated changes of net positions over the prior 8 weeks are considerably predictive to short-run swings in the British pound over the horizons of 1 through 8 weeks.

It is also interesting to note that changes in speculators' net positions tend to negatively covary with future spot market developments in the British pound while changes in hedgers' net positions relate positively to future pound changes. This negative covariation suggests that speculators hold more long contracts on pound futures before the spot rate of the pound sterling moves downward, and vice versa. On the contrary, hedgers of the British pound futures are generally able to judge correctly the direction of future pound movements. These findings are particularly striking as the popular view of hedging pressure posits that hedgers pay a risk premium to speculators for transferring nonmarketable risks and accordingly, hedgers lose money while speculators make profits. Various studies have provided evidence of the existence of hedging pressure effects in futures markets (e.g., Bessembinder, 1992; De Roon et al, 2000; Wang, 2003). As our study focuses on spot rates instead of futures prices, this unusual phenomenon suggests futures prices of the British pound may deviate from their spot counterparties in the near-term with a different pattern when compared to other currencies.

¹⁰ Our exercise shows that net positions remain significantly informative to future euro for extended forecasting horizons with econometrically meaningful R^2 .

Tables 4 and 5 report the connection between futures market sentiment and subsequent changes in spot currency rates. Table 4 presents the regression results based on the level of sentiment index with different lookback periods. By and large, there is no pervasive evidence that the level of market sentiment is able to forecast future spot price movements in currency markets. There are, nevertheless, a few cases where the slope coefficients are statistically significant at conventional levels. When constructed through a three-year lookback rolling window, for example, the sentiment indexes are quite predictive of spot rate changes over 12-week ahead or longer horizons in the pound and euro markets. Particularly, both speculator and hedger sentiments predict approximately 3 percent of the change in the pound sterling and 6 percent of the change in the euro over a period of 12 weeks (roughly a quarter). Similar results are found when sentiment indexes are constructed using a five-year lookback rolling window in these two currency markets. Irrespective of their statistical significance, the slope coefficient estimates for speculator sentiment are generally positive, suggesting price continuations in spot rates, while the slope coefficient estimates for hedger sentiment are generally negative, suggesting price reversals in these currency markets.

The weak linkage between the level of sentiment and future spot rate changes is arguably attributed to the intrinsically controversial nature of the sentiment index. According to Eq.(4), a net position on the upward trend and another one on the downward trend, both of which stand at the historical midpoint (within a lookback period), can have the same value of 0.5 for the index. In fact, each single value of the sentiment index, except those extremes ($SI = 1$ or $SI = 0$), can stand for both observations with rising and falling rank. Since net positions, both with rising and falling rank, generally have offsetting impacts on market price behavior, the sentiment index *per se* is somewhat ambiguous in connecting price movements although it is still the case that a higher value of the sentiment index corresponds to a higher net position. As a result, many researchers and market practitioners suggest using extreme sentiment instead of the level of sentiment to forecast future market price movements. In light of the preceding discussion, extreme sentiment with values of 1 and 0 would presumably be the strongest predictor. However, we may have only a few of these kinds of observations. Thus, we typically define the upper 10th percentile of market sentiment ($SI \geq 0.9$) as the extremely bullish positions and the lower 10th percentile of market sentiment ($SI \leq 0.1$) as extremely bearish positions.

Table 5 presents regression results based on extreme sentiments constructed using a three-year lookback rolling window. Contrary to expectation, including extremely bullish and bearish indicator variables does not significantly improve the forecastability of market sentiment. Consistent with results shown in Table 4, sentiment index variables appear to be predictive to subsequent spot rate movements in

the euro market while there are some sporadic cases in other currency markets where coefficients for extreme sentiment dummies are significant. For example, speculators' extremely bearish positions help moderately predict the spot rate changes in the pound at horizons over 12 weeks and in the yen at shorter horizons of 1 week and 4 weeks, respectively. Likewise, hedgers' extremely bullish positions appear to be more informative in forecasting 4- and 8-week changes in the peso. In anticipating subsequent price movements, extremely bullish and bearish positions by both types of traders in the pound and euro markets tend to suggest price reversals while in the yen market, speculators' extremely bearish and hedgers' extremely bullish positions are more likely associated with price continuations.

Our finding that extreme sentiments are weakly linked to future spot exchange rate movements is consistent with Sander et al's (2004) study on energy futures markets but quite different from Wang's (2001) work on agricultural futures markets. Sander et al (2004) showed that extreme position levels rarely succeed in predicting subsequent prices in crude oil, gasoline, heating oil, and natural gas futures markets. In contrast, Wang's (2001) systematical analysis demonstrated that speculators' positions consistently predict price continuations and hedgers' positions consistently predict price reversals in corn, soybeans, soymeal, wheat, cotton, and world sugar futures markets. Therefore, our analysis largely reinforces Sander et al's verdict that the information contained in the COT data plays different roles across different markets.

Table 6 shows the predictive power of indicator variables for peaks and troughs. The results appear to be quite encouraging. The slope coefficient estimates for speculators' peak positions are uniformly positive and statistically significant at conventional levels for the forecasting periods of 1 week through 20 weeks across all currencies. On average, the subsequent changes in the spot rates associated with speculators' net positions at peak areas are 0.23 percent (weekly), 0.76 percent (monthly), and 2.31 percent (quarterly) in the pound sterling, 0.48 percent (weekly), 1.44 percent (monthly), and 2.97 percent (quarterly) in the euro, 0.54 percent (weekly), 1.43 percent (monthly), and 2.59 percent (quarterly) in the yen, 0.33 percent (weekly), 1.10 percent (monthly), and 2.43 percent (quarterly) in the peso, respectively. Hedgers' trough positions are analogous to speculators' peak positions. They tend to suggest price continuations in spot rates with comparable magnitudes of weekly, monthly, and quarterly changes. In contrast, the slope coefficient estimates for speculators' trough positions and those for hedgers' peak positions are nearly all negative and generally statistically insignificant across currencies except for the British pound and cases of longer forecast horizons. To summarize, speculators' peak positions have significant positive connections with future spot exchange rate changes while their trough positions are contrary indicators to subsequent price movements but have very weak forecasting power. Likewise,

hedgers' trough positions are strongly informative to future spot rate changes while their peak positions are weakly linked to future price reversals.

Comparing the results to those in Table 1, it is interesting to note that including peak/trough indicator variables changes the forecasting power of the level of net positions. As we have seen in Table 1, the level of net positions is generally poor in forecasting future price movements except in the case of the euro. Peak/Trough indicator variables, however, make the level of net positions no longer informative to future euro developments. In contrast, these extreme position dummies further enhance the predictive power of the level of net positions for the Japanese yen and in the case of forecast horizons over 20 weeks. Collectively, this suggests that peak/trough positions dominate in forecasting near-term spot rate changes. In the meantime, the predictive power of the level of net positions becomes more significant as the forecast horizon increases, a conclusion consistent with the results shown in Table 1.

5. Summary and Conclusion

We present an empirical analysis in this paper investigating the relation between speculation and hedging in the currency futures markets and changes in spot exchange rates. We are particularly interested to know whether futures trading activities convey valuable information upon potential price movements in major currencies including the British pound, euro, Japanese yen, and Mexican peso. To extract the information content of futures trading activities, we transform trader positions into several econometric measures. Other than the routine usage of net positions by type of traders, we construct an investor sentiment index which presents a relative rank of the current net position within the context of the historical range and thus largely reflects investors' belief on the degree of bullishness or bearishness of the markets. Investment sentiments are further distinguished by indicators of extremely bullish sentiment and extremely bearish sentiment. In addition, we develop a dating algorithm which facilitates us to identify the peaks and troughs of traders' net position. By design, these identified peaks and troughs represent the *de facto* extreme positions held by speculators or hedgers.

We show that peaks of speculative positions and troughs of hedging positions are highly predictive of future price continuations while troughs of speculative positions and peaks of hedging positions are generally negatively associated with future spot rate changes over short horizons. Our results, nevertheless, do not offer persuasive evidence that traders' net positions *per se* and investor sentiments are systematically informative to potential price movements of foreign currencies examined except for the euro. For the latter case, we find that an increase of 10,000 euro contracts in speculators' net long positions forecasts a rise in spot euro rate by about 0.04 percent, 0.16 percent, and 0.45 percent over subsequent 1 week, 4 weeks, and 12 weeks, respectively, while the same increase in hedgers' net long

positions predicts a drop in subsequent euro changes with comparable magnitudes. Similar results emerge when sentiment index is used as predictor. We also document a strong contemporaneous connection between trader positions and spot exchange rate evolvments.

Our findings may have important implications for market practitioners, policymakers, and academics. It is particularly interesting, for example, to know whether the documented significant predictive power of the peaks/troughs of net position could be translated to profitability of trading strategies utilizing this sort of information. Monetary authorities may also closely watch the trader position data to keep track of future exchange rate dynamics, and in turn insulate their effects on inflation and on economic growth. The results show that, regardless of statistical significance, speculative position measures are typically straight signals of future price movements while hedging position measures are generally contrarian indicators of potential spot rate changes. Researchers may be interested in this finding as it lends support to competing theories such as hedging pressure or positive feedback trading. Moreover, it also merits further investigation on why the euro movements display a different pattern from other counterparties. All these issues are worthwhile topics for future research.

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Table 1
Summary Statistics

	British Pound	Euro	Japanese Yen	Mexican Peso
Panel A: Change of spot exchange rates				
Mean	-0.013	0.034	-0.002	-0.117 **
Std. err.	(0.045)	(0.061)	(0.056)	(0.047)
Median	-0.018	0.047	-0.119	0.029
Std. dev.	1.209	1.403	1.498	1.265
No. of Obs.	719	521	719	710
Panel B: Net Positions				
Speculator				
Mean	0.601	-1.994	1.554	-1.378
Median	0.218	-1.485	1.366	-0.360
Std. dev.	2.327	3.010	3.847	2.775
ADF test	-4.711 ***	-2.827 ***	-4.377 ***	-3.471 ***
Mean of ΔNP	0.005	0.001	-0.005	0.000
Mean of $ \Delta NP $	0.542	0.599	0.861	0.462
Hedger				
Mean	-0.800	3.528	-1.784	1.481
Median	-0.522	3.316	-2.275	0.497
Std. dev.	3.001	3.758	4.466	2.935
ADF test	-5.107 ***	-2.372 **	-5.235 ***	-3.489 ***
Mean of ΔNP	-0.004	0.001	0.007	-0.001
Mean of $ \Delta NP $	0.731	0.763	1.144	0.518
Panel C: Sentiment Index				
Speculator				
Mean	0.494	0.579	0.518	0.546
Median	0.469	0.622	0.503	0.560
Std. dev.	0.264	0.292	0.292	0.308
% of High	0.087	0.153	0.115	0.182
% of low	0.090	0.074	0.096	0.081
Hedger				
Mean	0.496	0.469	0.482	0.459
Median	0.507	0.432	0.506	0.431
Std. dev.	0.280	0.295	0.287	0.304
% of High	0.101	0.104	0.083	0.086
% of low	0.110	0.117	0.110	0.169

Note: Exchange rates are measured in logarithms of Tuesday's closing prices. Net positions are measured in unit of 10,000 contracts. ADF test refers to Augmented Dickey-Fuller unit root test with the null hypothesis that a series contains a unit root. ΔNP denotes the change of net position and $|\Delta NP|$ is the absolute value of change of net positions. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

Table 2

Net positions and exchange rates regression

$$\Delta e_{t+k} = \alpha + \beta NP_t + \varepsilon_t$$

where Δe_{t+k} is k -period forward change in log of exchange rate and $k=0,1,2,\dots$. For $k=0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rate. NP_t is the level of net positions. The t -stat is the t -statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

		British Pound		Euro		Japanese Yen		Mexican Peso	
		Speculator		Hedger		Speculator		Hedger	
		coeff.	<i>t</i> -stat	coeff.	<i>t</i> -stat	coeff.	<i>t</i> -stat	coeff.	<i>t</i> -stat
$k=0$	α	-0.077 (-1.720)*	-0.085 (-1.940)*	-0.153 (-1.983)**	-0.241 (-2.802)***	0.108 (1.751)*	0.140 (2.391)**	-0.192 (-3.203)***	-0.197 (-3.268)***
	β	0.106 (4.968)***	-0.090 (-5.516)***	0.094 (4.569)***	-0.078 (-4.866)***	0.070 (4.451)***	-0.079 (-6.288)***	0.054 (5.617)***	-0.054 (-5.678)***
$k=1$	α	-0.020 (-0.391)	-0.021 (-0.408)	-0.035 (-0.407)	-0.089 (-0.919)	0.000 (-0.007)	0.011 (0.172)	-0.126 (-2.095)**	-0.124 (-2.040)**
	β	0.011 (0.509)	-0.009 (-0.528)	0.035 (1.722)*	-0.035 (-2.066)**	0.001 (0.066)	-0.007 (-0.610)	0.007 (0.541)	-0.005 (-0.376)
$k=4$	α	-0.063 (-0.339)	-0.078 (-0.425)	-0.188 (-0.617)	-0.384 (-1.095)	-0.017 (-0.073)	0.017 (0.074)	-0.465 (-2.134)**	-0.449 (-2.059)**
	β	0.037 (0.469)	-0.046 (-0.734)	0.158 (2.196)**	-0.144 (-2.377)**	0.003 (0.062)	-0.022 (-0.509)	0.016 (0.325)	-0.004 (-0.087)
$k=8$	α	-0.131 (-0.390)	-0.157 (-0.467)	-0.441 (-0.883)	-0.864 (-1.549)	-0.141 (-0.346)	-0.073 (-0.184)	-0.908 (-2.494)**	-0.879 (-2.413)**
	β	0.092 (0.624)	-0.100 (-0.838)	0.327 (2.963)***	-0.303 (-3.272)***	-0.020 (-0.269)	-0.019 (-0.269)	0.023 (0.214)	-0.002 (-0.022)
$k=12$	α	-0.194 (-0.444)	-0.230 (-0.527)	-0.577 (-0.907)	-1.234 (-1.785)*	-0.316 (-0.596)	-0.238 (-0.460)	-1.228 (-2.699)***	-1.190 (-2.616)***
	β	0.217 (1.161)	-0.205 (-1.351)	0.454 (3.770)***	-0.439 (-4.223)***	-0.072 (-0.799)	0.021 (0.246)	-0.053 (-0.292)	0.074 (0.428)
$k=20$	α	-0.058 (-0.106)	-0.142 (-0.260)	-0.635 (-0.768)	-1.682 (-1.871)*	-0.799 (-1.133)	-0.743 (-1.086)	-1.731 (-3.069)***	-1.705 (-3.048)***
	β	0.204 (1.309)	-0.242 (-1.784)*	0.678 (4.897)***	-0.669 (-5.378)***	-0.213 (-1.769)*	0.155 (1.411)	-0.144 (-0.517)	0.152 (0.591)

Table 3

Change of Net positions and exchange rates regression

$$\Delta e_{t+k} = \alpha + \beta \Delta NP_{t,j} + \varepsilon_t$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k-period forward change in log of exchange rates and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rates. $\Delta NP_{t,j} = NP_t - NP_{t-j}$ is the change (in level) over previous periods' net positions and $j = 1, 2, \dots$. The t -stat is the t -statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). To save space, the estimate for the intercept, α , is not reported, which is not significant except for the Mexican peso. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	<i>j=1</i>		<i>j=4</i>		<i>j=8</i>		<i>j=12</i>		
	Speculator		Hedger		Speculator		Hedger		
	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	
Panel A: British pound									
<i>k=0</i>	β	0.711 (10.746)***	-0.631 (-13.164)***	0.181 (8.357)***	-0.144 (-8.674)***	0.099 (5.333)***	-0.081 (-6.219)***	0.083 (4.744)***	-0.064 (-5.033)***
<i>k=1</i>	β	0.036 (0.884)	0.011 (0.286)	-0.006 (-0.232)	0.012 (0.526)	-0.037 (-2.088)**	0.029 (1.994)**	-0.028 (-1.297)	0.025 (1.540)
<i>k=4</i>	β	-0.016 (-0.147)	0.021 (0.243)	-0.047 (-0.721)	0.021 (0.425)	-0.154 (-2.680)***	0.103 (2.379)**	-0.079 (-1.001)	0.062 (1.069)
<i>k=8</i>	β	-0.215 (-1.770)*	0.167 (1.751)*	-0.238 (-2.148)**	0.166 (2.053)**	-0.205 (-1.633)	0.156 (1.713)*	-0.090 (-0.669)	0.085 (0.859)
<i>k=12</i>	β	-0.160 (-0.825)	0.142 (0.940)	-0.107 (-0.624)	0.092 (0.719)	-0.078 (-0.474)	0.079 (0.655)	0.088 (0.609)	-0.028 (-0.260)
<i>k=20</i>	β	0.013 (0.052)	0.005 (0.028)	-0.008 (-0.042)	0.013 (0.094)	-0.005 (-0.033)	0.013 (0.105)	0.215 (1.223)	-0.136 (-1.088)
Panel B: Euro									
<i>k=0</i>	β	0.678 (9.904)***	-0.534 (-9.344)***	0.172 (5.482)***	-0.137 (-5.225)***	0.133 (5.003)***	-0.094 (-4.390)***	0.135 (4.547)***	-0.088 (-3.915)***
<i>k=1</i>	β	-0.049 (-0.978)	0.004 (0.082)	0.001 (0.032)	-0.011 (-0.419)	0.020 (0.674)	-0.016 (-0.679)	0.020 (0.587)	-0.013 (-0.526)
<i>k=4</i>	β	-0.014 (-0.110)	-0.023 (-0.210)	0.051 (0.494)	-0.035 (-0.410)	0.108 (1.096)	-0.057 (-0.747)	0.050 (0.413)	-0.017 (-0.200)
<i>k=8</i>	β	0.091 (0.479)	-0.073 (-0.437)	0.149 (0.848)	-0.080 (-0.583)	0.123 (0.649)	-0.051 (-0.366)	0.061 (0.341)	-0.034 (-0.257)
<i>k=12</i>	β	0.101 (0.399)	-0.066 (-0.304)	0.084 (0.355)	-0.033 (-0.180)	0.067 (0.318)	-0.039 (-0.244)	-0.020 (-0.104)	0.003 (0.018)
<i>k=20</i>	β	-0.058 (-0.189)	0.011 (0.040)	-0.037 (-0.144)	0.017 (0.085)	-0.045 (-0.167)	0.030 (0.149)	-0.030 (-0.108)	0.022 (0.105)

Table 3 (Continued)

		<i>j=1</i>		<i>j=4</i>		<i>j=8</i>		<i>j=12</i>		
		Speculator		Hedger		Speculator		Hedger		
		<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	
Panel C: Japanese yen										
<i>k=0</i>	β	0.598 (11.524)***	-0.527 (-13.883)***	0.148 (8.713)***	-0.127 (-10.244)***	0.088 (5.100)***	-0.080 (-6.124)***	0.087 (5.049)***	-0.078 (-6.461)***	
<i>k=1</i>	β	0.003 (0.065)	-0.014 (-0.424)	0.011 (0.586)	-0.011 (-0.734)	0.007 (0.395)	-0.009 (-0.597)	0.012 (0.841)	-0.013 (-1.085)	
<i>k=4</i>	β	0.041 (0.539)	-0.041 (-0.656)	0.027 (0.386)	-0.022 (-0.399)	0.043 (0.834)	-0.044 (-1.002)	0.042 (0.957)	-0.046 (-1.185)	
<i>k=8</i>	β	0.038 (0.296)	-0.052 (-0.472)	0.074 (0.794)	-0.073 (-0.974)	0.079 (1.025)	-0.086 (-1.311)	0.091 (1.267)	-0.103 (-1.727) [~]	
<i>k=12</i>	β	0.100 (0.702)	-0.108 (-0.897)	0.091 (0.785)	-0.092 (-1.006)	0.105 (1.093)	-0.121 (-1.525)	0.109 (1.250)	-0.122 (-1.722) [~]	
<i>k=20</i>	β	0.080 (0.417)	-0.112 (-0.697)	0.101 (0.677)	-0.102 (-0.864)	0.103 (0.855)	-0.102 (-1.017)	0.040 (0.303)	-0.039 (-0.378)	
Panel D: Mexican peso										
<i>k=0</i>	β	0.529 (9.444)***	-0.547 (-9.371)***	0.102 (5.453)***	-0.109 (-5.676)***	0.090 (3.474)***	-0.089 (-3.611)***	0.071 (3.142)***	-0.069 (-3.242)***	
<i>k=1</i>	β	0.005 (0.123)	-0.018 (-0.474)	0.001 (0.026)	-0.003 (-0.135)	0.022 (0.708)	-0.020 (-0.691)	0.015 (0.609)	-0.011 (-0.518)	
<i>k=4</i>	β	0.006 (0.041)	-0.021 (-0.155)	0.013 (0.125)	-0.008 (-0.084)	0.136 (1.085)	-0.115 (-0.996)	0.068 (0.731)	-0.046 (-0.571)	
<i>k=8</i>	β	0.166 (0.772)	-0.153 (-0.759)	0.182 (1.115)	-0.157 (-1.024)	0.233 (1.252)	-0.180 (-1.097)	0.161 (1.074)	-0.122 (-0.935)	
<i>k=12</i>	β	0.154 (0.544)	-0.115 (-0.434)	0.134 (0.728)	-0.088 (-0.521)	0.242 (1.068)	-0.178 (-0.906)	0.167 (0.889)	-0.120 (-0.738)	
<i>k=20</i>	β	0.024 (0.099)	0.013 (0.061)	0.009 (0.070)	0.023 (0.200)	0.177 (0.935)	-0.124 (-0.717)	0.107 (0.710)	-0.073 (-0.514)	

Table 4
Sentiment Index and exchange rates regression

$$\Delta e_{t+k} = \alpha + \beta_1 SI_t(l) + \varepsilon_t$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period forward change in log of exchange rates and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rates. $SI_t(l)$ is sentiment index with l lookback periods. The t -stat is the t -statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). To save space, the estimate for the intercept, α , is not reported, which is not significant except for the Mexican peso. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

		$l=26$ (0.5 year)				$l=52$ (1 year)				$l=156$ (3 years)				$l=260$ (5 years)			
		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger	
		<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>
Panel A: British pound																	
$k=0$	β	0.998 (9.165)***		-0.996 (-9.366)***		1.054 (7.857)***		-1.010 (-7.921)***		1.206 (6.481)***		-1.130 (-6.426)***		1.441 (5.585)***		-1.284 (-5.352)***	
$k=1$	β	-0.031 (-0.218)		0.030 (0.205)		0.045 (0.258)		-0.046 (-0.272)		0.201 (0.845)		-0.218 (-0.982)		0.501 (1.600)		-0.456 (-1.596)	
$k=4$	β	-0.186 (-0.411)		-0.015 (-0.032)		0.053 (0.089)		-0.254 (-0.430)		0.635 (0.779)		-0.838 (-1.084)		1.530 (1.383)		-1.595 (-1.562)	
$k=8$	β	-0.339 (-0.408)		0.068 (0.079)		-0.117 (-0.105)		-0.248 (-0.227)		1.285 (0.861)		-1.590 (-1.136)		2.748 (1.322)		-2.916 (-1.544)	
$k=12$	β	0.368 (0.334)		-0.641 (-0.573)		0.721 (0.493)		-1.103 (-0.779)		2.905 (1.483)		-3.124 (-1.696)*		4.662 (1.672)*		-4.674 (-1.849)*	
$k=20$	β	1.120 (0.973)		-1.645 (-1.450)		2.027 (1.240)		-2.732 (-1.765)*		4.117 (1.890)*		-4.601 (-2.182)**		6.608 (2.006)**		-6.870 (-2.243)**	
Panel B: Euro																	
$k=0$	β	1.127 (6.435)***		-1.011 (-6.026)***		1.095 (5.447)***		-0.888 (-4.544)***		1.095 (4.225)***		-0.956 (-3.969)***		0.963 (3.277)***		-0.888 (-3.248)***	
$k=1$	β	0.089 (0.410)		-0.153 (-0.744)		0.168 (0.668)		-0.171 (-0.728)		0.321 (1.006)		-0.405 (-1.401)		0.277 (0.792)		-0.385 (-1.207)	
$k=4$	β	0.674 (0.894)		-0.589 (-0.807)		1.207 (1.365)		-0.947 (-1.105)		1.956 (1.796)*		-1.912 (-1.857)*		1.566 (1.282)		-1.711 (-1.505)	
$k=8$	β	0.592 (0.463)		-0.662 (-0.541)		2.025 (1.385)		-1.768 (-1.250)		4.266 (2.474)**		-4.229 (-2.619)***		3.670 (1.993)**		-3.794 (-2.278)**	
$k=12$	β	-0.023 (-0.014)		-0.409 (-0.275)		1.831 (1.007)		-1.790 (-1.036)		5.787 (2.652)***		-6.05 (-3.034)***		5.537 (2.520)**		-5.751 (-2.941)***	
$k=20$	β	-0.937 (-0.483)		0.151 (0.080)		2.006 (0.879)		-2.168 (-1.002)		8.560 (3.035)***		-8.889 (-3.507)***		9.405 (3.494)***		-9.444 (-3.890)***	

Table 4 (Continued)

		<i>l</i> =26 (0.5 year)				<i>l</i> =52 (1 year)				<i>l</i> =156 (3 years)				<i>l</i> =260 (5 years)			
		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger	
		<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>	<i>coeff.</i>	<i>t-stat</i>
Panel C: Japanese yen																	
<i>k</i> =1	β	0.129 (0.829)		-0.201 (-1.250)		0.054 (0.292)		-0.118 (-0.614)		0.171 (0.806)		-0.205 (-0.942)		0.116 (0.530)		-0.103 (-0.446)	
<i>k</i> =4	β	0.385 (0.713)		-0.545 (-0.969)		0.209 (0.326)		-0.382 (-0.577)		0.795 (1.071)		-0.868 (-1.148)		0.857 (1.098)		-0.696 (-0.861)	
<i>k</i> =8	β	0.555 (0.673)		-0.927 (-1.102)		0.106 (0.108)		-0.452 (-0.452)		1.256 (1.086)		-1.487 (-1.278)		1.789 (1.484)		-1.562 (-1.262)	
<i>k</i> =12	β	0.189 (0.178)		-0.668 (-0.632)		-0.370 (-0.293)		-0.049 (-0.039)		0.869 (0.570)		-1.017 (-0.675)		2.027 (1.378)		-1.574 (-1.060)	
<i>k</i> =20	β	-1.215 (-0.814)		0.940 (0.633)		-1.474 (-0.851)		1.148 (0.667)		-0.791 (-0.387)		1.170 (0.573)		2.594 (1.337)		-1.598 (-0.822)	
Panel D: Mexican peso																	
<i>k</i> =0	β	0.781 (5.547)***		-0.850 (-6.210)***		0.818 (5.392)***		-0.904 (-5.967)***		0.961 (6.098)***		-0.950 (-5.764)***		0.826 (5.533)***		-0.796 (-5.174)***	
<i>k</i> =1	β	0.059 (0.359)		-0.051 (-0.322)		0.082 (0.481)		-0.079 (-0.462)		0.100 (0.541)		-0.081 (-0.437)		0.071 (0.395)		-0.060 (-0.331)	
<i>k</i> =4	β	-0.017 (-0.028)		0.141 (0.239)		-0.057 (-0.107)		0.175 (0.319)		0.009 (0.015)		0.076 (0.125)		-0.049 (-0.078)		0.124 (0.194)	
<i>k</i> =8	β	0.238 (0.236)		0.097 (0.099)		-0.012 (-0.015)		0.282 (0.349)		0.126 (0.143)		-0.024 (-0.026)		0.070 (0.074)		0.094 (0.097)	
<i>k</i> =12	β	0.004 (0.003)		0.448 (0.371)		-0.340 (-0.343)		0.702 (0.678)		-0.553 (-0.480)		0.545 (0.434)		-0.864 (-0.715)		1.050 (0.846)	
<i>k</i> =20	β	-0.748 (-0.731)		0.920 (0.892)		-0.679 (-0.561)		0.837 (0.686)		-1.312 (-0.950)		1.194 (0.816)		-1.970 (-1.266)		2.107 (1.389)	

Table 5

Extreme sentiment index and exchange rates regression

$$\Delta e_{t+k} = \alpha + \beta_1 \Delta SI_t(l) + \beta_2 SI_t^{hi}(l) + \beta_3 SI_t^{lo}(l) + \varepsilon_t$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period forward change in log of exchange rates and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rates. $\Delta SI_t(l)$ is the change of investor sentiment at t with $l=156$ (3-year) lookback periods, SI_t^{hi} is indicator variable denoting extremely bullish sentiment, and SI_t^{lo} is indicator variable denoting extremely bearish sentiment. The t -stat is the t -statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). To save space, the estimate for the intercept, α , is not reported, which is not significant except for the Mexican peso. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	British Pound				Euro				Japanese Yen				Mexican Peso			
	Speculator		Hedger		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger	
	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat	coeff.	t -stat
$k=0$	β_1	0.959 (3.739)***	-0.869 (-3.651)***	0.243 (0.696)	-0.642 (-1.884)*	1.120 (3.712)***	-1.183 (-4.036)***	0.770 (2.864)***	-0.906 (-3.196)***							
	β_2	0.082 (0.509)	-0.224 (-1.054)	0.446 (2.496)**	-0.577 (-1.927)*	0.013 (0.057)	-0.206 (-1.132)	0.102 (0.870)	-0.102 (-0.436)							
	β_3	-0.334 (-1.413)	0.193 (1.305)	-1.151 (-3.584)***	-0.042 (-0.247)	-0.196 (-1.013)	0.149 (0.672)	-0.245 (-0.950)	-0.005 (-0.041)							
$k=1$	β_1	0.256 (0.718)	0.001 (0.003)	0.048 (0.121)	0.060 (0.172)	0.608 (1.683)*	-0.439 (-1.250)	0.283 (0.966)	-0.421 (-1.429)							
	β_2	-0.139 (-0.587)	-0.050 (-0.193)	-0.173 (-0.639)	-0.778 (-2.120)**	-0.262 (-1.033)	0.396 (1.431)	-0.088 (-0.566)	0.281 (1.057)							
	β_3	-0.048 (-0.168)	0.291 (1.320)	-0.835 (-2.010)**	0.012 (0.052)	0.502 (1.824)*	-0.057 (-0.216)	0.251 (0.866)	-0.263 (-1.581)							
$k=4$	β_1	0.442 (0.491)	-0.765 (-0.943)	-0.214 (-0.172)	-1.263 (-1.174)	1.874 (1.609)	-1.409 (-1.156)	0.203 (0.205)	-0.770 (-0.769)							
	β_2	-0.443 (-0.787)	-0.566 (-0.761)	0.722 (1.154)	-1.534 (-1.498)	-0.560 (-0.709)	0.715 (1.049)	0.179 (0.425)	1.386 (1.767)*							
	β_3	-0.787 (-1.234)	-0.414 (-0.695)	-3.454 (-3.082)***	-0.449 (-0.697)	1.342 (2.080)**	-0.299 (-0.326)	0.759 (0.877)	-0.230 (-0.520)							
$k=8$	β_1	0.894 (0.610)	-0.895 (-0.647)	2.836 (1.656)*	-4.310 (-2.678)***	2.199 (1.197)	-1.871 (-1.042)	-0.173 (-0.128)	-0.712 (-0.499)							
	β_2	-0.917 (-1.056)	-1.688 (-1.051)	-0.026 (-0.026)	-1.331 (-0.663)	-0.341 (-0.289)	0.777 (0.761)	0.967 (1.429)	2.158 (2.017)**							
	β_3	-1.713 (-1.088)	-0.431 (-0.431)	-2.896 (-1.319)	-1.433 (-1.235)	1.318 (1.372)	0.017 (0.015)	1.082 (0.980)	0.461 (0.670)							
$k=12$	β_1	0.994 (0.581)	-1.675 (-1.049)	4.620 (1.969)**	-5.401 (-2.597)***	2.075 (0.829)	-1.381 (-0.560)	-0.391 (-0.205)	0.055 (0.029)							
	β_2	-0.302 (-0.287)	-3.313 (-1.527)	-1.097 (-1.046)	-3.277 (-1.384)	-1.135 (-0.786)	0.172 (0.132)	0.904 (0.864)	1.734 (1.297)							
	β_3	-3.766 (-1.700)*	-0.722 (-0.620)	-4.200 (-1.409)	-1.867 (-1.512)	0.950 (0.795)	-0.445 (-0.296)	1.955 (1.430)	0.466 (0.448)							
$k=20$	β_1	2.492 (0.863)	-4.038 (-1.462)	11.173 (2.812)***	-10.675 (-3.133)***	-0.573 (-0.195)	1.830 (0.629)	-3.235 (-1.265)	2.778 (1.185)							
	β_2	-0.060 (-0.048)	-2.565 (-1.306)	-3.897 (-2.971)***	-1.798 (-0.853)	-0.634 (-0.393)	-1.107 (-0.615)	2.074 (1.275)	-1.034 (-0.730)							
	β_3	-3.346 (-1.660)*	-1.128 (-0.884)	-1.110 (-0.455)	-4.085 (-2.834)***	-0.285 (-0.175)	0.145 (0.082)	-0.455 (-0.324)	1.338 (0.843)							

Table 6

Peaks/Troughs of net positions and exchange rates regression

$$\Delta e_{t+k} = \alpha + \beta_1 \Delta NP_t + \beta_2 NP_t^{max} + \beta_3 NP_t^{min} + \varepsilon_t$$

where $\Delta e_{t+k} = e_{t+k} - e_t$ is k -period forward change in log of exchange rates and $k = 0, 1, 2, \dots$. For $k = 0$, $\Delta e_t = e_t - e_{t-1}$ is the current change in log of exchange rates. ΔNP_t is the change of net positions at time t , NP_t^{max} is indicator variable denoting net positions in peak areas, and NP_t^{min} is indicator variable denoting net positions in trough areas. The t -stat is the t -statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). To save space, the estimate for the intercept, α , is not reported, which is not significant except for the Mexican peso. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	British Pound				Euro				Japanese Yen				Mexican Peso			
	Speculator		Hedger		Speculator		Hedger		Speculator		Hedger		Speculator		Hedger	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
$k=0$	β_1	0.088 (3.783)***	-0.080 (-4.193)***	0.069 (2.664)***	-0.073 (-3.043)***	0.051 (3.223)***	-0.073 (-4.269)***	0.043 (3.293)***	-0.045 (-3.652)***							
	β_2	0.044 (0.368)	-0.089 (-0.748)	0.174 (1.093)	0.008 (0.042)	0.201 (1.393)	0.148 (1.014)	0.198 (1.748)*	-0.113 (-0.611)							
	β_3	-0.080 (-0.638)	-0.016 (-0.144)	0.120 (0.740)	-0.111 (-0.638)	0.013 (0.103)	0.067 (0.396)	0.028 (0.174)	0.031 (0.285)							
$k=1$	β_1	-0.031 (-1.313)	0.036 (1.715)*	-0.017 (-0.611)	0.011 (0.400)	-0.036 (-2.306)**	0.059 (3.175)***	-0.014 (-0.892)	0.023 (1.468)							
	β_2	0.233 (1.950)*	-0.390 (-3.171)***	0.479 (2.920)***	-0.079 (-0.411)	0.541 (3.536)***	-0.367 (-2.029)**	0.331 (3.038)***	-0.145 (-0.818)							
	β_3	-0.340 (-2.500)**	0.303 (2.571)**	0.055 (0.313)	0.367 (1.903)*	-0.121 (-0.911)	0.746 (4.237)***	0.056 (0.346)	0.301 (2.653)***							
$k=4$	β_1	-0.105 (-1.348)	0.102 (1.560)	-0.026 (-0.263)	-0.004 (-0.038)	-0.081 (-1.594)	0.131 (2.353)**	-0.050 (-0.908)	0.097 (1.615)							
	β_2	0.758 (1.839)*	-1.109 (-2.545)**	1.442 (2.410)**	-0.140 (-0.201)	1.429 (3.001)***	-0.820 (-1.417)	1.102 (2.933)***	-0.406 (-0.638)							
	β_3	-1.127 (-2.288)**	1.102 (2.855)***	-0.076 (-0.117)	1.138 (1.677)*	-0.136 (-0.295)	1.728 (3.560)***	0.382 (0.728)	1.118 (2.644)***							
$k=8$	α	-0.169 (-0.439)	-0.506 (-1.319)	-0.075 (-0.069)	0.140 (0.116)	-0.552 (-0.918)	-0.216 (-0.382)	-0.951 (-1.881)*	-0.416 (-0.984)							
	β_1	-0.177 (-1.249)	0.174 (1.507)	-0.024 (-0.150)	-0.094 (-0.567)	-0.111 (-1.450)	0.150 (1.703)*	-0.085 (-0.711)	0.168 (1.203)							
	β_2	1.605 (2.358)**	-1.813 (-2.504)**	2.386 (2.300)**	-0.604 (-0.499)	2.074 (2.593)***	-0.648 (-0.654)	1.704 (2.343)**	-0.815 (-0.803)							
	β_3	-1.858 (-2.259)**	2.197 (3.566)***	-0.737 (-0.646)	1.371 (1.241)	0.282 (0.371)	2.158 (2.732)***	0.724 (0.865)	1.670 (1.716)*							
$k=12$	β_1	-0.109 (-0.608)	0.145 (1.016)	-0.076 (-0.454)	-0.106 (-0.555)	-0.168 (-1.854)*	0.204 (2.103)**	-0.250 (-1.260)	0.349 (1.522)							
	β_2	2.311 (2.872)***	-2.001 (-2.042)**	2.973 (2.150)**	-1.725 (-1.143)	2.588 (2.397)**	-0.535 (-0.421)	2.427 (2.304)**	-1.130 (-0.983)							
	β_3	-1.865 (-1.665)*	3.115 (4.483)***	-1.870 (-1.228)	1.598 (1.232)	0.752 (0.776)	2.317 (2.266)**	0.267 (0.263)	2.705 (1.750)*							
$k=20$	β_1	-0.318 (-2.013)**	0.275 (2.089)**	-0.266 (-1.395)	0.025 (0.121)	-0.285 (-2.161)**	0.298 (2.299)**	-0.554 (-1.819)*	0.656 (1.991)**							
	β_2	3.527 (3.552)***	-2.735 (-1.695)*	4.844 (2.788)***	-3.625 (-2.068)**	2.856 (2.061)**	0.213 (0.133)	3.021 (2.212)**	-2.189 (-1.820)*							
	β_3	-2.429 (-1.384)	4.153 (4.327)***	-3.652 (-2.004)**	3.104 (2.158)**	1.564 (1.226)	1.874 (1.486)	-2.254 (-2.111)**	4.507 (2.144)**							

Figure 1 Speculative Net Positions (in 10,000 contracts) and Spot Exchange Rates (in logarithm)

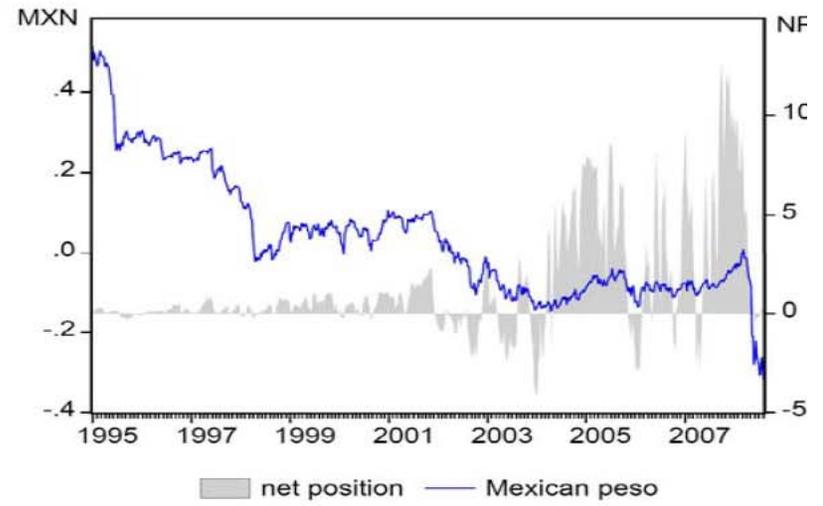
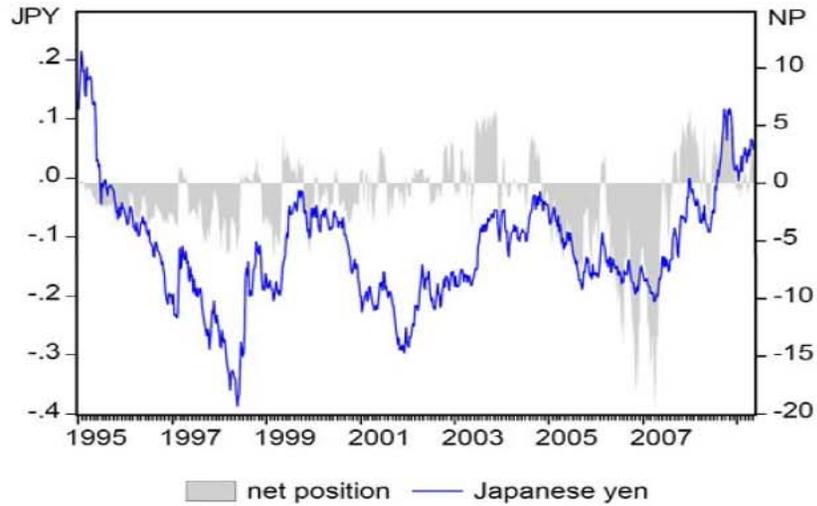
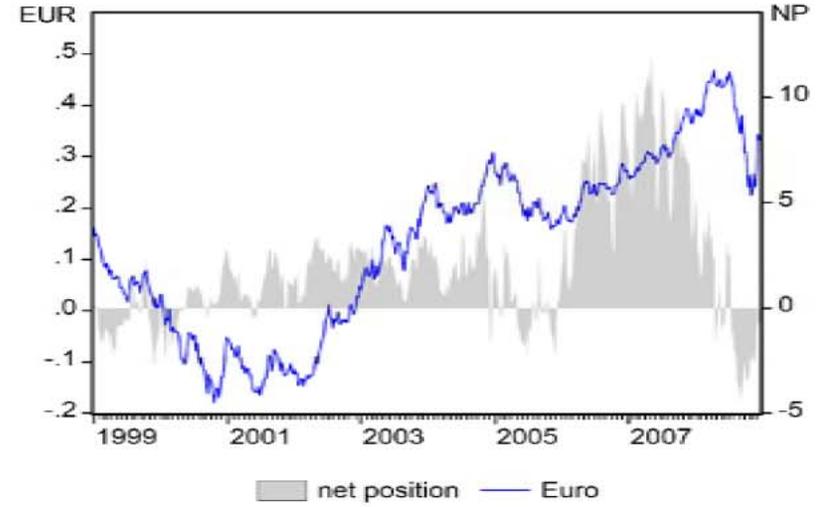
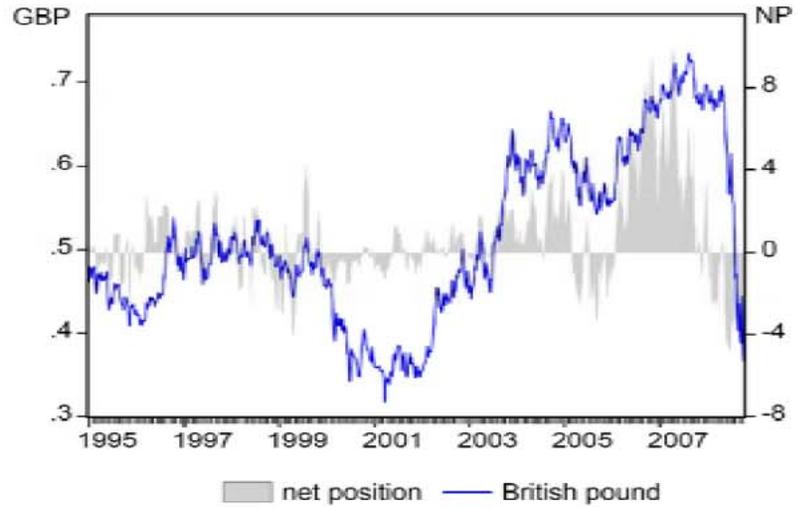


Figure 2 Hedging Net Positions (in 10,000 contracts) and Spot Exchange Rates (in logarithm)

