Summer 2011

Three Essays on Individual Currency Traders

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THREE ESSAYS ON INDIVIDUAL CURRENCY TRADERS

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A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirement for the Degree of

DOCTOR OF PHILOSOPHY

BUSINESS ADMINISTRATION – FINANCE

OLD DOMINION UNIVERSITY

August 2011

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ABSTRACT

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This dissertation examines the performance, skill and trading characteristics of individual currency traders by examining daily returns and transaction data for 428 individual currency traders from 2005 to 2009. Additionally, we examine whether technical trading strategies are profitable for individual currency traders.

The first essay examines the performance and trading characteristics of individual currency traders. Examination of daily returns for 428 accounts from March 2004 to September 2009 shows traders are able to earn positive excess 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 based on raw, passive benchmarks and on a risk-adjusted return basis. Furthermore, 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. Robustness checks of gross performance and trade activity, proxied by mean number of trades per day, are similar when analyzing a second data set that consists of 74 accounts from July 2010 to August 2011. Consistent with the prediction of the calibration theory the results also show that the more traders trade, the more feedback they receive, which, in turn, decreases their overconfidence and increases performance.

The second essay examines whether individual currency traders are skilled. Unlike previous studies that examine the predictability of R^2 for professional investors, who actively manage their portfolios and do not follow benchmarks, and find that R^2 can predict future performance, this study reveals just the opposite: R^2 does not predict future performance for individual currency traders. Despite the lack of predictive power of R^2, we report that individual currency traders are skilled. The R^2 measure lacks predictive power because R^2 is not persistent, which is because individual currency traders change their trading styles over time, while earning positive and persistent alphas. Our analysis of trade activity, drawdown, and market timing provides additional support that individual currency traders possess trading skills. Top traders also have the ability to mitigate downside losses, and a sizable percentage of them can time currency market factors. We find that 68.78 percent of trades executed by the top traders are profitable net of transaction costs, and profits do not arise from chance.

The third essay investigates whether technical currency trading is profitable. The results show that the use of technical analysis by individual currency traders is negatively associated with performance. Further, the technical trading model developed here adequately describes the cross-section of returns for individual currency traders. This result arises because individual currency traders use well-known technical indicators to trade currencies. This implies that such currency traders suffer from reduced performance.

This dissertation is dedicated to my grandmother for instilling in me that hard work can overcome a lack of talent.

ACKNOWLEDGMENTS

Almost a decade ago I was actively trading futures and stocks and I always dreamed of obtaining a Ph.D. in Finance. I never thought I would get accepted to a program. I remember applying to Old Dominion and anxiously awaiting for the rejection letter, only to be surprised by a packet announcing that I was accepted. Completing the program has been a challenge and I couldn't have made it through the program without the support of the following people.

First, I would like to thank the chair of my committee, Dr. John Doukas. I thoroughly enjoyed his classes and the critical feedback I have received throughout the entire process. I know his dedication and attention to detail has not only made me a better scholar but also a much better writer. I know I am well prepared to enter academia and succeed as a researcher because of the time and energy he dedicated to my development as a young scholar.

I would also like to thank the other members of the committee, Dr. Mohammed Najand, Dr. Licheng Sun and Dr. David Selover. Mohammed is an outstanding professor and was always available to assist me with all of the issues I faced during the program. Additionally, he also provided tons of assistance sharpening my SAS programming skills and expanding my knowledge of empirical methodology. Licheng's passion for teaching investments helped broaden my interests in research and his assignments allowed me to creatively solve problems and think outside of the box. David is an amazing professor of econometrics. I did not have a strong math background entering the program and I never would have made it through all of the econometric classes without his assistance. His ability to convey complex matters in a simple manner is amazing and I miss stopping by his office to talk about econometrics and economic issues.

Many other members of the ODU faculty and staff have also provided much needed support. I would like to thank Dr. Sylvia Hudgins for making me feel at home when I first arrived on campus. She is compassionate and has a true understanding of the needs of her students. I also thank Dr. John Ford for being supportive and understanding when I faced difficulties in the program. I also thank Katrina Davenport for all of her administrative support.

Finally, I wish to thank my fellow classmates, Maureen Mueller, who is an editing maestro, Jim Benton, Chatt Pongipitat, Sarah Mady, Joe Trendowski, and Denise Streeter for the love and support you all provided. I would not have made it through the program without all of your help.

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CHAPTER I

INTRODUCTION

In recent years trading volume of foreign exchange has increased significantly and it is believed the retail spot foreign exchange market is the fastest growing segment of retail trading (Luke, 2005). The growth of this market has raised awareness of currencies as an investment class amongst professional hedge funds and individual investors (Luke, 205; Pojarliev and Levich, 2008). Conventional theories hold that currency markets are efficient and the alpha generating abilities of currency traders should arise due to pure luck (Meese and Rogoff, 1983; Rogoff, 2002). However, many studies have revealed that technical trading strategies can generate positive abnormal returns in the currency markets (Sweeny, 1986; Schulmeister, 1988; Levich and Thomas, 1993; Menkhoff and Schlumberger, 1995; Neely, Weller, and Dittmar, 1997; Chang and Osler, 1999; Gencay, 1999; Gencay, Dacarogna, Olsen, and Pictet, 2003; Neely and Weller, 2003). Other studies analyzing the returns of professional currency traders demonstrate that some professional currency managers have alpha generating abilities (Pojarliev and Levich, 2008). Collectively, these studies imply that currency markets are not efficient and some currency managers possess skill.

Despite the studies that have shown technical trading rules and professional currency managers can earn positive abnormal returns not one study has examined the performance and trading characteristics of individual currency traders. Studies that have examined individual equity traders have shown that individual investors cannot beat the market. Poor performance arises because individual investors are overconfident and trade excessively (Odean, 1999; Barber and Odean, 2000). On the other hand, studies examining high-frequency traders have shown that these traders possess skill and are able to generate positive returns (by Jordan and Diltz, 2003; Garvey and Murphy, 2005). One possible explanation for the superior performance of day traders is that high-frequency traders are continually receiving feedback on their performance and this influences their trading behavior (Russo and Shoemaker 1992; Skata, 2008). Feedback trading posits that if day traders do well they will increase their trading and thus earn greater profits.

The major innovation of this dissertation is that it allows us to investigate the skill and trading characteristics of individual currency traders by examining transaction data and daily return data for 428 individual currency trader accounts from 2004 to 2009. Our unique database contains both high-frequency and short-term traders so it allows us to examine the differences in performance between each group to determine whether feedback is positively associated with performance and whether individual currency traders are able to generate positive abnormal returns.

In addition to analyzing the performance of individual currency traders we also investigate the source of their skill by extending studies of professional equity and currency managers. Studies of professional fund managers report that actively managed mutual and hedge funds earn superior abnormal returns over funds that closely track benchmarks (Pojarliev and Levich, 2008; Titman and Tiu, 2008; Sun, Wang, and Zheng, 2009; Amihud and Goyenko, 2010). Furthermore, professional currency managers have the ability to time the currency markets and performance is positively associated with loss mitigation, proxied by drawdown (Melvin and Shand, 2011). Once again a shortcoming of this literature stream is that not one study has examined individual currency trader active management prowess, timing skills, or loss mitigation abilities.

In summary, an investigation of individual currency trader trading abilities and trading characteristics will provide a rich insight as to why the retail spot industry is experiencing exponential growth and whether individual investors should add currencies to their investment portfolio.

CHAPTER 2

DO INDIVIDUAL CURRENCY TRADERS MAKE MONEY?

2.1 INTRODUCTION

Foreign exchange as an investment class for individual investors has grown rapidly over the past decade, as currency instruments once available only to large financial institutions have become widely available to individuals. 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.

No empirical studies, however, have analyzed the performance of individual currency traders. The primary objective of this paper is to examine the performance of these traders. Previous research reveals that currency returns are unpredictable, supporting the efficient market theory (Meese and Rogoff, 1983; Rogoff, 2002), which states that the expected returns of individual currency traders should be zero. Other studies, however, show that simple technical trading strategies applied to currency markets can result in abnormal returns and imply currency markets are not efficient (Sweeny, 1986; Schulmeister, 1988; Levich and Thomas, 1993; Menkhoff and Schlumberger, 1995; Neely, Weller, and Dittmar, 1997; Chang and Osler, 1999; Gencay, 1999; Gencay, Dacarogna, Olsen, and Pictet, 2003; Neely and Weller, 2003).

Although many studies examine the profitability of currency trading strategies, few study the returns of currency traders. Pojarliev and Levich (2008) examine the performance of currency hedge funds and find that such funds, on average, are unable to earn positive alpha, although approximately 24 percent of the currency managers have alpha generating skill, which suggests they are able to exploit market inefficiencies. It is unknown whether individual currency traders, however, are able to earn positive returns. This paper addresses this issue by examining two data sets, one which contains transaction data, net daily returns and gross daily returns, and a second data set that contains mean gross daily returns. We analyze the first data set by using three performance metrics: raw returns, a passive benchmark model, and alpha from the four-factor currency model of Pojarliev and Levich (2008). We perform robustness checks of gross performance with the second data set.

In addition, this paper analyzes the trading characteristics of high-frequency currency traders. 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; Barber, Lee, Liu, and Odean, 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.

This study's second major contribution is to show that high-frequency traders can earn positive excess returns. To investigate this issue we examine the performance of high-frequency currency traders (day traders) and non-day traders. We also examine trade activity proxied by the mean number of roundtrips per day and account turnover and their association with performance. This approach is taken because the psychological literature reveals that overconfidence can increase or decrease over time, based upon the level of feedback received (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).

The results in this paper differ from those of studies examining buy-and-hold equity investors, because high-frequency traders, unlike buy-and hold traders, receive daily feedback on the profitability of numerous trades, which, in turn, increases their degree of calibration. Buy-and-hold investors may not receive feedback on their trades for weeks or months, thus keeping their overconfidence high for long periods. For high-frequency traders, constant feedback can decrease the level of overconfidence and thus increase their level of calibration, implying a positive association between trading activity and performance.

Our analysis reveals 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. Alpha returns from the four-factor currency model are also positive and significant for gross returns, but net returns are statistically insignificant. Furthermore, analysis of a second data set, which consists of gross returns, yields similar results. Overall, our results show that some individual currency traders realize abnormal returns, even when accounting for transaction costs.

Our analysis of trading characteristics supports the contention that the currency traders analyzed are well-calibrated individuals, but any resulting benefit is eroded by transaction costs. More specifically, 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 also supports the calibration hypothesis. Finally, our analysis of a second data set yields similar results when examining trade activity, proxied by the mean number of trades per day, which provides additional support for calibration theory.

This paper contributes to the individual investor performance debate by revealing that not all traders are overconfident to the point where they reduce their performance: Some are well calibrated, which permits them to increase their trading activity, in turn increasing their performance on a gross basis. Approximately 25 percent of traders in this sample earn positive alphas, revealing that currency trading can still be profitable for some individuals, even after accounting for transaction costs.

The remainder of this essay is organized as follows. Section 2.2 provides a brief overview of the related literature and hypothesis development. Section 2.3 discusses the methodology, and Section 2.4 reports the empirical results. Section 2.5 presents a brief summary and concluding remarks.

2.2 HYPOTHESIS DEVELOPMENT

This essay applies two theoretical frameworks: efficient market theory, to examine performance, and the behavioral finance theory of overconfidence and calibration, to investigate trading characteristics.

2.2.1 Efficient Market Theory and Technical Currency Trading Strategies

Currency markets are generally believed to be efficient, although many studies have shown otherwise. For example, Meese and Rogoff (1983) examine currency returns and discover that random walk models outperform forecasting models, and a follow-up study by Rogoff (2002) provides similar arguments, revealing unpredictable currency returns and zero expected returns. Other authors refute the efficiency of currency markets by demonstrating the profitability of trend-following models (Sweeny, 1986; Levich and Thomas, 1993; Neely, Weller, and Dittmar, 1997). Furthermore, studies examining the use of daily data (Schulmeister, 1988; Menkhoff and Schlumberger, 1995; Chang and Osler, 1999; Gencay, 1999; Neely and Weller, 2003), as well as intraday data (Gencay, Dacarogna, Olsen, and Pictet, 2003) reveal that currency trading strategies remain profitable. Among the few studies that examine the performance of currency traders, Pojarliev and Levich (2008) investigate the returns of currency hedge funds and find that approximately 24 percent of individual currency managers earned positive alpha between 2001 and 2006, implying that currency markets may not be fully efficient and that some currency managers are more skilled than others at exploiting market inefficiencies.

In summary, since profitable currency trading strategies reveal the inefficiency of currency markets, currency traders generating positive excess returns would imply the currency markets are not fully efficient. Conversely, if the currency markets are efficient, the returns of the individual currency traders analyzed should not be able to forecast future returns or generate abnormal returns. To investigate this issue, we examine both gross and net returns, using three performance measures: raw returns, a passive benchmark model proxied by the DBCR, and alpha from the four-factor currency model of Pojarliev and Levich (2008).

2.2.2. Overconfidence, Calibration, and Individual Investor Performance

A review of the financial literature reveals that most individual investors trade to their detriment. Studies examining buy-and-hold equity investors reveal a negative association between overconfidence, proxied by trading activity, and performance. Odean (1999) examines performance for a comprehensive data set of individual investors: As they gain profits, overconfident traders overweight the strength of their private information, which leads to excessive trading and lowers 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), the authors predict that increased overconfidence increases trading activity and reduces performance.

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, the degree of calibration will be greater for high-frequency traders, who should outperform their overconfident, less-calibrated counterparts.

2.3. DATA AND METHODOLOGY

The primary data set for this research comprises account data from an online advisory service—a website that publishes the trades of its clients—for individual retail spot currency traders. We refer the reader to Fonda (2010) for a detailed discussion of this new industry. The sample consists of 428 accounts and 79,042 roundtrip transactions from March 2004 to September 2009, with the 428 accounts split into 263 day traders and 165 buy-and-hold traders (Panel A of Table 2.1). 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 account with 3 pips (1 pip equals 0.01 percent), or $3.00, to 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).

****Insert Table 2.1 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 2.1); 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 2.1). These data, along with the turnover data, reveal that the currency traders in this sample are very active.

We calculate transactions costs as the bid–ask spread for each transaction divided by the margin-adjusted capital required to open the position. The mean transaction cost is 0.89 percent (Panel B of Table 2.1), 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 2.1 shows that the mean trade size is $457,161.40 for the 77,666 transactions in the sample. 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 industry: Investors can open and close an online account at any time, unlike professional funds, which must meet stringent listing criteria. Age limitation is the primary reason why this study uses daily instead of weekly or monthly returns.

Panels C and D of Table 2.1 present the descriptive data 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, and transaction costs for day traders are all larger than for non-day traders. The differences in means reported in Panel E of Table 2.1 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. Frequent trading comes at a cost, however: Day traders' transaction costs are 0.18 percent larger than for non-day traders (t-statistic = 12.07), a statistically significant difference.

2.3.1. Methodology

2.3.1.1. 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 account in the sample from 2004 through 2009, where the P/L for each transaction for each account is summed for each day of trading. The daily gross returns for account *i* for day *t* ($R_{i,t}^{Gross}$) are equal to the difference between the end-of-day capital for account *i* on day *t + 1* ($K_{i,t+1}$) and the starting capital, $K_{i,t}$. The gross daily portfolio return for each account is

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

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

$$R_{i,t}^{Net} = \frac{K_{i,t+1} - \Sigma tc_{i,t}}{K_{i,t}} - 1 \tag{2}$$

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

$$REW_t^{GROSS} = \frac{1}{n_{i,t}}\Sigma \quad \text{and} \quad REW_t^{NET} = \frac{1}{n_{i,t}}\Sigma\ R_{i,t}^{NET} \tag{3}$$

2.3.1.2. Return Performance

This paper uses two measures of risk-adjusted performance: the four-factor currency model and 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. 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 apply the four-factor model of Pojarliev and Levich (2008), with a carry factor ($Carry_{it}$) measured by the Deutsche Bank (DB) G10 Currency Harvest, a momentum-following factor (Mom_{it}) measured by the DB FX Momentum, a value factor ($Value_{it}$) measured by the DB FX Purchasing Power Parity (PPP), and a volatility factor (Vol_{it}) 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; trend following consists of following patterns or reversals; value factors are used when traders seek to identify over- or undervalued currencies; and volatility is used because currency traders have been found to trade on currency volatility.

We then estimate alpha by regressing the daily net and gross returns earned by individual investors on the four factors:

$$REW_t^{Gross/Net} - R_{ft} = \alpha + \beta_{1i}Carry_{it} + \beta_{2i}Mom_{it} + \beta_{3i}Value_{it} + \beta_{4i}Vol_{it} + \varepsilon_t \qquad (4)$$

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 ($\mathrm{REW}_{i,t}^{\mathrm{Gross/Net}}$ –

R_{ft}) and the coefficient β measures the sensitivity of currency traders' returns to the four factors.

2.4. EMPIRICAL RESULTS

2.4.1. 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. Panel A of Table 2.2 presents these results on both a gross and a net basis. Traders can earn positive and significant gross returns across all three performance measures. The average account earns a raw 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 0.05 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, investors earn a positive daily net return of 0.05 percent that is insignificant (t-statistic = 0.91). These results indicate a substantial decrease in all three performance measures when transaction costs are taken into account.

Pojarliev and Levich (2008) provide similar results when accounting for the risk factors in currency hedge funds. The 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 2.2 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). 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 2.2 presents the three performance measures—raw returns, the passive benchmark model, and alpha—ranked by performance. 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 2.2 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 results remain similar for gross results for the passive benchmark strategy and alpha from the four-factor currency model. Overall, the results reveal 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 reveal 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 12.39 percent per month, assuming 21 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).

In summary, on average, the traders in this sample earn positive net and benchmark-adjusted returns, even after accounting for transactions costs, while alpha is also positive yet insignificant. The performance of these currency traders does not support the efficient market hypothesis (Meese and Rogoff, 1983; Rogoff, 2002) but suggests that currency markets are likely inefficient due to the profitability of technical trading strategies (Schulmeister, 1988; Menkhoff and Schlumberger, 1995; Chang and Osler, 1999; Gencay, 1999; Neely and Weller, 2003).

This paper's findings are similar to those of Pojarliev and Levich (2008), where the average currency manager is unable to generate positive and significant alpha but approximately 24 percent of professional currency managers are able to earn significant and positive risk-adjusted excess returns. In our sample, approximately 107 individual currency traders (25 percent) remain profitable after accounting for the risk factors of the four-factor currency model.

It is very important to take into consideration transaction costs when measuring the performance of currency traders. As shown in Table 2.1, 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 2.2, 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 possess more skill trading currencies than professionally managed currency hedge funds.

2.4.2. 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, both gross and net of transaction costs. 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 2.3 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 percent (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 percent (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 2.3 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 2.3 about here****

The mean differences between day traders and non-day traders are reported in Panel C of Table 2.3. 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 in 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 traders who receive more timely feedback will be better calibrated than traders who receive less timely feedback, with a higher degree of calibration decreasing overconfidence and thus improving performance. However, when transaction costs are accounted for, while day traders still outperform non-day traders, the differences are no longer significant, weakening the calibration hypothesis. 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.

2.4.3. Trading Activity Proxied by Turnover

We next examine accounts sorted on turnover to test the sensitivity of our results. Previous studies analyzing 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). 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 2.4 presents the results of our performance measures for both gross and net returns. The results of the performance measures calculated with gross returns 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 linearly to the top quartile Q1, where turnover is a sizeable 146.96 percent per day. All three performance measures follow this linear 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 linear 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 2.4 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 2.3. 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. This underperformance results from overconfidence, which leads to excessive trading. 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.

2.4.4. 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 2.5 reports the gross performance results and reveals a linear association between performance and trade activity, a pattern also observed for gross returns when sorted on turnover (Table 2.4). 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 2.5, 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 2.5 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 insignificant and show that there is no benefit to increased trading, after accounting for transactions costs.

Overall, the gross results support the calibration hypothesis, while the net 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 2.3 and sorts on turnover results presented in Table 2.4 above. Traders who trade the most, outperform the least active traders in 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 majority of its benefits. It is important to note that although transaction costs deteriorate performance, a sizable percentage of high-frequency traders are still able to earn positive and significant benchmark-adjusted returns and alpha. This finding contradicts previous studies of equity traders, which show increased trading results in underperformance relative to the benchmark index (Odean, 1999; Barber and Odean 2000).

2.4.5. Trading Activity Measured by the Mean Number of Trades per Day

The performance results from the main data set, presented in Panel B of Table 2.2, show that the top quartile of individual currency traders have alpha generating abilities, earning a statistically significant 0.59 percent per day (t-statistic=4.86). Additionally, our examination of trading characteristics shows that individual currency traders increase (decrease) trading based on the level of positive (negative) feedback received and outperform those who trade less frequently. These results are consistent with the calibration theory which predicts that individual currency traders who trade more frequently will outperform those who trade less frequently.

To test the robustness of the results we analyze a second data set which comprises account data from an additional online advisory service. This sample consists of 74 accounts from July 2010 to August 2011. The data include the account holder's name, the mean monthly gross return, the total number of trades, and the age of the account in weeks. To provide results comparable to those presented based on our primary data set we compute the mean daily gross return by dividing the mean monthly gross return by 20 (assuming 20 trading days per month) and calculate mean trades per day by dividing the total number of trades by the age of the account measured in days. Although the second data set does not contain transaction data, an analysis of the mean daily gross return provides insight into the performance of these traders. Furthermore, the mean number of trades per day allows us to test the calibration hypothesis, which predicts that individual currency traders who trade more frequently will outperform those who trade less frequently. One limitation of the secondary data set is that account holders who close their accounts are not included in the data set. This creates survivorship bias. Consequently, it is quite possible that the performance and mean age may be higher in the secondary data set since underperformers are removed. We address these concerns with the analysis of the data below. We present descriptive statistics, performance results, and feedback trading results in Table 2.6.

Panel A of Table 2.6 reports descriptive statistics of gross returns, trade activity and the age of all 74 accounts. The mean daily gross return is 0.357 percent with the top quartile (bottom) quartile earning a gross return of 0.648 (0.005) percent per day, respectively. These results are similar to the results of our primary data set reported in Panel B of Table 2.2 which display cross-sectional variation in performance. Panel B of Table 2.2 reveals that the top performers (Q1) in our primary data set earn a gross return of 1.04 percent per day and the worst performers (Q4) earn a gross return of -0.25 percent per day. It is notable that the worst performers in the second data set (.005 percent per day) outperform the worst traders in the primary data set (-0.25 percent per day) by 0.255 percent per day. A likely explanation for this is survivorship bias since the secondary data set does not contain closed accounts. Two other noteworthy observations are mean trades per day and the age of accounts. The mean number of trades per day for the second data set is 2.35 and the mean age of accounts is 201.30 days. The mean number of trades reveals that the individual currency traders in the secondary set are active traders but not as active as the traders in the primary data set where the mean trades per day is 3.31 (see Panel B of Table 1). A striking difference between the two data sets is the age of the accounts. As shown in Panel B of Table 2.1, the mean age for currency traders in the primary data set is 81.92 days. However, Panel A of Table 2.6 reports that the mean age for currency traders in the second data set is 201.30 days. A likely explanation for the age difference is that poor performing traders close their accounts and bias the results in the second data set.

****Insert Table 2.6 about here****

We next examine the performance of the second data set by sorting accountholders into tertiles and report the results in Panel B of Table 2.6. Tertiles are used due to the number of observations. Quartile ranks provide similar results. The results presented in Panel B of Table 2.6 reveal that the top performing currency traders outperform the worst performing currency traders by 1.44 percent per day and it is significant (t-statistic=8.37). These results are similar to the primary data set in Table 2.2 where the difference between the top and worst performers is 1.29 percent per day and significant (t-statistic=8.63). Consequently, both data sets show that the top performers earn positive gross returns and the difference between the best and worst performers is significant.

Our final robustness check tests the feedback hypothesis which predicts a positive association between trade activity and performance. We test this by sorting the secondary data set by trade activity, proxied by mean trades per day. Accounts are ranked by mean trades per day and then divided into three groups. This is similar to the primary data set analysis performed in Table 2.5 where we report the most active traders, proxied by mean trades per day, outperform the least active traders per day by 0.4359 percent per day and the difference is significant (t-statistic=3.43).

Panel B of Table 2.6 reports the results of sorts on trade activity for the second data set. The most active traders (T1) trade, on average, 4.873 times per day and earn a mean gross return of 0.628 per day. The least active traders (T3) trade, on average, 0.554 times per day and earn a gross return of 0.063 percent per day. The feedback hypothesis, which predicts that the difference in gross performance between the most active (T1) and least active traders (T3) will be positive is borne out in the data. Specifically, the most active traders outperform the least active by 0.57 percent per day and the difference is significant (t-statistic=3.45). This result is similar to all of the previous analyses performed on the primary data set which shows feedback can affect trading performance. Calibration theory predicts that as traders receive positive (negative) feedback through winning (losing) trades they will increase (decrease) trading. Overall, the results of both data sets not only show that some individual currency traders are able to earn positive gross returns, but also there is a positive association between trade activity and gross performance.

2.5. CONCLUDING REMARKS

This paper examines the daily returns of individual currency traders by analyzing their performance within the context of market efficiency, which predicts that their realized excess returns should be zero. Additionally, it examines the calibration hypothesis, which predicts a positive association between trade activity and performance. If traders receive timely feedback, their overconfidence will decrease and they will become better calibrated.

We examine daily raw returns, returns in excess of a passive benchmark model, and alpha from the 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, there are 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 alpha. These results imply that currency markets are not efficient.

To test the calibration hypothesis, we first categorize the sample into day traders and non-day traders. Day traders outperform non-day traders on all three of our gross and net return performance measures. Second, this study tests the calibration hypothesis by ranking accounts by trading activity proxied by the mean number of trades executed by each account per day. The results for day traders/non-day traders, turnover, and mean number of trades per day were uniform and reveal that the difference in gross performance between the most active and least active traders is positive and statistically significant, whereas the difference in net returns is not significant. These results imply there is only a limited benefit to being calibrated. Although gross return results reveal that if traders are receiving positive (negative) feedback, they increase (decrease) their trading frequency, net performance differences are insignificant and reveal that traders are not better off increasing their trading activity when accounting for transaction costs.

To test the robustness of our results we analyze a second data source and find similar patterns in terms of performance and trading characteristics. The top currency performers are able to earn positive gross returns and the difference in performance between the best and worst traders is significant. Furthermore, we examine whether trading activity, proxied by mean trades per day, is positively associated with performance and find that the most active traders in our second data set outperform the least active traders consistent with the prediction of the calibration theory.

Our analysis of trading characteristics reveals that not all trading has a negative effect on performance. Although previous studies have determined a negative association between trading activity and performance, they examine long-term buy-and-hold equity investors. A possible explanation for the difference in this paper's results is that the traders in this sample receive constant feedback, which lowers overconfidence, and highly calibrated traders increase trading based upon positive feedback, increasing performance.

Although the results reveal no significant difference in net performance when sorting on trading activity, a sizable percentage of currency traders are able to earn positive net benchmark adjusted returns and alpha. These results contradict previous studies of equity traders, which show that individual investors are overconfident and unable to beat a benchmark index (Odean, 1999; Barber and Odean, 2000).

CHAPTER 3

ARE INDIVIDUAL CURRENCY TRADERS SKILLED?

3.1. INTRODUCTION

Interest among professional hedge funds, individual investors, and government regulators in currency trading as an investment class has been growing over the past decade (Luke, 2005; Pojarliev and Levich, 2008; Commodities and Futures Trading Commission, 2010; King and Rime, 2010). Retail foreign exchange average daily turnover by households and non-bank institutions is estimated to be approximately $150 billion and total foreign exchange daily turnover increased by 75 percent from 2002 to 2007 (King and Rime, 2010). Despite the growth of the retail foreign exchange market, little is known about the trading skills of individual currency traders. This may be largely attributed to the lack of data.

A vital research question that arises is whether individual currency traders have superior trading skills. We address this issue by analyzing a unique database of 428 individual spot currency traders over a five-year period ending in 2009 by investigating whether performance, modeled as alpha from a factor model, can be predicted by active management, proxied by R^2. Additionally, we examine transaction data to determine whether profits arise due to skill or luck, and drawdown performance to determine whether individual currency traders have skill at moderating losses, and apply the Melvin and Shand (2011) timing model to detect whether these traders possess skill in terms of timing Pojarliev and Levich's (2008) currency model factors.

Investigating the trading abilities of these traders is a critical inquiry, because spot currency contracts trade on a 50:1 margin in the United States and up to a 400:1 margin in offshore markets. Individual investors trading highly levered instruments can be exposed to excessive risk, which can lead to financial ruin. Consequently, government regulators have recently raised concerns that individual currency traders may be using too much margin and exposing themselves to excessive risk (Commodities and Futures Trading Commission, 2010). An examination of individual currency traders' skill is also important because the retail spot currency market is said to be the fastest growing segment of the global currency market and thousands of individual investors now actively trade foreign exchange (Luke, 2005). If individual currency traders possess skill at generating profits, it would provide one explanation why the retail spot foreign exchange market has attracted individual investors and continues to grow. Finally, it is important to investigate the trading abilities of individual currency traders, because studies examining the association between R^2 and alpha have only focused on professionals, specifically, hedge funds, mutual funds, and professional currency managers (Pojarliev and Levich, 2008; Titman and Tiu, 2008; Sun, Wang, and Zheng, 2009; Amihud and Goyenko, 2010). It is an unanswered question whether individual currency trader's selective management can result in superior performance.

Our analysis of skill builds on and extends that of Fama (1972), who states that a fund's excess performance, a gauge of how well a fund performs relative to a naïve portfolio, can arise from selectivity, or active management. Funds that closely track benchmarks, however, are less selective and will naturally have an R^2, the coefficient of determination from a factor model, value close to unity (Amihud and Goyenko, 2010).

Actively managed funds that deviate from a benchmark index have low R^2 values and, if the fund manager possesses skill, will outperform the benchmark. This implies an inverse association between R^2 and performance.

Empirical studies that examine the association between R^2 and the contemporary performance of professional traders confirm a negative association between R^2 and performance, supporting the argument that professional fund managers possess skill (Pojarliev and Levich, 2008; Titman and Tiu, 2008; Sun, Wang, and Zheng, 2009). In a recent study analyzing mutual fund data, Amihud and Goyenko (2010) propose that the R^2 value from a multifactor model can predict future fund performance, modeled as alpha from a multifactor model. The authors also find that active management, proxied by lagged R^2, is negatively associated with future fund performance. In contrast, numerous studies of individual equity investors illustrate that individual equity traders are overconfident, trade excessively, and underperform relative to the market index (Odean, 1999; Barber and Odean, 2000; Barber and Odean, 2001). For example, Odean (1999) finds that individual equity investors at a discount brokerage would have performed better had they followed the market index, which implies that R^2 is positively associated with performance, contrary to the findings of Amihud and Goyenko (2010).

Following a similar approach to that of Amihud and Goyenko (2010), we regress lagged R^2 on future alpha to determine whether the individual currency traders in this sample are skilled. Our results are summarized as follows. Our analysis reveals that R^2 has no significant predictive power on individual currency trader performance. Our results remain robust to quartile ranks of performance, modeled as alpha from the four-factor currency model, and trade activity, proxied by account turnover, which implies that the performance of individual currency traders is not enhanced if it deviates from the four-factor currency benchmarks. Our analysis of the predictive power of R^2 also implies that individual currency traders lack skill.

Despite the lack of predictability of R^2, we find that individual currency traders are skilled. Amihud and Goyenko (2010) test the persistence of R^2 and state that performance should be stronger if a fund's strategy with respect to selectivity is stable. Consequently, we examine the persistence of performance and of R^2 to determine whether affects the outcome of our analysis. When we analyze the full sample, our results reveal that performance is marginally persistent and selectivity is persistent. However, when we analyze currency traders with greater longevity, for example, those who keep their accounts open for more than 80 days, performance is significantly persistent for the top quartile of traders, yet selectivity is not persistent. This persistence of performance reveals that certain currency traders are adept traders; however, the lack of persistence of R^2 reveals that these skilled traders change their strategies over time. Our analysis of performance and selectivity stability suggests that individual currency traders can earn significant, stable alphas over the life of their accounts, but they change their trading strategies, which may mean that R^2 possesses no predictive power. This provides one explanation why R^2 does not predict performance for individual currency traders in this sample.

This result is also supported by studies that have shown currency trading strategies can become crowded, causing a once profitable strategy to become unprofitable (Baillie and Change, 2010; Pojarliev and Levich, 2010b). Pojarliev and Levich (2010b) analyze crowded trades in currency markets. The authors discover an inverse association between style crowdedness and future performance. For example, the carry trade may be profitable in one period, but as more traders flock to the same strategy, future performance is reduced. Currency managers, who change their strategies over time, for example, no longer utilizing the carry trade when it becomes unprofitable, may earn higher returns than currency traders who stay with the same strategy. Our results of R^2 instability and persistent performance support the argument that currency traders who change their strategies over time may outperform their peers who do not adapt to the market.

Our analysis of trade activity, drawdown performance, and market timing provides supplemental support that the individual currency traders in this sample possess exceptional trading skills. We report that 68.78 percent of trades executed by the top traders in this sample are profitable net of transaction costs and profits do not arise from chance. Furthermore, the top traders have lower drawdown than the worst-performing traders, although this difference is not statistically significant. Finally, our results from Melvin and Shand's (2011) timing model reveal that some traders in this sample have the ability to time the factors of the Pojarliev–Levich (2008) four-factor currency model. For example, 21.03 percent of the individual traders possess the skill to time the carry trade. These findings are consistent with the results presented in the first essay 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.

Overall, the current study contributes to the literature by providing additional evidence that individual currency traders are adroit. This is a significant contribution, because the majority of studies analyzing individual investors determine that individual equity traders lack skill trading equities and underperform relative to the market (Odean, 1999; Barber and Odean, 2000; Barber and Odean, 2001). This study also provides some insights as to why the retail spot foreign exchange market is one of the fastest growing markets for individual investors. As shown in the first essay, not only are individual currency traders capable of earning positive excess returns, but also, as shown in this study, performance arises due to skill and not luck. The second major contribution of this study is that it reveals that R^2 may not be a good proxy for performance for all types of traders, specifically individual currency traders. Our results imply investors can change their trading styles over time while maintaining exceptional performance, and this undermines the basic premise of using R^2 to predict performance. This reveals that using R^2 may not always be an accurate proxy for skill and runs contrary to previous studies that have found an inverse association between performance and R^2 (Pojarliev and Levich, 2008; Titman and Tiu, 2008; Sun, Wang, and Zheng, 2009; Amihud and Goyenko, 2010).

The rest of the essay is organized as follows. Section 3.2 provides a literature review and develops the main hypothesis. Section 3.3 describes the methodology used and the performance measures of alpha and the information ratio (*IR*). Section 3.4 examines the entire sample to determine whether R^2 is a determinant of future performance and section 3.5 concludes.

3.2. HYPOTHESIS DEVELOPMENT

The financial literature has extensively analyzed investor performance. A recent trend in empirical analysis is to examine the R^2 of returns on systematic factors as a determinant of performance. The R^2 value determines a portfolio's diversification, and 1 - R^2 gauges the weight, relative to the variance of an investment, of idiosyncratic risk; thus 1 - R^2 estimates the selectivity of an investment strategy (Amihud and Goyenko, 2010). Framing performance relative to a benchmark, or a naïve portfolio, Fama (1972) states that portfolio performance may be due to active management. Funds that naïvely follow a benchmark will earn returns similar to those of the benchmark. However, managers who are selective in managing their portfolios will earn returns unlike those of the benchmark and, if skilled, in excess of them. Analyzing R^2 can provide some insights into a portfolio manager's trading style. A high R^2 reveals that the fund is tracking a broader benchmark index, and therefore its performance relative to the benchmark will be low. When managers actively manage their funds, R^2 is low, which should relate to increased performance if the managers possess skill.

Empirical studies confirm the importance of R^2 in evaluating performance. Pojarliev and Levich (2008) examine currency hedge funds and determine that R^2 is inversely associated with fund performance. Titman and Tiu (2008) find that hedge fund performance increases when funds employ strategies that hedge less frequently against benchmarks. Sun, Wang, and Zheng (2009) define $1 - R^2$ as the hedge fund distinctiveness index and demonstrate that R^2 is inversely related to fund performance. Amihud and Goyenko (2010) propose that R^2 can predict future fund performance. Analyzing mutual fund return data from the Center for Research in Security Prices, the authors confirm that R^2 predicts future performance when performance is modeled as the alpha from a multifactor model. These results suggest that fund selectivity, or active management, proxied by R^2, is negatively associated with fund performance.

While all these studies are very insightful about the performance of professional fund managers, no study has examined the association between future individual investor performance and lagged R^2. This study is therefore the first to examine the predictability of R^2 for individual investors and, more specifically, individual currency traders.

The first two studies to address individual investor performance are those of Schlarbaum, Lewellen, and Lease (1978a, b), who analyze the performance of clients at full-service brokerage firms in the 1960's and 1970's. Both studies reveal that individual investors possess skill in selecting stocks. Other studies examining individual investors, however, show the opposite. Odean (1999) analyzes the trades of 10,000 individuals at discount brokerage firms from 1987 to 1993 and determines that these investors trade too often and consequently earn lower returns. Barber and Odean (2000) analyze the portfolio performances of 66,465 households with accounts at a discount brokerage firm from 1991 to 1996. They find that the average investor does not beat the market and that the higher the portfolio turnover, the lower the net return due to transaction costs. In a subsequent study investigating a similar sample, Barber and Odean (2001) document that women outperform men because men are overconfident and trade excessively. Glaser (2003) examines a sample of 3,000 online broker investors over a 51-month period and reports that online investors trade frequently, with a median turnover of approximately 30 percent per month and trading activity concentrated in technology, Internet, and software stocks. Additionally, the author shows that investor stock portfolio value is negatively related to turnover. Coval, Hirshleifer, and Shumway (2005) analyze 115,856 accounts from a discount brokerage and find that the top 10 percent of traders earn excess returns of 12 and 15 basis points per day, yet the overall majority of traders do not earn positive excess returns.

The sample analyzed in this essay consists of individual currency traders. A review of the currency trading literature reveals that few studies examine traders' alpha-generating abilities. For example, Pojarliev and Levich (2008) investigate the returns of professional currency managers and develop a four-factor model that uses proxies for trading strategies as their independent variables. Their model does an exceptional job of explaining the cross section of returns for professional currency managers, and their results are similar to those of the studies mentioned above. Specifically, their findings show that some professional currency managers earn positive and significant alphas, and that currency managers who follow the benchmarks are less likely to earn positive abnormal returns.

In summary, the research clearly shows that individual investors on average trade excessively and do not perform well relative to the market index and thus lack skill, while certain professional fund managers possess skill and are able to earn positive abnormal returns. In the context of selectivity, or active portfolio management, individual investor studies infer that active management by individuals *reduces* performance, contrary to the results of numerous studies on professional investors (Titman and Tiu, 2008; Sun, Wang, and Zheng, 2009; Amihud and Goyenko, 2010). Consequently, active management by individual investors may not result in a negative association between R^2 and performance.

The main objective of this essay is to test whether individual currency traders are skilled. To test this empirically, we examine whether individual currency trader performance, measured by the alpha of the Pojarliev–Levich (2008) four-factor currency model, can be predicted by active management, proxied by R^2. If active management results in greater future performance, we expect a negative association between lagged R^2 and future performance. We refer to this as the skilled investor hypothesis. Melvin and Shand (2011), however, argue that, unlike equity markets, currency markets have no established market portfolio, buy-and-hold portfolios do not exist due to the long/short characteristic of currency trading, and alternative methods of construction of the factors may lead to different results. Therefore, the lack of a currency market portfolio and, as a result, the possible limitations associated with the four-factor currency model of Pojarliev and Levich (2008) may influence our results. For this reason, in Section 6, we perform two robustness tests. First, we estimate Pojarliev and Levich's (2008) four-factor model for all 428 individual accounts to determine whether the four-factor model provides sufficient explanatory power for the returns of individual currency traders. Second, we estimate an alternative currency specification model using the Deutsche Bank Currency Return Index (DBCR) as our explanatory variable.

To further examine the skill of individual currency traders, we perform three additional analyses. First, we examine transaction data to determine whether profits arise from skill or luck by investigating whether the percentage of winning traders is statistically significant. Second, we examine the skill of loss mitigation by examining drawdown performance. Third, we apply the timing model of Melvin and Shand (2011) and investigate whether individual currency traders can time the Pojarliev–Levich (2008) currency model factors.

3.3. DATA AND METHODOLOGY

3.3.1. Performance measures

To assess the performance of individual currency traders, two performance metrics are utilized. First, the Pojarliev–Levich (2008) four-factor currency model is applied and is defined in equation (1):

$$R_{i,t} - R_{ft} = \alpha + \beta_{1i}Carry_{it} + \beta_{2i}Mom_{it} + \beta_{3i}Value_{it} + \beta_{4i}Vol_{it} + \varepsilon_t \qquad (1)$$

Excess return is defined as the return for account i on day t ($R_{i,t}$) less the daily return on the one-month London Interbank Offered Rate (R_{ft}). The coefficient β measures the sensitivity of the currency traders' returns to systematic risk factors. The four factors are the *carry factor* ($Carry_{it}$), measured by the Deutsche Bank (DB) G10 Currency Harvest; the *momentum-following factor* (Mom_{it}), measured by the DB FX Momentum; the *value factor* ($Value_{it}$), measured by the DB FX purchasing power parity (PPP); and the *volatility factor* (Vol_{it}), measured by the DB FX Volatility Index. Carry trades consist of borrowing a low interest rate currency and investing in a high interest rate currency. Carry trade risk arises when a high interest rate currency depreciates more than the interest rate differential between the low and high interest rate currencies. Trend following consists of following patterns or reversals. Trend-following risks arise from reversals of the trend, misidentified patterns, and excessive trading costs arising from entering and exiting trades while attempting to catch the trend. The value factor is used when traders seek to identify over- and undervalued currencies. Value risks arise when PPP does not revert to parity over time or when currency values overshoot parity. Volatility risk is inherent in any open position held by the currency trader.

The second performance measure used in our analysis is *IR*, which measures the extent of an individual currency trader's excess performance relative to idiosyncratic risk:

$$IR_j = \frac{\alpha_j}{RMSE_j} \tag{2}$$

where α_j is from the four-factor model and $RMSE_j$ is the squared root of the mean-squared errors, or residuals $(\sqrt{\varepsilon_{jt}})$, from equation (1) from time period t to $t + n$. We use *IR* because currency traders can have a high alpha, representing superior performance, yet risky strategies can also increase the probability of failure. Scaling performance by idiosyncratic risk is important in this study because spot currency traders trade instruments with a significant amount of inherent risk. This risk arises from the 33:1 margin utilized by the traders in this sample. Brown et al. (1992) state that *IR* also helps mitigate survivability bias, which can arise in this sample due to individual currencies being exposed to this risk, which can increase the probability of failure. Additionally, this study utilizes *IR* as a performance metric, because it is used when investigating the returns of professional fund managers (Brands, Brown, and Gallagher, 2006; Kacperczyk, Sialm, and Zheng, 2005) and currency traders (Pojarliev and Levich, 2008). In addition, Titman and Tiu (2008) examine hedge funds and determine that funds with a low R^2 have higher *IR* values, and Amihud and Goyenko (2010) find that lagged R^2 predicts future performance proxied by *IR* for professional fund managers.

3.3.2. Predicting performance methodology

The skilled investor hypothesis states that future performance, as measured by alpha and *IR*, can be predicted from the logarithmic transformation of R^2 (TR^2) from the previous time period, where $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$. To test whether lagged R^2 predicts future performance, we take the following steps.

First, the daily return 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 total daily return data for each account (total number of observations used in each regression), which varies by account. The split of the time series is its midpoint.[1] The minimum number of daily returns for each account in the sample is 28, which allows for 14 observations each time period. The low number of observations is of concern, so we perform robustness checks and eliminate all accounts with fewer than 80 observations, leaving 40 observations each period, with quantitatively similar results.

Second, we use Pojarliev and Levich's (2008) four-factor model by regressing the daily net excess return earned by currency traders on the four factors in model (1) for both the first and second time periods.

Third, we estimate equation (3), where alpha is the dependent variable, and equation (4), where *IR* is the dependent variable, to determine whether lagged TR^2_{it-n} is a determinant of future performance:

$$alpha_{i,t+n} = \alpha + \beta_{1i}TR^2_{it-n} + \beta_{2i}Turnover_i + \beta_{3i}alpha_{i,t-n} + \varepsilon_t \quad (3)$$

$$IR_{i,t+n} = \alpha + \beta_{1i}TR^2_{it-n} + \beta_{2i}Turnover_i + \beta_{3i}alpha_{i,t-n} + \varepsilon_t \quad (4)$$

where $alpha_{i,t+n}$ is the risk-adjusted return for account i obtained from model (1) for the second time period; $IR_{i,t+n}$ is the *IR* for account i obtained from model (1) for the second

[1] The split of the time series of returns is arbitrary. One limitation of the data in this sample is that account holders do not keep their accounts open for long periods of time. The mean age, defined as the time in days between the first and last trades executed by the account holder, of an account is only 81.92 days (see Table 1 below), which is due to the nature of the industry: Currency traders who post their data online have no barriers to entry and exit and can open and close their accounts with ease, unlike professional managers, who must meet stringent Securities and Exchange Commission requirements. Consequently, setting a uniform number of observations for each regression is not possible because, unlike mutual funds, which have years of daily returns, observations are limited to the short account lives. Age is not included as a control variable in equations (3) and (4), because there is no significant variation in the distribution to provide explanatory power. To test the sensitivity of our results, we performed all analyses in this paper using age as a control variable, and the results remained quantitatively similar. Furthermore, age provided no explanatory power in every specification.

time period; $TR^2_{it-n}$is the logarithmic transformation of lagged R^2 obtained from model (1) for the first time period; and $Turnover_i$ is the turnover for account *i*, defined as the mean of the daily margin-adjusted market value of currency contracts divided by the daily capital amount and lagged $alpha_{i,t-n}$. The control variables *Turnover,* which captures the frequency of trading activity, and lagged alpha, which captures performance persistence and may reflect currency trading skill, are commonly employed in studies that examine professional fund performance (Cremers and Petajisto, 2009; Amihud and Goyenko, 2010) and individual investors (Odean, 1999; Barber and Odean, 2000). For example, Odean (1999) and Barber and Odean (2000) examine individual investors and discover that turnover is inversely associated with performance for buy-and-hold equity traders. Conversely, in our first essay we report that turnover is positively associated with performance for high-frequency currency traders. The positive association arises due to frequent feedback received by high-frequency traders. As traders receive positive feedback, by earning profits on their trades, they increase trading, thus increasing performance. Since we analyze the same sample in this essay as in the first essay, it is hypothesized that feedback, proxied by turnover, will have a positive association with performance.

3.3.2. Data and Sample Selection

The primary data set for this research consists of the daily returns from an online advisory service that records data for individual investors that trade spot currencies. An online advisory service is a financial innovation where individual investors post their trading activity online for other investors to view (Fonda, 2010). Fonda (2010) reports that online advisor websites such as Covestor and ka-Ching have thousands of subscribers, and users who visit the online advisory website can use posted transaction data to manage their own trading accounts. Advisory service websites also contain discussion forums where investors can share strategies, discuss the markets, and provide critical feedback. Furthermore, these websites contain charts of daily returns and performance metrics such as the Sharpe ratio and account rankings, so traders can gauge their performance relative to their peers. This creates an environment where individual currency traders not only attempt to earn abnormal returns but also compete against their peers. The most unique aspect of this industry is that, unlike professionally managed funds, which are not required to disclose trading activity, online advisory websites are completely transparent. This, in turn, provides a very detailed database of transaction data, including each 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 was short or long, the number of contracts opened and closed, and the net profit and loss in US dollars. The sample consists of 428 accounts from March 2004 to September 2009. These data are supplemented with data for the four-factor currency model, obtained from the DB's online database of investable indices, the DBIQ.

Table 3.1 provides summary statistics for the accounts. Panel A presents the descriptive statistics for the dependent and independent variables and Panel B shows their correlation coefficients. Panel A of Table 3.1 reveals that the alpha from the four-factor model for the currency traders in this sample is negative (-0.183 percent per day), which means that the average trader in this sample loses money. Furthermore, the distribution of alpha is right skewed, showing that alpha is concentrated on negative returns. The result that the currency traders in this sample are not producing positive excess returns is also supported by a mean *IR* of -0.08. The distribution of *IR* is more symmetric than that of alpha and negative, which reveals that accounting for risk, as measured by the root mean squared error in the *IR* formula, normalizes the performance of the individual currency traders in this sample. It is notable that the mean R^2 for the estimation period $t - n$ to $t - 1$ is 0.192, which demonstrates that approximately 19.2 percent of the risk-adjusted returns of this sample are explained by the four-factor model. This value for R^2 shows that the currency traders in this sample actively manage their portfolios by tracking benchmark portfolios less closely, indicating greater selectivity.

The correlation coefficient of 0.926, as shown in Panel B of Table 3.1, displays the strong association expected between R^2 and TR^2, the logistic transformation of R^2. The only other notable association is between *IR* and alpha, with a correlation coefficient of 0.581. This result is not surprising, since both variables are the primary proxies for performance and alpha is in the numerator of the formula for *IR* in equation (2).

*****Insert Table 3.1 about here*****

3.4 EMPIRICAL RESULTS

The analysis now focuses on the association between investor performance and R^2. To examine this relation, we regress the estimated alpha from equation (1) and *IR* from equation (2) on the fund's lagged TR^2, as shown in equations (3) and (4).

3.4.1. Fund alpha performance

The central prediction under the skilled investor hypothesis is that future alphas will have a negative association with lagged R^2. Table 3.2 presents the results of the regression of alpha and *IR* on TR^2 and the control variables *Turnover* and lagged alpha. These equations are estimated for the entire sample of 428 accounts from March 2004 to September 2009.

****Insert Table 3.2 about here****

The results in Table 3.2 show that R^2 is not a strong predictor of alpha, which is inconsistent with the skilled investor hypothesis. In Panel A of Table 3.2, the results for equation (3), where alpha is the dependent variable, show that the coefficient of TR^2 is -0.011 (t-statistic = -0.06) for specification (1), which contains all of the control variables. Specification (2), which has TR^2 as the sole explanatory variable, has a coefficient of 0.022 (t-statistic = 0.13). Both are statistically insignificant. This result is consistent with previous studies that analyze the performance of individual investors and imply that following benchmarks leads to increased performance (Odean, 1999; Barber and Odean, 2000). Furthermore, the results are inconsistent with Amihud and Goyenko (2010), who find that TR^2 is a predictor of future performance for professional mutual fund investors, and do not support the hypothesis that the future performance of individual investors is a function of lagged R^2. It is notable that the coefficient for lagged alpha is 0.132 and significant (t-statistic = 1.96), which reveals that performance is persistent when the full sample is analyzed, and this implies these traders have skill. The coefficient for *Turnover* is 0.002 and significant (t-statistic = 2.07), which reveals that performance increases as turnover increases. This result is similar to those presented in the first essay that supports feedback trading: As traders receive more positive feedback via winning trades, they increase their trading activity, which in turn increases performance.

We run two additional regressions, employing equation (4) with *IR* as the dependent variable. Panel B of Table 3.2 presents the results for specification (1) with *IR* as the dependent variable and *Turnover* and lagged alpha as controls, and specification (2) with TR^2 as the sole explanatory variable. The results in Panel B of Table 3.2 are similar to those in Panel A of Table 2, which uses alpha as the dependent variable. Here TR^2 has a negative coefficient, -0.026, that is statistically insignificant (t-statistic = -1.24). This result does not support the skilled investor hypothesis, which states that R^2 is a predictor of future performance. Furthermore, this result is confirmed by specification (2), where the coefficient for TR^2 is -0.028 and also not reliably different from zero (t-statistic = -1.32). Thus far, R^2 does not predict future performance for the individual currency traders in this sample. It is also notable that the coefficient of 0.00 for *Turnover* is not significant when *IR* is the dependent variable (t-statistic = -0.670). This reveals that when accounting for idiosyncratic risk, performance is not positively associated with trading activity. Consequently, although performance modeled as alpha may increase as turnover increases, these traders encounter more risk when *Turnover* increases.

Overall, these results are consistent with the individual investment stream of research that documents that individual investors who actively manage their portfolios and deviate from the benchmarks hurt their performance (Odean, 1999; Barber and Odean, 2000; Glaser, 2003; Coval, Hirshleifer, and Shumway, 2005). Hence, our results thus far imply that individual currency traders would have better performance if they followed the factors of the currency model and they lack skill as proxied by R^2.

3.4.2. Modeling on performance sorts

Next we test the sensitivity of our results on performance sorts based on the significance of alphas from the four-factor currency model. This is mainly motivated by two reasons: First, previous studies examining the performance of professional currency traders show that there is variation in the cross section of performance and that R^2 is inversely associated with performance (Pojarliev and Levich, 2008, 2010a). The second reason stems from the results of the first essay, which indicate that there is cross-sectional variation in the performance of individual currency traders.

We replicate the previous regression analysis by sorting the sample into quartile ranks on alpha significance. One explanation for the lack of support for the skilled investor hypothesis is that the currency traders in this sample all underperform. As shown in Table 3.1, the average currency trader earns an alpha of -0.183 percent per day. If, in the aggregate, currency traders underperform, the results will be biased toward rejecting the skilled investor hypothesis. If low-performing currency traders bias the results, the worst-performing currency traders should have the same results as before, an insignificant coefficient for TR^2. This would provide additional evidence against the skilled investor hypothesis. Conversely, it is possible that the currency traders in the top-performing quartile are skilled (as shown in the first essay), and thus their success is due to active management. If so, there should be a negative and statistically significant association between R^2 and future performance for the top currency traders in this sample.

We next form quartile performance ranks as follows. Alpha is estimated using equation (1), and all 428 accounts are ranked by their alpha significance. Currency traders are then categorized into four portfolios based on their alpha t-statistic rank, where each portfolio contains 107 accounts. Similar to the previous analysis, we then estimate regressions for each portfolio with the logarithmic transformation of R^2 as the independent variable (TR^2) and alpha in equation (3) and *IR* in equation (4) as the dependent variables. Table 3.3 presents the results. Quartile 1 contains the best-performing currency traders and quartile 4 contains the worst-performing ones. Quintile and decile sorts provide similar results.

****Insert Table 3.3 about here****

A notable observation in Panel A of Table 3.3 is that the coefficient for TR^2 is statistically insignificant in every quartile, providing additional support that active management by individual currency traders is not associated with future performance. Furthermore, the sign of the coefficient changes across rankings: positive for quartiles 1 and 4 but negative in quartiles 2 and 3. This result indicates there is no discernable pattern between lagged R^2 and future performance when sorting on currency trader performance. Thus, underperformance is not biasing the results.

Panel B of Table 3.3, which displays the results of equation (4), where *IR* is the dependent variable, provides additional evidence against the skilled investor hypothesis. The coefficient for TR^2 in quartile 1 (best performers) through quartile 3 is positive and statistically insignificant. Furthermore, there is no reliable pattern moving from quartile

1 to quartile 4. If underperformance is driving the insignificant coefficient for TR^2 in the full-sample analysis, then in the cross section the lowest-performing currency traders would have an insignificant coefficient for TR^2, while the top-performing traders would have a negative and statistically significant coefficient for TR^2. This is not, however, borne out in the data. It is also notable that the coefficient of TR^2 in quartile 4 is -0.80 and significant (t-statistic = -2.00). This result is supportive of the skilled investor hypothesis, but is significant only for the worst-performing currency traders, who do not possess skill. The lack of skill of the traders in quartile 4 is also supported by the statistically significant negative coefficient of -0.052 for lagged alpha (t-statistic = -2.21). This reveals that a trader who earns a positive alpha of 1 percent in the first period will earn a negative -0.52 percent in the next period, implying unstable performance. Consequently, despite the sole significant coefficient for TR^2 in quartile 4, the results do not collectively support the skilled investor hypothesis.

3.4.2. Modeling on turnover and trade activity sorts

Previous studies show that individual investors trade frequently and that this hurts their performance (Odean, 1999; Barber and Odean, 2000; Coval, Hirshleifer, and Shumway, 2005). It is possible that there is variation in the cross section when currency trader accounts are sorted on trade activity. The skilled investor hypothesis predicts that the most active traders will have superior return performance relative to their peers who are less active in managing their currency portfolios. This hypothesizes that the coefficient for TR^2 will be negative and statistically significant for the most active currency traders in this sample.

To test whether trade activity has any association with the predictive ability of R^2, we first calculate trade activity, utilizing daily data. Trade activity is proxied by (i) the mean number of roundtrip trades executed for each account per day and (ii) account turnover, calculated as the mean of the daily margin-adjusted market value of roundtrip transactions per day divided by the daily amount of capital. Next we divide the accounts into quartiles, with quartile 1 containing the most active traders and quartile 4 containing the least active traders. Each quartile contains 107 accounts. Finally, for each quartile we regress TR^2 and the control variables on the two performance measures, alpha in equation (3) and *IR* in equation (4). Table 3.4 presents the results for sorts on trade activity proxied by the mean number of roundtrip transactions per day, and Table 3.5 presents the results for quartile sorts on turnover.

3.4.2.1. Modeling on trade activity proxied by mean trades per day

Panel A of Table 3.4 presents the results for equation (3), where alpha is the dependent variable, and Panel B presents the results for equation (4), where *IR* is the dependent variable. Overall, the results support the previous analyses that reject the skilled investor hypothesis. A review of quartiles 1 through 4 in Panel A of Table 3.4 reveals that TR^2 has no predictive ability for alpha. All of the coefficients for TR^2 are insignificant. An interesting observation is that TR^2 appears to follow a linear pattern when we sort on trade activity. The least active traders in quartile 4 have the lowest (negative) TR^2 coefficient, which increases up to quartile 1, where it is positive. Although the coefficients are statistically insignificant, this linear pattern reveals that as traders become more active, the closer R^2 moves to unity, increasing performance. Similar to the results of Odean (1999), who analyzes the performance of equity investors, this finding provides additional support that individual traders can increase their performance if they simply follow the benchmarks.

Another remarkable observation in Panel A of Table 3.4 is that turnover is statistically significant for all four quartiles. The economic significance of quartile 1 is particularly remarkable: A 1 percent increase in trade activity increases alpha by 0.015 percent per day (t-statistic = 8.32). This reveals that certain traders are skilled in one aspect and can increase performance by increasing the number of trades per day. This result is similar to those of the first essay, which shows that individual currency traders respond to feedback. Furthermore, the coefficient for trade activity is positive, meaning that the traders in this quartile can increase performance by actively managing their portfolios, but instead they increase performance by following strategies that closely track the benchmarks, which in turn increases R^2. This is why TR^2 is positive (although insignificant).

****Insert Table 3.4 about here****

The results in Panel B of Table 3.4 for equation (4) with *IR* as the dependent variable also indicate that TR^2 has no predictive ability for future performance. None of the coefficients for TR^2 are reliably different from zero. It also appears that there is no strong linear relation between TR^2 and *IR*, unlike the results presented in Panel A of Table 3.4 when alpha is the dependent variable.

The only coefficient that is statistically significant is the lagged alpha in quartile 4, which contains the least active traders. The economic significance of the coefficient for the lagged alpha, -0.065 (t-statistic = -3.10), demonstrates that if a trader has a negative (positive) alpha of 1 percent per day in the first period, that trader will have a positive (negative) alpha of 0.065 percent per day in the next time period. This reveals that the performance of the least active traders is not persistent, and this result is similar to those reported in Table 3.3, which presents performance sorts.

A noteworthy observation when comparing the results of Panels A and B in Table 3.4 is that *Turnover* is statistically significant for all four specifications when alpha is the dependent variable, as shown in Panel A, yet it is insignificant when *IR* is the dependent variable, as shown in Panel B. A likely explanation for this is that *IR*, which accounts for the idiosyncratic risk (the squared root of the variance), reduces the explanatory power of *Turnover*. Thus, as traders increase *Turnover*, proxied by the mean number of roundtrip transactions per day, performance is not increased, because these traders are exposing themselves to more risk. This implies that these traders may be taking excessive risks, which deteriorates future performance. This result is not surprising, since the traders in this sample are trading currency spot contracts on margin.

3.4.2.2. Modeling on trade activity proxied by turnover

To test the sensitivity of our results on trade activity proxied by mean trades per day, we next examine accounts sorted on *Turnover*, calculated as the daily mean value of the margin-adjusted market value of all roundtrip transactions per day divided by the daily amount of capital. This is done because turnover is used in previous studies that examine investor performance, which show a negative association between turnover and individual equity investor performance (Odean, 1999, Barber and Odean, 2001; Barber et al., 2005). Quartile sorts are created in the same manner as trade activity, proxied by the mean number of roundtrip transactions, as presented in Table 3.4. Quartile 1 contains the most active traders and quartile 4 contains the least active. Table 3.5 presents the results for turnover ranks.

Panel A of Table 3.5 contains the regression results from equation (3), where alpha is the dependent variable. The results are similar to ours when turnover is proxied by the mean number of roundtrips per day reported in Table 3.4. None of the coefficients for TR^2 are reliably different from zero. The only significant coefficients are for *Turnover* and lagged alpha. The coefficient for *Turnover* in quartile 1 is 0.008 and significant (t-statistic = 3.10). Currency traders who increase their turnover by 1 percent can increase alpha by 0.008 percent per day. This supports the calibration hypothesis from our first essay, that is, traders who receive timely feedback on their performance will increase their trading, which in turn increases their performance. It is also notable that the coefficient for lagged alpha is 0.185 (t-statistic = 2.29) for quartile 3 and 0.587 (t-statistic = 7.23) for quartile 4. The alpha coefficient remains positive for quartiles 1 and 2 but is not statistically significant. This reveals that the performance is persistent only for the two least active quartiles of traders when ranked on turnover.

****Insert Table 3.5 about here****

Panel B of Table 3.5 contains the regression results where *IR* is the dependent variable. Similar to the results for alpha in Panel A of Table 3.5, the results for *IR* provide additional evidence against the skilled investor hypothesis. None of the coefficients for TR^2 are reliably different from zero. The only other significant coefficient is for lagged alpha in quartile 4, indicating that the least active traders have persistent performance in this case. The lagged alpha has a coefficient of 0.359 and is statistically significant (t-statistic = 6.14). This implies that underperforming currency traders continue to underperform.

Overall, the results, regardless of specification, uniformly show that the lagged logarithmic transformation of R^2 fails to predict performance in the next period, revealing that currency traders cannot outperform mimicking portfolio benchmarks. Individual investors may be active traders, but active management of their currency accounts does not necessarily lead to superior performance.

3.4.2. Robustness checks with R^2 as the explanatory variable and accounts with R^2 < 0.05 removed

We now perform two robustness checks to ensure the uniformity of our results. First, following Amihud and Goyenko (2010), we replicate the previous analysis by estimating equations (3) and (4) with R^2 instead of its logarithmic transformation (TR^2). Second, we truncate the sample and remove 69 accounts with a four-factor $R^2 < 0.05$, leaving 359 accounts from the full sample of 428 accounts. This step is carried out because Amihud and Goyenko (2010) state that very low R^2 values can signify that investors are using alternative or outlier strategies, which can bias the results. Panel A of Table 3.6 presents the results of equations (3) and (4) with R^2 as an explanatory variable, and Panel B presents the results when accounts with $R^2 < 0.05$ are removed.

The results in Table 3.6 do not support the skilled investor hypothesis. The coefficient for R^2 in Panel A is 0.044 (t-statistic = 0.07) for equation (3), where alpha is the dependent variable, and the coefficient for R^2 is -0.096 (t-statistic = -1.22) for equation (4), where *IR* is the dependent variable. Neither coefficient is reliably different from zero, indicating that R^2 does not predict future performance.

****Insert Table 3.6 about here****

Panel B of Table 3.6, for accounts with $R^2 < 0.05$ removed from the sample, reports results similar to those of all of our previous analyses, which uniformly reveal that R^2 has no explanatory power for future performance. The coefficient for TR^2 for the alpha specification is a positive 0.034 and statistically insignificant (t-statistic=0.13). The result for the *IR* specification shows a coefficient of -0.019 for TR^2, which is also not reliably different from zero (t-statistic = -0.59). Overall, the results demonstrate that individual investors who deviate from the benchmarks do not have superior alpha-generating abilities. This result remains the same when R^2 is used as an explanatory variable and when accounts with $R^2 < 0.05$ are removed.

3.4.3. The persistence of performance and selectivity

We now examine the persistence of performance and selectivity to gain additional insights into why certain individual currency managers can earn significant alphas, as reported in the first essay and which implies they have skill, yet R^2 does not predict performance, which infers managers lack proficiency in trading currencies. Amihud and Goyenko (2010) test the persistence of R^2 and state that performance should be stronger if a fund's strategy with respect to selectivity is stable and persistent. If individual currency traders possess skill, then we hypothesize that lagged alphas should be positively associated with future alphas. Similarly, if currency traders are skilled and have persistent performance, active management, proxied by R^2, should also be stable and persistent.

To test whether there is a positive association between lagged and future performance and lagged and future R^2, we estimate equation (1), the four-factor currency model, for each time period, similar to our previous analysis. Once we obtain the alphas and R^2 values from each period, we regress alpha and R^2 from the second time period on lagged alpha and R^2 values, respectively. Similar to our quartile performance sorts presented in Table 3.3, we form quartile portfolios with ranks based on alpha significance. Each quartile contains 107 accounts. If the currency traders in this sample lack skill, we hypothesize that the coefficients for lagged alpha and lagged R^2 will be insignificant for all quartiles. However, if the top-ranked traders in quartile 1 do possess skill, as shown in the first essay, the coefficients for lagged alpha and lagged R^2 will be positive and significant.

In addition to examining persistence for the full sample, we also examine persistence for all accounts with over 80 days of return data. This is done because one limitation of the data is the short account life span. As reported in Table 3.1, the mean account age is 81.921 days. Removing all accounts with fewer than 80 days of daily return data helps mitigate biases due to short life span. For robustness controls, we also perform the analysis with 90-, 100-, and 120-day cutoffs, with quantitatively similar results.

Panel A of Table 3.7 reports the full-sample results for the persistence of performance and active management, proxied by R^2, and Panel B reports the results when accounts with fewer than 80 days of daily return data are removed.

****Insert Table 3.7 about here****

The results of the persistence of alpha reveal no persistence across performance-sorted quartiles. It is notable that the coefficients for lagged alpha and lagged R^2 are insignificant in quartile 1 (the top performers). As reported in our first essay, this group of traders is able to earn positive and significant alphas. Here we report that their performance is marginally persistent at the 11 percent level of confidence (t-statistic = 1.63). It is important to note that selectivity, proxied by R^2, is significantly persistent for three out of four quartiles. These results can help explain why R^2 has no predictive power for future performance. Although for the full sample selectivity can remain stable over the two time periods, alpha is not persistent. Thus, a low (high) R^2 in one period may not be associated with a high (low) alpha in the next period because performance changes over time across performance quartiles.

It is also important to emphasize that the traders in this sample have a limited number of daily return data (as shown by the account age in Table 3.1), unlike the mutual fund data analyzed by Amihud and Goyenko (2010), which have hundreds of observations for each account. The low number of daily observations can bias the results. Thus, we report the results for the persistence regressions in Panel B of Table 3.7, where we remove all accounts with fewer than 80 days of daily return data.

For the top performers in quartile 1, the coefficient for lagged alpha is 1.185 and significant (t-statistic = 4.51). This augments the results from our first essay, which reports that the top 25 percent of traders earned a significant alpha of 0.59 percent per day, by showing that the ability to generate positive alphas is persistent, at least for the top quartile of account holders who have longevity over 80 days. Another remarkable observation is that R^2 does not remain significant when accounts under 80 days old are removed. In fact, all coefficients are insignificant, revealing that the individual currency traders in this sample change their strategies over time. This result also provides more support for why R^2 does not predict future performance. Amihud and Goyenko (2010) emphasize that performance should be stronger if selectivity is stable and persistent. However, we witness the opposite here, where performance is stronger for the top traders in this sample yet selectivity is not persistent. This finding reveals that it is possible to earn positive and significant alphas with a strategy that is not stable over time, which undermines the basic premise of using R^2 as a predictor of performance.

The lack of persistence of selectivity and the persistent performance of top-performing account holders with longevity over 80 days can be explained by studies that have examined popular currency trading styles. Recent empirical research reveals that currency trading strategies can become crowded, causing profitable strategies to become unprofitable, and this implies that a stable R^2 will not lead to superior performance (Pojarliev and Levich, 2008; Baillie and Change, 2010). Pojarliev and Levich (2010b) analyze how carry trades can become crowded, which leads to deterioration in performance, and discover an inverse association between style crowdedness and future performance for the carry trade. This implies that currency traders who change their strategies over time may have higher returns than currency managers who follow the same strategy.

3.4.4. Skill measured by the percentage of winning trades and drawdowns

We next determine whether the traders in this sample possess skill by conducting two alternative tests. Our analysis so far has revealed that R^2 does not predict future performance for individual currency traders. This implies that currency traders who deviate from the benchmarks described by the currency model of Pojarliev and Levich (2008) do not increase their performance, and hence the evidence seems to suggest that they are not skilled traders. On the other hand, our analysis also shows that the top-performing currency traders have superior alpha-generating abilities, implying they have skill, and their performance is persistent, which reveals that their ability to generate positive abnormal returns remains stable over time. To examine the skill of these traders in a more direct fashion, we first examine individual transactions to determine whether their performance is determined by skill or luck and then examine drawdown to find out whether individual currency traders possess skill in moderating losses.

To determine whether individual currency traders are skilled, we examine the percentage of winning trades for each account and then determine whether this percentage is statistically different from chance (a 50 percent win percentage). We start by counting the number of winning and losing trades for each account, where winning trades are defined as trades with a net profit greater than zero and losing trades are those with a net loss equal to or less than zero. The percentage of winning trades is the number of winning trades divided by the total number of trades per account. We then examine the full sample and performance-ranked quartiles (similar to our performance-based sorts above), with each quartile containing 107 accounts. The null hypothesis is that the percentage of winning trades will not be statistically different from chance (50 percent).

We estimate t-statistics to determine the statistical significance. Table 3.8 presents the results of the analysis of individual trades.

****Insert Table 3.8 about here****

Panel A of Table 3.8 reports the full-sample results and shows that, on average, currency traders have winning trades 53.97 percent of the time, which is reliably different from 50 percent (t-statistic = 53.97). This supports the argument that the traders in this sample possess skill.

Panel B of Table 3.8 reports the results for the quartile performance sorts. Quartile 1, which contains the top-performing currency traders, shows that this group earns a profit on 66.78 percent of their trades, which is significantly different from 50 percent (t-statistic = 9.65). Quartile 2 traders earn a profit on 58.50 percent of their trades (t-statistic = 4.64). Quartile 3 traders have winning trades 48.33 percent of the time, which is not statistically different from 50 percent. Finally, the lowest-performing currency traders in quartile 4 are not skillful. They earn a profit, on average, on 42.26 percent of their trades, and this is significant (t-statistic = 4.50).

Next we examine skill by focusing on drawdowns. This test is expected to reveal the extent individual currency traders are able to moderate their losses. If top traders are skilled, it is expected they will mitigate their losses and thus have a lower drawdown than the worst-performing traders. To address this issue, we define drawdown as the maximum daily loss, proxied by the daily percentage return, for an individual currency trader. The evidence from our drawdown analysis will also permit us to compare our findings with those of Melvin and Shand (2011), who examine drawdown performance for professional currency traders and find that some professional currency traders are adept at moderating losses. Table 3.9 presents the results: Panel A reports the full-sample results for all 428 account and quartile rankings based on the significance of alpha from the Pojarliev–Levich (2008) four-factor currency model. Panel B presents the results for account holders with age over 80 days with similar rankings on performance. We also report the difference in means between the top performers in Q1 and the worst performers in Q4 for both the full sample and the age-truncated sample.

For the full sample of 428 accounts, the evidence reveals that the full-sample mean drawdown is -16.81 percent. The quartile ranks of the full sample show that the top performers have a mean daily drawdown of -16.07 percent. This is lower than the worst performers in Q4, who have a mean daily drawdown of -19.15 percent, and also lower than Q3 traders, who have a mean daily drawdown of -16.84 percent. It is notable that Q2, which contains the second highest group of performers, has a lower drawdown, -15.19 percent, than the top performers. Although the top performers in Q1 have a drawdown that is 3.08 percent lower than the worst-performing traders in Q4, the difference is not statistically significant (t-statistic = 1.29).

****Insert Table 3.9 about here****

Panel B of Table 3.9 reports the results for the truncated sample, where we remove currency account holders with account lives under 80 days. This is done because it was noted above that the performance of the top traders with lives greater than 80 days had persistent performance. The persistence of performance may result from the traders' ability to mitigate downside losses. Panel B of Table 3.9 reveals that the top quartile of traders does have the lowest drawdown of -16.02 percent, and there is a linear trend moving from the top performers in Q1 to the worst performers in Q4. Drawdown decreases as performance increases, and this implies skill. Despite this increase, the difference between Q1 and Q4 is 3.89 percent, still insignificant (t-statistic = 1.08).

In summary, the analysis of individual currency trades shows that a sizable percentage of traders in this sample are able to beat the odds and earn a profit on their trades, significantly different from pure chance. This implies these traders possess skill. Furthermore, the analysis of drawdown reveals that the top-performing traders have a better ability to mitigate downside losses than the worst-performing traders (i.e., they have lower drawdown than the worst-performing traders), yet the difference is not significant. These results, in conjunction with the results of the persistence of alpha presented in Table 3.7, demonstrate that approximately 25 percent of the traders in this sample are able to earn significant and stable abnormal returns, and not due to luck.

3.4.5. Skill measured by timing ability

Melvin and Shand (2011) argue that the ability of currency traders to time their exposure to systematic factors is an important contribution to performance. The authors examine the returns of professional currency traders and find there is some evidence of timing ability among professional currency managers. Specifically, they show that out of the 42 currency managers analyzed, 13 timed the carry trade, five timed the PPP, and nine timed momentum factors.

Our final inquiry of skill, then, explores the ability of individual currency traders to time the Pojarliev–Levich (2008) currency factors. Consequently, if the individual currency traders in our sample possess skill, they should also exhibit timing abilities. Following Melvin and Shand (2011), we test the timing abilities of the individual currency traders by estimating the following equation:

$$r_{j,t} = \alpha_j + \sum_{i=1}^{3} \beta_{i,t} \left[F_{i,t} \middle| F_{i,t} > 0 \right] + \sum_{i=1}^{3} \gamma_{i,t} \left[F_{i,t} \middle| F_{i,t} < 0 \right] \qquad (5)$$

where r is the return of individual currency trader *j* at time *t*, *F* is the return associated with factor *i*, and the factors are decomposed into positive and negative return observations. Individual currency trader timing ability is inferred from whether traders load positive (negatively) on the factors when factor returns are positive (negative). We estimate this regression for all 428 accounts. For the sake of brevity, and since our main inquiry is whether the coefficients are significant, we report a summary of all significant coefficients (at the 5 percent level of significance) in Table 3.10. The full sample result for all 428 accounts is available from the author.

The results of the timing model, reported in Table 3.10, support that some traders in this sample possess skill at timing the Pojarliev–Levich (2008) factors. We first focus on the coefficients associated when the carry trade has a positive return (CarryPos). As can be seen, 36 individual currency traders (8.41 percent) timed the carry trade. This implies that 36 traders have skill at timing the carry trade when the carry trade earns a positive daily return. A total of 54 individual currency traders have significant coefficients when the carry factor earns negative returns (CarryNeg), suggesting that a sizable percentage, 12.62 percent of all individual traders, have the ability to successfully time the carry trade when it earns negative returns.

The last column of Table 3.10 reports the percentage of coefficients that is significant for each Pojarliev–Levich (2008) factor. The coefficient with the lowest total percentage of significance is negative momentum (MomNeg), at 7.71, which implies that 33 out of 428 accounts were able to time momentum. The coefficient CarryNeg has the highest percentage, at 12.62 percent. It is interesting to note that Melvin and Shand (2011) report that five out of 42 (approximately 11.9 percent) of professional currency traders successfully timed the PPP (referred to the value trade in this essay), 13 timed the carry (30.95 percent), and nine timed momentum (21.4 percent). Here we report that approximately 17.29 percent of the individual traders successfully timed the value trade (ValuePos and ValueNeg), 17.52 percent timed momentum, and 21.03 percent timed carry. Although a direct comparison between the professional traders in the study of Melvin and Shand (2011) and our sample warrants caution, our results suggest that individual currency traders have somewhat similar timing ability skills to those of professional currency traders.

****Insert Table 3.10 about here****

3.4.6. Discussion

The results of the analysis of spot currency trades and the persistence of alpha are not supported by the results of the predictability of R^2 regressions. One possible reason for this discrepancy is the relevance of the currency model of Pojarliev and Levich (2008) in the context of individual spot currency traders. In a recent study, Melvin and Shand (2011) examine the limitations of the four-factor currency model. They note that, unlike equity markets, currency markets have no established market portfolio, buy-and-hold portfolios do not exist due to the long/short characteristic of currency trading, and alternative methods of construction of the factors can lead to different results. In the context of this essay, the threshold issue thus becomes whether the four-factor currency model is appropriate for the analysis of individual spot currency traders. Pojarliev and Levich (2008, 2010a) show that the four-factor model does an exceptional job of explaining the returns of professional currency managers. This demonstrates that professional currency traders are utilizing trading strategies that mimic the factors, namely, the carry, value, and momentum trades. However, the individual currency traders in this sample are high-frequency spot traders, and they may not be utilizing trading strategies based on carry, value, or momentum benchmarks. It is possible the four-factor currency model does not provide sufficient explanatory power for the returns of individual currency traders. Furthermore, an alternative specification of the currency factor model may lead to different results (Melvin and Shand, 2011).

To investigate these issues, we perform two additional tests. First, we estimate four-factor regressions in equation (1) on all individual 428 accounts to determine whether the four-factor model provides sufficient explanatory power for the returns of individual currency traders. Second, we estimate an alternative specification of equation (1), using the Deutsche Bank Currency Return Index (DBCR) as our explanatory variable.

We now summarize our findings of equation (1) on 428 individual accounts. Due to the breadth of the results, we present a summary of the full sample results below. Regression results for all 428 accounts are available from the author. The most salient observation is that the mean R^2 is 0.11 (standard deviation = 0.10), which reveals that the four-factor model explains approximately 11 percent of the returns of the high-frequency traders. This R^2 value is low, but a closer examination reveals that R^2 ranges from a minimum of 0.001 to 0.59, which indicates that some individual spot currency traders utilize the carry, value, and momentum trades, since the model explains a significant portion of the return distribution for some individual currency traders in this sample. The issue of low R^2 values is addressed in Table 3.6, where all accounts with an R^2 below 0.05 are removed. As reported in Table 3.6, the results remain quantitatively similar to those of our full-sample regressions. Thus, it seems unlikely that a low coefficient of determination will bias this study's results.

Next we test the sensitivity of the results to an alternative benchmark. To do so, we execute equation (1) with the DBCR as the sole explanatory variable. The DBCR is an investable index that consists of currencies and represents a passive benchmark that currency traders can utilize to manage their funds. We repeat the analysis above and, for the sake of brevity, only present the full-sample results for equations (3) and (4) in Table 3.11. All the results remain quantitatively similar to those reported earlier when the DBCR is the sole risk factor.

Table 3.11 presents the results of equations (3) and (4) that test whether the logarithmic transformation of R^2 predicts performance. The primary result is that TR^2 is insignificant for both specifications. This result is similar to those of all the previous analyses using the four-factor currency model. Lagged R^2 does not predict future performance for the individual currency traders in this sample. It is also notable that lagged alpha is positive and significant for both the alpha and *IR* specifications, which reveals that performance is persistent. This implies that, on average, the currency traders in this sample have stable returns and are adept at trading spot currencies.

****Insert Table 3.11 about here****

A secondary issue that can affect the results is account holder longevity. Table 3.1 reports that the mean age for each account is 81.92 days. One explanation for the short lives of currency traders is that this group of traders posts their trades online, where there are no barriers to entry or exit. Account holders can open and close their accounts with ease and migrate from one website to another. There is no way to track why currency traders leave the platform, and we are unable to report on their performance once their results are no longer in the database. To test the robustness of our results, we remove all accounts with fewer than 80 days of daily return data, and the results remain similar to the full-sample results. Consequently, the age of the accounts does not seem to bias the results presented in this essay, although an examination of other samples of individual currency traders who post their results online will provide future insight into their performance and trading characteristics. To date, no other such data source is available to this author.

3.5. CONCLUDING REMARKS

This essay tests whether individual currency traders are skilled. We do this by examining whether the future performance of individual currency traders is predicted by R^2, as obtained from the Pojarliev–Levich (2008) four-factor model. Prior research shows that a lower R^2 value is a measure of active management, or fund selectivity, revealing that fund managers do not passively follow the benchmark index. The R^2 value is negatively associated with future fund performance in professionally managed mutual funds, as measured by fund alpha and the fund *IR*.

Previous studies are limited in that they focus on one segment of investors: professional investors, namely, hedge funds and mutual funds. This study fills a gap in the literature by analyzing individual investor currency traders. Using a unique database of daily return data for individual currency traders, we show that R^2 does not predict future performance for all types of currency investors. These results remain robust to sorts on performance, turnover, and trade activity. Individual currency traders actively manage their accounts, yet, unlike for professional fund managers, R^2 provides no predictive power for future performance.

To examine this finding in more detail, we examine the persistence of performance and active management. We discover that when we truncate the sample by removing all accounts with fewer than 80 days of return data, performance is significantly persistent but selectivity is not stable. Consequently, although alpha is stable over time, implying that these traders possess skill, R^2 changes, and thus there is no strong association between the variables, and this is a likely explanation why R^2 does not predict future performance.

Finally, we investigate skill by examining transaction data, drawdown, and timing ability. We find that approximately 50 percent of the individual currency traders in this sample are able to earn a net profit on their trades due to skill and not luck. Additionally, top-performing currency traders have lower drawdown than the worst-performing traders, although the difference is not considerably dramatic. Individual currency traders also appear to have skill in timing currency factors. Interestingly, in comparison to the evidence of Melvin and Shand (2011), our results further suggest that individual currency traders have somewhat similar timing ability skills to those of professional currency traders. Overall, the results reveal that, despite R^2 possessing no predictable power for currency traders, a sizable percentage of currency traders do possess skill at trading currencies.

This study has broad implications for future research on trader performance. Studies using R^2 as a predictor of performance should recognize that utilizing R^2 as a determinant of performance may not apply to all samples of traders. Analysts and investors using R^2 for fund selection and evaluation purposes must be aware that R^2 does not always provide an accurate assessment of future performance. As shown in previous studies, a low R^2 can be construed to mean that investors actively manage their funds by not following established benchmarks, which can lead to future positive performance. Conversely, as shown in this study, a low R^2 can reveal that investors actively manage their funds, but this does not necessarily lead to a negative association between R^2 and performance, because the traders change their strategies over time.

CHAPTER 4

IS TECHNICAL ANALYSIS PROFITABLE FOR INDIVIDUAL CURRENCY TRADERS?

4.1. INTRODUCTION

It is widely recognized that technical analysis is a popular tool used by individual investors and currency traders (Taylor and Allen, 1992; Cheung and Chinn, 2001; Park and Irwin, 2004). In 1978, J. Wells Wilder published *New Concepts in Technical Trading Systems*, widely considered the definitive work on technical analysis. The use of technical analysis has since flourished, fostering an entirely new industry. For example, trade publications such as *The Technical Analysis of Stocks and Commodities*, popular trading websites, and virtually every security trading software platform has technical indicators. Numerous academic studies have shown that technical trading strategies can generate abnormal returns (Sweeny, 1986; Levich and Thomas, 1993; Cheung and Wong, 1997; Neely, 1997; Acar and Lequeux, 2001; Lee, Pan and Liu, 2001; Okunev and White, 2003), yet not one of these studies analyzed the returns of professional or individual traders, these studies simply examine the performance of technical trading rules applied to currency rates. Consequently, it remains unclear whether the popular technical indicators such as the Relative Strength Index (RSI), Bollinger Bands (BB), Moving Average Convergence Divergence (MACD) and 8 and 18-day moving average crossover (MA) produce positive abnormal returns for individual currency traders.

This essay addresses whether the use of technical analysis is positively associated with the performance of individual currency traders. To examine this issue, we develop a factor model that consists of currency indices constructed for technical analysis. Specifically, we employ the four most popular technical trading indicators identified by Wilder (1978) and used in the TradeStation version 9.0 trading software platform, which is recognized as one of the most popular trading platforms used by frequent traders (Stocks and Commodities, 2010; Carey, 2011). We then examine a proprietary database of 428 individual currency traders over the period March 2004 to September 2009 to determine whether the use of technical analysis, proxied by R^2 from our technical trading model, is positively associated with performance, modeled as alpha. Determining whether technical individual currency traders use popular technical indicators, and whether the use of these indicators is profitable, provides much needed insight into the source of profits and losses for individual currency traders. In our first two essays we reveal that individual currency traders are skilled. Specifically, we report the top quartile of individual currency traders earn positive abnormal returns of 0.59 percent per day. In our second essay we reveal that performance is significantly persistent for the top quartile of traders with account lives over 80 days and some individual currency traders have the ability to time the currency markets. Despite documenting the superior alpha generating abilities of these traders, the source of their skill is unknown. Investigating whether technical analysis is positively associated with performance will reveal if technical analysis is the source of individual currency trader profits or losses. This study is also motivated by previous studies that have found technical trading strategies can produce abnormal returns yet none of these studies examined the returns of individual currency traders. For example, Sweeny (1986) applies filter rules to nine currencies, Cheung and Wong (1997) analyze the profitability of filter rules on Asian currencies and Levich and

Thomas (1993) examine filter rules and moving averages on five currency futures markets. Analyzing the returns of individual currency traders allows us to overcome the shortcomings (i.e., data-snooping, ex post selection of trading rules, and difficulties in estimating transaction costs (Park and Irwin, 2004)) of previous technical analysis studies. Examining the association between net returns and technical analysis provides an accurate assessment of the profitability of technical analysis that is not plagued by the limitations of previous studies.

To examine the cross-section of individual currency trader returns we develop a factor model with explanatory variables derived from four technical indicators, the Relative Strength Index, Bollinger Bands, Moving Average Convergence Divergence, and 8 and 18-day moving average crossover. The theoretical foundation of our model derives from Anson (2008), who posits that different types of beta exist. Beta can exist as a risk factor, under the traditional capital asset pricing model (CAPM), or it can consist of other factors in the market, for example, exposure to bonds, credit, or commodities. Extending the Anson (2008) beta logic, we develop a "technical currency model" that uses four popular technical indicators to create investable currency indices. Our approach is similar to that of Pojarliev and Levich (2008) who analyze the performance of currency hedge funds and set forth a factor model with factors that mimic common trading styles used by professional currency managers. If individual currency traders use technical analysis, factors constructed from technical indicators should provide explanatory power with respect to the cross-section of returns. To test the explanatory power of the technical currency model, we estimate regressions on both equal-weighted portfolios and on individual-account net returns for all 428 accounts in the sample.

We next investigate the association between technical analysis and performance. To examine this relationship, we regress the R^2 of the technical currency model, our proxy for the utilization of technical analysis, on the alpha of the technical currency model, our proxy for performance. A high (low) R^2 indicates a high (low) use of technical analysis. If technical analysis is positively associated with performance, we expect a positive relationship R^2 and alpha.

Our results are summarized as follows. The technical currency model provides little explanatory power when analyzing equally-weighted portfolios net returns. A likely explanation for the low explanatory power of the model is that equally-weighted portfolios mask the idiosyncratic trading styles of individual currency traders. However, the technical currency model satisfactorily explains the cross-section of returns when analyzing daily net returns of individual currency trader accounts. Our regressions of individual account holder returns indicate that approximately 20 percent of the coefficients for the technical currency model are statistically significant which reveals that individual currency traders in this sample utilize common technical indicators to trade spot currencies. Finally, our analysis of the association between the use of technical analysis and performance reveals that the use of well-known technical indicators is negatively associated with performance. This implies that currency traders who use the technical indicators employed in this study underperform relative to their peers who do not use these technical indicators.

Our primary contribution is that we provide an explanation for the source of profits and losses of individual currency traders. Our results reveal that the use of popular technical indicators is detrimental to performance implying that individual currency investors who seek superior performance may need to avoid the technical indicators examined in this essay. This is significant because a majority of currency traders use technical analysis (Taylor and Allen, 1992; Cheung and Chinn, 2001; Park and Irwin, 2004) and our results imply that traders who do use popular indicators may hurt their performance. Additionally, the evidence reveals that there are other factors present in currency markets that can be used to explain the cross-section of returns for individual currency traders. Pojarliev and Levich (2008) develop a four-factor currency model that does an exceptional job of analyzing the returns of professional currency managers. However, Melvin and Shand (2011) reexamine the four-factor currency model and show that the construction of factors can change the results. This arises because of the unique characteristics of the currency markets: there is no buy-and-hold portfolio, no market portfolio, and currency trading involves both short and long positions. The gist of their article is that there is no generic trading strategy in the foreign exchange market and this implies that there are other factors that can explain the cross-section of returns for currency traders. Our results support the contention that other currency trading strategies, namely four popular technical indicators, can provide explanatory power for the returns of currency traders. Finally, we contribute to the literature a possible explanation for the lack of performance of other individual investors. Published studies of equity investors reveal that individual investors underperform relative to the market (Odean, 1999; Barber and Odean, 2000) yet none of these studies examined whether technical analysis was a source of the profits or losses of individual equity traders. One possible explanation for the underperformance of individual investor equity traders may be the use of technical analysis.

The rest of the essay is organized as follows. In Section 4.2, we present a brief overview of the related literature and hypothesis development. Data and methodology are discussed in Section 4.3, and we report our empirical results in Section 4.4. Finally, Section 4.5 sets forth a brief summary and our concluding remarks.

4.2. HYPOTHESIS DEVELOPMENT

The theoretical foundation of our work derives from Anson (2008), who states that there exist different types of beta. Beta can be a risk factor under the traditional CAPM, or it can consist of other factors, for example, factors that mimic trading styles utilized by traders. Pojarliev and Levich (2008) apply the Anson (2008) theoretical framework to currency returns and develop a four-factor currency model. These factors consist of trading strategies used by professional currency managers, namely the carry, momentum, value trades and volatility. Applying the same logic as in Pojarliev and Levich (2008), it is arguable that other trading methodologies could also be used to construct factors to analyze the returns of currency traders.

Numerous studies examine the role of technical trading methodologies, also known as technical analysis, in the currency markets. Levich and Thomas (1993) and Acar and Lequeux (2001), show that trend-following strategies can lead to profits. Further, Okunev and White (2003) analyze moving averages and find similar results. Other studies go beyond simple trading strategies and find that advanced technical strategies can lead to positive abnormal returns. Sweeny (1986) examines nine currencies from 1973 to 1980 and shows that profits generated from these strategies generate statistically significant profits. Cheung and Wong (1997) apply filter rules to Asian currencies and find that filter rules can earn positive returns. Lee, Pan, and Liu (2001) examine technical trading rules applied to nine Asian currencies and finds abnormal returns only for the Taiwan Dollar.

In addition to studies that examine the profitability of technical trading strategies, it is well established that individual currency traders use technical analysis (Taylor and Allen, 1992; Cheung and Chinn, 2001; Park and Irwin, 2004). Selecting technical trading indicators with which to analyze individual currency trader returns is not a straightforward task. Despite the existence of thousands of technical indicators, some are broadly recognized and used by individual traders. We select the four most popular technical trading indicators identified by Wilder (1978) and used in the TradeStation version 9.0 trading software platform, which is recognized as one of the most popular trading platforms used by frequent traders (Stocks and Commodities, 2010; Carey, 2011). We hypothesize, then, that if traders use these technical indicators, our technical currency model will have explanatory power with respect to individual currency trader returns. Further, if technical analysis, based on the four most popular technical trading factors, produces positive excess returns, we conclude that the use of technical analysis is positively associated with performance.

4.3. DATA AND METHODOLOGY

4.3.1. Data Description

We use two data sources in this essay. The primary data set is daily net returns from a proprietary online advisory service that records data for individual retail spot currency traders. The sample consists of 428 accounts and 33,952 daily net returns for the period March 2004 to September 2009. An online advisory service is defined as a website that publishes the trades of its clients for other individuals to view. Registered users of these sites can view the trades that individual investors post and can use these trades to manage their own money (Fonda, 2010). Online advisory services provide a rich database of transaction data that 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. To construct our factor model, we obtain daily currency return data from TradeStation Securities.

4.3.2. Methodology

Our primary four-factor technical currency model is defined as:

$$REW_{i,t}^{Net} - R_{ft} = \alpha + \beta_{1i}\text{BBIndex}_{it} + \beta_{2i}\text{MAIndex}_{it} + \beta_{3i}\text{MACDIndex}_{it} + \beta_{4i}\text{RSIIndex}_{it} + \varepsilon_t \qquad (1)$$

where $REW_{i,t}^{Net} - R_{ft}$ is the daily, equal-weighted net return less the daily risk-free rate, proxied by daily return for the one-month London Interbank Offered Rate. The explanatory variables consist of the daily returns of variable-weighted investible indices, calculated by using four well-known technical indicators (defined below) on a variable weighted currency index.

To proceed, first we define the four technical indicators, then we define the variable weighted currency index, and finally we apply the technical indicators to the variable weighted currency index to obtain four indices used to calculate daily returns for the factors of the technical currency model.

4.3.2.1. Definitions of Technical Indicators.

We first identify and define the technical indicators of model (1). The first technical indicator is Bollinger bands, BB, defined as:

$$MA = \frac{\sum_{i=1}^{n} P_t}{n} \tag{2}$$

$$UpperBB = MA + 2\sqrt{\frac{(P_t - MA)^2}{n}} \tag{3}$$

$$LowerBB = MA - 2\sqrt{\frac{(P_t - MA)^2}{n}} \tag{4}$$

where *MA* is the moving average of the price of currency P_t. Bollinger bands are a set of three curves, the MA, upper band (UpperBB) and lower band (LowerBB) drawn in relation to currency rates; the middle band is a measure of the intermediate-term trend, which serves as the base for the upper band and the lower bands. The interval between the upper and lower bands and the middle band is determined by volatility, which is two-times the standard deviation of the average, or middle band (MA). The BB identifies when traders purchase (short) currencies that have moved below (above) two-standard deviations from the current trend and are trading volatile currency price movements.

The second indicator is the 8- and 18-day simple moving average (MA) crossover, defined above in equation (2). Equation (3) is calculated for both the 8- and 18-day simple moving averages and buy (sell) signals are generated when the 8-day MA moves over (under) the 18-day simple MA. The MA is a common technical indicator to determine short-term trends.

The third indicator is the Moving Average Convergence Divergence (MACD), defined as:

$$\text{MACD} = \text{XAVG1} - \text{XAVG2} \tag{5}$$

$$\text{XAVG1} = P_{t-1} + \frac{2}{13} + x \ (P_t - P_{t-1}) \tag{6}$$

$$\text{XAVG2} = P_{t-1} + \frac{2}{25} + x \ (P_t - P_{t-1}) \tag{7}$$

where XAVG1 and XAVG2 are the exponential moving averages for a currency where P_t is the price for the currency. The MACD is an indicator that identifies long-term trends and momentum through the difference and the average of 12- and 24-day exponential moving averages.

The final factor is the Relative Strength Index (RSI), defined as:

$$RSI = 100 - \frac{100}{1 - \sum_{i=1}^{14} G / \sum_{i=1}^{14} L} \tag{8}$$

where G (L), is the average dollar gain (loss) of a currency measured over a 14 day period. The RSI is a technical indicator that compares the magnitude of recent gains to recent losses in an attempt to determine whether currencies are overbought and oversold.

4.3.2.1. Definition of Weighted Currency Indices and Construction of Independent Variables.

To construct the four technical indices of our technical currency model (1), we proceed as follows. First we create a weighted currency portfolio consisting of the top five currencies traded by individual currency traders, as reported in Table 4.1. The weighted currency portfolio consists of the following currency pairs and weights: EURUSD (30 percent), GBPJPY (28 percent), GBPUSD (14 percent), USDJPY (14 percent), and USDCHF (14 percent).

Second, we calculate the four technical indicator indices, using the four technical indicators defined in equations (2) to (8), as follows: for the Bollinger Band Index (BBIndex) a trader enters a long position when the closing price of the weighted currency portfolio crosses above the lower Bollinger band and sells short when the closing price crosses beneath the upper Bollinger band. Bollinger bands are volatility bands placed above and below the 20-day moving average and traders who utilize Bollinger bands to trade are attempting to profit from volatile currency movements.

For the 8-day and 18-day Moving Average Index (MAIndex) a trader goes long (buys) on a currency when the 8-day moving average crosses over the 18-day moving average and goes short (sells) when the 8-day moving average crosses under the 18-day moving average. Traders who utilize moving averages obtain profits by going long when the trend is moving up and shorting when the short-term trend is moving down.

For the Moving Average Convergence Divergence Index (MACDIndex) a trader enters a long position when the MACD difference (calculated using the 12- and 24-day exponential moving averages) crosses over zero and establishes a short position when the MACD difference crosses below zero. Traders that utilize the MACD difference are capitalizing on the strength of momentum to generate profits. Momentum of the intermediate trends is strongest when the difference between the 12- and 24-day exponential moving averages is greatest. Traders will enter long positions when momentum is moving up (MACD difference > 0) and short when momentum is moving down (MACD difference < 0).

According to the Relative Strength Index (RSIIndex) strategy, a trader goes long the weighted currency index when the RSI technical indicator reaches 30, then sells short when the RSI technical indicator reaches 70. An RSI value of 70 (30) indicates to a trader that the currency is currently overbought (oversold) and a trader will then enter a short (long) position anticipating that the currency rate will move down (up) in the future. Our final step requires computing daily returns for each technical indicator index.

4.3.3. Data Description

Table 4.1 reports the types of currency pairs traded in our sample, the total number of roundtrip trades, and the percentage of trades for each pair. It is notable that the top currency pair traded is the EURUSD. 17,199 roundtrip transactions of the EURUSD, or approximately 21.76 percent of all trades, are executed in the sample period, March 2004 to September 2009. Individual currency traders trade a variety of the 28 currency pairs listed. The top five contracts traded account for approximately 50 percent of all contracts traded.

****Insert Table 4.1 about here****

Table 4.2 shows the mean, median, maximum, and minimum standard deviation, and skewness of the equal-weighted portfolio excess net returns and the technical indicator indices. The data reveal that currency traders in this sample earn positive, equal-weighted excess net returns of 0.0576 percent per day. The most remarkable observation from Table 4.2 is the high skewness of the equal-weighted portfolio daily net returns. This reveals that individual currency traders, on average, sustain frequent small losses while earning fewer, yet significantly large gains. The remainder of Table 4.2 reports data for the technical indicator indices. The most notable observation is that individual currency traders are able to beat the technical indices. The index with the highest return is the MAIndex, which earned an average of 0.0192 percent per day. Furthermore, it is surprising that both the MACDIndex and the MAIndex earned positive returns over the

2004–2009 period. This reveals that two out of four simple trading strategies based on technical indicators are profitable on a gross return basis.

****Insert Table 4.2 about here****

Panel B of Table 4.2 reports correlation coefficients for the dependent and independent variables. The highest association arises between the MAIndex and the BBIndex, with a correlation coefficient of -0.5861. This reveals that the technical indicator Bollinger bands may be a good hedge against moving-average strategies. It is notable that all correlation coefficients for the net daily excess returns are low, which shows that there is little association between the equal-weighted excess returns and technical currency indices.

4.4. EMPIRICAL RESULTS

4.4.1. Full-Sample Results based on the Technical Currency Model

Table 4.3 reports regression results for all relevant specifications of the technical currency model. The most notable observation is that alpha is insignificant in all specifications. Specification 7, which contains all four technical indices, produces an alpha of 0.0528 and it is insignificant (t-statistic = 0.83). This result is similar to the full-sample equally-weighted portfolio results of our first essay (see Table 4.2 Panel A) where we report alpha from the Pojarliev and Levich (2008) four-factor currency model is 0.05 percent and insignificant (t-statistic = 0.91). The highest alpha of 0.574 is found in specification 3 which contains the MACDIndex, which measures momentum, as the sole explanatory yet it is insignificant (t-statistic = 0.90). It is important to note that in specifications 1 through 4, which contain technical indices as the sole explanatory variable, only the BBIndex (specification 1) and the RSIIndex (specification 4) are statistically significant. The BBIndex identifies when traders purchase (short) currencies with volatile exchange rate movements that have moved below (above) two-standard deviations from the current trend. The significant BBIndex coefficient of -0.1525 (t-statistic = -2.27) in specification 1 implies that individual currency traders realize negative (positive) returns when the BBIndex increases (decreases). The BBIndex is our proxy for volatile currency rate movements and traders enter a long (short) position when volatility moves currency rates two-standard deviations below (above) the 20-day moving average. The negative and significant coefficient reveals that individual currency trader returns are diminished when traders enter short (long) positions when the BBIndex increases (decreases). This implies that when volatility drives currency rates up or down individual currency traders should not trade against these volatile movements. The RSIIndex coefficient of -0.1705 (t-statistic = -2.54) in specification 4 is also significant. Currency traders go long when the RSI technical indicator reaches 30 (indicating oversold conditions), and sell short when the RSI technical indicator reaches 70 (indicating overbought conditions). The negative coefficient for the RSIIndex, reveals that currency traders who buy (short) oversold (overbought) currencies realize negative returns. This also implies that if the RSI reaches 30 or 70 currency traders should not trade against the trend and this implication is similar to the results for the BBIndex discussed above.

****Insert Table 4.3 about here****

The contention that trend following would result in a positive association with returns is further supported, albeit weakly, in specification 2 which contains the 8- and 18- day moving average crossover (MAIndex). Traders who use moving average crossovers realize profits following the short-term trend by going long when the trend is moving up and shorting when the short-term trend is moving down. The coefficient for the MAIndex in specification 2 is 0.1437 yet marginally significant (t-statistic = 1.55). This implies that individual currency traders who enter long (short) positions when the MAIndex is increasing (decreasing) will realize positive, although insignificant, returns.

It is notable that specification 7, which contains all four indices, provides little explanatory power and only one coefficient, the RSIindex of -0.1297, is marginally significant at the 10 percent level of confidence (t-statistic = -1.66). Additionally, the coefficient of determination is low for all specifications and it only explains 0.0069 percent of the return distribution when all four indices are used in specification 7. This suggests that the technical currency model provides very little explanatory power when analyzing equally-weighted indices of individual currency traders returns. One factor that could affect the results is that individual currency traders in this sample are high-frequency traders. We report in our first essay that the individual currency traders in this sample turnover 50.76 percent of their account each day and execute 3.31 trades per day. Additionally, we identified that out of 428 accounts, 165 are day traders (traders who on average open and close their positions during the same trading day) and 263 are non-day traders (traders who on average open and close their positions longer than one trading day). Consequently, analyzing equally-weighted portfolios of daily net returns may mask the idiosyncratic trading characteristics of these traders. To address the low explanatory power of the full-sample equally-weighted portfolio results presented in Table 4.3 we perform two additional tests. First, we analyze in section 4.4.3 individual accounts using the technical currency model and report the results in Table 4.5. Second, we divide the sample into day traders and non-day traders and analyze individual accounts in section 4.4.4 using the technical currency model and report the results in Table 4.6.

4.4.2. Day Trader and Non–Day Trader Results for Technical Currency Model

Next we examine the explanatory power of the technical currency model by dividing the sample into day traders and non–day traders. This is necessary because in our first essay we tested the feedback hypothesis, which predicts day traders will outperform non-day traders because they receive constant feedback on their trading. Traders who receive positive (negative) feedback by winning (losing) trades will increase (decrease) their trading activity and consequently increase (decrease) their performance. We discovered in our first essay day traders outperformed non-day traders which supports feedback trading. Thus, in this essay, we predict that day traders will outperform non-day traders when applying the technical currency model. A second reason to analyze the cross-section is because day traders may employ high-frequency strategies that may not be captured using daily returns. This could bias the results of the model; specifically, it could be one reason why the coefficient of determination is low, as shown in the full-sample results presented in Table 4.3 above. If trading frequency is biasing the results of the model then we expect the explanatory power to increase for non-day traders.

We proceed as follows. We define day traders as traders who, on average, open and close their positions within one trading day, and non–day traders as traders who, on average, open and close positions over a period longer than one trading day. We identify 165 day traders and 263 non–day traders in the sample, then calculate equal-weighted portfolio returns for both groups and estimate model (1).

Table 4.4 presents the technical currency model results with day traders in Panel A and non–day traders in Panel B. The main observation from these results is that none of the coefficients for the day traders in Panel A is statistically significant. It is also noteworthy to point out that the R^2 for day traders, as shown in Panel A, is very low, revealing that the technical currency model explains a small portion of returns for day traders when modeling on equal-weighted portfolio net returns. This shows that either day traders are not using any of the technical indicators employed as benchmarks, or that in the aggregate, the factors are unable to accurately explain the cross-section of returns for day traders because such traders utilize high-frequency trading styles that cannot be captured by daily returns. To address this issue, we divide individual accounts into day traders and non-day traders and estimate regressions on individual accounts and report the results in Table 4.7 of section 4.4.3 below.

We next discuss the results for non-day traders in Panel B of Table 4.4. The most important observation for the non-day trader results is that the explanatory power of the model increases which supports our contention that day traders may be employing strategies that are difficult to capture with the technical currency model. First, the R^2 for non-day traders in Panel B increases to 0.0134, significantly higher than the coefficient of determination of 0.0015 for the day traders reported in Panel A. Another significant observation is that the coefficient of the RSIIndex for non–day traders is -0.1721 and significant at the 1 percent level of significance (t-statistic = -2.41). This suggests that non–day traders use contrarian strategies that focus on shorting oversold currencies and going long overbought currencies. In summary, the results indicate that the technical currency model explains a small portion of equal-weighted returns of individual currency traders. However, it has more explanatory power for currency traders that hold their positions open longer, on average, than one day.

Finally, the alpha difference between the two types of currency traders indicates that day traders outperform non-day traders by 0.1566 percent per day and this is significant (t-statistic = 2.37). This provides support for the feedback hypothesis which predicts that traders who receive more frequent positive feedback will increase trading and thus perform better than traders who do not receive timely feedback. Day traders outperforming non-day traders is also supported by our first easy where we documented similar results when analyzing raw returns, a passive benchmark model and alpha from the Pojarliev and Levich (2008) four-factor currency model.

****Insert table 4.4 about here****

4.4.3. Regression Results for Individual Trader Accounts

The results of the analysis of equal-weighted portfolios of net returns reveal that the technical currency model provides little explanatory power for individual currency traders and that it provides more explanatory power for non-day traders than for day traders. One possible explanation for the low explanatory power is that equally-weighted portfolios mask the idiosyncratic trading styles of these currency traders. To test the sensitivity of our results we next analyze the net returns of all 428 individual accounts in the sample. This is necessary because analyzing returns of individual accounts and examining the significance of the coefficients provides a more accurate description of what technical trading method each individual accountholder is using to trade currencies. The proposed analysis is consistent with the approach followed by Pojarliev and Levich (2008), who examine professional currency traders and discover significant variation in the cross-section.

To analyze the net returns of individual accounts, we estimate equation (1), the technical currency model for all 428 individual accounts using daily net returns. Due to the large volume of these results, available upon request, we present a summary of the statistically significant positive and negative coefficients (at the 10 percent level of significance) and coefficient of determination in Table 4.5.

We first address the significance of alpha. Panel A of Table 4.5 reports the significant positive and negative alphas for the technical currency model and reveals that 22 out of 428 currency traders (approximately 5.14 percent) are able to earn positive and significant alphas. However, the Panel A of Table 4.5 also reveals that 45 of 428 accounts earn negative and significant alphas. This reveals that there is cross-sectional variation in the performance of these traders. This result is similar to the results of our first essay where the top quartile of individual currency traders earns a positive alpha of .59 percent per day while the bottom quartile experiences a loss of -0.69 percent per day. We next examine the coefficients, the four technical indices, of the technical currency model. The MAIndex coefficient is significant for 86 out of 428 accounts (20.09 percent).

The 35 (8.18 percent) positive coefficients reveal that individual currency traders utilize short-term, trend-following strategies and trade in the same direction as the current trend. The 51 (11.92 percent) negative coefficients for the MAIndex reveal that some traders are contrarians and bet against the current trend. A similar pattern is found in the remainder of the coefficients for the technical indicator indexes. The MACDIndex is significant for 88 accounts (20.56 percent). 57 individual currency traders (13.32 percent) load positively and significant on the MACDIndex and 31 (7.24 percent) load negatively on the MACDIndex which implies that more individual currency traders trade with momentum rather than trade against it. The BBIndex is significant for 98 accounts (22.9 percent) with 44 accounts (10.28 percent) having positive exposure to the BBIndex and 54 accounts (12.62 percent) having negative exposure. It is also notable that overall the BBIndex has the largest number of significant coefficients. This not only implies that Bollinger bands are a popular technical indicator but also shows individual currency traders trade volatile currency movements, for example they short (buy) when currency pairs move two or more standard deviations from the current trend.

Our final factor, the RSIIndex is significant for 86 accounts (20.09 percent). 40 individual currency traders (9.35 percent) have positive exposure to the RSIIndex while 46 (10.75 percent) have negative exposure. The RSIIndex measures when currency pairs have become overbought (oversold). Traders go long (short) when the RSI indicator reaches 30 (70) as each value indicates oversold (overbought) conditions. Overall, approximately 20 percent of the coefficients for the RSIIndex are significant and this implies that not only is the RSI a popular technical indicator but also individual currency traders utilize technical trading strategies that exploit overbought and oversold currency rate movements. These traders may expect to earn profits when currency rates revert to the mean by shorting (buying) when currency rates move too high (low).

We next examine R^2 of the technical currency model. Panel B of Table 4.5 reports the coefficients of determination for the full sample (428 accounts), for accounts with positive alpha (190 accounts) and accounts with negative alpha (238 accounts). We divide the sample by positive and negative alpha because if technical analysis has a negative association with performance, R^2, our proxy for the use of technical analysis, should be negatively associated with performance. Thus, we expect accounts with negative alpha to have a higher coefficient of determination relative to accounts with positive alpha. The first column in Panel B of Table 4.5 reveals that for the full-sample of 428 accounts the mean R^2 is 0.12. R^2 ranges from a minimum of 0.0008 to a maximum of 0.71. This indicates that there is significant cross-sectional variation of explanatory power of the technical currency model. A closer look at the variation shows that R^2 ranges from 0.039, for the lower quartile, to 0.165, for the upper quartile (each quartile contains 107 accounts). These results imply that some traders, namely the 107 account holders in the lower quartile, may not use the technical indicators we employ in the technical currency model. However, the upper quartile R^2 of 0.165 reveals that some traders may be using the technical trading strategies identified in this essay to trade currencies.

The final two rows in Panel B of Table 4.5 reports the coefficient of determination for the 190 individual currency traders that have positive alpha and the 238 individual currency traders that have negative alpha. The results reveal there is little difference between both groups. The mean R^2 is 0.13 for account holders with positive alpha and 0.12 for negative alpha. Furthermore, the lower quartile for positive (negative) alpha is 0.038 (0.039) which reveals there is little difference between individual currency traders when dividing them by positive and negative alphas. The results are similar for the upper quartile where positive (negative) alphas have R^2 of 0.173 (0.162) respectively. These results do not provide preliminary support for the contention that there is a negative association between performance, proxied by alpha, and the use of technical analysis, proxied by R^2 from the technical currency model. However, the results of Panel A in Table 4.5, which reported the number of significant coefficients for the technical currency model, and the coefficients of determination presented in Panel B, both reveal that individual currency traders do utilize common technical indicators to trade currencies. Approximately 20 percent of the coefficients of the technical currency model are statistically significant and our results for R^2 reveal that the technical currency model explains, on average, 12 percent of the return distribution of individual currency traders when modeling on net returns for individual accounts. This is a sizable improvement from the equal-weighted portfolios we analyzed previously in Tables 4.3 and 4.4 which revealed that the technical currency model doesn't do a satisfactory job of explaining the net returns of equally-weighted portfolios.

****Insert Table 4.5 about here****

4.4.4. Individual Account Analysis for Day Traders and Non–Day Traders

We next examine the explanatory power of the technical currency model for individual accounts by dividing the sample into day traders and non–day traders. This is necessary because we reported that the technical currency model provides more explanatory power for non-day traders than for day traders in Table 4.4 of Section 4.4.2. Thus, it is expected that for individual accounts, non–day traders should have more statistically significant coefficients and, on average, higher R^2. We repeat the same analysis presented in Table 4.5 and report the results in Table 4.6.

Panel A (B) of Table 4.6 reports the results of significant coefficients (at the 10 percent level) and the coefficient of determination for the 165 day (263 non-day) traders. As expected, the technical currency model explains a smaller portion of returns for day traders than the full-sample results presented in Table 4.5 above. For the day trader sample in Panel A, alpha has 20 significant coefficients, 5 positive and 15 negative, respectively and this reveals in Panel A that a very small percentage (1.17 percent) of individual day traders earn positive and significant alpha. The same low percentage rate is seen with the significance of the coefficients of the technical indices. The results for the day-traders in Panel A reveal that the MAIndex has 29 out of 428 significant coefficients (6.78 percent); the MACDIndex has 24 (5.61 percent), the BBIndex has 30 (7.01 percent), and the RSIIndex has 23 (5.37 percent). The most likely explanation for these results is that daily returns of the technical indices are not fully capable of capturing a significant portion of the technical trading styles used by some high frequency day traders, or day traders are utilizing other technical trading rules. The mean coefficient of determination reported in Panel A for day traders is 0.09 and varies from a minimum of 0.001 to a maximum of 0.54. This indicates that, on average, the technical currency model explains approximately 9 percent of the net returns of day traders. It is also notable that the upper quartile of day traders has a mean R^2 of 0.12. This suggests that approximately 12 percent of the return distribution for day traders is explained by the technical currency model. In summary, the results for day traders in Panel A demonstrates that the technical currency model provides some explanatory power for the individual currency day traders analyzed in this sample. This is a remarkable improvement when compared to the equally-weighted portfolio results for day traders presented in Panel A of Table 4.4 above which reported a R^2 of .0015 and no significant coefficients.

****Insert Table 4.6 about here****

We now turn to Panel B of Table 4.6 which reports the statistically significant coefficients and R^2 for non–day traders. The most important observation that emerges from these results is that the model provides greater explanatory power for traders who hold their positions open, on average, for longer than one day. There are 17 (3.97 percent) non-day traders that realize significant positive abnormal returns. The MAIndex, which proxies for trading strategies that follow the short-term trend, has 57 (13.32 percent) significant coefficients. The 24 (33) significant positive (negative) coefficients imply that approximately 5.61 percent (7.71 percent) of the individual currency traders in this sample realize positive (negative) returns following (not following) the short-term trend. The MACDIndex has 64 (14.95 percent) significant coefficients. The MACD technical indicator is a proxy for momentum and the 42 (22) positive (negative) significant coefficients reveal that approximately 14.95 of all individual currency traders in this sample utilize strategies that attempt to exploit momentum in currency pairs. The BBIndex which goes long (short) when volatility moves currency pairs two standard deviations below (above) the current trend reveals that 68 (15.89 percent) of the individual currency traders use strategies that exploit volatile currency movements. The BBIndex also has the largest number of significant positive and negative coefficients and this reveals that trading volatile currency movements is a popular strategy amongst individual currency traders. Finally, the RSIIndex has 63 (14.72 percent) significant coefficients. The RSI technical indicator identifies overbought (oversold) conditions and the 31 positive (32 negative) coefficients imply that individual currency traders attempt to both short and purchase currencies when currency pairs are overbought or undersold.

We next focus on the R^2 estimates for non-day traders. The R^2 for non–day traders reported in Panel B of Table 4.6 is also greater than the corresponding value for day traders presented in Panel A. The mean R^2 is 0.15, with a minimum of 0.0008 and a maximum of 0.71. This result is not surprising, since currency traders that hold their positions open for periods longer than one day utilize technical indicators over a multi-day basis, and the factors of the technical currency model, which makes use of daily returns, capture this. The lowest and highest quartiles of R^2 also reveal that there is substantial variation in the use of technical analysis. The lowest quartile ($R^2 = 0.051$) and the highest quartile ($R^2 = 0.20$) highlight that although the bottom 107 accounts may not use popular technical indicators 107 traders with the highest R^2 have approximately 20 percent of their return distribution explained by the technical currency model.

Overall, the results for both day traders and non–day traders suggest that individual currency traders utilize trading strategies that mimic the four technical indices of model (1). This implies that individual currency traders and in particular non–day traders use well-known technical indicators to trade currencies. This evidence is supportive of previous studies that document currency traders use technical analysis to trade currencies (Taylor and Allen, 1992; Cheung and Chinn, 2001). Moreover, this result is significant because it reveals that there are other factors in the currency markets that can explain the returns of currency traders. This finding is not surprising because there is ultimately no uniform strategy in the currency markets (Melvin and Shand, 2011). Although the Pojarliev and Levich (2008) four-factor model uses proxies for well-known strategies used by professional currency managers, namely the carry, momentum, and purchasing-power-parity trades, Melvin and Shand (2001) show that currency markets are unique, in that, there is no uniform market portfolio. This is mainly due to the long/short nature of currency trading and the lack of a buy-and-hold strategy. Consequently, as shown here, other factors exist than the ones identified by Pojarliev and Levich (2008). Pojarliev and Levich (2008) also report that for the returns of professional currency managers, some factor model results have a low R^2, which implies that factors other than carry, momentum, and purchasing power parity exist. One possible explanation for this result is that professional currency traders may employ some form of technical analysis as we have documented for individual currency traders.

4.4.4. The Association between Technical Analysis and Performance

Our final inquiry asks whether the use of technical analysis is positively associated with performance. We examine the association between technical analysis and performance because we reveal in our first two essays that individual currency traders possess skill. In our first essay we show that the top quartile of currency individual currency traders earn positive abnormal excess returns of 0.59 percent per day and in our second essay we revealed that the performance of the top quartile of individual currency traders with account ages over 80 days have persistent performance. By examining the association between popular technical indicators and performance we can shed light on the source of profits and losses for individual currency traders.

Furthermore, this inquiry is necessary because published studies show that technical trading styles can lead to abnormal returns (Sweeny, 1986; Levich and Thomas, 1993; Cheung and Wong, 1997; Neely, 1997; Acar and Lequeux, 2001; Lee, Pan and Liu, 2001; Okunev and White, 2003) yet no study has examined whether popular trading indicators can produce abnormal returns for individual currency traders. Finally, since we have shown that popular technical indicators can explain a portion of the returns of individual currency traders when examining individual accounts, we can now test whether there is a positive or negative association between the use of technical analysis and performance.

To determine whether there is an inverse association between the use of technical analysis (beta) and performance (alpha), we follow a similar approach to Pojarliev and Levich (2008) who examine the performance of professional currency managers. The authors develop a four-factor currency model that consists of factors that proxy for well-know technical trading strategies used by professional currency traders. The empirical approach the authors take is as follows. First, they estimate four-factor model regressions on individual accounts and obtain alpha and R^2 from these regressions. Second, the authors regress alpha on R^2. Pojarliev and Levich (2008) find an inverse association between R^2 (i.e., reliance on commonly used strategies) and alpha which implies that professional currency managers with the best performance do not follow strategies commonly used by other professional currency managers. Following the Pojarliev and Levich (2008) approach is to estimate the following model (9) as:

$$alpha_i = \alpha + \beta_{1i} R_i^2 + \varepsilon_t \qquad (9)$$

Alpha and R^2 values are obtained from estimating the technical currency model in model (1) from regressions on 428 individual accounts. A high (low) R^2 implies that the currency trader is actively (not actively) using technical indicators. Once we obtain R^2 and alpha estimates from model (1) we then estimate model (9) for the entire sample of 428 accounts. Since we have already demonstrated a variation between day traders and non-day traders, we also examine the cross-section of returns by double-ranking accounts by day trader and non–day trader, and on performance measured by the statistical significance of alpha.

Table 4.7, Panel A presents the full-sample results of model (9), and Panel B presents the results of the double ranks of day trader/non-day traders and performance. Panel A shows that the coefficient for R^2 is 0.0543 and statistically insignificant (t-statistic = 0.11). This demonstrates that there is no association between the use of technical analysis and performance for the full sample. This result is similar to our full-sample result presented in Table 4.5, Panel B where we divide individual accounts by positive and negative alpha and then examined R^2. We report in Panel B, Table 4.5 there is little difference between the R^2 of positive and negative alpha accountholders.

We next examine model (9) by double-sorting the sample by performance and day/non-day traders and report the results in Table 4.7, Panel B. The most notable result in Panel B is that the coefficients for the worst-performing currency traders in quartile 4 are both negative and significant. The coefficient of R^2 for day traders is -2.004 (t-statistic = -1.97) and for non–day traders it is -1.23 (t-statistic = -1.71); both coefficients are significant. A high (low) R^2 implies that the currency trader is actively (not actively) using technical indicators. The negative and significant coefficients for the worst performing individual currency traders imply the use of technical analysis (high R^2) is negatively associated with performance (low alpha).

A notable observation is that a linear pattern seems to prevail across both day and non-day traders when moving from the worst to best performing individual currency traders. The coefficient for the worst-performing day traders and non–day traders is negative and significant and it increases in value and becomes positive (yet insignificant) for both groups in quartile 1 (the best performers). This pattern suggests that as individual currency traders rely less on well-known technical indicators (low R^2), performance increases (high alpha). These results run contrary to studies that show that the use of technical indicators is profitable (Sweeny, 1986; Levich and Thomas, 1993; Cheung and Wong, 1997; Neely, 1997; Acar and Lequeux, 2001; Lee, Pan and Liu, 2001; Okunev and White, 2003). Furthermore, our result for the worst performing individual currency traders in quartile 4, which show a negative and statistically significant coefficient for R^2, is similar to Pojarliev and Levich (2008), who find an inverse association between R^2 and alpha for professional currency managers when applying their four-factor currency model. The authors show that there is a trade-off between beta and alpha. Professional currency managers who follow common trading styles like momentum, value and carry trades have high coefficients of determination, yet they underperform (have lower alphas) relative to currency managers that do not follow common trading styles utilized by professional currency managers. Our result is significant because the MACD, MA, RSI and Bollinger band indicators are widely used and well established in the individual investment community. Our result implies that the use of these indicators is detrimental to performance.

Overall, the results of model (9), which regresses alpha from the technical currency model on R^2, imply that individual currency traders, who rely on well-known technical indicators to make trading decisions, end up realizing losses. The results of the technical analysis augment our previous research by providing further insight on the source of profits and losses for individual currency traders. We report in our first essay that the top quartile (best performing) individual currency traders earn positive and significant abnormal returns of 0.59 percent per day while the bottom quartile (worst performing) lose -0.69 percent per day. Additionally, we reveal in our second essay that performance is significantly persistent for the top quartile of traders with account lives over 80 days. In this essay we show that the best performing currency traders do not use well-known technical indicators while the worst performing currency traders rely on well-known technical indicators. Collectively, these results imply that individual currency traders who do not employ well-known technical indicators outperform their peers who use popular technical strategies to trade spot currency pairs.

****Insert Table 4.7 about here****

4.5. CONCLUDING REMARKS

This essay examines whether individual currency traders use well-known technical indicators to trade currencies, and whether technical analysis is positively associated with performance. We develop a technical currency model that consists of indices based on four well known technical trading rules. The results of equal-weighted portfolio daily net returns and of individual account daily net returns show that the technical currency model provides little explanatory power for the net returns of equally-weighted portfolios. When we divide the sample into day traders and non–day traders we find that the technical currency model provides greater explanatory power for non–day traders, who hold their trades open, on average, for longer than one day. However, our results improve considerably when we analyze individual accounts. Our full-sample and cross-sectional analysis of individual currency accounts reveals that the technical currency model provides sufficient explanatory power for the net returns of individual currency traders. These results imply that individual currency traders employ well-known technical indicators to trade currencies.

We also examine the association between technical analysis and performance by regressing R^2 from the technical currency model on alpha from the technical currency model. Our evidence shows that the use of well-known technical indicators is negatively associated with performance. Sorts on performance reveal that the worst-performing traders have a significant and negative association between performance and the use of technical analysis. This implies that currency traders who use technical indicators underperform when compared to their peers who rely on other trading strategies.

A major implication of this study is that individual currency traders, who depend on well-known technical indicators to make trading decisions, end up realizing losses. Consequently, future studies of individual currency traders, and quite possibly, individual investor equity traders, should take into account the use of technical analysis when analyzing the performance of individual investors. Another implication of our study is that future research should examine the association between technical analysis and the returns of professional currency traders. Pojarliev and Levich (2008) report low R^2 for some traders in their sample, which implies that a few professional currency managers do not use strategies that mimic the authors' factors, namely the carry, momentum, and value trades. One question that remains unanswered is whether technical indicators can explain the cross-section of returns for professional currency managers.

CHAPTER 5

CONCLUSIONS

This dissertation examines the performance, skill, and trading characteristics of individual currency traders. We analyze both the net and gross daily returns and transaction data for 428 individual currency traders from 2005 to 2009. Additionally, we examine whether technical trading strategies are profitable for individual currency traders by developing a factor model that consists of indices constructed by four popular technical trading strategies.

The first essay examines the performance and trading characteristics of individual currency traders by analyzing net and gross raw returns, along with a passive benchmark strategy and the alpha from Pojarliev and Levich's (2008) four-factor currency model. We show traders are able to earn positive excess returns before and after accounting for transaction costs. Additionally, we divide the sample into day traders and non-day traders and discover day traders outperform non-day traders on a raw return, passive benchmark and on a risk-adjusted return basis. The results are robust to alternative specifications of trade activity, measured as the mean number of trades per day per account, and account turnover. These results support feedback trading, which holds that the more traders trade, the more feedback they receive, which, in turn, decreases their overconfidence and increases performance.

The second essay examines whether individual currency traders are skilled by examining the association between R^2 from the four-factor currency model and alpha from the four-factor currency model. Contrary to previous studies of professional fund managers that find a positive association between R^2 and performance, our study determines R^2 does not predict future performance for individual currency traders. The R^2 measure lacks predictive power because R^2 is not persistent, since individual currency traders change their trading styles over time. Although R^2 is not persistent, we determine individual currency traders are able to earn positive and persistent alphas. To further investigate the skill of these traders, we also examine trade activity, drawdown, and market timing. Our analysis of trade activity, drawdown, and market timing provides additional support that individual currency traders possess trading skills. The best-performing individual currency traders can mitigate downside losses, and a sizable percentage of them can time currency market factors. Finally, we examine transaction data to determine whether winning trades arise due to luck or skill. We find that 68.78 percent of trades by the top traders are profitable net of transaction costs, revealing that profits do not arise due to luck.

The third essay investigates whether technical currency trading is profitable. The results show that the use of technical analysis by individual currency traders is negatively associated with performance. Furthermore, the technical trading model developed here adequately describes the cross section of returns for individual currency traders. This result arises because individual currency traders use well-known technical indicators to trade currencies. This implies that currency traders who utilize common technical trading strategies will reduce their performance.

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Table 2.1. 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
Transaction Costs (%)	0.97	0.09	0.23	1.00	42,442
Age (days)	78.77	40.00	61.00	91.00	263

Table 2.1. 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
Transaction Costs (%)	0.79	0.08	0.22	0.50	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	Transaction Costs (%)	Age (days)
Difference in Means	51,140.73	26.68	0.60	0.18	-9.00
	(5.38)**	**(36.68)****	**(2.03)****	**(12.07)****	(-1.23)

Table 2.2. 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 (2008), 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 BM	Four-Factor Alpha	Raw Returns	Passive BM	Four-Factor Alpha
Panel A. Full-Sample Equal-Weighted Portfolio Performance Results						
	0.51	0.5	0.05	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	0.4	0.4	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 2.3. 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 (2008), 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 2.4. 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 (2008), 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 BM	Four-Factor Alpha	Raw Returns	Passive BM	Four-Factor Alpha
Panel A. Full-Sample Equal-Weighted Portfolio Results Sorted on Turnover							
Q1 (High)	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 (Low)	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 2.5. 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 (2008), 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 BM	Four-Factor Alpha	Raw Returns	Passive BM	Four-Factor Alpha
Panel B. Full-Sample Equal-Weighted Portfolio Results Sorted on Performance							
Q1	6.64	0.8303	0.8199	0.71115	0.4921	0.4817	0.3827
		(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	-0.0820
		(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	-0.0253
		(5.19)**	**(5.07)****	**(3.87)****	(1.22)	(1.07)	(-0.31)
Q4	1.42	0.3944	0.3851	0.26782	0.1517	0.1424	0.0238
		(5.19)**	**(5.03)****	**(3.53)****	(1.64)	(1.54)	(0.26)
Panel B. Difference in Means Between Q1 and Q4							
Q1 - Q4		0.4359	0.4348	0.44333	0.3404	0.3393	0.3588
		(3.43)**	**(3.38)****	**(2.71)****	(1.29)	(1.28)	(0.90)

Table 2.6. Robustness Checks with Secondary Data Set of 74 Accounts from July 2010 to August 2011

This table reports summary statistics, performance results and trade activity results for 74 individual currency traders at a proprietary online advisory service from July 2010 to August 2011. Panel A reports mean daily returns, trades per day and the age of accounts. 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. The age of the account is measured in days. Panel B reports tertile sorts on gross performance and the difference in means between the top performers (T1) and the worst performers (T3). Panel C reports the results of sorts on trade activity, proxied my mean trades per day. Account holders are sorted into tertiles based on the mean number of trades executed for each trading day. Tertile 1 contains the account holders with the highest mean number of trades executed per day, and tertile 3 contains those with the lowest mean number of trades executed per day. The difference in means between the most active traders (T1) and the least active traders (T3) are also reported. The t-statistics are in parentheses and significant values are bold; ** denotes statistical significance at the 1% level.

A Descriptive Statistics of Returns, Trade Activity and Age of Accounts

	Mean	25th Percentile	Median	75th Percentile	Obs
Daily Gross Return	0 357	0 005	0 138	0 648	74
Trades Per day	2 35	0 64	1 69	3 14	74
Age (days)	201 30	133 00	171 50	266 00	74

B Full Sample Results of Gross Returns with Sorts on Trade Activity

	Mean Gross Return	25th Percentile	Median	75th Percentile	Obs
T1 (Best Performers)	1 154	0 648	1 073	1 302	25
T2	0 174	0 093	0 119	0 265	25
T3 (Worst Performers)	-0 283	-0 276	-0 125	0 003	24
Diff Q1 - Q3	1 44				
	(8.37)**				

C Full Sample Results of Gross Returns with Sorts on Trade Activity

Item	Mean Trades Per Day	Mean Gross Return	Obs
T1 (Most Active Traders)	4 873	0 628	25
T2	1 544	0 367	25
T3 (Least Active Traders)	0 554	0 063	24
Diff Q1 - Q3	4 32	0 57	
	(7.26)**	**(3.45)****	

Table 3.1. Descriptive Statistics for Dependent and Independent Variables.

This table reports the account data for 428 accounts of retail spot foreign exchange traders. The sample time period is from March 2004 to September 2009. The performance measure alpha is the intercept from a regression of daily excess returns in Pojarliev and Levich's (2008) four-factor model; R^2 is obtained from the four-factor regression and $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$, which is the logistic transformation of R^2; IR_t is the information for each account and is calculated as $IR_j = \frac{\alpha_j}{RMSE_j}$. *Turnover* is calculated as the daily mean of the margin-adjusted daily market value of all roundtrip transactions divided by the daily amount of capital; and *Age* is calculated as the life span of the account, measured in days.

A. Descriptive statistics

Variable	Mean	Maximum	Minimum	Std Dev	Skewness
$Alpha_{t+1}$	-0.183	16.482	-8.209	1.921	3.034
IR_{t+1}	-0.080	0.692	-1.822	0.243	-1.286
Turnover	58.278	858.718	0.968	80.808	5.015
Age	81.921	896.000	30.000	66.845	5.272
R^2_{t-n}	0.192	0.855	0.006	0.150	1.282
TR_{t-n}	-0.884	0.885	-2.599	0.565	-0.240

B. Correlation coefficients

	$Alpha_t$	IR_t	Turnover	Age	R^2_{t-n}
$Alpha_{t+1}$	1.000				
IR_{t+1}	0.581	1.000			
Turnover	0.091	-0.043	1.000		
Age	0.011	0.046	-0.114	1.000	
R^2_{t-n}	0.007	-0.064	0.080	-0.399	1.000
TR_{t-n}	0.006	-0.064	0.102	-0.481	0.926

Table 3.2. Regression of Account Performance Using the Four-Factor Model Alpha and IR.

This table reports the results of the four-factor model alpha from equation (1) and *IR* from equation (2) from regressions of daily excess returns on the factor returns. Alphas obtained from the four-factor model from time period t to $t+n$ are regressed on the independent variables from time period $t-n$ to $t-1$, where t is the monthly return from each account. Here R^2_{t+n} is obtained from the four-factor currency model and then used to calculate $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. Alpha as the dependent variable		
Variable	(1)	(2)
TR^2_{t-1}	-0.011	0.022
	(-0.06)	(0.13)
Turnover	0.002	
	(2.07)**	
Alpha_{t-1}	0.132	
	(1.96)*	
R^2	0.018	0.000

B. *IR* as the dependent variable		
	(1)	(2)
TR^2_{t-1}	-0.026	-0.028
	(-1.24)	(-1.32)
Turnover	0.000	
	(-0.670)	
Alpha_{t-1}	0.01	
	(0.75)	
R^2	0.007	0.004

Table 3.3. Regression Results with Quartile Sorts on Performance.

This table reports the results of the four-factor model alpha from equation (1) and *IR* from equation (2) from regressions of daily excess returns on the factor returns. The alpha values obtained from the four-factor model from time period t to $t + n$ are regressed on the independent variables from time period $t - n$ to $t - 1$, where t is the monthly return from each account. Here R^2_{t+n} is obtained from the four-factor currency model and then used to calculate $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$ Performance quartile ranks are based on the significance of alpha t-statistics. Each quartile contains 107 accounts. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. Alpha as the dependent variable				
Variable	(1 Best)	(2)	(3)	(4 Worst)
TR^2_{t-n}	0.085	-0.231	-0.029	0.080
	(0.22)	(-0.50)	(-0.14)	(0.39)
Turnover	-0.004	0.012	-0.001	-0.005
	(-0.84)	**(4.55)****	(-0.42)	**(-2.96)****
$Alpha_{t-n}$	0.054	-0.426	1.566	-0.129
	(0.36)	(-0.82)	**(3.57)****	(-1.03)
R^2	0.008	0.181	0.118	0.084

B. *IR* as the dependent variable				
TR^2_{t-n}	-0.002	-0.057	0.022	-0.080
	(-0.03)	(-1.56)	(0.61)	**(-2.00)****
Turnover	-0.001	0.000	0.000	0.000
	(-1.74)	(-0.13)	(0.72)	(-1.43)
$Alpha_{t-n}$	-0.004	0.038	0.210	-0.052
	(-0.20)	(0.93)	**(2.77)****	**(-2.21)****
R^2	0.033	0.026	0.074	0.064

Table 3.4. TR^2 Regressions with Sorts on Trade Activity Proxied by Mean Roundtrips Per Day.

This table reports the results of the four-factor model alpha from equation (1) and *IR* from equation (2) from regressions of daily excess returns on the factor returns with quartile ranks on trade activity. Trade activity is defined as the mean number of roundtrip transactions per account per day. The dependent variables are obtained from the four-factor model from time period t to $t + n$ and are regressed on the independent variables from time period $t - n$ to $t - 1$, where t is the daily return from each account. The R^2 value is obtained from the four-factor currency model and then used to calculate $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. Alpha as the dependent variable				
Variable	(1 Most)	(2)	(3)	(4 Least)
TR^2_{t-n}	0.516	0.473	-0.134	-0.347
	(1.53)	(1.70)	(-0.63)	(-1.07)
Turnover	0.015	-0.007	-0.006	-0.008
	(8.32)**	**(-2.94)****	**(-2.27)****	**(-3.40)****
$Alpha_{t-n}$	-0.017	0.247	0.311	-0.544
	(-0.13)	**(2.14)****	**(3.04)****	**(-3.49)****
R^2	0.409	0.194	0.128	0.172

B. *IR* as the dependent variable				
TR^2_{t-n}	-0.041	0.030	-0.053	-0.037
	(-0.87)	(0.77)	(-1.43)	(-0.85)
Turnover	0.000	0.000	-0.001	-0.001
	(1.36)	(-1.43)	(-1.14)	(-1.82)
$Alpha_{t-n}$	0.011	0.021	0.033	-0.065
	(0.62)	(1.33)	(1.87)	**(-3.10)****
R^2	0.029	0.065	0.065	0.102

Table 3.5. TR^2 Regressions with Sorts on Trading Activity Proxied by Turnover.

This table reports the results of the four-factor model alpha from equation (1) and *IR* from equation (2) from regressions of daily excess returns on the factor returns with quartile ranks on turnover. The dependent variables are obtained from the four-factor model from time period t to $t + n$ and regressed on the independent variables from time period $t - n$ to $t - 1$, where t is the daily return from each account. Here R^2 is obtained from the four-factor currency model and then used to calculate $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. Alpha as the dependent variable				
Variable	(1 Most)	(2)	(3)	(4 Least)
TR^2	-0.186	0.173	-0.020	0.029
	(-0.31)	(0.49)	(-0.15)	(0.54)
Turnover	0.008	0.009	-0.028	-0.008
	(3.10)**	(0.44)	(-1.88)	(-1.12)
$Alpha_{t-n}$	0.175	0.028	0.185	0.587
	(1.28)	(0.18)	**(2.29)****	**(7.23)****
R^2	0.091	0.005	0.072	0.337

B. *IR* as the dependent variable				
TR^2	-0.016	0.008	-0.035	-0.037
	(-0.27)	(0.24)	(-1.10)	(-0.94)
Turnover	0.000	0.000	-0.003	-0.004
	(-0.30)	(0.03)	(-0.91)	(-0.74)
$Alpha_{t-n}$	-0.008	-0.011	0.032	0.359
	(-0.57)	(-0.75)	(1.66)	**(6.14)****
R^2	0.004	0.006	0.041	0.275

Table 3.6. Robustness Checks with R^2 and the Truncated Sample.

This table reports the regressions where R^2 replaces TR^2 as the primary independent variable in equations (3) and (4). Panel B presents the results of the regressions when all accounts with $R^2 < 0.05$ are removed. The sample size is reduced from 428 accounts in Panel A to 359 accounts in Panel B. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. R^2 as the independent variable		
Variable	Dependent Variable	
	Alpha	IR
R^2_{t-n}	0.044	-0.096
	(0.07)	(-1.22)
Turnover	0.002	0.000
	(2.07)*	(-0.71)
$Alpha_{t-n}$	0.132	0.006
	(1.96)*	(0.69)
R^2	0.017	0.007

B. Accounts with $R^2 < 0.05$ removed		
	Dependent Variable	
	Alpha	IR
TR^2_{t-n}	0.034	-0.019
	0.13	-0.59
Turnover	0.002	0.000
	(1.99)*	-0.72
$Alpha_{t-n}$	0.096	0.003
	1.28	0.32
R^2	0.014	0.003

Table 3.7. Results for the Persistence of Performance and Active Management.

This table reports the regressions results for the persistence of performance and active management for 428 currency trade accounts. The left column reports the regression results when lagged alpha is regressed on future alpha values, and the right column reports the regression results when lagged R^2 is regressed on future R^2 values. Quartile portfolios are formed by ranking all 428 accounts by the statistical significance of alpha. Each quartile contains 107 accounts. Here t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

A. Full sample

Quartile	Obs.	Dependent Variable	
		Alpha Persistence	R^2 Persistence
		Lagged Alpha	Lagged R^2
1 (top performers)	107	0.285	0.270
		(1.63)	**(3.77)****
2	107	-0.001	0.153
		(-0.03)	(1.61)
3	107	0.016	0.367
		(0.32)	**(4.03)****
4 (worst performers)	107	-0.050	0.386
		(-0.46)	**(3.82)****

B. All accounts with more than 80 days of return data

	Obs.	Lagged Alpha	Lagged R^2
1 (top performers)	41	1.185	0.032
		(4.51)***	(0.27)
2	39	0.046	-0.109
		(0.81)	(-0.69)
3	29	0.017	0.541
		(0.22)	(1.38)
4 (worst performers)	37	0.213	-0.089
		(0.76)	(-0.57)

Table 3.8. Skill Based on the Percentage of Winning Trades.

This table reports the percentage of winning trades for all 428 accounts from 2004 to 2009. The percentage of winning trades is calculated as the total number of winning trades, defined as a trade with a net profit greater than zero, divided by the total number of trades for each account. Panel A reports the results for the full sample of 428 accounts. Panel B reports the percentage of winning trades based on performance sorts, where quartile 1 contains the top-performing currency traders and quartile 4 contains the worst-performing traders. Each quartile contains 107 accounts. Panel C reports the difference in means between quartiles 1 and 4. The t-statistics are reported in parentheses and test whether the percentage of winning trades is significantly different from 50 percent. Significant values are bold and * denotes statistical significance at the 1 percent level.

A. Percentage of winning trades for the full sample

	Mean Percentage of Winning Trades	Std Dev	Minimum	Maximum
Full Sample	53.97	20.13	4.05	100
	(4.08)*			

B. Percentage of winning trades sorted on performance

	Mean Percentage of Winning Trades	Std Dev	Minimum	Maximum
1 (Top performers)	66.78	17.99	21.36	100
	(9.65)*			
2	58.50	18.95	8.89	100
	(4.64)*			
3	48.33	16.61	11.76	88.64
	(1.04)			
4 (Worst performers)	42.26	17.81	4.05	79.71
	(4.50)*			

C. Difference in means of winning trades

	Mean Diff.
Q1 - Q4	24.53
	(4.50)**

Table 3.9. Drawdown Proxied by the

Largest One-Day Percent Decline.

This table reports drawdown for all 428 accounts from 2004 to 2009. Drawdown is calculated as the largest daily negative return for an individual currency trader. Panel A reports the results for the full sample of 428 accounts and for quartile ranks based on the statistical significance of alpha from the Pojarliev–Levich (2008) four-factor currency model, where quartile 1 contains the top-performing currency traders and quartile 4 contains the worst-performing traders. Panel B reports the results for currency traders with an account age over 80 days (accounts of age under 80 days are removed). Both panels report the difference in means between the top-performing traders in quartile 1 and the worst-performing traders in quartile 4. The t-statistics are reported in parentheses.

	Largest Daily Percentage Decline		
	Mean	Std. Dev.	Obs.
Panel A. Full-sample results			
Full Sample	-16.81	16.45	428
Q1 (top performers)	-16.07	16.45	107
Q2	-15.19	15.50	107
Q3	-16.84	15.11	107
Q4 (worst performers)	-19.15	18.48	107
Diff Q1 - Q4	3.08		
	(1.29)		
Panel B. Accounts with age over 80 days			
Age > 80 days	-17.73	16.62	146
Q1 (top performers)	-16.02	16.86	34
Q2	-16.40	17.88	30
Q3	-17.89	16.21	40
Q4 (worst performers)	-19.91	16.24	42
Diff Q1 - Q4	3.89		
	(1.08)		

Table 3.10. Summary of Statistically Significant Coefficients for the Timing Model.

This table reports regression results based on the timing model (5) for all 428 accounts. The timing model is defined as $r_{j,t} = \alpha_j + \sum_{i=1}^{3} \beta_{i,t}[F_{i,t}|F_{i,t} > 0] + \sum_{i=1}^{3} \gamma_{i,t}[F_{i,t}|F_{i,t} < 0]$, where r is the return of individual currency trader j at time t; F is the return associated with factor i, and the factors are decomposed into positive and negative return observations. Individual currency trader timing ability is inferred from trader skill to load positively (negatively) on the factors when factor returns are positive (negative). Here CarPositive (CarryNeg), ValuePos (ValueNeg), and MomPos (MomNeg) are the explanatory variables in the timing model when the daily returns for the carry (Carry), value (Value) and momentum (Mom) are positive (negative). These variables are then regressed on the daily net returns of individual currency traders. The number of statistically significant coefficients, at the 5 percent level of significance, is reported below.

Variable	Number of Significant Coefficients	Percentage
CarryPos	36	8.41%
CarryNeg	54	12.62%
ValuePos	38	8.88%
ValueNeg	36	8.41%
MomPos	42	9.81%
MomNeg	33	7.71%

Table 3.11. Full-Sample Regression Results with the DBCR as the Independent Variable.

This table reports the regression results of equations (3) and (4), using the DBCR as the sole independent variable in equation (1). Alphas obtained from the DBCR factor model from time period t to $t + n$ are regressed on the independent variables from time period $t - n$ to $t - 1$, where t is the monthly return from each account. Here R^2_{t+n} is obtained from the four-factor currency model and then used to calculate $TR^2 = \log\left(\frac{\sqrt{R^2}}{1-\sqrt{R^2}}\right)$. The t-statistics are in parentheses and significant values are bold, and ** and * denote statistical significance at the 1 percent and 5 percent levels, respectively.

Variable	Dependent Variable	
	Alpha	IR
TR^2	0.077	-0.001
	(0.94)	(-0.08)
Turnover	0.003	0.000
	(2.59)**	(-1.15)
$Alpha_{t-n}$	0.255	0.020
	(3.16)**	**(2.39)****
R^2	0.017	0.007

Table 4.1. Frequency of Contracts Traded.

This table reports trading activity from 79,042 roundtrip transactions of 428 individual currency trader accounts from March 2004 to September 2009. It reports currency pairs, total number of roundtrip transactions, and total percentage of contracts traded

Currency Pair	Number of Contracts	%
EURUSD	17,199	21.76
GBPUSD	14,835	18.77
USDJPY	7,593	9.61
GBPJPY	7,566	9.57
USDCHF	7,360	9.31
EURJPY	5,724	7.24
USDCAD	3,608	4.56
AUDUSD	3,597	4.55
EURGBP	1,964	2.48
GBPCHF	1,369	1.73
AUDJPY	1,235	1.56
EURCHF	1,197	1.51
CHFJPY	1,095	1.39
NZDUSD	927	1.17
EURAUD	867	1.1
EURCAD	768	0.97
CADJPY	410	0.52
GBPCAD	349	0.44
GBPAUD	317	0.4
AUDNZD	254	0.32
AUDCHF	212	0.27
AUDCAD	201	0.25
NZDJPY	110	0.14
USDSGD	110	0.14
USDDKK	95	0.12
GBPNZD	68	0.09
USDNOK	10	0.01
USDHKD	2	0.01

Table 4.2. Descriptive Statistics for Dependent and Independent Variables.

This table reports descriptive statistics for the dependent variable and the independent variables of model (1). Net daily returns are obtained from account records of 428 individual currency traders from March 2004 to September 2009. The technical indicator indices consist of Bollinger Band Index (BBIndex), Moving Average Convergence Divergence Index (MACDIndex), 8- and 18-day Moving Average Index (MAIndex), and the Relative Strength Index (RSI). Each technical indicator index is calculated using a variable weighted formula consisting of the following currency pairs and percentage weights, 30% EURUSD, 28% GBPJPY, 14% GBPUSD, 14% USDJPY, and 14% USDCHF.

Panel A – Descriptive Statistics

Variable	Mean	Max	Min	Std Dev	Skew
Net Daily Excess Returns	0.0576	43.1505	-12.881	2.2197	6.1793
BBIndex	-0.0288	8.2200	-5.1900	0.9460	-0.1489
MACDIndex	0.0019	3.5500	-4.2700	0.7147	0.1666
RSIIndex	-0.0185	8.5400	-5.3900	0.9486	-0.1328
MAIndex	0.0192	3.2900	-4.4400	0.6889	0.1780

Panel B – Correlation Coefficients

	Net Daily Excess Returns	BBIndex	MACD Index	RSIIndex	MAIndex
Net Daily Excess Returns	1.000				
BBIndex	-0.0650	1.000			
MACDIndex	0.0231	-0.0444	1.000		
RSIIndex	-0.0729	0.5062	0.0227	1.000	
MAIndex	0.0446	-0.5861	0.4273	-0.3086	1.000

Table 4.3. Technical Currency Model Regression Results for Equally Weighted Portfolios 2004-2009.

This table reports performance results for the technical currency model for the period March 2004–September 2009. Performance measures are computed from daily net returns, which are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Alpha is the intercept from the technical currency model, where the excess equal-weighted portfolio return is regressed on indices constructed from technical indicators: the Bollinger Band Index (BBIndex), the Moving Average Index (MAIndex), the Moving Average Convergence Divergence Index (MACDIndex); and the Relative Strength Index (RSI). Each technical index is calculated using a variable-weighted formula consisting of the following currency pairs and percentage weights, 30% EURUSD, 28% GBPJPY, 14% GBPUSD, 14% USDJPY, and 14% USDCHF. Excess returns are calculated by subtracting the daily LIBOR rates from the equal-weighted portfolio return. t-statistics are in parentheses and significant values are bold. *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Observations: 1212

Specf.	Alpha	BB Index	MA Index	MACD Index	RSI Index	R^2
1	0.0532	-0.1525				0.0042
	(0.84)	**(-2.27)****				
2	0.0548		0.1437			0.002
	(0.86)		(1.55)			
3	0.0574			0.0717		0.0005
	(0.9)			(0.80)		
4	0.0544				-0.1705	0.0053
	(0.86)				**(-2.54)****	
5	0.053	-0.1389	0.0319			0.0043
	(0.83)	(-1.67)	(0.28)			
6	0.0532	-0.1547	-0.0106	0.067		0.0046
	(0.83)	(-1.79)	(-0.08)	(0.65)		
7	0.0528	-0.0931	-0.0214	0.079	-0.1297	0.0069
	(0.83)	(-0.99)	(-0.16)	(0.77)	**(-1.66)***	

Table 4.4. Technical Currency Model Regression Results for Equal-Weighted Portfolios of Day Traders and Non–Day Traders, 2004-2009.

This table reports performance results for the technical currency model for the period March 2004–September 2009. Panel A shows the results for 165 day traders, defined as traders who, on average, open and close their positions within the same trading day, and Panel B presents the results for 263 non–day traders, defined as traders who, on average, open and close the same position over a period longer than one day. Performance measures are computed from daily net returns, which are calculated from account records, and equal-weighted portfolios are formed with the daily return data. Alpha is the intercept from the technical currency model, where the excess equal-weighted portfolio return is regressed on indices constructed from technical indicators: the Bollinger Band Index (BBIndex), the Moving Average Index (MAIndex), the Moving Average Convergence Divergence Index (MACDIndex); and the Relative Strength Index (RSI). Each technical index is calculated using a variable weighted formula consisting of the following currency pairs and percentage weights, 30% EURUSD, 28% GBPJPY, 14% GBPUSD, 14% USDJPY, and 14% USDCHF. Excess returns are calculated by subtracting the daily LIBOR rates from the equal-weighted portfolio return. t-statistics are in parentheses and significant values are bold. *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A. Day Traders (1020 Observations)

Alpha	BB Index	MA Index	MACD Index	RSI Index	R^2
0.1389	-0.0833	0.1579	-0.1363	-0.0912	0.0015
(1.14)	(-0.49)	(0.86)	(-0.56)	(-0.65)	

Panel B. Non–Day Traders (1212 Observations)

Alpha	BB Index	MA Index	MACD Index	RSI Index	R^2
-0.0177	-0.1070	0.0204	0.0115	-0.1721	0.0134
(-0.30)	(-1.24)	(0.22)	(0.09)	**(-2.41)***	

Table 4.5. Coefficient Summary for Technical Currency Model Regressions for Individual Accounts.

This table reports a summary of statistically significant coefficients, at the 10% level of significance, for regressions of the technical currency model in equation (1). Performance measures are computed from daily net returns, which are obtained from account records. Panel A reports the statistically significant coefficients for the full sample, and Panel B reports descriptive data for R^2.

Panel A - Statistically Significant Coefficients for Technical Currency Model

	Positive Coefficients		Negative Coefficients			
Variable	Number of Sig. Coeff.	%	Number of Sig. Coeff.	%	Total Number of Sig. Coeff.	Total %
Alpha	22	5.14%	45	10.51%	67	15.65%
MAIndex	35	8.18%	51	11.92%	86	20.09%
MACDIndex	57	13.32%	31	7.24%	88	20.56%
BBIndex	44	10.28%	54	12.62%	98	22.90%
RSIIndex	40	9.35%	46	10.75%	86	20.09%

Panel B - Coefficient of Determination for Technical Currency Model

	Obs.	Mean	Min	Max	Lower Quartile	Upper Quartile
Full Sample R^2	428	0.12	0.0008	0.71	0.039	0.165
Positive Alpha R^2	190	0.13	0.0008	0.71	0.038	0.173
Negative Alpha R^2	238	0.12	0.001	0.70	0.039	0.162

Table 4.6. Coefficient Summary for Technical Currency Model Regressions for Day Traders and Non-Day Traders.

This table reports a summary of statistically significant coefficients, at the 10% level of significance, for regressions of the technical currency model in equation (1) for 428 individual currency trader accounts for the period 2004–2009. Performance measures are computed from daily net returns, which are obtained from account records. Panel A reports the statistically significant coefficients and R^2 for 165 day traders and Panel B reports the same for 263 non–day traders.

Panel A - Day Trader Statistically Significant Coefficients for Technical Currency Model

	Positive Coefficients		Negative Coefficients			
Variable	Number of Sig. Coeff.	%	Number of Sig. Coeff.	%	Total Number of Sig. Coeff.	Total %
Alpha	5	1.17%	15	3.50%	20	4.67%
MAIndex	11	2.57%	18	4.21%	29	6.78%
MACDIndex	15	3.50%	9	2.10%	24	5.61%
BBIndex	18	4.21%	12	2.80%	30	7.01%
RSIIndex	9	2.10%	14	3.27%	23	5.37%

Coefficient of Determination for Technical Currency Model

	Obs.	Mean	Min	Max	Lower Quartile	Upper Quartile
R^2	165	0.09	0.001	0.544	0.039	0.12

Table 4.6. Coefficient Summary for Technical Currency Model Regressions for Day Traders and Non-Day Traders Continued.

Panel B - Non-Day Trader Statistically Significant Coefficients for Technical Currency Model

Variable	Positive Coefficients: Number of Sig. Coeff.	Positive Coefficients: %	Negative Coefficients: Number of Sig. Coeff.	Negative Coefficients: %	Total Number of Sig. Coeff.	Total %
Alpha	17	3.97%	30	7.01%	47	10.98%
MAIndex	24	5.61%	33	7.71%	57	13.32%
MACDIndex	42	9.81%	22	5.14%	64	14.95%
BBIndex	26	6.07%	42	9.81%	68	15.89%
RSIIndex	31	7.24%	32	7.48%	63	14.72%

Coefficient of Determination for Technical Currency Model

	Obs.	Mean	Min	Max	Lower Quartile	Upper Quartile
R^2	263	0.15	0.0008	0.71	0.051	0.2

Table 4.7. Regression Results for Technical Analysis as a Determinant of Performance.

This table reports regression results for $alpha_t = \alpha + \beta_{1t}R_i^2 + \varepsilon_t$, where alpha and R_i^2 are obtained from the technical currency model in equation (1). Panel A reports the results for the full sample of 407 accounts. Panel B reports the results for portfolios ranked on performance and 165 day traders and 263 non–day traders. t-statistics are in parentheses and significant values are bold. ** denotes statistical significance at the 5% level and * at the 10% level.

Panel A. Full-Sample Results

	R^2 (explanatory variable)	R^2	Obs.
Coefficient	0.0543	0.0000	428
	(0.11)		

Panel B. Quartile Ranks on Performance for Day Traders and Non–Day Traders

Day Traders	1 (best)	2	3	4 (worst)
R^2 (explanatory variable)	1.752	-0.136	-0.821	-2.004
	(0.30)	(-0.26)	(-1.64)	**(-1.97)****
R^2	0.002	0.002	0.073	0.090
Observations	44	44	36	41

Non–Day Traders	1 (best)	2	3	4 (worst)
R^2 (explanatory variable)	2.1238	-0.2864	-1.5400	-1.2307
	(0.98)	(-0.96)	(-0.57)	**(-1.71)***
R^2	0.060	0.015	0.033	0.044
Observations	63	63	71	66

VITA

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