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Futures trading activity and predictable foreign exchange market movements

Changyun Wang *

Department of Finance and Accounting, School of Business, National University of Singapore, 10 Kent Ridge Crescent, Singapore 119260, Singapore

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Abstract

In this paper, we examine the relation between futures trading activity by trader type and returns over short horizons in five foreign currency futures markets – British pound, Canadian dollar, Deutsche mark, Japanese yen, and Swiss franc. Transforming trading activity into a sentiment measure, we find that speculator sentiment is positively related to future returns. In contrast, hedger sentiment covaries negatively with future returns. We also find that extreme sentiment by trader type is more correlated with future market movements than moderate sentiment. Our results suggest that hedgers lose to speculators in these futures markets, on average. Based on equilibrium pricing models that futures risk premiums are determined by both market risk and hedging pressure, we show that the profits to speculators are in general compensation for bearing risk.

JEL classification: G13; F31
Keywords: Trading activity; Return predictability; Currency futures; Hedging pressure; Risk premiums

1. Introduction

The efficiency of foreign exchange (FX) markets has long been a central issue in international finance research. A large volume of literature applies technical trading rules in spot and futures FX markets and documents unexploited profit opportunities. Examples of this literature include Sweeney (1986), Taylor and Allen (1992),

* Tel.: +65-6874-4555; fax: +65-6779-2083.
E-mail address: bizwcy@nus.edu.sg (C. Wang).

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Levich and Thomas (1993), Kho (1996), and LeBaron (1999). Other FX puzzles such as forward bias and deviations from uncovered interest parity raise further questions about the efficiency of FX markets. [1]

More recent research applies tools from the market microstructure literature to study currency price dynamics in terms of order flow between various types of FX dealers. These studies find that the information structure between FX dealers influences the dynamics of prices and the patterns of trades. The observed correlation between order flow and currency returns is generally interpreted to mean that some agents possess private information (e.g., Lyons, 1995; Evans, 2002; Evans and Lyons, 2002).

This paper adds to the recent literature by examining whether a specific trader type consistently beats the market in five actively traded foreign currency futures markets that include the British pound (BP), Canadian dollar (CD), Deutsche mark (DM), Japanese yen (JY), and Swiss franc (SF). We thus provide a test of FX market efficiency in the futures context. To accomplish this, we examine the relation between futures returns and lagged net positions of speculators and hedgers. [2] To facilitate comparisons across markets and to allow for an intuitive measure, we construct a sentiment index based on net trader positions. We then focus on the profitability of sentiment-based timing strategies.

We find that investor sentiment by trader type varies systematically with returns over short horizons in the futures markets in our sample. However, the relation between sentiment and future returns differs for speculators and hedgers. Whereas speculator sentiment varies positively with future returns, hedger sentiment varies negatively with future returns. We also find that extreme sentiment is more correlated with future market movements than is moderate sentiment. Our results suggest that speculators profit from trading currency futures, but hedgers lose money, on average.

At first glance, our results appear to contradict the efficient markets hypothesis (EMH). However, if speculator sentiment varies with expected risk premiums, the superior performance of speculators does not necessarily imply market inefficiency. Various asset pricing studies have documented evidence of time varying risk premiums in currency futures markets (e.g., McCurdy and Morgan, 1991, 1992; Bessembinder, 1992; Kho, 1996). Unless risk premiums implicit in sentiment-based timing strategies are properly addressed, concluding that the profits to speculators are unusual may be premature.

To adjust for risk, we analyze the sources of speculative profits based on the equilibrium pricing model of Hirshleifer (1990) who shows that futures risk premiums are determined by both systematic market risk and hedging pressure. Market risk arises from the correlation of the futures price with a market portfolio. Hedging pressure

[1] Hodrick (1987) and Engel (1996) provide surveys of the large literature in this area.

[2] These traders are categorized on the basis of whether a trader holds a reportable position to hedge a risk as defined by the Commodity Futures Trading Commission (CFTC). The trader position information has been published in the CFTC's weekly Commitments of Traders (COT) reports since October 1992. Data are described more fully in Section 2.

results from risks that agents cannot, or do not want to trade because of market frictions. Hedgers participate in futures markets to reduce risk. Thus, their net supply of futures contracts, or hedging pressure, is related to risk premiums. Bessembinder (1992) and De Roon et al. (2000) provide empirical support for the combined role of systematic risk and hedging pressure in determining futures prices in broad markets.

We adopt a two-stage procedure to investigate whether the profits to speculators are attributable to market risk premiums, hedging pressure, or rewards to superior forecasting ability. In the first stage, we adjust futures returns for time varying market risk. After controlling for market risk, we capture hedging pressure effects in the negative relation between future returns and hedger sentiment. The second stage allows us to disentangle the rewards to superior forecasting ability from the premium associated with hedging pressures. Taking both market risk and hedging pressure into consideration, we find that speculative profits disappear in the BP, CD, JY, and SF markets, but not for the DM futures if we use classical *t*-statistics. When we employ Bayesian inference procedures to adjust for sample size (as in Jeffreys (1961) and Connolly (1991)), the apparent speculative profits in the DM futures market also disappear.

Our finding that the relation between speculator sentiment and returns remains positive and significant after accounting for market risk and becomes insignificant after hedging pressure is accounted for suggests that hedging pressure is an important risk in currency futures markets, which has been ignored in the prior studies (e.g., McCurdy and Morgan, 1992; Levich and Thomas, 1993; Kho, 1996). Failure to consider this risk is likely to result in misleading inferences with regard to market efficiency. [3] Our results also suggest that classical hypothesis tests with fixed significance levels lead to excessive rejection of the null hypothesis even if sample sizes are only moderately large.

The remainder of this article is organized as follows. Section 2 provides the data and empirical design. Section 3 presents the empirical results. Brief conclusions are provided in Section 4.

2. Data and methodology

2.1. Data

This study analyzes weekly trader position data on the BP, CD, DM, JY, and SF futures contracts traded on the International Monetary Market division of the Chicago Mercantile Exchange from January 1993 to March 2000. [4] The sample period is

[3] A recent study by Tien (2002) also provides empirical support for the role of hedging pressure in explaining currency futures returns. Tien uses hedging demand as a proxy for risk premiums and shows that hedging demand explains 45% of variation in returns in five currency futures markets.

[4] The sample period for the DM market is up to September 1999 because the contract demand becomes negligible after September 1999 due to the introduction of euro.

chosen because the COT data were unavailable on a weekly basis prior to the end of 1992. The five foreign currency futures contracts are selected because they represent the most active currency futures markets in terms of overall open interest and trading volume, and because they have been extensively studied in the literature.

The data on trader positions come from the CFTC's COT reports and are provided by Pinnacle Data Corp., New York. The COT data provide a decomposition of positions held by categorized traders. In each market, the CFTC defines large traders as those holding a futures position exceeding the reporting threshold, and large traders are further classified as either commercial or noncommercial. A trader is classified as a commercial trader if he/she engages in a business activity hedged by the use of a futures contract. A trader is regarded as a noncommercial trader if he/she takes futures positions for reasons other than hedging. Following the literature, we interpret noncommercial traders as speculators, and commercial traders as hedgers. [5] The positions by trader type in the COT reports represent closing positions aggregated for all outstanding contracts, filed by futures commission merchants, clearing members, and foreign brokers. This trader position information, which has been published in the CFTC's COT reports every Friday since October 1992, relates to closing positions on the preceding Tuesday.

We also collect weekly settlement prices for these futures contracts over the sample period from Datastream International. A return is computed as the first difference in logarithmic Tuesday's settlement prices. When the prices are missing on Tuesday, Wednesday prices are used. To obtain a representative futures return series, we use the settlement price of the contract closest to expiration, except within the delivery month in which case we use the price of the second nearest contract. Our use of weekly data reduces potential biases due to nonsynchronous trading.

Panel A of Table 1 presents summary statistics for futures contracts and their weekly returns over the sample period. The average returns are positive for the BP (0.017%) and JY (0.047%) futures, but negative for the CD (−0.034%), DM (−0.057%), and SF (−0.028%) futures. DM, JY and SF returns exhibit larger standard deviations than the other futures. Most return series show positive skewness and excess kurtosis, indicating nonnormality in returns. The Bera–Jarque's test confirms this formally. [6]

We use net positions (the long open interest less the short open interest) as a proxy for trading activity. Panel B of Table 1 presents summary statistics for this measure. Contrary to the conventional assumption that speculators are net long and hedgers are net short, panel B shows the opposite for all contracts except BP futures. In

[5] This interpretation of trader types has been widely used in the literature, for example, Bessembinder (1992), Chang et al. (1997), De Roon et al. (2000), and Wang (2001). It is unclear from the COT reports whether the trading motive of nonreportable traders is hedging or speculation, and we exclude these traders from our analysis.

[6] To relieve the concern about the possible impact of nonnormality in returns on our results, we conduct a robustness test by removing 1% of extreme returns (highest and lowest) as well as the associated observations on investor sentiment. Although not reported, the results from the trimmed data are very similar to those reported in this paper.

Table 1
Summary statistics (January 1993–March 2000)

Return series	BP		CD		DM		JY		SF	
Panel A: Summary statistics for futures contracts and weekly futures returns										
Contact size	£62,500		C$100,000		DM125,000		¥12.5m		SFr125,000	
Delivery month	3, 6, 9, 12		3, 6, 9, 12		3, 6, 9, 12		3, 6, 9, 12		3, 6, 9, 12	
Return series										
Mean	0.0169		−0.0338		−0.057		0.0472		−0.0284	
Median	0.0062		−0.0678		−0.093		−0.147		−0.0734	
Std. dev.	1.1668		0.7251		1.429		1.837		1.6327	
Maximum	3.5957		2.3593		6.952		9.306		9.0289	
Minimum	−6.2904		−3.0212		−4.882		−6.248		−5.6229	
Skewness	−0.4391		0.0413		0.259		0.778		0.4650	
Kurtosis	5.2025		4.0104		4.607		6.375		5.7615	
Jarque–Bera	88.55		16.19		44.54		217.547		133.74	
No. of Obs.	379		379		354		379		379	
Panel B: Average futures trading activity variables										
S	0.039		−0.006		−0.633		−1.361		−0.590	
H	−0.053		−0.731		1.271		2.176		1.063	
OI	4.459		5.202		8.521		8.508		5.005	
MV	5.815		4.007		14.232		11.730		8.646	
	BP		CD		DM		JY		SF	
	SI_S	SI_H	SI_S	SI_H	SI_S	SI_H	SI_S	SI_H	SI_S	SI_H
Panel C: Summary statistics for sentiment index by trader type										
Mean	48.91	50.82	46.17	50.67	53.614	46.774	45.238	53.829	43.399	58.222
Median	47.71	53.05	45.01	52.28	52.56	47.49	39.423	59.334	37.478	61.138
Std. dev.	27.27	28.09	26.27	27.24	23.724	24.508	27.876	27.028	26.688	27.246
Correlation	−0.941		−93.39		−0.960		−0.963		−0.968	

The return is measured as the change in logarithmic Tuesday's settlement prices, in percent S and H represent net open interest of speculators and hedgers respectively. OI and MV denote overall open interest and trading volume. Trading activity variables are in unit of 10,000 contracts. SI_S and SI_H denote the constructed investor sentiment using Eq. (1) for speculators and hedgers respectively.

absolute terms, average net positions are largest for JY futures, with speculators short 13,610 contracts and hedgers long 21,760 contracts. Net positions are smallest for BP futures, with speculators long 390 contracts and hedgers short 530 contracts, on average. The DM futures market (142,320 contracts) has the highest weekly trading volume, and the CD futures market (40,070 contracts) has the lowest.

2.2. Measuring investor sentiment

We construct a sentiment index that is similar to the COT index in the market place (e.g., Briese, 1994). A sentiment index for a trader type is constructed on the basis of the current net position and its historical extreme values. The primary difference between our sentiment index measure and the COT index is that we measure sentiment using historical extreme values in a moving window prior to the current date (see Eq. (1) below). The forward-looking nature of this measure allows us to use the sentiment index for forecasting purposes. Since our sentiment index is constructed using actual trader positions, it differs from the sentiment indexes in previous studies that are based on analysts' opinions (e.g., Clarke and Statman, 1998; Fisher and Statman, 2000). The sentiment index for trader type i in week t, SI_t^i, is given by

$$\mathrm{SI}_t^i = \frac{\mathrm{NOI}_t^i - \mathrm{Min}(\mathrm{NOI}_t^i)}{\mathrm{Max}(\mathrm{NOI}_t^i) - \mathrm{Min}(\mathrm{NOI}_t^i)} \times 100, \tag{1}$$

where NOI_t^i represents net positions of trader type i in week t, and i denotes speculators and hedgers. $\mathrm{Max}(\mathrm{NOI}_t^i)$ and $\mathrm{Min}(\mathrm{NOI}_t^i)$ denote the maximum and minimum net positions over the three years prior to week t for trader type i. [7]

An advantage of using a sentiment index rather than the number of long or short positions in studying return predictability is that the sentiment index is fairly intuitive and facilitates comparisons across markets, irrespective of their nature and size. Moreover, the sentiment index makes our analysis comparable to other studies in equity markets, such as Solt and Statman (1988), Clarke and Statman (1998), and Fisher and Statman (2000). Except Fisher and Statman (2000) who find that the sentiments of small investors and Wall Street strategists are reliable contrary indicators for future S&P 500 stock returns, the other studies find that various sentiment indexes are hardly useful in predicting future stock returns.

Panel C of Table 1 presents summary statistics for sentiment by trader type. The average sentiment level is lower for speculators than for hedgers with the exception of the DM futures, where the reverse is true. The weekly standard deviation of sentiment index ranges from 24% to 28% across these markets. The lower part of panel

[7] To measure investor sentiment in early weeks of the sample period, we use the max and min net positions starting from 1990 calculated from the CFTC's bi-weekly COT reports. We also use max and min net positions in one-year and five-year moving windows. The qualitative results remain largely unaltered if the five-year moving window is employed. However, the regression results from the sentiment measured using the one-year moving window are less significant, most likely because the frequency of extreme sentiment values (0 or 100) is rather high in this case.

C shows the correlations between sentiments of trader types. For all these markets, speculator sentiment is highly negatively correlated with hedger sentiment, with the strongest correlation (in absolute terms) of −0.968 in the SF futures. These strong correlations between speculator and hedger sentiments are not surprising given that the two types of large traders account for more than 70–80% of total open interest in a typical futures market.

2.3. Sentiment and future returns

To assess whether sentiment by trader type covaries with future market movements, we follow Solt and Statman (1988) and Fisher and Statman (2000) by examining the relation between the level of sentiment by trader type and subsequent returns for each futures market. The empirical model is of the following form:

$$R^j_{t+K} = \alpha^j_{0i} + \alpha^j_{1i}\mathrm{SI}^j_{it} + \varepsilon^j_{it}, \tag{2}$$

where R^j_{t+K} represents the percentage return for market j over the subsequent K weeks, $K = 2$, 4, and 8, and i represents speculators and hedgers. [8] OLS estimation of Eq. (2) produces consistent parameter estimates, but the usual OLS standard errors are incorrect due to the overlapping weekly observations of futures returns. We use Newey and West's (1987) procedures to adjust for heteroskedastic and autocorrelated errors in the regressions.

Classical t-statistics with a fixed significance level can lead to excessive rejection of a null hypothesis if the sample size is large (e.g., Connolly, 1991). We thus compute posterior odds based on the procedures of Jeffreys (1961) and Connolly (1991). An important feature of the posterior odds approach is that it is free of sample size-related distortions. Assuming equal prior odds, the posterior odds of H_0 relative to H_1, $P(H_0)/P(H_1)$, are approximately equal to

$$\frac{P(H_0)}{P(H_1)} \approx \left[\frac{\pi(n-1)}{2}\right]^{0.5} \Bigg/ \left[1 + \frac{t^2}{n-1}\right]^{((n-2)/2)}, \tag{3}$$

where H_0 and H_1 denote the null and alternative hypotheses respectively, n denotes the sample size, and t is the classical t-statistic.

The correlation between the level of sentiment and future returns is typically weak (e.g., Clarke and Statman, 1998; Fisher and Statman, 2000). However, several market practitioners contend that extreme sentiment is a more useful predictor of future returns (e.g., Briese, 1994; Investor Intelligence; Consensus Inc.). We thus examine the relation between future returns and extreme sentiment. Examining that relation also allows us to test the hedging pressure theory, which we discuss in more detail below. To investigate the relation between extreme sentiment and returns, we sort sentiment by trader type into five equal-size groups, and compute the subsequent mean returns for the groups with extremely bullish (top 20%) and extremely bearish

[8] Unlike the sentiment studies in equity markets (e.g., Clarke and Statman, 1998), we focus on the value of forecasts over short horizons, because the life cycle of these currency futures contracts is three months.

(bottom 20%) sentiments. We also calculate the mean excess return of the extremely bullish group over the extremely bearish group in subsequent periods.

2.4. Sources of futures return predictability

To test the validity of the EMH, we need to investigate whether potential profits to speculators result from superior forecasting ability or are solely compensation for bearing risk. Stoll (1979) and Hirshleifer (1988, 1990) present equilibrium models to show that futures risk premiums are determined by both market risk and hedging pressure. Carter et al. (1983), Bessembinder (1992), and De Roon et al. (2000) provide evidence on the combined role of market risk and hedging pressure in determining futures prices. In this study, we analyze the sources of speculative profits relative to the model of Hirshleifer (1990).

Based on Hirshleifer (1990), after accounting for market risk and hedging pressure, a positive return earned by speculators suggests that speculators possess superior timing ability. To determine whether potential profits to speculators result from futures risk premiums or superior forecasting ability, we adopt a two-stage procedure. In the first stage, we estimate expected returns for each futures market based on a conditional version of the CAPM. We then attempt to disentangle the profits to superior forecasting ability possessed by speculators from hedging pressure effects, with an assumption that the negative market risk-adjusted performance of hedgers represents hedging pressure effects.

Conditional versions of modern asset pricing theories imply a linear relation between expected return and systematic risk, stated as [9]

$$E(R_t^i|\Phi_{t-1}) = \gamma_{0,t-1} + \gamma_{1,t-1}\beta_{t-1}^i \quad \text{for asset } i, \tag{4}$$

where R_t^i is the return on asset i at time t, β_{t-1}^i is the conditional beta of asset i, $\gamma_{0,t-1}$ is the expected return on a 'zero-beta' portfolio, $\gamma_{1,t-1}$ is the price of market risk, and Φ_{t-1} denotes the common information set of investors at time $t-1$. Since futures trading requires zero capital investment, the intercept, $\gamma_{0,t-1}$ in Eq. (4), should be zero. [10] Thus, the expected return on a futures contract, j, can be written as

$$E(R_t^j|\Phi_{t-1}) = \gamma_{1,t-1}\beta_{t-1}^j. \tag{5}$$

We use the procedure outlined in Fama and MacBeth (1973) to estimate Eq. (5). The conditional beta is obtained by a rolling regression of time series returns on the

[9] Several studies find that the static CAPM is unable to explain cross-sectional variation in average returns (e.g., Fama and French, 1992; Chan et al., 1985). However, Jagannathan and Wang (1996) show that the conditional CAPM explains nearly 30% of cross-sectional variation in average returns as compared to the 1% in Fama and French (1992). McCurdy and Morgan (1992) and Kho (1996) report evidence of the co-variation of returns on foreign currency futures with those of a market portfolio.

[10] Futures trades are facilitated by the operation of margins. Compared to securities markets, the term 'margin' in futures markets has a different meaning and serves a different purpose. Rather than providing a down payment in equity trading, the margin required to buy or sell a futures contract merely serves as performance bond under the contract. Further, margin can be deposited in marketable securities that continue to earn returns in equity or money markets.

jth futures market against returns on the value-weighted CRSP index using data for the 52 weeks prior to week t. [11] Bessembinder (1992) also employs the CRSP index as a benchmark portfolio, despite Roll's (1977) critique.

The Fama–MacBeth procedure allows the price of market risk to vary over time by estimating that price cross-sectionally for each period. To obtain a more accurate estimate, we use a broad cross-section of equity portfolios and futures contracts, based on evidence and procedures in Bessembinder (1992). [12] Specifically, for each year from January 1992 to March 2000, we sort all securities listed in the CRSP daily tape into 20 equal-size portfolios based on firms' market capitalization at the end of the prior year. We then compute weekly (Tuesday close to Tuesday close) equal-weighted portfolio returns and estimate portfolio betas using data for the previous 52 weeks. The price of market risk is estimated with cross-sectional regressions of the following form:

$$R_{p,t-1} = \gamma_{0t} + \gamma_{1,t-1}\hat{\beta}_{p,t-1} + \varepsilon_{p,t-1}, \tag{6}$$

where $R_{p,t-1}$ is the return on equity portfolio or futures contract p, and $\hat{\beta}_{p,t-1}$ is the estimated conditional beta.

Eq. (6) is estimated each week across the 20 equity portfolios and five foreign currency futures contracts under study. [13] This procedure yields a time series of estimates for the price of risk. We estimate market risk premiums in week t as the product of the time varying price of risk and the conditional beta estimated using information up to week $t-1$, i.e., $\hat{\gamma}_{1,t-1}\hat{\beta}^{j}_{t-1}$. After obtaining the expected return implied by the CAPM, we compute the abnormal return by subtracting the expected return from the raw return series.

Finally, we disentangle speculative profits to superior forecasting ability of speculators from hedging pressure effects based on the model of Hirshleifer (1990). To do this, we follow the same procedure discussed previously and compute average market risk-adjusted returns associated with extreme investor sentiment. [14] Since

[11] To estimate the conditional beta for the first week of 1993, we used the weekly data from the beginning of 1992 to the end of 1992. A similar method is applied in the estimation of betas for the other early weeks of the sample period.

[12] Stambaugh (1982) shows that the inference with regard to asset pricing models is sensitive to exclusion of securities from the cross-sectional analysis. Therefore, the inclusion of equity portfolios ensures a more accurate estimation of the price of risk.

[13] We also use a broader cross-section consisting of 20 equity portfolios and 20 futures contracts. In addition to the five currency futures, the other 15 contracts included are Eurodollar, Treasury bills, Treasury bonds, S&P 500 index, cattle, corn, cotton, soybeans, sugar, wheat, coffee, cocoa, gold, silver, and copper. Although not reported, the estimation results are generally consistent with those reported in this study.

[14] The equilibrium futures pricing model requires the identification of the sign of net hedging to estimate hedging pressure effects (e.g., Hirshleifer, 1990; Bessembinder, 1992). The use of extreme hedger sentiment in this study is to ensure that hedgers take on net long (short) positions when they are extremely bullish (bearish). For weekly observations over the January 1993–March 2000 interval, hedgers' net positions are net short for 185, 242, 128, 274, and 130 weeks for the BP, CD, DM, JY, and SF futures respectively.

hedging pressure effects must correlate with net hedging, the average market risk-adjusted return associated with extreme hedger sentiment measures hedging pressure effects. After controlling for market risk and hedging pressure effects, the profits to speculators measure superior forecasting ability of speculators.

3. Empirical results

3.1. Profitability of sentiment-based timing strategies

Table 2 reports the results of estimating Eq. (2) for the BP, CD, DM, JY, and SF futures markets. The slope coefficient estimates for speculators are uniformly positive and significant at conventional significance levels for all except the CD and SF futures in the periods of 2 and 8 weeks. Therefore, speculator sentiment is, on average, positively associated with subsequent returns. For example, in the JY futures market, an increase of 1% point in speculator sentiment is associated with 0.032% point (0.42% per annum) increase in the futures return over the subsequent 4 weeks. Given that the weekly standard deviation of investor sentiment ranges from 24% to 28% (see Table 1), the relation between sentiment and future returns appears to be economically significant. However, we note that classical and Bayesian hypothesis tests yield conflicting inferences. Classical t-statistics indicate that the slope coefficients in Eq. (2) are significant in most cases. However, the posterior odds favor the alternative hypothesis in only 3 out of 15 cases. Therefore, classical hypothesis tests tend to lead to excessive rejection of a null hypothesis when the sample size is even moderately large.

In contrast to the results for speculators, the slope coefficients for hedgers are mostly negative and significant at conventional significance levels. For example, an increase of 1% point in hedger sentiment in the JY futures market is, on average, associated with 0.030% point (0.39% per annum) decrease in the return over the subsequent 4 weeks. [15] However, as was the case with speculators, the posterior odds favor the alternative hypothesis in many fewer cases (2 of 15) than classical t-tests suggest.

Although Bayesian posterior odds ratios in Table 2 favor the alternative hypothesis over the null in very few cases, we are interested in whether focusing on extreme investor sentiment increases the correlations with future returns. To investigate that hypothesis, we sort sentiments by trader type into two groups: H and L. H (L)

[15] We also estimate Eq. (2) for the spot FX exchange rates. The slope coefficient estimate for each spot market shows a similar pattern to that in the relevant futures market. That is, speculator sentiment is positively associated with future returns in the spot FX exchange rates, while hedger sentiment is negatively related to future returns. This result is not surprising given the high correlation between spot exchange rates and futures prices. We therefore do not report these results. It appears that, however, the slope coefficient estimate is generally smaller in magnitude for the spot market than that for the relevant futures market.

Table 2
The level of sentiment by trader type and subsequent futures returns

	2 week		4 week		8 week	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
BP						
Speculator	−0.056	0.011	−0.043	0.018	−0.115	0.021
	(−3.12)	(3.08)	(−1.22)	(1.99)	(−2.36)	(2.17)
	[0.20]	[0.23]	[11.58]	[3.41]	[1.14]	[2.35]
Hedger	0.051	−0.010	0.024	−0.016	0.076	0.018
	(2.14)	(−2.97)	(0.67)	(−1.87)	(1.28)	(1.93)
	[2.51]	[0.32]	[19.43]	[4.28]	[10.71]	[3.83]
CD						
Speculator	−0.016	0.006	−0.049	0.019	−0.093	0.014
	(−1.20)	(0.98)	(−2.91)	(2.74)	(−2.42)	(1.98)
	[14.45]	[15.06]	[0.37]	[0.59]	[1.12]	[3.26]
Hedger	−0.041	−0.008	0.026	−0.017	0.017	−0.010
	(−0.31)	(−1.12)	(1.55)	(−2.34)	(0.47)	(1.56)
	[23.16]	[3.04]	[7.36]	[1.49]	[21.75]	[7.21]
DM						
Speculator	−0.021	0.019	−0.122	0.022	−0.033	0.026
	(−1.76)	(1.79)	(−1.47)	(1.98)	(−0.51)	(2.17)
	[5.03]	[4.76]	[7.99]	[3.35]	[20.50]	[2.26]
Hedger	0.056	−0.013	0.078	−0.020	0.039	−0.022
	(0.49)	(−1.80)	(1.12)	(−1.90)	(0.80)	(−2.03)
	[20.77]	[4.68]	[12.51]	[3.90]	[17.02]	[3.04]
JY						
Speculator	−0.026	0.018	−0.128	0.032	−0.135	0.037
	(−0.89)	(1.98)	(−2.65)	(3.32)	(−1.47)	(2.27)
	[13.37]	[3.27]	[0.75]	[0.11]	[8.28]	[1.82]
Hedger	0.045	−0.007	0.178	−0.030	0.199	−0.032
	(1.10)	(−1.80)	(2.68)	(−3.08)	(1.82)	(−1.89)
	[13.31]	[4.75]	[0.69]	[0.22]	[4.53]	[4.12]
SF						
Speculator	−0.086	0.004	−0.059	0.012	−0.013	0.006
	(−0.32)	(0.62)	(−1.75)	(1.78)	(−0.15)	(0.38)
	[23.08]	[20.05]	[5.30]	[5.01]	[20.42]	[22.61]
Hedger	0.208	−0.003	0.171	−0.014	0.029	−0.002
	(0.58)	(0.92)	(1.46)	(−2.01)	(0.91)	(−0.78)
	[20.55]	[15.94]	[8.41]	[3.18]	[16.07]	[17.35]

This table reports results of estimating $R^j_{t+K} = \alpha^j_{0i} + \alpha^j_{1i}\mathrm{SI}^j_{it} + \varepsilon^j_{it}$. R^j_{t+K} is the percentage return for market j in subsequent K weeks, and $K = 2$, 4, and 8. SI^j_{it} is the sentiment for trader type i in market j in week t, and i denotes speculators and hedgers. The sample period is from January 1993 to March 2000. The numbers in parentheses are t-statistics, corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). The numbers in brackets are posterior odds $(P(H_0)/P(H_1))$ assuming equal prior odds, calculated using the method of Jeffreys (1961) and Connolly (1991).

represents extremely bullish (bearish) sentiment, which correspond to sentiment index values in the top (bottom) 20%. We compute the mean holding-period return for each group over the periods of 2, 4, and 8 weeks. The results are presented in

Table 3
Extreme sentiment by trader type and future returns (January 1993–March 2000)

	2 week			4 week			8 week		
	H	L	HML	H	L	HML	H	L	HML
BP									
Specu-	0.669	−0.238	0.907	0.555	−0.121	0.676	0.985	−0.497	1.482
lator	(4.54)	(−1.29)	(3.92)	(2.39)	(−0.39)	(1.92)	(3.41)	(−1.41)	(3.15)
	[0.00]	[4.78]	[0.01]	[0.71]	[10.00]	[1.82]	[0.05]	[4.09]	[0.11]
Hedger	−0.142	0.655	−0.797	−0.091	0.620	−0.711	−0.222	1.069	−1.290
	(−0.76)	(4.27)	(−3.10)	(−0.29)	(2.59)	(2.63)	(−0.81)	(3.71)	(−2.92)
	[8.11]	[0.00]	[0.13]	[10.34]	[0.45]	[0.45]	[7.81]	[0.02]	[0.20]
CD									
Specu-	0.081	−0.220	0.302	0.074	−0.549	0.623	0.162	−1.102	1.267
lator	(0.74)	(−1.92)	(1.97)	(0.53)	(−4.15)	(3.34)	(0.58)	(−4.97)	(3.88)
	[8.23]	[1.82]	[1.66]	[9.39]	[0.01]	[0.06]	[9.14]	[0.00]	[0.01]
Hedger	−0.061	0.233	−0.295	−0.395	0.170	−0.565	−1.044	0.082	−1.125
	(−0.47)	(1.78)	(−1.92)	(−2.63)	(1.24)	(−2.53)	(−4.40)	(0.38)	(4.63)
	[9.69]	[2.33]	[1.82]	[0.41]	[5.09]	[0.52]	[0.00]	[10.04]	[0.00]
DM									
Specu-	0.273	−0.497	0.771	0.101	−0.812	0.912	0.544	−0.509	1.049
lator	(1.14)	(−2.11)	(2.97)	(0.35)	(−2.69)	(2.88)	(1.68)	(−1.23)	(2.34)
	[5.71]	[1.25]	[0.17]	[0.14]	[0.36]	[0.22]	[2.75]	[5.15]	[0.79]
Hedger	−0.553	0.242	−0.795	−0.752	0.355	−1.087	−0.598	0.481	−1.080
	(−2.31)	(1.36)	(−2.67)	(−2.23)	(1.77)	(−2.86)	(−1.75)	(1.44)	(−1.98)
	[0.84]	[4.37]	[0.37]	[0.99]	[2.37]	[0.23]	[2.45]	[2.93]	[1.62]
JY									
Specu-	0.799	−0.095	0.895	1.443	0.111	1.333	1.996	0.135	1.865
lator	(2.29)	(−0.54)	(3.34)	(2.95)	(0.36)	(2.83)	(3.55)	(0.30)	(3.09)
	[0.88]	[9.33]	[0.06]	[0.19]	[10.11]	[0.25]	[0.03]	[10.31]	[0.13]
Hedger	0.125	0.718	−0.593	0.331	1.369	−1.039	0.588	1.893	−1.305
	(0.23)	(2.03)	(−1.96)	(0.60)	(2.79)	(−2.43)	(1.05)	(3.18)	(−2.64)
	[10.50]	[1.49]	[1.69]	[9.03]	[0.28]	[0.65]	[6.58]	[0.10]	[0.40]
SF									
Specu-	0.069	−0.231	0.301	0.196	−0.901	1.096	0.239	−1.057	1.296
lator	(0.30)	(−1.55)	(1.88)	(0.58)	(−3.59)	(2.54)	(0.81)	(−2.07)	(2.50)
	[10.31]	[3.35]	[1.96]	[9.13]	[0.03]	[0.51]	[7.81]	[1.38]	[0.56]
Hedger	−0.358	0.053	−0.402	−1.064	0.117	−1.181	−1.455	−0.108	−1.347
	(−1.72)	(0.27)	(−1.90)	(−4.68)	(0.38)	(−3.23)	(−2.96)	(−0.12)	(−2.66)
	[2.57]	[10.04]	[1.88]	[0.00]	[10.04]	[0.09]	[0.18]	[10.70]	[0.38]

The return is measured as the holding-period return, in percent. Investor sentiment is measured as in Eq. (1). Each week, investor sentiment is sorted into extreme sentiment group. H represents the group with extremely bullish sentiment (top 20%). L represents the group with extremely bearish sentiment (bottom 20%). EHML represents a strategy of buying H and selling L. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero, and are corrected for heteroskedasticity and autocorrelation based on the Newey–West adjustment. The numbers in brackets are posterior odds ($P(H_0)/P(H_1)$) assuming equal prior odds, calculated using the method of Jeffreys (1961) and Connolly (1991).

Table 3. We also report the mean returns for HML, representing a timing strategy of simultaneously purchasing H and selling L.

Mean returns for H and L for speculators are positive and negative respectively for all except the 4- and 8-week periods in the JY futures market. Mean returns for H and L for hedgers are negative and positive respectively except for H in the JY futures market. As expected, therefore, extreme investor sentiment is indeed associated with stronger future returns. This can be better understood by evaluating the profitability of HML. For extreme speculator sentiment in the 4-week prediction period, mean returns for HML are 0.67%, 0.62%, 0.91%, 1.33%, and 1.10% for the BP, CD, DM, JY, and SF futures markets respectively. Mean returns for hedgers are −0.71%, −0.57%, −1.09%, −1.04%, and −1.18% respectively. Annualized HML returns to speculators range from 8.10% to 17.29%, and annualized returns to hedgers range from −7.41% to −15.34%. These profits to extreme sentiment-based timing strategies are nontrivial, and are unlikely to be explained by the low transaction cost of futures trading or the small serial correlation in futures returns.

Moreover, based on classical *t*-statistics, the mean returns for HML are significant for both speculators and hedgers for all horizons. The posterior odds ratios also favor the alternative hypothesis in 12 and 11 out of 15 cases for speculators and hedgers respectively. Thus, the profits from extreme sentiment strategies appear both economically and statistically significant.

3.2. What explains the speculative profits?

One possible explanation for the apparent profits to speculators in Table 3 is that they represent compensation for risk. Alternatively, they may result from the superior forecasting ability of speculators. To examine to what extent speculative profits are compensation for risk, or rewards to superior timing ability, we adopt the two-stage procedure described in Section 2. We first obtain estimated market risk premiums based on the CAPM. We then subtract estimated market risk premiums from the raw return series for each market to get market risk-adjusted returns.

Table 4 reports summary statistics for conditional betas, the price of market risk, and market risk premiums over the sample period. The time series mean of the betas is negative and significant for all except the CD futures market, which is positive and significant. Other researchers also report estimated betas for currency futures. For example, Bessembinder (1992) uses monthly observations and shows that the beta is positive for the CD, BP and DM futures, negative for the JY and SF futures, but only the beta for the CD futures is significant. De Roon et al. (2000) analyze semi-monthly data and finds the estimated beta is negative and insignificant for all except the CD futures market. The sign of estimated betas in this study is broadly consistent with that reported in the prior studies; however, the estimated betas are significantly different from zero in our regressions.

The time series mean of the estimated price of risk is 0.21, indicating that an increase of one unit of market risk is associated with an increase of 0.21% point in the required rate of return. The average market risk premiums, consistent with the sign

Table 4
Conditional beta, price of market risk, and futures risk premiums (January 1993–March 2000)

	BP	CD	DM	JY	SF
Conditional beta					
Mean	−0.0876	0.0731	−0.2307	−0.0904	−0.2643
Std. dev.	0.1911	0.0613	0.2279	0.2152	0.2854
t-value	−4.91	6.88	−5.23	−2.86	−6.20
$P(H_0)/P(H_1)$	0.00	0.00	0.00	0.42	0.00
Price of risk					
Mean			0.2115		
Std. dev.			1.8058		
t-value			2.27		
$P(H_0)/P(H_1)$			1.86		
Market risk premium					
Mean	−0.0410	0.0129	−0.0656	−0.0587	−0.0828
Std. dev.	0.2955	0.1778	0.4953	0.3265	0.6042
t-value	−2.69	1.83	2.57	−3.49	−2.66
$P(H_0)/P(H_1)$	0.67	4.53	0.92	0.06	0.73

Beta is the slope coefficient obtained by rolling regressions of futures returns against the return on the CRSP index over the previous 52 weeks. Price of market risk is slope coefficient obtained by regressing futures or equity portfolio returns on betas of futures contracts or equity portfolios, based on Eq. (6). 20 size-ranked equity portfolios of all firms listed on the CRSP daily tape and the five foreign currency futures contracts are included in the cross-sectional regressions. Risk premium is computed as the product of conditional beta and price of risk in week t based on Eq. (5). The t-value is the t-statistics corrected for heteroskedasticity and autocorrelation based on Newey and West (1987). $P(H_0)/P(H_1)$ denotes the posterior odds assuming equal prior odds, calculated using the method of Jeffreys (1961) and Connolly (1991).

of beta estimate in the respective futures market, are negative for all except the CD market. The time series means of estimated market risk premiums (per week) are −0.041%, 0.013%, −0.066%, −0.058%, and −0.083% for the BP, CD, DM, JY, and SF futures respectively. All these estimates are significant based on classical hypothesis tests, and all but the CD futures favor the alternative over the null based on Bayesian posterior odds ratios.

Despite the statistical significance of these estimates, their economic significance is doubtful. Therefore, we do not tabulate separate risk-adjustment results. In general, when we re-estimate Eq. (2) using risk-adjusted returns or recalculate profits to extreme sentiment trading strategies, the adjustment has almost no impact on the results presented in Tables 2 and 3. This finding is not surprising given the small estimate of the market price of risk in Table 4.

Given our inability to explain the predictive relationships between extreme investor sentiment and futures returns based on market risk, we now examine their relationship to hedging pressures. After accounting for the trivial economic effects of market risk, the negative performance associated with hedger sentiment captures hedging pressure effects, and the positive performance associated with speculator sentiment reflects the rewards to bearing nonmarketable risks and/or to superior forecasting ability. [16] Therefore, the difference between the return to a timing strategy following extreme speculator sentiment and the return to a strategy contrary to extreme hedger sentiment roughly measures the rewards to superior timing ability possessed by speculators.

Let SH (SL) represent the group with extremely bullish (bearish) speculator sentiment, HH (HL) represent the group with extremely bullish (bearish) hedger sentiment. Thus, the mean returns for HH and HL measure hedging pressure effects, or compensation for bearing nonmarketable risk (e.g., Hirshleifer, 1990). Let SHMHL (SLMHH) be a timing strategy following extremely bullish (bearish) speculator sentiment in excess of the return to a strategy contrary to extreme bearish (bullish) hedger sentiment. Thus, a positive return for SHMHL and a negative return for SLMHH suggest that speculators possess superior forecasting power.

Evidence on superior forecasting ability of speculators is presented in Table 5. The mean returns for SHMHL and SLMHH have mixed signs for the BP, CD, and SF futures, and are mostly insignificant based on classical t-statistics. The lone exception, for SLMHH in the SF futures over the period of 8 weeks (the mean return of 0.435% ($t = 1.79$)), indicates that hedgers are paying more than what speculators earn. Thus, speculators appear to lack forecasting power in this instance. The mean returns for SHMHL (SLMHH) are positive (negative) for the DM and JY futures over the periods of 2, 4, and 8 weeks, but significant only for SHMHL in the DM futures based on conventional t-statistics. This suggests that speculators often initiate correct trades in buying and selling futures contracts in the DM and JY futures markets, but speculators appear to possess some forecasting ability when they are extremely bullish (and hedgers are extremely bearish) in the DM futures market. For example, using the 4-week projection period, the mean return for SHMHL is 0.44% (5.72% per annum). However, the posterior odds favor the null hypothesis (a zero mean return for SHMHL or SLMHH) for all the markets and holding horizons. The conflicting inferences from the two hypothesis-testing procedures are attributable to the moderately large sample size. Therefore, the significance level of classical hypothesis tests should be adjusted to avoid excessive rejection of a null hypothesis.

In summary, although speculator sentiment is positively correlated with future market movements, our results indicate that speculators are not associated with private information or superior forecasting power. Thus, risk premiums in these futures markets explain the negative performance of hedgers and the positive performance of speculators.

[16] De Roon et al. (2000) report that both the futures own hedging pressure and cross-hedging pressures in closely related futures markets affect futures returns. However, their results indicate that the cross-hedging pressures are much weaker in currency futures markets than those in financial, agricultural and commodity futures markets. We also checked the correlations of extreme hedger sentiments for the markets in our sample, and find the cross-correlations are hardly significant. Therefore, failure to adjust cross-hedging pressures is unlikely to significantly affect our results in this study.

Table 5
Sources of speculative profits: hedging pressure effect or superior forecasting ability

	BP		CD		DM		JY		SF	
	SHMHL	SLMHH	SHMHL	SLMHH	SHMHL	SLMHH	SHMHL	SLMHH	SHMHL	SLMHH
2 week	0.116	−0.108	0.034	−0.122	0.204	−0.084	0.065	−0.116	0.021	0.040
	(0.35)	(−0.42)	(0.22)	(−0.69)	(1.75)	(−0.88)	(0.31)	(−0.71)	(0.33)	(0.17)
	[10.15]	[9.88]	[10.52]	[8.53]	[2.45]	[7.37]	[10.28]	[8.41]	[10.21]	[10.62]
4 week	−0.097	−0.221	−0.079	−0.156	0.441	−0.110	0.030	−0.121	−0.030	0.043
	(−0.22)	(−0.59)	(−0.40)	(−0.71)	(1.92)	(−1.35)	(0.25)	(−0.52)	(−0.29)	(0.31)
	[10.52]	[9.08]	[9.96]	[8.41]	[1.82]	[4.43]	[10.09]	[9.11]	[9.98]	[9.92]
8 week	−0.224	−0.210	0.253	0.085	0.559	−0.029	0.312	−0.232	−0.009	0.435
	(−0.39)	(−0.88)	(1.36)	(0.59)	(1.88)	(−0.39)	(0.84)	(−0.89)	(−0.18)	(1.79)
	[9.65]	[7.12]	[4.23]	[8.77]	[1.90]	[9.65]	[7.36]	[7.06]	[10.24]	[2.22]

The return is measured as the market risk-adjusted return, computed by subtracting the expected return (Eq. (5)) from the raw return series, in percent. SHMHL represents a strategy of purchasing SH and selling HL. SLMHH is a strategy of purchasing SL and selling HH. SH (SL) denotes the group with extremely bullish (bearish) speculator sentiment. HH (HL) is the group with extremely bullish (bearish) hedger sentiment. The numbers in parentheses are t-statistics under the null hypothesis that the relevant parameter is zero, and are corrected for heteroskedasticity and autocorrelation based on the Newey–West adjustment. The numbers in brackets are posterior odds $(P(H_0)/P(H_1))$ assuming equal prior odds, calculated using the method of Jeffreys (1961) and Connolly (1991).

4. Conclusions

We examine the relation between trading activity by trader type and future returns over short horizons in five major foreign currency futures markets – BP, CD, DM, JY, and SF. Transforming trading activity into a sentiment measure, we document that speculator sentiment is positively correlated with future returns, but hedger sentiment is negatively related to future returns in these futures markets. Moreover, extreme sentiment by trader type is more correlated with future market movements than is the level of sentiment. Thus, it appears that speculators profit from trading these currency futures over reasonable return horizons, whereas hedgers lose money, on average.

We further examine the role of futures risk premiums in explaining the speculative profits based on the equilibrium futures pricing model of Hirshleifer (1990). The evidence shows that futures risk premiums largely explain the profits to speculators. Therefore, the positive performance of speculators does not appear to contradict the EMH. We also find that the interpretation of classical t-statistics can be distorted even if the sample size is moderately large. Classical hypothesis-testing procedures indicate that speculators possess some forecasting ability in the DM futures market, which is indicative of market inefficiency. However, the evidence of market inefficiency is not supported by the posterior odds approach. Therefore, the significance level of classical hypothesis tests should be adjusted to avoid possible sample size-related distortions (e.g., Connolly, 1991).

Our results suggest that the fact that hedgers lose to speculators in the foreign currency futures markets is not surprising. These losses generally represent compensation to speculators for insuring hedgers. Therefore, this study provides a test of hedging pressure theory in foreign currency futures markets from a different angle. A related argument in the line of Friedman's reasoning is that investors who lose money consistently may not survive for long. This argument does not appear to be valid for hedgers because they can benefit from risk reduction in several ways, as shown in the modern corporate hedging literature (e.g., Stulz, 1984; Smith and Stulz, 1985).

Our findings have implications for academics. We have shown that hedging pressure effects tend to be strong in foreign currency futures markets. Consistent with our findings, Tien (2002) finds that hedging pressure explains a large portion of variation in foreign currency futures returns. Therefore, inference with regard to currency futures market efficiency in the previous studies can be misleading if hedging pressure effects are not properly accounted for. Moreover, sample size can distort the interpretation of classical test statistics even with a moderately large sample, and therefore, the significance level should be adjusted to avoid excessive rejection of a null hypothesis. Our results also have practical implications. Given that hedging pressure is priced in currency futures markets, a timing strategy contrary to hedgers' position changes and following speculators' position changes can be profitable.

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