Do Individual Currency Traders Make Money?

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Abstract

Using a unique online currency transactions dataset, we examine the performance, trading activity, drawdown, and timing abilities of individual currency traders. Evidence from 428 accounts during the 2004-2009 period shows that currency traders earn positive abnormal returns, even after accounting for transaction costs. Additionally, the results reveal that day traders not only trade more frequently than non-day traders, but also outperform them in terms of raw, a passive benchmark and risk-adjusted returns. Finally, sorts on trade activity, measured as the mean number of trades per day per account, and account turnover, show a positive association between performance and trade activity.

Keywords: Individual currency traders, performance, trading activity, drawdowns, timing ability

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1. Introduction

Interest among individual investors in currency trading as an investment class has increased considerably over the past decade. This growing interest in foreign exchange market is due largely to the online trading by retail investors.[1] However, government regulators are greatly concerned that individual currency traders have been losing significant amounts of money (Commodities Futures Trading Commission (2010)). This concern arises because leverage at some currency brokers is as high as 400:1. Such leverage creates an environment where investors can gain, and lose, significant amounts of capital.

Previous research reveals that some professional currency managers are able to earn positive and significant alphas (Pojarliev and Levich (2008), (2010b), (2011)). Pojarliev and Levich (2008) examine the performance of currency hedge funds and find that such funds, on average, are unable to earn positive alphas, although approximately 24 percent of the currency managers have alpha generating skill. Addressing the question of how active professional currency managers should be evaluated, Melvin and Shand (2011) show that certain managers have timing and loss avoidance abilities.

To date, however, it is unknown whether individual currency traders are able to earn positive abnormal returns and whether they possess skill trading spot currencies. To the best of our knowledge, no empirical study has analyzed the performance and skill of individual currency traders. This is mainly due to the lack of individual currency trading data. The primary objective

[1] See, for example, Luke (2005), King and Rime (2010). The 2010 Triennial (http://www.bis.org/publ/rpfxf10t.htm) shows a 20% increase in foreign exchange market trading over the past three years with the average daily turnover reaching $4 trillion.

of this paper, then, is to address these issues by using online advisory service currency data which consist of spot currency transactions, net daily returns and gross daily returns. To gauge the performance of individual currency traders, we employ three performance metrics: raw returns, a passive benchmark model, and alpha from the four-factor currency model of Pojarliev and Levich (2010b). Furthermore, to assess the skill of individual currency traders we first examine individual transactions to find out whether their performance is driven by skill or by luck and then examine drawdown to detect whether individual currency traders possess skill at moderating losses. Our second inquiry of skill explores the ability of individual traders to time the Pojarliev and Levich (2010b) currency factors by following the Melvin and Shand (2011) timing approach.

The theoretical stream of behavioral finance reveals that individual equity investors tend to be overconfident, which can lead to excessive trading and underperformance (Odean (1999); Barber and Odean (2000), Barber, Lee, Liu, and Odean (2004), (2006)). On the other hand, studies by Jordan and Diltz (2003) and Garvey and Murphy (2005) examine the performance of high-frequency equity traders and show that investors can earn profits despite trading frequently. In the context of this study we also aim to shed light on this issue by analyzing the trading characteristics of high-frequency currency traders.

To investigate this issue we examine the performance of high-frequency currency traders (day traders) and non-day traders. We also examine performance based on trade activity proxied by the mean number of roundtrips per day and account turnover. This approach is taken because the psychological literature shows that overconfidence can increase or decrease over time, based upon the level of feedback received from trading (Russo and Shoemaker (1992); Skata (2008)). Feedback can decrease overconfidence and thus increase one's ability to determine probabilistic outcomes (Russo and Shoemaker (1992); Skata (2008)), implying a positive association between trading activity and performance. Finally, since it has been documented that equity traders tend to increase their trading activity by selling winners at a higher rate than losers in response to increased recent past performance (Barber and Odean (2000)), we examine the association between past performance and current trade activity to determine whether the disposition effect gains support in the context of currency markets.

Our analysis demonstrates that the average trader is able to earn positive and statistically significant net and gross returns when using raw returns and a passive benchmark model. Alphas from a four-factor currency model are also positive and significant when gross returns are used, but statistically insignificant when estimated using net returns (i.e., accounting for transactions costs). Overall, our results show that approximately 25 percent of individual currency traders realize abnormal returns, even when accounting for transaction costs.

The analysis of trading characteristics supports the contention that individual currency traders are well-calibrated, but any resulting benefit is eroded by transaction costs. More specifically, we find that day traders outperform non-day traders on a gross return basis, but the difference in net performance is insignificant. Additionally, sorting on trading activity, proxied by the mean number of roundtrip transactions per account per day, and on turnover the results show to be consistent with the prediction of the calibration hypothesis. Furthermore, we find a positive association between past trade activity and future performance suggesting that trade activity can predict future performance. Finally, we find a positive relation between current currency trade activity, proxied by the number of trades per day, and past return performance. This result supports the view that the traders in this sample are prone to the disposition effect.

Our analysis of trade activity, drawdown, and market timing suggests that the individual currency traders in this sample possess exceptional trading skills. We report 68.78 percent of trades executed by the top traders are profitable net of transaction costs and profits do not arise from chance. Furthermore, we find that the top quartile of traders earn a mean $248.31 USD per trade and this is reliably different from zero. Top traders have lower drawdown than worst performing traders, but the drawdown difference between the two groups of traders is not statistically significant. Finally, our results based on the Melvin and Shand (2011) timing model indicate that some traders in this sample have the ability to time the factors of the four-factor currency model. For example, 21.03 percent of the individual traders possess the skill to time the carry trade factor. These findings are consistent with our results of risk-adjusted returns that imply individual currency traders are skilled, that is, top traders are able to earn a positive and significant alpha of 0.59 percent per day.

This study contributes to the currency investing stream of the literature by revealing currency trading is very profitable for some individual investors, even after accounting for transaction costs. While individual currency traders are able to earn positive and significant risk adjusted returns, the top traders earn 0.59 percent per day which is economically significant. The ability of individual currency traders to earn positive alphas is consistent with studies that have examined professional currency traders which point out that some professional currency managers are able to earn positive abnormal returns (Pojarliev and Levich (2008)). Second, this paper contributes to the individual investor performance debate by documenting that not all retail traders are overconfident to the point where overconfidence reduces their performance: Some are well calibrated, which permits them to increase their trading activity and their performance on a gross basis. Third, this paper expands our understanding of the trading characteristics of individual currency traders by showing that some retail currency traders have skill at moderating drawdown and timing currency factors. Collectively, our results show that individual currency traders possess somewhat similar alpha generating abilities, and trading characteristics, as professional currency traders. Furthermore, these results help explain why currency investing has become popular amongst retail traders and should allay government concerns that spot currencies are unsuitable investments for individual investors.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the related literature and hypothesis development. Section 3 discusses the data. Section 4 discusses the methodology, and Section 5 reports the empirical results. Section 6 concludes.

2. Related Literature and Hypothesis Development

The use of currencies as an asset class has grown over the past decade, which in turn has led to research investigating the performance of professional currency managers (Pojarliev and Levich (2008), (2010a), (2010b), (2011); Melvin and Shand, (2011)). Pojarliev and Levich (2008) examine the returns of currency hedge funds and reveal that after accounting for fees and transaction costs the average currency manager earns -9 basis points per month. On the other hand, when examining individual currency managers they show that approximately 24 percent of managers can earn positive alpha. In 2010 the same authors examine professional currency traders in the Deutsche Bank FXSelect platform and find that, on average, currency managers are unable to generate alpha (Pojarliev and Levich (2010a)). However, in a follow-up study examining the same sample over a longer time period, the authors find persistence of alpha for the top and lowest performing professional currency managers (Pojarliev and Levich (2010b)). Melvin and Shand (2011) study the timing ability and drawdown of professional currency managers. They discover that managers who are able to time currency factors performed best during the financial crisis. They also find that managers have the ability to mitigate drawdown. Collectively, the literature on professional currency traders has shown that some managers possess skill trading currencies and are able to generate positive and significant alphas. However, a literature review illustrates that no study has examined the performance of individual currency traders. This study addresses this shortcoming by analyzing the returns of individual currency traders.

A review of the financial literature shows that most individual investors trade to their detriment. Studies examining buy-and-hold equity investors report a negative association between overconfidence, proxied by trading activity, and performance. Odean (1999), using a comprehensive data set, examines the performance of individual investors and finds that as they realize gains, overconfident traders overweight the strength of their private information leading to excessive trading and lower performance. Gervais and Odean (2001) expand this theory and determine, however, that overconfidence is greatest in the earliest part of a trader's career, decreasing with experience. Similar to Odean (1999), these authors predict increased trading activity reduces performance and infer these traders are overconfident.

Although many authors analyzing equity traders find empirical evidence to support the hypothesis that frequent trading reduces performance, numerous studies also show that high-frequency traders (day traders)—investors who open and close their positions within the same day―can generate profits. For example, Harris and Schultz (1998) analyze the day trading performance of Small Order Entry System bandits—individual day traders who trade frequently and hold positions for only a few minutes—and determine that they earn a small profit per trade. Jordan and Diltz (2003) examine a small sample of day traders and also find these traders can earn profits net of transaction costs, although small. Garvey and Murphy (2005) investigate the performance of equity day traders from a US direct access broker and discover that approximately 50 percent of the day trades in their sample were profitable, net of transaction costs.

Studies documenting the profits of high-frequency traders are not in line with the overconfidence models, in which frequent trading leads to suboptimal performance. Odean (1999) and Barber and Odean (2000) examine buy-and-hold investors, whose feedback is not as timely as that of high-frequency day traders. Psychology studies find that levels of overconfidence can increase or decrease over time, depending on the level of feedback received (Skata (2008)). Russo and Shoemaker (1992) show that, because they receive timely feedback, weather forecasters, racetrack bettors, and public accountants, for example, can correctly assess their abilities and are thus "well calibrated" and less overconfident. High-frequency traders are similar, in that they receive feedback on a frequent, daily basis, whereas buy-and-hold investors may not receive feedback for weeks or months. Consequently, this strand of the literature predicts that the degree of calibration will be greater for high-frequency traders, who should outperform their overconfident, less-calibrated, counterparts. We address the merits of this hypothesis in the context of the foreign exchange market by analyzing the performance of high frequency (day traders) currency traders and non-day traders.

3. Data

The primary data set for this research comprises account data from an online advisory service obtained from Collective2.com for individual retail spot currency traders (www.collective2.com). Based upon our research of the online advisory services industry, Collective2.com, founded in 2001, is one of the oldest and persistent platforms in the industry. Other platforms have been developed over the past decade but no longer exist, such as Rentasignal.com. The proprietary database used in this study is available upon request from the authors. We refer the reader to Fonda (2010) for a detailed discussion of this new industry.

Currency traders were selected for this study for numerous reasons. First, there is a dearth of research on individual currency traders. Our research reveals there are no published articles on individual currency traders other than Abbey and Doukas (2012). Second, Collective2.com is similar to industry brokers who segregate accounts and data by the type of financial instruments traded. For example, if one visits Collective2.com and searches for accounts they are divided into Forex, Futures, Stocks and Options. Individuals who subscribe to accounts to view trades can build portfolios by subscribing to multiple accounts, for example combing Forex, Futures, Stocks and Option accounts. This is common in the industry. Tradestation.com, one of the largest online brokers, requires accountholders to open separate accounts for Forex, Futures, and Equities. They cannot be traded from the same account. Third, combining Forex, Option, Equity and Futures traders in the same paper poses econometric issues. There are no established factor models for Futures and Options. Consequently, a comparison of risk-adjusted returns between all four financial instruments would not provide robust results. Fourth, our approach is similar to other authors, who may have for the sake of brevity, limited their analysis to one financial instrument type. For example, Barber and Odean (2000) focused solely on stocks in their study and did not analyze other financial instruments in their database. Finally, selecting only Forex accounts provides an unbiased sample of forex traders in this sample. If an individual traded any other instrument, including Equities, Options or Futures, as long as they have one Forex trade, it would be captured in our sample.

The sample consists of 428 accounts and 78,362 roundtrip transactions from March 2004 to September 2009. Our sample was selected from Collective2's database consisting of 9,282 registered accountholders which includes equity, future, option and forex traders and individuals who do not trade. Collective2's database contains all accounts that have been created since the inception of the firm and does not suffer from survivorship bias. The site also provides real time broker results identifying the broker the account holder trades with to verify trades are real. For the purposes of this study, we obtained 428 accounts by filtering accounts to those that exclusively trade forex, have at least 10 roundtrip transactions, and have at least 30 daily return observations.[2]

The 428 forex accounts are split into 263 day traders and 165 buy-and-hold traders (Panel A of Table 1). Day traders are defined as traders who, on average, hold their position open for less than 1,440 minutes (one day), and non-day traders are traders who, on average, hold their positions for more than 1,440 minutes (longer than one day). The data include the individual trader's name, a unique account identification number, a description of the account, when the position was opened and closed, the open and close prices, whether the position is short or long, the number of contracts opened and closed, and the net profit and loss (P/L) in US dollars. Unlike equity brokers, retail spot currency brokers do not charge a per-contract fee or per-trade commission on purchases and sales, and commissions consist of only the bid–ask spread. To account for the bid–ask spread, the net P/L is calculated for each trader account with 3 pips (1 pip equals 0.01 percent), or \$3.00, subtracted from each contract for each sale and purchase. Spreads on the major currencies are widely recognized to be between 2 and 3 pips (Archer (2008); Sether (2009)).

[2] When the authors collected this data account holders on this platform did not pay a fee for trading for the first 30 days and after the trial period a monthly fee was charged. It is also notable Collective2.com's subscriber policy has changed since it was founded in 2001. As of August 2014, one can open an account for free and after s/he executes 5 trades the individual pays a platform fee of \$120 every six months. Additionally, the 30 daily return observations were required to balance the need to have robust regression results without excessively truncating the sample size. For example, if we limit our sample to 80 daily return observations the sample will be reduced from 428 to 128 accounts which would not be large enough to generate meaningful results. The traders in this sample are not like professional forex traders or professional equity traders who have years of return rata and this is confirmed in Table 1 which shows the mean account age is 86.03 days.

****Insert Table 1 about here****

For each account, we estimate the mean daily turnover, mean number of trades per day, and transaction costs per contract. We calculate daily turnover as the daily margin-adjusted market value of all sales for each account, divided by the daily amount of capital for each account. The mean daily turnover in this study is 50.76 percent (Panel B of Table 1); that is, these traders turn over all of their capital approximately every two days.

We calculate trades per day as the mean number of roundtrip transactions executed by an account holder for one day. The mean number of trades per day is 3.31, above the median of 2.46, which reveals that the data are positively skewed (Panel B of Table 1). These data, along with the turnover data, show that the currency traders in this sample are very active.

We report transactions costs as the bid–ask spread for each transaction divided by the margin-adjusted capital required to open a trading position. The mean transaction cost is 0.89 percent (Panel B of Table 1), which is lower than the total commissions reported in previous equity analyses, as in Barber and Odean (2000), who report transaction costs of approximately 2 to 3 percent for equity traders. Transaction costs for currency traders are therefore low relative to those for equity traders.

Panel B of Table 1 shows that the mean trade size is $457,161.40 for the 77,666 transactions in the sample. Individuals are able to trade with a 33:1 margin which means they can trade $33 in currency with only $1 in their account. This level of margin is established by Collective2.com, which is their corporate policy, and common in the retail forex industry since the CFTC limits margin to 50:1. With a 33:1 margin, traders therefore require an average of only $13,853.37 in capital for each trade. The mean price per contract is $14,171.52.

The age of an account is calculated as the time, in calendar days, between the first and last trades recorded in the database. The mean account age in this sample is 86.03 calendar days, a very short life span. One explanation for the short lives of these accounts is the nature of the online currency trading industry: Investors can open and close an online account at any time, unlike professional funds, which must meet stringent listing criteria. Additionally, the low age of the accounts may be due to currency traders having few subscribers. The business model of the website requires individual investors pay a monthly subscription fee to view the trades posted by the currency traders' online trading platform. Discussions with currency traders reveal that individual investors primarily subscribe to the top performing online trading platforms with long and profitable track records. They also state it is difficult getting subscribers if a currency trader doesn't have a long history of superior performance. If a currency trader's online trading platform is not attracting subscribers they will close their account. Additionally, Collective2 conducted an interview, available on the website, with one top performing trading platform developer, Dr. René Koch. Dr. Koch has operated a trading platform on Collective2 for over two years and has generated over $425,000 dollars of subscription revenue in one year. This highlights how individual investor subscribers focus on top performing accounts with a long track record and reveals that this site is a legitimate business that attracts many individual investors. Finally, the age limitation is the primary reason why this study uses daily instead of weekly or monthly returns.

Panels C and D of Table 1 present the descriptive statistics for day and non-day traders, respectively, with the difference in means between the two groups reported in Panel E. The values for trade size, daily turnover, trades per day for day traders are all larger than for non-day traders. The differences in means reported in Panel E of Table 1 show that they are statistically significant for every variable except age. Day traders trade larger amounts per trade than non-day traders, turn over their capital more frequently, and trade more often per day than non-day traders.

4. Methodology

4.1 Return Performance

This analysis focuses primarily on the performance of currency traders, both gross and net of transaction costs. The first performance measurement is the raw daily return of each trader in the sample from 2004 through 2009. Daily returns are calculated as follows. First we calculate the daily profit and loss ($PL_{x,t}$) for each trader account x on day t. Daily $PL_{x,t}$ is defined as the dollar sum of all roundtrip transactions for transaction i, for trader x, on day t ($RT_{i,x,t}$) plus the dollar change in value of open positions for transaction i, for trader x, on day t ($OP_{i,x,t}$).

$$PL_{x,t} = \sum_{i=1}^{n} RT_{i,x,t} + \Sigma OP_{i,x,t} \quad (1)$$

We start by obtaining the daily closing spot currency price for currency pair *c* on day *t* ($CP_{c,t}$) for each currency pair from Tradestation[3] securities database. The daily closing spot price for all currency pairs is established by Tradestation and is the price of the currency pair at 4:00 p.m. eastern time.[4] Next we obtain the dollar sum of the round trip transactions for transaction *i*, for trader *x* on day *t* ($RT_{i,x,t}$), the purchase price of the contract for transaction *i*, for trader *x*, on day *t* ($PP_{i,x,t}$) and the selling price for transaction *i*, for trader *x*, on day *t* ($SP_{i,x,t}$) for every individual transaction from each trader account from the Collective2 database. Next, using these variables we use three similar formulas (2 and 3) to calculate the daily change in account capital for each currency trader account. First we calculate $OP_{x,t}$ which is the value of the open position for trader *x* on day *t* on the day the position is opened. The dollar change in open positions, as shown in (2), is defined as the difference ($CP_{c,t} - PP_{i,x,t}$) from in currency pair ($CP_{c,t}$) *c* for day *t* less the purchase price ($PP_{i,x,t}$) of the transaction, times the dollar sum of the round trip transaction ($RT_{i,x,t}$) for transaction *i*, for trader *x*, on day *t* divided by the difference between the purchase price ($PP_{i,x,t}$) of transaction *i*, for trader *x*, on day *t* less the selling price ($SP_{i,x,t}$) of transaction *i*, for trader *x*, on day *t*.

[3] TradeStation is an online financial brokerage services company which provides access to historical spot forex data. Additionally, Tradestation was awarded by Barron's magazine in 2014 for being the number one online broker. Tradestation data was used in this study due to their superior reputation in the industry and the lack of a standardized forex database, unlike equities, which have Compustat and CRSP.

[4] The open price is not equal to the close price of the last day. Currencies trade 24 hours a day. Using a time cut-off was required for regression analysis. This is similar, yet not identical to equities, where the open price is not the same as the closing price of the last day due to after-market activity. For example, the NASDAQ offers after hour quotes and extended trading activity data after the stock market closes for US and world markets.

$$OP_{x,t} = (CP_{c,t} - CP_{c,t-1})\left(\frac{RT_{i,x,t}}{PP_{i,x,t} - SP_{i,x,t}}\right) \qquad (2)$$

Second, we calculate $OP_{x,t}$ for each day after the position is opened and one day prior to the close of the position. The dollar change in open positions, as shown in (3), is defined as the change $(CP_{c,t} - CP_{c,t-1})$ in currency pair *c* for days *t* and *t-1* , respectively, times the dollar sum of the round trip transaction $(RT_{i,x,t})$ of transaction *i*, for trader *x*, on day *t* divided by the difference between the purchase price $(PP_{i,xt})$ of transaction *i*, for trader *x*, on day *t* less the selling price $(SP_{i,x,t})$ of transaction *i*, for trader *x*, on day *t.*

$$OP_{x,t} = (CP_{c,t} - CP_{c,t-1})\left(\frac{RT_{i,x,t}}{PP_{i,x,t} - SP_{i,x,t}}\right) \qquad (3)$$

Third we calculate $OP_{x,t}$ on the day the position is closed. The dollar change in open positions, as shown in (4), is defined as the difference $(SP_{i,x,t} - CP_{c,t-1})$ in the selling price of the transaction from currency pair *i* for trader *x*, on day *t* less the closing price for currency pair *c* for day *t-1* times the dollar sum of the round trip transaction $(RT_{i,x,t})$ of transaction *i*, for trader *x*, on day *t* divided by the difference between the purchase price $(PP_{i,x,t})$ of transaction *i*, for trader *x*, on day *t* less the selling price $(SP_{i,x,t})$ of transaction *i*, for trader *x*, on day *t*

$$OP_{x,t} = (SP_{i,x,t} - CP_{c,t-1})\left(\frac{RT_{i,x,t}}{PP_{i,x,t} - SP_{i,x,t}}\right) \qquad (4)$$

Fourth, we calculate daily account balances for each trader account beginning with the initial capital account balance which is provided in the Collective2 database. $PL_{x,t}$ defined in equation (1) is then summed for each day for each trader account and added to the starting capital amount for trader account *x* and then a time series of daily account balances are created for each trader *x* on day *t*. The daily gross returns for trader account *x* for day *t* ($R_{x,t}^{Gross}$) are equal to the difference between the end-of-day US dollar account balance (the amount of money in their account) for trader account *x* on day *t + 1* ($K_{x,t+1}$) and the starting dollar account balance, $\mathrm{K}_{\mathrm{x,t}}$ (the starting amount of money in their account) on day *t*. The starting account balance ($K_{x,t}$) when the trader opens their account was obtained from the database. The gross daily return for each currency trader is

$$R_{x,t}^{Gross} = \frac{K_{x,t+1}}{K_{x,t}} - 1 \tag{5}$$

In addition to daily gross raw returns, daily net raw returns ($\mathrm{R}_{\mathrm{x,t}}^{\mathrm{Net}}$) are calculated in a similar manner, where Σtc_i is the sum of transaction costs, calculated as \$3 US Dollar for each contract executed on day *t*:

$$R_{x,t}^{Net} = \frac{K_{x,t+1} - \Sigma \mathrm{tc}_{i,t}}{K_{x,t}} - 1 \tag{6}$$

We then aggregate returns into equally weighted portfolios and estimate their gross and net returns as

$$REW_t^{GROSS} = \frac{1}{n_{x,t}} \sum_{i=1}^{n} R_{x,t}^{GROSS} \quad \text{and} \quad REW_t^{NET} = \frac{1}{n_{x,t}} \sum_{i=1}^{n} R_{x,t}^{NET} \tag{7}$$

4.2 Risk-Adjusted Performance

This study uses two measures of risk-adjusted performance: (i) a passive benchmark model proxied by the Deutsch Bank Currency Return Index (DBCR), an investible index that consists of a basket of currencies and represents a passive strategy currency traders can utilize to manage their money and (ii) a slightly modified version of the four-factor currency model of Pojarliev and Levich (2010b).[5] While Pojarliev and Levich (2010b) use the AFX Index, as a proxy of the trend-following (momentum) factor, to perform tests based on monthly returns, daily returns for the AFX Index are not publically available for the purposes of the present study. Consequently, we employ the DB FX Momentum index to proxy the trend-following factor. The other factors used in the context of our analysis are the same as in Pojarliev and Levich (2010b). It is not uncommon to use different sources for currency factors. For example Pojarliev and Levich (2008) construct their factors using Citibank currency indices while Pojarliev and Levich (2010b) use factors from Deutsche Bank.[6] Advantages of using the DB FX Momentum factor in estimating adjusted-currency returns are that all four factors employed in our analysis come from the same source, Deutsche Bank's DBIQ database, and this dataset is publically available. Thus our empirical methodology is simple to replicate as it relies on data that can be easily accessed

[5] A similar currency factor model has been used before (Pojarliev and Levich (2010b), Melvin and Shand (2011) to analyze whether four well-known currency trading strategies can explain currency returns earned by professional currency managers.
[6] Melvin and Shand (2011), who examine currency performance benchmarks, conclude there are no generally accepted benchmarks for active currency managers.

and factors that have been used in previous studies addressing the performance of currency managers.

We calculate the mean daily index-adjusted abnormal return of each account by subtracting the return of the DBCR from the daily return earned by individual investors' equally weighted portfolios. Next, we define the modified four-factor model of Pojarliev and Levich (2010b), with a carry factor ($Carry_t$) measured by the Deutsche Bank (DB) G10 Currency Harvest, a momentum-following factor (Mom_t) measured by the DB FX Momentum, a value factor ($Value_t$) measured by the DB FX Purchasing Power Parity (PPP), and a volatility factor (Vol_t) measured by the DB FX Volatility Index. Carry trades consist of borrowing a currency with a low interest rate and investing in a high interest rate one;[7] momentum-following consists of following patterns or reversals;[8] value factors are used when traders seek to identify over- or undervalued currencies;[9] and volatility is used because currency traders have been found to trade on currency volatility.[10] Data for these factors are obtained from Deutsche Bank's publically available DBIQ database available at index.db.com/dbiqweb2.

[7] In a carry trade, the risk is that the high interest currency may depreciate, and probably more than the interest rate differential;

[8] The risk in momentum-following strategy arises mostly from sudden reversals, trading on false signals and excessive trading costs

[9] The risk of the value strategy is rooted in the misalignment of the purchasing power parity (PPP). That is, exchange rates will be slow to revert towards PPP.

[10] The risk of this strategy emerges when traders take open currency positions. That is, when they are long (short) volatility when volatility declines (increases).

We then estimate alpha, the portion of return that is not explained by the systematic components of currency returns (betas),[11] by regressing the daily gross and net returns, respectively, earned by individual currency traders on the four factors:

$$(REW_t^{Gross/Net} - R_{ft} = \alpha + \beta_{1i}Carry_t + \beta_{2i}Mom_t + \beta_{3i}Value_t + \beta_{4i}Vol_t + \varepsilon_t \qquad (8)$$

where excess returns are the daily returns of an equally weighted portfolio on day *t* less the daily returns on the one-month London Interbank Offered Rate $(REW_t^{Gross/Net} - R_{ft})$ and the coefficient β measures the sensitivity of currency traders' returns to the four factors.

5. Results

5.1 Full-Sample Results

The performance of currency traders is examined with the full-sample results of equally weighted portfolios, using the three measures of performance—raw returns, a passive benchmark model, and four-factor alphas—for all data from March 2004 through September 2009.[12] Panel A of Table 2 presents these results on both a gross and a net basis. Traders earn positive and significant gross returns across all three performance measures. The average account earns a raw

[11] We should note here that unlike the equity market where the popular concept of market portfolio exists, a similar benchmark that can be applied in the currency market does not exist (Melvin and Shand (2011)). Pojarliev and Levich (2010b), however, suggest that only returns beyond those explained by the factors of carry, momentum, value, and volatility should be considered as a measure of skill (alpha).

[12] An analysis of value-weighted portfolios is also performed and the results are provided in Table 2a in the online appendix. The returns of the value-weighted portfolios were slightly larger than the equally-weighted portfolios. These results suggest large volume traders increase return performance and may outperform small volume traders. These results, along with additional robustness checks beginning with section 5.7, are available at the author's website (http://efmaefm.org/0DOUKAS/publications/pdf/DoCurrencyTradersMakeMoney_Appendix.pdf).
Additionally, the online appendix analyzes the following: (1) a second data set of retail forex traders returns obtained from ZipSignals.com in Section 5.7; (2) skill measured by the percentage of winning trades, the economic significance of profits, drawdown and timing ability of Collective2.com retail forex traders in Section 5.8.

gross return of 0.51 percent per day that is statistically significant (t-statistic = 9.25). The results for the DBCR passive benchmark strategy are similar, at 0.50 percent per day, and also statistically significant (t-statistic = 8.88). The four-factor alpha is much lower, at 0.39 percent, and reliably different from zero (t-statistic = 7.15). On average, currency traders can earn sizable profits before transaction costs.

After commissions, however, the results change: Raw returns and passive benchmark returns are 0.17 percent and 0.16 percent per day, respectively, both significantly different from zero. Conversely, after adjusting for the risk factors of the four-factor model, currency traders earn a positive daily net return of 0.05 percent that is statistically insignificant (t-statistic = 0.91). These results indicate a substantial decrease in performance when transaction costs are taken into account regardless of performance measure used.

Pojarliev and Levich (2008) provide similar results for currency hedge funds when accounting for the same risk factors. They report an average excess return in the Barclays Currency Traders Index earned 25 excess basis points per month between 1990 and 2006. When Pojarliev and Levich (2008) account for the four factors, risk-adjusted excess returns become negative (-9 basis points per month) and insignificant. Their results are similar to ours, in that the average currency trader is unable to earn statistically significant alpha.

****Insert Table 2 about here****

Previous studies have examined the returns of currency traders and find significant variations in the cross section of returns (Pojarliev and Levich (2008), (2010a), (2011)). To gain further insight into the performance of these traders, a cross-sectional analysis of performance is undertaken.

We proceed as follows. Returns are examined on quartiles sorted on performance and ranked by the statistical significance of alpha, the intercept from the four-factor currency model. Ranks on passive benchmark returns provide quantitatively similar results. Panel B of Table 2 presents results based on the three performance measures—raw returns, the passive benchmark model, and alpha from the four-factor currency model. Each quartile contains 107 accounts, with quartile 1 (Q1) containing the top performers and quartile 4 (Q4) containing the worst.

The results in Panel B of Table 2 reveal significant cross-sectional variation in returns. The top quartile of traders, Q1, earns a gross daily raw return of 1.04 percent per day (t-statistic = 15.25), and Q2 and Q3 also earn positive daily gross raw returns of 0.77 percent (t-statistic = 7.02) and 0.4 percent, respectively (t-statistic = 3.59). However, performance is negative in the worst-performing group, Q4, which earns a -0.25 percent raw gross return per day (t-statistic = -3.38). The gross return results remain similar for the passive benchmark strategy and alpha from the four-factor currency model. Overall, the results suggest that, on average, the majority of currency traders earn positive returns on a raw, passive benchmark and risk-adjusted basis, and the results are statistically significant.

Although the gross performance results demonstrate that currency traders in this sample are able to earn positive returns, the results show that transaction costs significantly reduce performance. All three performance measures indicate that the top 107 traders in Q1 earn positive and statistically significant returns, with net raw returns, passive benchmark returns, and alpha of 0.71 percent, 0.70 percent, and 0.59 percent per day, respectively, all statistically significant. Currency traders in Q2 earn a statistically significant positive net raw return of 0.28 percent (t-statistic = 3.12) and a net DBCR passive benchmark return of 0.27 percent (t-statistic = 2.98); the four-factor alpha is positive at 0.17 and significant at the 10 percent level of confidence (t-statistic = 1.88). Finally, the returns of the worst-performing traders in Q4 reveal that they all earn negative returns, and these results are statistically significant. The bottom quartile reports a net raw return of -0.57 percent (t-statistic = -6.66), a passive benchmark return of -0.58 percent (t-statistic = -6.71), and a four-factor alpha of -0.69 percent (t-statistic = -7.97).

The cross-sectional results of the individual currency traders are somewhat similar to those of the professional currency managers analyzed by Pojarliev and Levich (2008), but there are sizable differences in performance. In their analysis of currency hedge funds, Pojarliev and Levich (2008) find that approximately 24 percent of professional currency managers are able to earn positive and significant alpha, even though the average manager cannot beat the benchmark. In this paper, 107 out of 428 individual currency traders, or 25 percent, are able to beat the benchmark and earn 0.59 percent in risk-adjusted excess returns *per day* (approximately 11.80 percent per month, assuming 20 trading days per month). The average of the top professional currency traders in Pojarliev and Levich (2008) earned 104 basis points per month (1.04 percent per month). The difference in performance between professional and individual currency traders is remarkable and may be explained by the differential amount of leverage employed by the two types of currency traders. Pojarliev and Levich (2011) note that leverage for currency hedge funds varies and may be as high as 10:1 while the currency traders in this sample are leveraged 33:1. Increased leverage will magnify gains and losses. Individual currency traders have a monthly return that is approximately 10.76 percent more than the professional currency traders analyzed by Pojarliev and Levich (2008). This return difference may arise from individual currency traders' significantly higher margin than that of professional currency hedge funds, perhaps by a magnitude over 10.

It is very important to take into consideration transaction costs when measuring the performance of currency traders. As shown in Table 1, the total transaction costs consist of only the bid–ask spread, which represents approximately 0.89 percent of the cost of a transaction, but, as shown in Table 2, transaction costs can significantly reduce performance. A remarkable result of our study is that, even after accounting for transaction costs, 25 percent of individual currency traders still earn positive alpha. It is also worth noting that the top individual currency traders in this sample outperform the currency hedge fund managers analyzed by Pojarliev and Levich (2008) by approximately 11.35 percent per month on a risk-adjusted basis. This implies that top-performing individual currency traders may use strategies similar with those used by professional currency hedge fund managers. To the extent that the foreign exchange markets have become more efficient over the years, as Neely, Weller and Ulrich (2009) claim and as a result more complex trading strategies may be needed to produce trading profits, our results also imply that the top quartile of traders may be using advanced trading strategies that earn positive and significant alpha.

5.2 Day Traders Versus Non-Day Traders

After dividing the sample into day traders and non-day traders, we calculate for each account holder both the net and gross returns and compute the raw, passive benchmark, and four-factor alpha for both day traders and non-day traders. Finally, we calculate t-statistics to determine the significance of the differences between day traders and non-day traders.

Panels A and B of Table 3 present the results for the three performance measures for both day traders and non-day traders. Day traders earn a raw gross (net) return of 0.071 (0.26) percent per day that is statistically significant (t-statistic = 11.05 and 2.17). The results are similar for the DBCR passive benchmark model. Individual currency traders beat the DBCR and still earn a positive and statistically gross (net) return of 0.70 (0.26) percent per day. The four-factor alpha for day traders is positive for both gross (0.59 percent) and net (0.15 percent) daily returns, but this is not different from zero once transactions costs are taken into account (t-statistic = 1.19).

The results for non-day traders in Panel B of Table 3 reveal a similar pattern for gross performance measures, but none of the results are statistically significant on a net basis. Non-day traders earn a gross raw daily return of 0.40 percent (t-statistic = 6.28). The raw net return is much lower, at 0.11 percent, and not significant (t-statistic = 1.61). The same pattern emerges for the DBCR passive benchmark model. The gross daily return on the passive benchmark strategy for buy-and-hold currency traders is 0.70 percent (t-statistic = 10.8), reduced to 0.26 percent per day on a net basis (t-statistic = 0.26).

****Insert Table 3 about here****

The mean differences between day traders and non-day traders are reported in Panel C of Table 3. Comparing the results of the day traders in Panel A and the non-day traders in Panel B shows that currency day traders, as a group, are able to earn larger returns based on all three performance measures than non-day traders. Day traders' gross returns exceed non-day traders' returns by 0.31 percent for raw returns (t-statistic = 3.44), 0.32 percent for the passive benchmark (t-statistic = 3.44), and 0.31 percent for alpha (t-statistic = 8.81), with all three differences being statistically significant. These differences remain positive when accounting for transactions costs, but the results become statistically insignificant. Day trader net returns exceed non-day trader returns by 0.15 percent for raw returns (t-statistic = 1.25), 0.16 percent for the passive benchmark (t-statistic = 1.23), and 0.16 percent for alpha (t-statistic = 0.63).

The gross return results are consistent with the calibration hypothesis, which predicts that frequent traders, who receive more timely feedback, will outperform traders that trade less frequently as higher degree of calibration tends to improve performance by decreasing overconfidence. However, when transaction costs are accounted for, while day traders still outperform non-day traders, their performance difference is no longer significant. This finding suggests that, in the context of currency trading, a higher degree of calibration can improve gross performance, but transaction costs erode any resulting benefits.

5.3 Trading Activity Proxied by Turnover

We next examine accounts sorted on turnover to test the sensitivity of our results. Previous studies analyzing the performance of long-term investors in equities have used turnover as a proxy for trading activity, finding a negative association between trading activity and performance (Odean (1999); Barber and Odean (2000)). In this paper, we calculate turnover as the mean margin-adjusted market value of all contracts closed per day, divided by the amount of capital in the account that day. Turnover is calculated for each account, and the accounts placed in quartiles, with quartile 1 (Q1) containing accounts with the highest turnover and quartile 4 (Q4) containing those with the lowest turnover. Each quartile contains 107 accounts.

Table 4 presents the results of our performance measures for both gross and net returns. The gross returns results reveal the same pattern for day traders as for non-day traders: The lowest-turnover group, Q4, with a turnover of 9.6 percent per day, has the lowest returns, which increase monotonous to the top quartile Q1, where turnover is a sizeable 146.96 percent per day. All three performance measures follow this monotonous pattern. Regarding raw returns, we find that the least active traders earn a statistically significant (t-statistic = 4.52) 0.22 percent per day, which increases to 0.90 percent per day for the most active quartile of traders, in Q1. Similar results are shown for the passive benchmark strategy and the four-factor alpha. Overall, the evidence supports that currency traders in this sample are highly calibrated.

However, the evidence also indicates that transaction costs render performance insignificant for the most active traders in this sample. Net raw returns are 0.18 percent (t-statistic = 0.81), the passive benchmark net returns are 0.017 percent (t-statistic = 0.77), and alpha is 0.07 percent (t-statistic = 0.30), and all are insignificant for the most active traders in Q1. The monotonous pattern observed with gross returns, where the least active traders have the lowest returns and the most active traders have the highest (across all three performance metrics), is not present. When accounting for transaction costs, net raw, benchmark, and alpha increase from Q4 (the least active traders) to Q2, yet Q1 returns for all three performance metrics are lower than Q2 returns. The difference in means between Q1 and Q2 is insignificant (t-statistic=0.89), which reveals that, even after accounting for transaction costs, there is no difference between the most active traders, in Q1, and the second most active traders, in Q2.

****Insert Table 4 about here****

Overall, the results of gross and net performance with sorts on turnover are similar to those for the analysis of day traders and non-day traders in Table 3. The calibration hypothesis is supported by gross return measures, yet any performance increase is rendered statistically insignificant after taking transactions costs into consideration. In summary, the turnover results reveal that the performance differences between quartiles are economically and statistically significant for gross returns, but insignificant for net returns. Increased trading thus reduces performance, but not to the extent where investors recognize a loss. This result differs from that of Odean (1999), who analyzes individual equity traders and reports that their annual return was approximately 6.5 percent lower than the return on the market. The results here show that, although transaction costs arising from high-frequency trading erode performance, 75 percent of the traders, when sorted on turnover, are able to beat the DBCR. Furthermore, 25 percent of the traders in the second most active quartile are able to earn positive and significant risk-adjusted excess returns. Overall, these findings demonstrate that, unlike the equity traders analyzed by

Odean (1999), many high-frequency currency traders can beat the benchmark, even after accounting for transaction costs.

5.4 Trading Activity Measured by the Mean Number of Trades per Day

We examine the sensitivity of our turnover results in an alternative specification, by sorting accounts on trading activity proxied by the mean number of roundtrip transactions executed by each account holder per day. As before, each quartile contains 107 accounts. If the results from our previous analysis hold, we expect the most active traders, ranked by mean trades per day, to perform better than less active traders.

Table 5 reports the gross performance results and reveals a monotonous association between performance and trade activity, a pattern also observed for gross returns when sorted on turnover (Table 4). The least active traders execute 1.42 trades per day, on average, with the lowest performance earning 0.39 percent for raw returns, 0.38 percent for the passive benchmark strategy, and 0.26 percent in alpha. Even for the least active traders, all the gross returns are statistically significant. Another remarkable observation is that returns increase across all performance measures as trade frequency increases. Raw returns increase from 0.39 percent for the least active traders in Q4 to 0.83 percent in Q1 for the most active traders. This pattern is also present for the passive benchmark and four-factor alpha performance measures. Similar to the results for turnover presented in Table 4, the gross results imply a positive association between feedback, proxied by the mean number of trades per day, and performance. Since traders receive positive (negative) feedback via winning (losing) trades, trade activity increases (decreases), which leads to improved (lowered) performance.

****Insert Table 5 about here****

The net performance results, however, differ from the gross performance results. After accounting for transaction costs, the most active traders in Q1, who trade on average 6.64 times per day, perform better across all three performance measures than all other quartiles of traders. The net raw returns for the top quartile, Q1, are 0.49 percent per day and statistically significant, exceeding the least active quartile, Q1, by 0.34 percent per day, although this difference is not significant. Currency traders in Q1 outperform the least active traders in Q4 by 0.24 percent for raw returns, 0.33 percent for the passive benchmark, and 0.035 percent for alpha, but these are all statistically insignificant and show that there is no benefit to increased trading, after accounting for transactions costs.

Overall, the gross return results support the calibration hypothesis, while the net return results show that being well calibrated does not result in increased performance. These results reflect the day trader/non-day trader distinction reported in Table 3 and sorts on turnover results presented in Table 4 above. Traders who trade the most, outperform the least active traders in terms of both gross and net returns, but only the difference in gross returns is significant. This implies there is limited benefit in being calibrated within the context of individual high-frequency currency traders. As currency traders increase (decrease) their trading activity, their performance increases (decreases), implying that feedback does play a role in currency trading, although transaction costs cancel out the bulk of its benefits. It is important to note that even though transaction costs erode performance, a sizable percentage of high-frequency traders are still able to earn positive and significant benchmark-adjusted returns and alpha. This finding does not appear to be consistent with previous studies of equity traders, which show increased trading results in underperformance relative to the benchmark index (Odean (1999); Barber and Odean (2000)).

5.5 Prior trade activity and future performance

While the previous analysis established the association between contemporaneous trading activity and performance, it remains unknown whether increased past trading activity is a predictor of higher future returns. To shed additional light on the merits of the calibration hypothesis which predicts that frequent traders, who receive more timely feedback, will outperform traders that trade less frequently, we next examine the relation between previous trade activity and future performance. To perform this test, we proceed as follows. First, the data for each account are divided into two time periods, $t - n$ to $t - 1$ (the first time period) and t to $t + n$ (the second time period), where n is the age of the account in days which varies by account. Second, we estimate trade activity proxied by the mean number of trades per day for the first time period. Third, we estimate our performance measures for the second time period. Fourth, we divide accounts into quartiles with Q1 containing the most active traders and Q4 containing the least active traders. Sorts on turnover provide similar results. If previous trade activity is positively associated with future performance the most active traders in Q1 should have the best performance during the second time period.

Table 6 reports the gross performance results and reveals a monotonous association between future performance and previous trade activity. The most active traders in Q1 have on average 10.07 trades per day and are also the top performers based on all three performance measures, raw returns, the passive benchmark, and four factor alpha. Q1 traders earn a gross (net) alpha of 0.4194 (.0241) percent per day. A monotonous pattern exists for both gross and net returns with Q4 traders earning negative returns on both a gross and net basis. Overall, these results show that past trade activity is positively associated with future performance. This demonstrates that higher trading activity is a predictor of higher returns. Furthermore, these results are consistent with the calibration hypothesis, which predicts that frequent traders, who receive more timely feedback, will outperform traders that trade less frequently as higher degree of calibration tends to improve performance.

*****Insert Table 6 about here******

5.6 Previous Performance and Trade Activity

We next test the sensitivity of our results by examining whether there is a positive association between trade activity and prior performance by analyzing the relation between turnover and trades per day with past return performance. This analysis is motivated by previous research that shows that individual investors are susceptible to the disposition effect where investors tend to sell more quickly after realizing gains than losses (Barber and Odean (2000)). Our previous analysis has shown that trade activity is positively associated with performance yet the disposition effect could be driving the results. Traders who close their winning positions more frequently may have increased trading activity, which in turn could lead to increased performance. Consequently, if the disposition effect is a factor then it is predicted that prior performance (gains) will be positively associated with current trade activity.

To test whether traders who have had strong recent returns trade more often we proceed as follows. First, we sum the number of trades ($Trades_{it}$) and calculate turnover ($Turnover_{it}$) for each day *t* for all 428 accounts i. Second we calculate the magnitude of the prior performance PP_i (equation 9) by dividing the *t-1* return for account *i* ($R_{i,t-1}$) relative to the average of days *t-2* to *t-4* returns ($\sum_{i=1}^{n=3}\frac{R_i}{3}$).

$$PP_i = \frac{R_{i,t-1}}{\sum_{i=1}^{n=3}\frac{R_i}{3}} \tag{9}$$

Third, we estimate equations 10 and 11 for each account by regressing the magnitude of pervious performance (PP_i) on $Trades_{i,t}$ (equation 10), and on turnover $Turnover_{i,t}$ (equation 11) which provides with 428 individual observations for β.

$$Trades_{i,t} = \alpha + \beta_{1i}PP_i + \varepsilon_t \tag{10}$$

$$Turnover_{i,t} = \alpha + \beta_{1i}PP_i + \varepsilon_t \tag{11}$$

Fourth, similar to our previous analysis, we rank accounts by performance, measured by the significance of alpha from the four-factor currency model, and then place them in quartiles with quartile 1 containing the top performers and Q4 containing the worst performers. If the disposition effect is present, traders are expected to increase their trading activity subsequent to previous positive performance, the coefficient β is anticipated to be positive and statistically significant.

Table 7 reports the mean of the coefficients and t-statistics from equations 10 and 11 for each quartile. Panel A shows the results of equation 10 with $Trades_{i,t}$ as the independent variable and Panel B displays the results of equation 11 with $Turnover_{i,t}$ as the independent variable. Panel A reveals that all of coefficients are positive and statistically significant. Specifically, the coefficient for previous performance for the top performers (Q1) is 3.18 and statistically significant (t-statistic=13.41). It is interesting to note that there is a monotonous pattern moving from the top performers (Q1) to the worst performers (Q4). Although all coefficients are significant, their magnitude and significance decreases with Q4 being 1.31 and significant (t-statistic=6.01). This pattern seems to suggest that currency traders are disposition prone as they tend to sell winning trades at a faster rate resulting in increased trading activity. Interestingly, this is shown to be more pronounced for the top performers.

****Insert Table 7 about here****

The results in Panel B, where $Turnover_{it}$ as the dependent variable, also exhibit a monotonous pattern yet none of the coefficients for prior performance are significant. Furthermore, the signs of the coefficients change with the top performers' past performance being positively linked to turnover with a coefficient of 0.12 (t-statistic=1.24) yet the association becomes negative for quartiles 2 (coefficient= -0.34 and t-statistic= -0.63) through 4 (coefficient= -4.11 and t-statistic= -1.07). One possible explanation for the difference between the results in Panel A and Panel B is that turnover may not be a suitable proxy for trade activity in this context because of the leverage used by currency traders. In summary, the results of past performance on trade activity show that the disposition effect is another reason that may be causing the positive association between past performance and trade activity.

6. Conclusion

Using a unique online individual currency transactions dataset, we study the performance and skill characteristics of currency traders. Specifically, we examine the performance, trading activity, drawdown, and timing abilities of individual currency traders. We draw performance inferences from the analysis of daily raw returns, returns in excess of a passive benchmark model (Deutsch Bank Currency Return Index (DBCR)), and alpha from a four-factor currency model, as well as the cross section of returns by sorting on performance. Our results show that individual currency traders are able to earn positive and statistically significant raw, benchmark-adjusted, and alpha returns. Furthermore, we find notable differences in the cross section: Approximately 50 percent of traders are able to earn positive and statistically significant benchmark-adjusted returns, and 25 percent earn statistically significant alphas.

These results reveal that retail forex traders outperform professional forex traders, however, one possible explanation for this is that they are willing to assume much more risk than professional traders. For example, Pojarliev and Levich (2011) state that leverage for currency hedge funds may be as high as 10:1 while the currency traders in this sample are leveraged 33:1. Consequently, the performance of the top performing retail forex traders is magnified by the greater level of margin they utilize. Although our results show that the top performing retail forex traders outperform professional forex traders, Table 2 reveals the worst performing retail forex traders lose significant amounts of money. Overall, these results may be indicative that retail forex traders may be gambling rather than making informed investing decisions.

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Table 1. Descriptive Statistics of Account Holders, Trade Activity, and Returns

This table reports summary statistics for 428 individual currency traders at a proprietary online advisory service from March 2004 to September 2009. Daily turnover is calculated as the market value of all sales for account *i* on day *t* divided by the amount of capital in that account on that day. Trades per day for each account are calculated by dividing the total number of trades executed by account *i* over its account life, divided by the life of account *i* measured in days. Transaction costs are calculated as 3 pips ($3) per contract for each opened and closed transaction, divided by the margin-adjusted amount of capital needed to open a position. Age is calculated as the time between the first and last trades recorded in the database. The margin used by traders in this sample is 33:1. The t-statistics are in parentheses and significant values are bold; ** denotes statistical significance at the 1% level.

A. Summary Data for Account Holders

	Total Accounts	Day Traders	Non-Day Traders
Accounts	428	263	165

B. Full-Sample Summary Data for Trading Activity Characteristics

Item	Mean	25th Percentile	Median	75th Percentile	Obs.
Trade Size ($)	457,161.40	56,662.20	177,523.65	498,750.00	77,666
Price/Contract ($)	14,171.62	9,989.90	13,422.00	15,997.31	77,666
Daily Turnover (%)	50.76	15.89	33.78	62.25	33,952
Trades per Day	3.31	1.76	2.46	3.71	77,666
Transaction Costs (%)	0.89	0.08	0.22	0.70	77,666
Age (days)	81.92	43.00	64.50	96.00	428

C. Summary Data for Day Traders

Item	Mean	25th Percentile	Median	75th Percentile	Obs.
Trade Size ($)	480,690.45	39,572.00	172,832.13	438,088.00	42,442
Price/Contract ($)	14,311.38	9,993.80	13,576.78	15,896.96	42,442
Daily Turnover (%)	66.46	25.74	41.31	79.16	13,963
Trades per Day	3.68	1.79	2.66	4.53	42,442
Age (days)	78.77	40.00	61.00	91.00	263

Table 1. Descriptive Statistics of Account Holders, Trade Activity, and Returns (continued)

D. Summary Data for Non-Day Traders

Item	Mean	25th Percentile	Median	75th Percentile	Obs.
Trade Size ($)	429,549.72	79,837.20	180,145.13	500,664.47	35,328
Price/Contract ($)	14,003.74	9,985.26	13,212.50	16,245.24	35,328
Daily Turnover (%)	39.79	11.43	26.71	44.91	19,989
Trades per Day	3.08	1.75	2.39	3.48	35,328
Age (days)	86.03	49.00	66.00	100.00	165

E. Difference in Means Between Day Traders and Non-Day Traders

Item	Trade Size ($)	Daily Turnover (%)	Trades per Day	Age (days)
Difference in Means	51,140.73	26.68	0.60	-9.00
	(5.38)**	**(36.68)****	**(2.03)****	(-1.23)

Table 2. Full-Sample Results of the Daily Abnormal Return Measures for All Individual Currency Trader Accounts, 2004–2009

This table reports performance results for 428 individual currency traders at a proprietary online advisory service from March 2004 through September 2009. Performance measures are computed from daily gross and net returns, which are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Net returns account for a 3-pip ($3.00) transaction cost applied to each round trip transaction. Panel A presents results for the gross (net) return on equally weighted portfolios. Raw returns are calculated as the daily returns earned in aggregate by the account holders. Passive benchmark returns are calculated by subtracting the daily return of the DBCR from the daily raw return. The four-factor alpha is the intercept from the four-factor currency model of Pojarliev and Levich (2010b), where the excess equally weighted portfolio returns is regressed on four factors that mimic strategies used by professional currency traders: carry trade, momentum, PPP, and volatility. Excess returns are calculated by subtracting the daily LIBOR rates from the equally weighted portfolio return. Panel B sorts the account holders into performance quartiles. Ranks are calculated by four-factor alpha t-statistic rankings, with the top-performing accounts (with the highest alpha t-statistic) in quartile 1 and the lowest-performing currency traders in quartile 4. The t-statistics are in parentheses and significant values are bold; ** and * denote statistical significance at the 1% and 5% levels, respectively.

	Gross Returns			Net Returns		
	Raw Returns	Passive Benchmark	Four-Factor Alpha	Raw Returns	Passive Benchmark	Four-Factor Alpha
Panel A. Full-Sample Equal-Weighted Portfolio Performance Results						
	0.51	0.50	0.39	0.17	0.16	0.05
	(9.25)**	**(8.88)****	**(7.15)****	**(2.74)****	**(2.54)****	0.91
Panel B. Full-Sample Equal-Weighted Portfolio Results Sorted on Performance						
Q1 (Top performers)	1.04	1.03	0.91	0.71	0.7	0.59
	(15.25)**	**(14.8)****	**(13.41)****	**(5.84)****	**(5.71)****	**(4.86)****
Q2	0.77	0.76	0.65	0.28	0.27	0.17
	(7.02)**	**(6.89)****	**(5.97)****	**(3.12)****	**(2.98)****	(1.88)
Q3	0.40	0.40	0.27	0.04	0.03	-0.09
	(3.59)**	**(3.51)****	**(2.39)****	(0.32)	(0.27)	(-0.68)
Q4 (Worst performers)	-0.25	-0.26	-0.36	-0.57	-0.58	-0.69
	(-3.38)**	**(-3.46)****	**(-4.92)****	**(-6.66)****	**(-6.71)****	**(-7.97)****
Panel C. Difference in Means Between Q1 and Q4						
Q1 – Q4	1.29	1.29	1.27	1.28	1.28	1.28
	(8.63)**	**(12.53)****	**(15.55)****	**(8.71)****	**(8.63)****	**(6.82)****

Table 3. Daily Abnormal Return Measures for Day Traders and Non-Day Traders, 2004–2009

This table reports performance results for 428 individual investor currency traders at a proprietary online advisory service from March 2004 through September 2009, dividing the sample into day traders and non-day traders. Panel A contains performance results for day traders, defined as currency traders who, on average, open and close their trades within one trading day. Panel B contains performance results for buy-and-hold investors, defined as currency traders who, on average, open and close their trades for longer than one trading day. Daily gross and net returns are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Net returns account for a 3-pip ($3.00) transaction cost applied to each round trip transaction. Raw returns are calculated as the daily returns earned in aggregate by the account holders. Passive benchmark returns are calculated by subtracting the daily return of the DBCR from the daily raw return. The four-factor alpha is the intercept from the four-factor currency model of Pojarliev and Levich (2010b), where the excess equally weighted portfolio returns are regressed on four factors that mimic strategies used by professional currency traders: carry trade, momentum, PPP, and volatility. Excess returns are calculated by subtracting the daily LIBOR rates from the equally weighted portfolio returns. The t-statistics are in parentheses and significant values are bold; ** and * denote statistical significance at the 1% and 5% levels, respectively.

Gross Returns			Net Returns		
Raw Returns	Passive Benchmark	Four-Factor Alpha	Raw Returns	Passive Benchmark	Four-Factor Alpha
Panel A. Day Trader Equal-Weighted Portfolio Performance Results					
0.71	0.7039	0.59	0.26	0.26	0.15
(11.05)**	**(10.8)****	**(9.11)****	**(2.17)****	**(2.08)****	(1.19)
Panel B. Non-Day Traders Equal-Weighted Portfolio Performance Results					
0.40	0.3894	0.28	0.11	0.10	-0.01
(6.28)**	**(6.01)****	**(4.41)****	(1.80)	(1.61)	(-0.24)
Panel C. Difference in Means Between Day Traders and Non-Day Traders					
0.31	0.32	0.31	0.15	0.16	0.16
(3.44)**	**(3.44)****	**(8.81)****	(1.23)	(1.23)	(0.63)

Table 4. Full-Sample Results of the Daily Abnormal Return Measures with Sorts on Turnover

This table reports performance results for 428 individual investor currency traders at a proprietary online advisory service from March 2004 through September 2009, sorted on turnover. In Panel A, account holders are sorted into quartiles based on account turnover, defined as the mean of the margin-adjusted market value of all daily transactions divided by the daily amount of capital. Quartile 1 contains the account holders with the highest daily turnover, and quartile 4 contains those with the lowest daily turnover. Performance measures are computed from daily gross and net returns, which are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Net returns account for a 3-pip ($3.00) transaction cost applied to each roundtrip transaction. Raw returns are calculated as the daily returns earned in aggregate by the account holders. Passive benchmark returns are calculated by subtracting the daily return of the DBCR from the daily raw return. The four-factor alpha is the intercept from the four-factor currency model of Pojarliev and Levich (2010b), where the excess equally weighted portfolio returns are regressed on four factors that mimic strategies used by professional currency traders: carry trade, momentum, PPP, and volatility. Excess returns are calculated by subtracting the daily LIBOR rates from the equally weighted portfolio returns. Panel B presents the results for the differences in returns between the most and least active quartiles from Panel A. The t-statistics are in parentheses and significant values are bold; ** and * denote statistical significance at the 1% and 5% levels, respectively.

		Gross Returns			Net Returns		
	Turnover (%)	Raw Returns	Passive Benchmark	Four-Factor Alpha	Raw Returns	Passive Benchmark	Four-Factor Alpha
Panel A. Full-Sample Equal-Weighted Portfolio Results Sorted on Turnover							
Q1 (Most Active)	146.96	0.90	0.89	0.77	0.18	0.17	0.07
		(6.65)**	**(6.55)****	**(5.72)****	(0.81)	(0.77)	(0.30)
Q2	49.83	0.75	0.74	0.61	0.36	0.35	0.22
		(7.69)**	**(7.61)****	**(6.33)****	**(3.53)****	**(3.45)****	**(2.21)****
Q3	26.70	0.43	0.42	0.31	0.17	0.16	0.06
		(6.57)**	**(6.26)****	**(4.81)****	**(2.67)****	**(2.45)****	(0.86)
Q4 (Least Active)	9.60	0.22	0.21	0.10	0.12	0.11	0.00
		(4.52)**	**(4.23)****	**(2.11)****	**(3.78)****	**(3.28)****	(-0.08)
Panel B. Difference in Quartiles Ranked on Turnover							
Q1 - Q4		0.68	0.68	0.67	0.06	0.06	0.07
		(4.69)**	**(4.61)****	**(2.26)****	(0.27)	(0.27)	(0.16)

Table 5. Full-Sample Results of the Daily Abnormal Return Measures with Sorts on Trades per Day

This table reports performance results for 428 individual investor currency traders at a proprietary online advisory service from March 2004 through September 2009, sorted on trades per day. Account holders are sorted into quartiles based on the mean number of trades executed for each trading day. Quartile 1 contains the account holders with the highest mean number of trades executed per day, and quartile 4 contains those with the lowest mean number of trades executed per day. Performance measures are computed from daily gross and net returns, which are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Net returns account for a 3-pip ($3.00) transaction cost applied to each roundtrip transaction. Raw returns are calculated as the daily returns earned in aggregate by the account holders. Passive benchmark returns are calculated by subtracting the daily return of the DBCR from the daily raw return. The four-factor alpha is the intercept from the four-factor currency model of Pojarliev and Levich (2010b), where the excess equally weighted portfolio returns are regressed on four factors that mimic strategies used by professional currency traders: carry trade, momentum, PPP, and volatility. Excess returns are calculated by subtracting the daily LIBOR rates from the equally weighted portfolio returns. The t-statistics are in parentheses and significant values are bold; ** and * denote statistical significance at the 1% and 5% levels, respectively.

		Gross Returns			Net Returns		
	Trades Per Day	Raw Returns	Passive Benchmark	Four-Factor Alpha	Raw Returns	Passive Benchmark	Four-Factor Alpha
Panel B. Full-Sample Equal-Weighted Portfolio Results Sorted on Performance							
Q1 (Most Active)	6.64	0.8303	0.8199	0.71115	0.4921	0.4817	0.38273
		(8.09)**	**(7.90)****	**(6.92)****	**(1.96)***	(1.91)	(1.52)
Q2	3.06	0.4938	0.4838	0.37454	0.0363	0.0263	-0.08208
		(5.57)**	**(5.44)****	**(4.22)****	(0.43)	(0.31)	(-0.97)
Q3	2.09	0.3944	0.4613	0.34583	0.1018	0.0911	-0.02533
		(5.19)**	**(5.07)****	**(3.87)****	(1.22)	(1.07)	(-0.31)
Q4 (Least Active)	1.42	0.3944	0.3851	0.26782	0.1517	0.1424	0.02386
		(5.19)**	**(5.03)****	**(3.53)****	(1.64)	(1.54)	(0.26)
Panel B. Difference in Means Between Q1 and Q4							
		0.4359	0.4348	0.44333	0.3404	0.3393	0.35887
Q1 - Q4		**(3.43)****	**(3.38)****	**(2.71)****	(1.29)	(1.28)	(0.90)

Table 6. Full Sample Results of Past Trade Activity on Future Performance

This table reports the results of previous trade activity and future performance. First, the data for each account are divided into two time periods, t - n to t - 1 (the first time period) and t to t + n (the second time period), where n is the age of the account in days which varies by account. Second, we estimate trade activity proxied by the mean number of trades per day for the first time period. Third, we estimate our performance measures, both gross and net raw returns, passive benchmark returns and alpha from the Pojarliev and Levich (2010b) four factor model, for the second time period. Fourth, we divide accounts into quartiles with Q1 containing the most active traders and Q4 containing the least active traders. The t-statistics are in parentheses and significant values are bold; ** and * denote statistical significance at the 1% and 5% levels, respectively.

		Gross Returns			Net Returns		
	Trades Per Day	Raw Returns	Passive Benchmark	Four Factor Alpha	Raw Returns	Passive Benchmark	Four Factor Alpha
Panel B. Full Sample Results of Gross Returns with Sorts on Performance							
Q1	10.07	0.4964	0.4849	0.4194	0.0992	0.0878	0.0241
		(4.89)**	**(4.79)****	**(3.75)****	0.39	0.34	0.10
Q2	3.99	0.5852	0.5903	0.4473	0.0976	0.1026	-0.0599
		(3.79)**	**(3.83)****	**(2.79)****	0.54	0.57	-0.36
Q3	2.46	0.3623	0.3558	0.2182	0.00399	-0.00243	-0.1959
		(2.31)**	**(2.26)****	1.16	0.02	-0.01	-0.99
Q4	1.96	-0.1184	-0.1122	-0.1974	-0.3735	-0.3673	-0.4707
		(-1.02)	-0.97	-1.67	**(-2.67)****	**(-2.62)****	**(-3.49)****

Table 7. Full Sample Results of Trade Activity and Previous Performance

This table reports the association between trade activity and pervious performance for all 428 accounts from 2004 to 2009. In Panel A we report the results of equation 10 defined as:

$Trades_{it} = \alpha + \beta_{1i}PP_i + \varepsilon_t$ where $Trades_{it}$ is defined as the number of trades for account *i* on day *t*.

The independent variable is the *t-1* return for account *i* divided by the average of returns from account *i* from days *t-2* to *t-4* defined in equation 9. Panel B reports the results of equation 10 with Turnover as the dependent variable. Accounts are sorted by performance, measured by the statistical significance of alpha from the four-factor currency model with Q1 containing the best performers and Q2 containing the worst performers. Significant values are bold, and * denotes statistical significance at the 1 percent level.

	Coefficient	R^2	Coefficient	R^2
	Panel A. Trades on day *t* and previous performance		Panel B. Turnover on day *t* and previous performance	
Q1 (top performers)	**3.18**	0.02	0.12	0.02
	(13.41)*		(1.24)	
Q2	**2.18**	0.01	-0.34	0.03
	(8.27)*		(-0.63)	
Q3	**2.00**	0.02	-0.33	0.03
	(7.68)*		(-0.27)	
Q4 (worst performers)	**1.31**	0.02	-4.11	0.04
	(6.01)*		(-1.07)	