Momentum and Reversals in Weekly Euro FX Futures Returns during Periods of Extreme Trading Imbalance

An-Sing Chen
Department of Finance,
National Chung Cheng University,
Ming Hsiung, Chia Yi 621, Taiwan, ROC
Tel:+886-5-2720411 x 34201; Fax:+886-5-2720818
E-mail: finasc@ccu.edu.tw

Erin H. C. Kao*
Department of Finance
Ling Tung University
No.1, Ling Tung Road, Taichung 408, Taiwan, R.O.C.
Tel: +886-4-3600-8600
E-mail: erinkao@mail.ltu.edu.tw

* Corresponding author.

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Abstract

We analyze the relation between trading imbalance metrics that are observable by investors to future momentum and reversals in weekly returns of the Euro FX futures contracts trading on the CME. Standard regression analyses do not show any significant dynamic relation between weekly returns and trading imbalance, regardless of whether they are lagged, contemporaneous or lead. However, when the analyses are focused on periods with extreme imbalance levels, we find weekly returns in Euro FX futures exhibit significant reversals following periods of extreme (negative) trade imbalances. We also find some evidence of residual momentum in consecutive weekly futures returns following periods of extreme (high) trade imbalances and high returns. Trading tests and directional accuracy tests show these effects to be economically significant, even after accounting for transaction costs.

Keywords: momentum, reversals, imbalance, trading test, predictability

JEL Codes: G14, G13, G12, G11, C53

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I. Introduction

Existing research examining the relation between return and measures of trading or order imbalance mostly focus on short term intervals such as daily or intraday data (i.e. Chordia et al. (2002), Chordia and Subrahmanyam (2004), and Chordia, et al.(2005)). However, according to Lo and Wang (2000), and Connolly and Stivers (2003), examining weekly return horizon is a good compromise between maximizing sample size while minimizing daily volume and return fluctuation that may have less direct economic relevance. This is especially true if research results are to be used by real-world traders who have to take into consideration transaction costs of trading and may be more likely to adopt trading strategies researched from weekly analyses. In addition, prior studies examining imbalance metrics mainly focus on equity market, such as stock indexes (Chordia et al. (2002, 2005)) or individual stocks (Chordia and Subrahmanyam (2004)). This paper examines momentum and reversals in weekly Euro FX futures returns during periods of extreme trading imbalance. We focus on weekly returns and analyze the dynamic relation between return and various computed imbalance measures.

The importance of trading activity in price formation is clear. Price and quantity are the fundamental building blocks of any theory of market interactions. But prior literatures examining return anomalies or the predictability of returns have focused mainly on past returns. The implications from trading activities have received far less attention. Lo and Wang (2000) conclude that trading activity is fundamental to a deeper understanding of economic interactions, and they suggest that the most pressing issues are the time-series variation in volume and the relations between volume, prices and other economics quantities. Llorente et al. (2002) suggest that "intensive trading volume can help to identify the period in which either allocational or information shocks occurs." They use turnover as a measure of trading volume to examine the dynamic relation between return and volume. Connolly and Stivers (2003) document the dynamics between returns and volume. In their paper, they use turnover shocks and dispersion shocks as a measure of trading activity.

Wang (1994) presents a dynamic model of competitive trading volume where volume conveys important information about how assets are priced in the economy. In his model, the dynamic relation between volume and returns varies depending upon the motive for trading by the "informed investors" who have access to private information about the stock and also have investment opportunities outside the public stock exchange. Llorente et al. (2002) present a model closely related to the Wang framework, where turnover is motivated by either hedging purposes or by asymmetric information about a stock's fundamentals. They examine the predictive role of volume on the autocorrelation of daily returns.

A less studied variable, "trading imbalance", can also influence returns. Chordia et al (2004) mentions that there are at least two reasons why imbalance measures can provide additional power beyond trading activity measures such as volume in explaining stock returns. First, a high absolute imbalance can alter returns as market makers struggle to re-adjust their inventory. In addition, imbalances can signal excessive investor interest in a stock, and if this interest is autocorrelated, then imbalances could be related to futures returns. In a related paper, Chorida et al. (2002) point out that price should be more strongly affected by more extreme order imbalances, regardless of volume, for two reasons. First, order imbalances sometimes signal private information, which could move the market price permanently, as suggested by the well-known Kyle (1985) theory of price formation. Second, random large order imbalance exacerbate the inventory problem faced by the market maker. Consequently, imbalances can have important influences on stock returns and liquidity, conceivably even more important than volume. In fact, the inventory models of Stoll (1978a), Ho and Stoll (1983), and Spiegel and Subrahmanyam (1995) involve market makers accommodating buying and selling by outside investors, and liquidity as well as returns are influenced by inventory concerns and imbalances. Other studies that analyze imbalance measures include Ho and Stoll (1983), Spiegel and Subrahmanyam (1995), Chordia and Subrahmanyam (2004), and Subrahmanyam (2005).

Our empirical exploration differs substantially from earlier studies. **First,** prior papers often directly use trading volume as a measure that relates to returns (i.e. Connolly and Strivers (2003), and Llorente et al (2002). We focus on trading imbalance measures, which can provide additional power beyond trading activity measures such as volume in explaining stock returns. **Second,** prior works often evaluate the role of volume in predicting serial correlation in return, we evaluate whether serial correlation in returns varies with lagged, contemporaneous, and lead imbalance measures. **Third,** existing research on imbalance measures mostly focus on short term intervals such as daily or intraday data to examine the relation between return and imbalance (i.e. Chordia et al. (2002), Chordia and Subrahmanyam (2004), and Chordia, et al.(2005)). In this paper, we focus on weekly returns to examine the dynamic relation between return and imbalance measures. According to Lo and Wang (2000), Connolly and Stivers (2003), examining weekly return horizon is a good compromise between maximizing sample size while minimizing daily volume and return fluctuation that may have less direct economic relevance. **Fourth**, prior studies examining imbalance measures mainly focus on equity market, such as stock indexes (Chordia et al. (2002, 2005)) or individual stocks (Chordia and Subrahmanyam (2004)). We focus on the currency futures market in this paper, in particular the Euro FX futures traded on the Chicago Mercantile Exchange (CME). In the context of trading imbalance and weekly returns, this has not been done before. Further given the increasing importance of the EURO in the world economy, deeper research on momentum and reversals of its FX futures is warranted. **Finally** and most importantly, the trading imbalance metric analyzed in this paper is carefully constructed to be a metric that is observable by investors at the time he is making an investment decision and, thus, its associations with future momentum or reversals in returns, if significant, should be usable by investors in their trading decisions. This differs greatly from past research such as Connolly and Stivers (2003) that linked momentum and reversals in equity-index returns during periods of dispersion shocks in that their dispersion shock metric was defined as a regression residual using all data and, therefore, in practice, unobservable to investors at the time the trading decision is made, rendering their results to be mainly descriptive and of academic interest but not usable by traders.

Our major finding and contribution to the study of futures return-imbalance dynamics is that we find weekly returns in foreign exchange futures exhibit significant reversals following periods of extreme trade imbalance, suggesting that return predictability can be substantially improved if traders incorporate the trading imbalance metrics described in this study (which are observable at the time of trading decision) into their information set.

This rest of the paper is organized as follows. Section II discusses related theory and literatures to provide additional motivation and intuition for our analyses. Section III details the construction of our trading imbalance metrics. Section IV describes the data and presents the preliminary statistics. Section V discusses the experimental design and presents the empirical results. Section VI concludes.

II. Related Literatures

Recently, some researchers (such as Chordia, Roll and Subrahmanyam (2002)) suggest that order imbalance provide additional power beyond trading activity measures such as volume and turnover in explaining returns. Large order imbalance exacerbates the inventory problem faced by the market maker, who can be expected to respond by revising price quotations. Hence, order imbalance should be important influences on stock returns, conceivably even more important than volume.

The inventory models of Stoll (1978), Ho and Stoll (1983), and Spiegel and Subrahmanyam (1995) involve market makers accommodating buying and selling by outside investors. Returns are influenced by inventory concerns in this paradigm. Chordia, Roll and Subrahmanyam (2002) examine the relation between marketwide order imbalance and returns. They find that aggregate order imbalance is contrarian in the sense that buying activity is more pronounced following market crashes, and selling activity is more pronounced following market rises. Their evidence is consistent with the inventory paradigm where temporary inventory imbalances and price pressures are being countervailed effectively by astute traders.

Chordia and Subrahmanyam (2004) study the relation between order imbalances and daily returns of individual stocks. They find that after controlling for the current imbalance, lagged imbalances are negatively related to current price movement. Their results support inventory paradigm as well, wherein risk-averse market makers with inventory concerns charge premium to accommodate order imbalance.

Subrahmanyam (2005) analyze return reversals in context of a specific equilibrium model that incorporates both risk-aversion-related inventory phenomena and behavioral effects. He examines the relation between current returns, past returns and past order flows. Different from the prior two papers, he finds that inventory effects alone do not appear to fully account for monthly return reversals.

Bharadwaj and Wiggins (2003) investigate how order imbalance affect price in S&P 500 Index options and find evidence that order imbalances create price pressure in the S&P 500 LEAPS put market. Cushing and Madhavan (2000) analyze stock returns at the last 5 min of the trading day and find systematic return reversals following order imbalance publications consistent with temporary price pressure related to liquidity trading. Their results further show positive (negative) overnight return following publicized sell (buy) imbalances and provide evidence that price over-react to order imbalance at the close.

To summarize, the existing literatures dealing with the imbalance metrics focus mainly on the concept and testing of the inventory hypothesis. While these studies advance our knowledge of how prices are set, they are by nature descriptive. The focus of this study, on the other hand, is to highlight the relation between imbalance metrics that are constructed to be observable to investors and its relation to future momentum and reversals in returns. In particular, how extreme values of these constructed imbalance metrics may convey significant information regarding future momentum and reversals in returns.

Ⅲ. Construction of Trading Imbalance Metrics

We construct two trading imbalance metrics from intraday tick data. In our data base, an up tick is defined as a tick that is higher than the previous tick (or the same as the previous tick). Conversely, a down tick is likewise defined as a tick that is lower than the previous tick (or the same as the previous tick). The intraday tick data enable us to construct two trading imbalance metrics, one based on the *number* of up (and down) ticks in a prescribed time interval and the other based on the *volume* of up (and down) ticks. For ease of exposition, we define the variable “up-tick-number” to be the number of up ticks within a particular time interval whose value is higher than the tick immediately preceding it or the same as the previous tick. Similarly, we define the variable “up-tick-volume” to represent the volume of up ticks within a particular time interval. For example, up-tick-number would be 5 if there were 5 ticks within a particular time interval whose value was higher than the tick immediately preceding it or the same as the previous tick. On the other hand, up-tick-volume would be 25 if there were 5 up ticks within a particular time interval and whose total volume was 25 contracts. The following trading imbalance metrics can now be constructed from the previous definitions:

$$I_t^{num} = \frac{(up\_tick\_number - down\_tick\_number)}{(up\_tick\_number + down\_tick\_number)} \qquad (1a)$$

$$I_t^{volm} = \frac{(up\_tick\_volume - down\_tick\_volume)}{(up\_tick\_volume + down\_tick\_volume)} \qquad (1b)$$

The metric based on volume measures the information content of the volume of contracts traded within a particular time interval as well as the frequency of their trades within this time interval. If there is extra information in the volume of contracts traded, this metric should pick it up. The metric based on number, on the other hand, does not contain this information, and hence may have the effect of weighing trades with lower volume of contracts more heavily than they might otherwise be. For the analysis, the individual futures contracts are spliced together from “Roll-Over-Day” to “Roll-Over-Day” to form one continuous time series (continued futures contract).[1]

[1] For example, on the Euro FX futures, roll over date comes 10 days before expiration date. There

IV. Data and Preliminary Statistics

We focus on the Euro FX futures contract traded on the Chicago Mercantile Exchange (CME), the largest futures exchange in the United States. CME offers futures and options on futures primarily in four product areas: interest rates, stock indexes, foreign exchange and commodities. In 1972, CME transformed global finance with the launch of the first financial futures contracts via the newly organized International Monetary Market (IMM). The FX markets are open 24 hours per day during the FX business week. Today, CME is the largest market for exchange-traded foreign exchange futures in the world. At the CME, futures are traded by open outcry on the floor of the exchange in the futures pits and also electronically on the GLOBEX trading system. Coppejans and Domowitz (1999) conclude that Globex system performs well when the flow of liquidity traders is likely to be relatively low. Hasbrouck (2003) demonstrate that instead of being an informational satellite of the trading floor, the electronic trading system appears to play an important role in the price discovery. Under the CME Globex system as well as its trading floor, CME offers liquidity, transparency, cost-effective and secure place for trading FX futures.

The Euro FX futures contract listed at the CME is based on the Euro. The Euro was established by the European Monetary Union (EMU) on January 1, 1999. The Euro has officially replaced the national currencies of the member EU countries, and now only Euros are legal tender for EMU participants[2]. Among many of FX futures traded in CME, this contract is heavily traded by the world's largest governments,

is a last active trading day of the current contract on Wednesday (a week before expiration week) and there is a first active trading day of the next contract on Thursday (a week before expiration week).

[2] The current members of the EMU are Germany, France, Belgium, Luxembourg, Austria, Finland, Ireland, the Netherlands, Italy, Spain and Portugal.

banks and currency traders. The CME Euro FX future is one of the most active FX futures contracts trading on the CME.

The price of the Euro futures contract is quoted in terms of the number of U.S. Dollars per one Euro. The contract size is 125,000 Euros, and the minimum tick is $0.0001 per Euro, worth $12.50 per contract. Open-outcry trading is conducted from 7:20 AM until 2:00 PM Chicago time. Euro futures also trade on the CME's Globex system from 5:00 PM non-stop until 4:00 PM the following day. Sunday trading begins at 5:00 PM. Floor-traded and electronically-traded Euro futures have identical contract specifications. Euro futures trade on a quarterly cycle, with the primary contracts being March, June, September, and December.

Our Euro FX futures data span from December 17, 1999 to March 4, 2005. The regression analyses in this study focus on weekly frequencies. Intraday tick data, however, are used to compute the weekly imbalance metrics.

Table 1 presents various descriptive statistics of returns and trading imbalances in Euro FX futures. For the sample period used in this study, both of our constructed trading imbalance metrics have negative means, more so when measured by tick number, indicating that there are more times with down-tick pressure than with up-tick pressure. We also report the autocorrelation. The computed trading imbalances exhibit positive autocorrelation in first lag in our sample. This is consistent with the findings in Chordia and Subrahmanyam (2004) and Chordi, Roll and Subrahmanyam (2005) for order imbalance metrics[3].

V. Methodology and Results

To examine whether the autoregressive behavior of futures returns varies with

[3] The "trading imbalance" metric used in this study should be distinguished from "order imbalance" metrics used in prior studies. Order imbalance requires observation of order flows whereas trading imbalance can be computed directly from intraday trading data as described in section III.

trading imbalance and extreme trading imbalance, we estimate the following model:

$$R_t = \beta_0 + (\beta_1 + \beta_2 \cdot I_j) R_{t-1} + (\beta_3 + \beta_4 \cdot I_j) \cdot R_{t-1} \cdot DumI_t + \varepsilon_t \qquad (2)$$

The coefficient of interest is β_4. R_t is the futures return in week t; I_j is the trading imbalance metric in week j; j=t, t-1 or t+1 so that we may investigate contemporaneous, lagged, and lead associations; and the β's are the estimated coefficients. The dummy variable (Dum_I) in the regression captures periods of extreme trading imbalance. It is set equal to 1 when trading imbalances are at the highest 10% or lowest 10% levels and zero otherwise.

1. Relation of Return and Imbalance

In our tables, we report coefficients estimated by OLS with t-statistics based on heteroskedastic and autocorrelation-consistent standard errors, using the Newey-West (1987) method.

Table 2 presents the regression results. Panel A gives the results for I_t^{num} and Panel B the results for I_t^{volm}. For the regressions without the dummy variables, we do not find any significant dynamic relation between return and trading imbalance, regardless of whether they are lagged, contemporaneous or lead. In addition, we do not find significant return autocorrelation as β_1 is not significant in any of the regressions. The Euro FX futures market on the surface appears quite efficient at the weekly level.

For the regressions that include the dummy variables corresponding to periods of extreme imbalance, the results differ significantly. Here, we find statistically significant dynamic relation between return and trading imbalance at the lagged period under both I_t^{num} and I_t^{volm} metrics. These results show that the dynamic relations between return and trading imbalance are not be easily found for liquid and efficient markets like the currency futures market when regressions do not include the dummy variables corresponding to periods of extreme imbalance. Results also show that extreme imbalance levels contain stronger information. Hence, we focus our analyses on extreme imbalance levels in the remainder of the paper.

Tables 3 shows sub-sample results for periods when the imbalance metrics are at the highest and lowest 10% levels. Here, the implied first-order autoregressive coefficients corresponding to the j=t-1 case for the lowest 10% levels of both I_t^{num} and I_t^{volm} become statistically significant and the 5% levels or better. Two additional implied first-order autoregressive coefficients corresponding to j=t and t+1 periods are not significant for the lowest 10% level of I_t^{num} and the highest 10% level of I_t^{volm}. These two periods are not, however, of interest to traders since they are not observable at the time of investment decision for a trader situated at time t-1. What is of interest to traders is implied first-order autoregressive coefficients corresponding to the j=t-1 case because under this scenario, a trader situated at time t-1 can observe the t-1 imbalance metric, thereby giving him information as to the return next period (time t). The results of Tables 3 show that when the imbalance metrics are at the lowest 10% levels, return reversals the next period are statistically significant. Thus, the two imbalance metrics described in this study can be in theory feasibly used by traders in Euro FX futures markets as a signal of impending return reversals when they are at their extreme low levels. The results of Tables 3 are, however, not symmetric with respect to high and low extremes of imbalance in that they do not carry over to the periods when the imbalance metrics are at the highest 10% levels for the j=t-1 case. Specifically, the implied first-order autoregressive coefficients corresponding to the j=t-1 case when the imbalance metrics are at the highest 10% levels are insignificant regardless of whether the imbalance metric is I_t^{num} or I_t^{volm}. In words, our results show that extreme low (negative) levels of the imbalance metrics provide useful information in forecasting return reversals while extreme positive levels do not provide significant forecasting information in Euro FX futures markets. The effect of trading imbalance is therefore asymmetric with excess selling pressure having larger impacts than excess buying pressure. From a behavioral standpoint, these results seem reasonable since historically sell-offs in asset markets are sharper and more short-lived than market rises, which generally are slower and lasts for longer periods. Our results also provide support to Chorida et al. (2002), that price should be more strongly affected by more extreme order imbalances.

2. Discrete Comparison

To better illustrate the imbalance-return dynamic, we next use discrete comparisons to contrast the momentum and reversals in the weekly returns of our sample. We identify conditions based on the magnitude of R_{t-1} and I_{t-1}. Then, we compare the mean of the identified R_{t-1} observations to the mean of the subsequent R_t observations that follow these R_{t-1} periods. Table 4 presents the results. Panels A and B report results for I_{t-1}^{num} and I_{t-1}^{volm}, respectively.

The results of the discrete comparisons show return reversals following the low return, low imbalance metric cases (R_{t-1} less than negative two percent and imbalance metric less than its 10th percentile).[4] For observations where R_{t-1} is

[4] Other discrete levels of return-imbalance combinations were run in preliminary experiments. We report only the 2% return and 10% imbalance results as they produce results that are most significant and of interest to traders in formulating trading strategies. Setting the return threshold too high, for

less than negative two percent and I_{t-1}^{num} (I_{t-1}^{volm}) is less than its 10th percentile, the mean return in week t-1 is -2.92 (-3.05) percent, and the mean return in the subsequent week t is +0.59 (+0.45) percent. In short, these discrete comparison results confirm the previous regression results of return reversals following periods with extreme, low imbalance metrics.

In addition to confirming regression results of return reversals following periods of extreme, low imbalance, the discrete comparisons of Tables 4 uncovers an additional pattern that does not show up in the regression analyses, of (positive) return momentum following periods with extreme, high imbalance metrics. Specifically, in the Euro FX futures market, for observations where R_{t-1} is greater than two percent and I_{t-1}^{num} (I_{t-1}^{volm}) is greater than its 10th percentile, the mean return in week t-1 is +2.89 (+2.26) percent, and the mean return in the subsequent week t is +0.28 (+0.19) percent. To summarize, in the Euro FX futures market, results of the discrete analyses show that periods with extreme, low imbalance metrics are associated with return reversals the following period, whereas periods with extreme, high imbalance metrics are associated with (positive) return continuation (momentum). These results again support what is observed in typical asset markets, of sharp, short-lived sell-offs with reversals and slower, longer duration market rises associated with some momentum.

3. Economic Significance

3.1 Trading Test

Given that our constructed imbalance metrics are observable to traders at the time of their trading decision, it is of interest to see if our results are useful to actual

example, would overly reduce the number of usable observations (trades). Likewise, setting the return threshold too low would overly increase the number of non-significant observations.

traders in assessing future momentum or reversals in returns.

To get an idea whether the relations between extreme imbalance and future return momentum and reversals are economically significant, we conduct a trading test of a hypothetical investor who trades according to the trading imbalance metric that is observable to her at the time of the trading decision. Results support economic significance if trading in accordance to these observable imbalance metrics produce substantial positive profits after accounting for transaction costs of trading.

We construct a trading strategy based upon the results of the previous discrete comparison analyses of Table 4 documenting that periods with extreme, low imbalance metrics are associated with return reversals the following period, whereas periods with extreme, high imbalance metrics are associated with (positive) return continuation (momentum).

The following trading strategy is tested: when the observed imbalance metric is in the lowest 10 percentile[5] and the return for the prior week is less than -2%, buy and hold for one week; when imbalance is in the highest 10 percentile (larger than 90 percentile) and the return for the prior week is larger than +2%, buy and hold for one week (since previous discrete analyses show that positive returns tend to continue in periods of extreme positive imbalance); other than for these two cases, we keep our money in the bank and earn the risk free rate of interest[6].

The results of following the proposed trading strategy applied to the Euro FX futures are shown on Table 5. The table presents the average weekly returns based on the trading strategy for various levels of transaction costs. When transaction

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5 Strictly speaking, this should be the lowest 10 percentile of a sample of previously observed imbalance metrics and should not include imbalance metrics that have not yet been observed.

6 The risk-free rate used for this trading test is the three-month T-Bill rate published by Federal Reserve Bank of St. Louis.

costs are not considered, the average weekly return of trading the Euro FX futures contract is 0.07% per week for the strategy based on I_{t-1}^{num} and 0.06% per week for the strategy based on I_{t-1}^{volm}. These returns are all substantially larger than the corresponding average weekly risk-free rates for the trading test periods.

Transaction costs vary across futures contracts. A futures trader typically incurs transaction costs of commissions and spread.[7] The transaction cost is about \$10 per lot for Euro FX futures. The spread for Euro FX futures is about 0.00008. Thus, one-way transaction costs for Euro FX futures are about 0.015% of notional value[8]. Locke and Venkatesh (1997) estimate that transaction costs of futures contracts range from 0.0004% to 0.033%, which are much less than those often cited for equities. To be conservative, we select the level of transaction costs ranging from 0.01% to 0.10% in our analysis.

Table 5 shows that the trading strategies remain profitable even after accounting for various levels of transaction costs. Trading results are more profitable than risk-free rate for all levels of transaction costs. For example, at transaction cost of 0.1%, the average weekly return trading the Euro FX futures is about 0.063% using I_{t-1}^{num} (0.059% using I_{t-1}^{volm}), which is 0.012% (0.008%) per week larger than the average weekly risk-free rate. On an annualized basis, this translates to 0.62% (0.42%) larger than the risk-free rate per annum. To sum up, the trading results of Table 5 show that trading in accordance to observable imbalance metrics can produce substantial positive profits over and above the

[7] Futuresbetting.com provides various futures contract transaction costs and spreads.

[8] The one-way transaction cost for EuroFX futures are computed as $\frac{\$10+0.00008\times125000}{1.035\times125000}\approx0.015\%$, where 1.035 is the assumed EuroFx level (we use mean value of EuroFX futures in our sample period), and 125000 denotes the trade unit.

corresponding risk-free rate even after accounting for transaction costs of trading.[9] These results can be interpreted as supporting the premise that the information contained in these imbalance metrics can be useful to and should be economically significant to traders in the real world.

3.2 Directional Accuracy Robustness Check

As a robustness check of the economic significance of the previous trading test, we compare the out-of-sample forecasts from the trading rule using a directional accuracy (DA) test. DA tests are alternatives to trading tests for testing economic significance of forecasts (i.e. Henriksson and Merton (1981)). We employ the Pesaran and Timmermann (1992) test.

This test is based on the comparison of momentum or reversal in the forecast observation, $\hat{\Theta}_i$, with the momentum or reversal in the true withheld observation, Θ_i, for the observations (i=1,2,…..,m.) satisfying the conditions of the trading rule. In implementing the DA test, if you forecast reversal next week let $\hat{\Theta}_i$ be (-). If you forecast momentum next week let $\hat{\Theta}_i$ be (+). If there is an actual reversal next week, let Θ_i be (-). If there is actual momentum next week, let Θ_i be (+). We define the success ration (SR) as

$$SR = m^{-1}\sum_{i=1}^{m} I_i\left[\Theta_i\hat{\Theta}_i > 0\right] \tag{3}$$

where $I_i[\cdot]$ is an indicator function that takes the value of 1 when its argument is true and 0 otherwise. We also define P and $\hat{P}$ as

$$P = m^{-1}\sum_{i=1}^{m} I_i\left[\Theta_i > 0\right] \tag{4}$$

[9] We use the risk-free rate as the basis of comparison since it represents the opportunity cost of taking the money out of the bank and putting it in the in margin accounts required to speculate on the EuroFX futures.

$$\hat{P} = m^{-1}\sum_{i=1}^{m} I_i\left[\hat{\Theta}_i > 0\right] \tag{5}$$

The success rate in the case of independence (SRI) of Θ_i and $\hat{\Theta}_i$ is given by

$$SRI = P \cdot \hat{P} + (1-P)\cdot(1-\hat{P}) \tag{6}$$

with variance

$$\mathrm{var}(SRI) = m^{-2}\left[m(2\hat{P}-1)^2 P(1-P) + m(2P-1)^2 \hat{P}(1-\hat{P}) + 4P\hat{P}(1-P)(1-\hat{P})\right] \tag{7}$$

The variance of SR is given by

$$\mathrm{var}(SR) = m^{-1} SRI(1-SRI) \tag{8}$$

On the basis of the above, the Pesaran and Timmermann (1992) DA test is given by

$$DA = \left[\mathrm{var}(SR) - \mathrm{var}(SRI)\right]^{-1/2}(SR - SRI) \sim N(0,1) \tag{9}$$

Pesaran and Timmermann (1992) show that under the null hypothesis that Θ_i and $\hat{\Theta}_i$ are independently distributed, the DA test follows the standard normal distribution.

The results from the DA tests are presented in Table 6. As shown in the table, the null hypothesis that the trading rule generated forecasts and the actually observed returns are independent is rejected for the Euro FX futures at the 5% significance level or better regardless of whether the trading rule is based on both I_{t-1}^{num} or I_{t-1}^{volm}. Thus, we conclude that information contained in our constructed imbalance metrics are economically significant and can predict the directional change of the actually observed out-of-sample futures returns for the Euro FX futures when applied at the extreme imbalance levels and satisfying the conditions of our trading rule. To sum up, the results of DA test are consistent with the previous findings of Table 5 and thus support the robustness of the trading test results.

VI. Conclusions

The existing literatures dealing with the imbalance metrics focus mainly on the concept and testing of the inventory hypothesis. While these studies advance our knowledge of how prices are set, they are by nature descriptive. In this study, the focus is on the information content of imbalance metrics, its usefulness to traders, and its economic significance. We analyze the relation between imbalance metrics that are observable to investors to future momentum and reversals in returns. In particular, how extreme values of these constructed imbalance metrics may convey significant information regarding future momentum and reversals in returns. The trading imbalance metrics analyzed in this paper are carefully constructed to be metrics observable by investors at the time they are making the investment decision and, thus, their associations with future momentum or reversals in returns, if significant, should be usable to investors in their trading decisions.

For our investigations, we construct and examine two trading imbalance metrics from intraday tick data and investigate its relation with weekly returns of the Euro FX futures contracts trading on the CME. Standard regression analyses do not show any significant dynamic relation between return and trading imbalance, regardless of whether they are lagged, contemporaneous or lead. We also do not find significant return autocorrelation. The Euro FX futures market, on the surface, appears quite efficient at the weekly level. However, when analyses are focused on the extreme imbalance levels, we find weekly returns exhibit significant reversals following periods of extreme (negative) trade imbalance. Conversely, using discrete analyses, we find some evidence of residual momentum in consecutive weekly futures returns following periods of extreme (high) trade imbalance, a result that does not show up when we used standard regression analyses.

We then construct trading rules based on these findings and perform trading tests to see whether the found reversal and momentum effects are economically significant and whether futures return predictability can be improved if traders incorporate trading imbalance metrics (that are observable at the time of trading decision) into their information set. These trading test results show that investors who trade in accordance to trading rules based on these observable imbalance metrics can generate substantial positive profits over and above the corresponding risk-free rate even after accounting for transaction costs of trading. The results support the premise that the information contained in our imbalance metrics can be economically significant for traders in the real world.

As a robustness check of the economic significance of the trading test, we also compare the out-of-sample forecasts from the trading rule using directional accuracy (DA) tests, which are alternatives to trading tests for testing economic significance of forecasts. The results of DA test are consistent with and support the robustness of the trading test results, showing that the information contained in the analyzed imbalance metrics are economically significant and can predict cases of momentum and reversals in the Euro FX futures when applied at the extreme imbalance levels that satisfy the conditions of the proposed trading rule.

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Table 1: Statistics Description

The data used are Euro FX futures contracts trading in CME, spanning from December 17, 1999 to March 4, 2005. The data frequency is weekly. R_t is the futures return in week t. I_t^{num} is the trading imbalance metric based on the number of up (and down) ticks in the prescribed time interval. I_t^{volm} is the trading imbalance metric based on the volume of up (and down) ticks in the prescribed time interval. HI_t^{num} is the highest 10% of I^{num}; LI_t^{num} is the lowest 10% of I^{num}. HI_t^{volm} is the highest 10% of I^{volm}; LI_t^{volm} is the lowest 10% of I^{volm}.

Variables	Mean	Std. Dev.	Mini.	Maxi.	Autocorrelations(ρ)			No. of observations
					ρ_1	ρ_5	ρ_{10}	
R_t	0.0010	0.014	-0.043	0.049	-0.029	0.018	-0.023	272
I_t^{num}	-0.0062	0.035	-0.333	0.089	0.200	0.213	-0.020	
I_t^{volm}	-0.0023	0.066	-0.430	0.196	0.132	0.116	0.038	
HI_t^{num}	0.0040	0.013	0.023	0.089	0.139	0.154	0.015	
HI_t^{volm}	0.0107	0.033	0.062	0.191	0.059	0.119	0.154	
LI_t^{num}	-0.0078	0.030	-0.333	-0.035	0.249	0.116	0.061	
LI_t^{volm}	-0.0133	0.046	-0.430	-0.064	0.218	0.166	0.096	

Table 2: Relation of Euro FX Futures returns to trading imbalance metrics

Panel A: trade imbalance by tick number

$$R_t = \beta_0 + (\beta_1 + \beta_2 \cdot I_j^{num}) \cdot R_{t-1} + (\beta_3 + \beta_4 \cdot I_j^{num}) \cdot R_{t-1} \cdot DumI_t^{num} + \varepsilon_t$$

	Base	Lag (j=t-1)		Contemp. (j=t)		Lead (j=t+1)	
β_1	-0.029	-0.028	-0.087	-0.036	-0.039	-0.008	-0.036
	(-0.47)	(-0.53)	(-1.52)	(-0.71)	(-0.76)	(-0.07)	(-0.71)
β_2		0.247	4.110	-1.975	7.961	0.448	3.757
		(0.14)	(1.60)	(-0.65)	(1.62)	(0.22)	(1.46)
β_3			0.184		0.144		0.148
			(1.08)		(1.05)		()0.89
β_4			**-5.399****		**-12.712****		-5.533
			(-2.01)		**(-2.09)**		(-1.30)
R^2 (%)	0.08	0.09	2.23	0.35	2.82	0.05	1.62

Panel B: trade imbalance by tick volume

$$R_t = \beta_0 + (\beta_1 + \beta_2 \cdot I_j^{volm}) \cdot R_{t-1} + (\beta_3 + \beta_4 \cdot I_j^{volm}) \cdot R_{t-1} \cdot DumI_t^{volm} + \varepsilon_t$$

	Base	Lag (j=t-1)		Contemp. (j=t)		Lead (j=t+1)	
β_1	-0.029	-0.029	-0.090	-0.024	-0.075	-0.032	-0.078
	(-0.47)	(-0.57)	(-1.62)	(-0.46)	(-1.34)	(-0.61)	(-1.40)
β_2		0.325	1.655	-1.101	0.060	0.297	0.497
		(0.29)	(1.32)	(-0.83)	(0.04)	(0.40)	(0.41)
β_3			0.204		0.295		0.230
			(1.20)		(1.60)		(1.38)
β_4			**-2.476***		-2.871		-0.447
			(-1.82)		(-1.02)		(-0.30)
R^2 (%)	0.08	0.14	2.02	0.42	2.08	0.12	0.92

R_t is the futures return in week t; I_j is the trading imbalance metric in week j; j=t, t-1 or t+1 so that we may investigate contemporaneous, lagged, and lead associations; and the β's are the estimated coefficients. I_j^{num} denotes the trading imbalance metric based on the number of up (and down) ticks in the prescribed time interval. I_j^{volm} denotes the trading imbalance metric based on the volume of up (and down) ticks in the prescribed time interval. The dummy variable (Dum_I) in the regression captures periods of extreme trading imbalance. It is set equal to 1 when trading imbalances are at the highest 10% or lowest 10% levels and zero otherwise. Specifically, $Dum\_I_t^{num}$ is equal to 1 when I_t^{num} belongs to the highest 10% or lowest 10% group and zero otherwise. Likewise, $Dum\_I_t^{volm}$ is equal to 1 when I_t^{volm} belongs to the highest 10% or lowest 10% group and zero otherwise. The R^2 statistics are expressed in percentage.

**Statistically significant at the 5% significance level.

*Statistically significant at the 10% significance level.

Table 3: First-order autoregressive coefficient of Euro FX Futures returns during periods of extreme trading imbalance

Panel A: trade imbalance by tick number							
	Highest 10 % of I_j^{num}				Lowest 10% of I_j^{num}		
	Lag (j=t-1)	Contemp. (j=t)	Lead (j=t+1)		Lag (j=t-1)	Contemp. (j=t)	Lead (j=t+1)
AR(1)	0.082	0.105	0.074	AR(1)	**-0.405****	-0.09	-0.069
	(0.40)	(0.73)	(0.73)		**(-2.31)**	(-0.41)	(-0.51)
R^2 (%)	0.96	0.85	0.75	R^2 (%)	8.71	0.78	0.70
Panel B: trade imbalance by tick volume							
	Highest 10 % of I_j^{volm}				Lowest 10 % of I_j^{volm}		
AR(1)	0.043	-0.172	0.073	AR(1)	**-0.386****	-0.149	0.005
	(0.14)	(-0.84)	(0.38)		**(-2.24)**	(-0.76)	(0.06)
R^2 (%)	0.14	5.01	0.48	R^2 (%)	11.29	1.24	0.01

**Statistically significant at the 5% significance level.

Table 4: Discrete assessment of return momentum and reversals in Euro FX Futures returns under various return and imbalance conditions

Conditions	Mean of R_{t-1} (%)	Mean of R_t (%)	% of observations
Panel A: trading imbalance by tick number(I_{t-1}^{num})			
R_{t-1} <-2.0% and I_{t-1}^{num} >90% percentile	none	none	none
R_{t-1} <-2.0% and I_{t-1}^{num} <10% percentile	-2.92	+0.59	2.30%
R_{t-1} >+2.0% and I_{t-1}^{num} >90% percentile	+2.89	+0.28	3.38%
R_{t-1} >+2.0% and I_{t-1}^{num} <10% percentile	none	none	none
Unconditional mean of R_{t-1}	+0.10	+0.10	100%
Panel B: trading imbalance by tick volume(I_{t-1}^{volm})			
R_{t-1} <-2.0% and I_{t-1}^{volm} >90% percentile	none	none	none
R_{t-1} <-2.0% and I_{t-1}^{volm} <10% percentile	-3.05	+0.45	2.36%
R_{t-1} >+2.0% and I_{t-1}^{volm} >90% percentile	+2.26	+0.19	4.39%
R_{t-1} >+2.0% and I_{t-1}^{volm} <10% percentile	none	none	none
Unconditional mean of R_{t-1}	+0.10	+0.10	100%

Table 5: Average weekly trading returns from trading during periods of extreme imbalances and returns for various transaction costs

		Round-Trip Transaction Costs			
Trading strategy	**R_f**	**0%**	**0.02%**	**0.10%**	**0.20%**
Euro FX Futures	0.05068				
R_{t-1} <-2%, I_{t-1}^{num} <10%; buy and hold for one week		0.06929	0.06810	0.06336	0.05744
R_{t-1} >+2%, I_{t-1}^{num} >90%; buy and hold for one week					
R_{t-1} <-2%, I_{t-1}^{volm} <10%; buy and hold for one week		0.06440	0.06449	0.05936	0.05232
R_{t-1} >+2%, I_{t-1}^{volm} >90%; buy and hold for one week					

The following trading strategy is tested: when the observed imbalance metric is in the lowest 10 percentile and the return for the prior week is less than -2%, buy and hold for one week; when imbalance is in the highest 10 percentile (larger than 90 percentile) and the return for the prior week is larger than +2%, buy and hold for one week; other than for these two cases, we keep our money in the bank and earn the risk free rate of interest. The average weekly returns are presented in percentage. R_f denotes the average weekly risk free rates for the trading test period.

Table 6: Directional accuracy (DA) tests

	Trading strategy	
	R_{t-1} <-2%, I_{t-1}^{num} <10%; buy and hold for one week R_{t-1} >+2%, I_{t-1}^{num} >90%; buy and hold for one week	R_{t-1} <-2%, I_{t-1}^{volm} <10%; buy and hold for one week R_{t-1} >+2%, I_{t-1}^{volm} >90%; buy and hold for one week
Euro FX Futures	2.56***	2.43***

The table reports the DA statistics (Pesaran and Timmermann, 1992). The DA test follows the standard normal distribution. This test is based on the comparison of momentum or reversal in the forecast observation, $\hat{\Theta}_i$, with the momentum or reversal in the true withheld observation, Θ_i, for the observations (i =1,2,…..,m.) satisfying the conditions of the trading rule. In implementing the DA test, if you forecast reversal next week let $\hat{\Theta}_i$ be (-). If you forecast momentum next week let $\hat{\Theta}_i$ be (+). If there is an actual reversal next week, let Θ_i be (-). If there is actual momentum next week, let Θ_i be (+).

**Statistically significant at the 5% significance level.

***Statistically significant at the 1% significance level.