Is Technical Analysis Profitable for Individual Currency Traders?

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Abstract

This study examines whether technical currency trading by individual currency traders is profitable. The results show technical analysis 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.

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It is widely recognized that technical analysis is a popular tool used by currency traders. In a comprehensive literature review Park and Irwin [2007] show that 24 out of 38 empirical studies report that technical analysis is profitable with a profit range of 5% to 10% per year. However, these studies simply examine the performance of technical trading rules applied to currency rates, not the returns generated by professional or individual traders. Furthermore, these studies are plagued by various limitations such as data snooping, *ex post* selection of trading strategies and difficulties of establishing transaction costs. Consequently, it remains unclear whether technical trading based on common 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), is profitable for individual currency traders.

This motivates the question empirically addressed in this paper: does the use of technical analysis generate abnormal gains for individual currency traders? To examine this issue, we develop a factor model that consists of currency indices constructed for technical analysis. Specifically, using a proprietary database of 428 individual currency traders obtained from an online advisory service over the period March 2004 to September 2009, we employ the four popular technical trading indicators 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. Foremost, this study is 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 and Levich and Thomas [1993] study 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 [2007]) of previous technical analysis studies. Additionally, the individual investor retail foreign exchange market is one of the fastest growing segments of foreign exchange (King and Rime [2010]) yet little is known about individual currency traders since most studies have focused on institutional currency traders. For example, Pojarliev and Levich [2008] examine the returns of currency hedge funds and discover that the average fund is not able to earn positive alpha. Melvin and Shand [2011] analyze professional currency managers and find that some have timing abilities and the skill to mitigate drawdowns. Froot, Arabadjis, Cates, and Lawrence [2011] look at institutional currency trader transaction data, under the theoretical context of dynamic loss aversion, and find that institutional investors tend to (i) cut risk by reducing both long and short positions when they experience losses and (ii) lower the propensity to add risk when they realize gains. Analyzing the performance of individual currency traders in the context of technical analysis is an important inquiry because government regulators have raised concerns that individual currency traders have been losing significant amounts of money (Commodities Futures Trading Commission [2010]). Our analysis is expected to provide vital insights about the use of technical analysis and the extent to which possible currency losses are associated with individual currency traders' technical trading strategies.

Our results are summarized as follows. First, 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 suggests that individual currency traders in this sample utilize common technical indicators to trade spot currencies. Second, our analysis reveals that technical currency traders that trade based on set of well-known technical indicators underperform relative to their peers who do not use these technical indicators.

The primary contribution of this study is that it offers 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 paper. This is significant because many currency traders use technical analysis (Park and Irwin [2007]) and our results imply that traders who do use popular indicators may hurt their performance. Additionally, the results of this study contribute to the literature by offering 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 losses realized by individual equity traders. One possible explanation for the underperformance of individual equity traders may be the use of technical analysis.

We use two data sources in this paper. The primary dataset 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]). To construct our factor model, we obtain daily currency return data from our secondary data source, TradeStation Securities.

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 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.

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:

$$MA = \frac{\sum_{i-1}^{n} P_t}{n} \qquad (2)$$

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

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

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.

Definition of Weighted Currency Indices and Construction of Independent Variables

To construct the four technical indices of the 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 Exhibit 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).

****Insert Exhibit 1 about here****

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 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).

For the Relative Strength Index (RSIIndex) strategy, a trader goes long the weighted currency index when the RSI technical indicator reaches 30, then goes 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.

Data Description

Panel A of Exhibit 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 and Panel B provides correlation coefficients.

Panel A reports descriptive statistics for the independent and dependent variables. 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 Exhibit 2 is the high skewness of the equal-weighted portfolio daily net returns. This indicates that individual currency traders, on average, experience frequent small losses while earning fewer, yet significantly large gains. The remainder of Exhibit 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 Exhibit 2 about here****

Panel B of Exhibit 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 suggests that the technical indicator Bollinger bands may be a good hedge against moving-average strategies. It is important to note that all correlation coefficients for the net daily excess returns are low, which implies that there is little association between the equal-weighted excess returns and technical currency indices.

REGRESSION RESULTS FOR INDIVIDUAL CURRENCY TRADER ACCOUNTS

To analyze the net returns of individual currency 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 Exhibit 3.

We first address the significance of alpha. Panel A of Exhibit 3 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 while 45 out of 428 accounts (10.51 percent) earn negative and significant alphas. This reveals that there is cross-sectional variation in the performance of these traders. This pattern is similar to the cross-sectional variation in the performance of professional currency hedge fund managers, as documented in Pojarliev and Levich [2008]. Specifically, they 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.

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 show 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. As noted earlier 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. This suggests that RSI not only is a popular technical indicator, but also individual currency traders employ 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 the R^2 of the technical currency model. Panel B of Exhibit 3 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 Exhibit 3 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 shows that some traders may be using the technical trading strategies identified in this paper to trade currencies.

The final two rows in Panel B of Exhibit 3 report 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 mean R^2 is 0.13 for account holders with positive alpha and 0.12 for negative alpha. Hence, there is little difference between the two groups. Furthermore, the lower quartile for positive (negative) alpha is 0.038 (0.039) also shows that there is little difference between individual currency traders when dividing them into 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 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.

****Insert Exhibit 3 about here****

Overall, the results suggest that individual currency traders use trading strategies that mimic the four technical indices of model (1), implying that individual currency traders use well-known technical indicators to trade currencies. This evidence is consistent with previous studies that document currency traders use technical analysis to trade currencies (Park and Irwin [2007]).

The Association between Technical Analysis and Performance

Our final inquiry asks whether the use of technical analysis is positively associated with performance. We address the association between technical analysis and performance because examining the association between popular technical indicators and performance can shed light on the source of profits and losses for individual currency traders. This is a significant inquiry because government regulators are concerned that individual currency traders may be exposing themselves to excessive risk trading currencies and losing significant amounts of money (CFTC [2010]). If the use of popular technical analysis is negatively associated with performance this would imply that individual currency traders may be able to trim down their losses by shunning generic technical trading strategies. Furthermore, this investigation is necessary because published studies show that technical trading styles can lead to abnormal returns (Park and Irwin [2007]) 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 relationship between the use of technical analysis and performance.

To determine whether there is an inverse linkage 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-known 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 estimates of alpha and R^2 from these regressions. Second, they regress alpha on R^2 and 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 we estimate the following model:

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

Alpha and R^2 values are obtained from estimating the technical currency model (1) for all 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 in the cross-section of returns we rank accounts on performance measured by the statistical significance of alphas.

Exhibit 4 presents the results of model (9) with quartile ranks of performance. The most interesting result in Exhibit 4 is that the coefficients for the worst-performing currency traders in quartile 4 are both negative and statistically significant. The coefficient of R^2 for the worst performers is -1.46 (*t*-statistic = -2.48) and statistically significant. As discussed earlier, a high (low) R^2 implies that the currency trader is actively (not actively) using technical indicators.

Hence, the negative and significant coefficients for the worst performing individual currency traders imply that the use of technical analysis (high R^2) results in performance (low alpha).

****Insert Exhibit 4 about here****

Another interesting observation is that a linear pattern seems to prevail when moving from the worst to best performing individual currency traders. The coefficient for the worst-performing traders is negative and significant and it increases in value and becomes positive (yet insignificant) 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 (Park and Irwin [2007]). 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 evidence is important because the MACD, MA, RSI and Bollinger band indicators are widely used and well established in the individual investment community. Hence, our results imply that the use of these indicators is detrimental to performance.

CONCLUSION

This paper 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. Our 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 suggests that currency traders who use technical indicators underperform when compared to their peers who do not rely on the same trading strategies. Overall, our results support CFTC concerns that some individual currency traders sustain excessive losses and add to the literature by showing that the use of popular technical trading strategies is one possible source for these losses.

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 considerable 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.

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Exhibit 1. Frequency of Top Five Contracts Traded

This exhibit reports trading activity from 79,042 roundtrip transactions of 428 individual currency trader accounts from March 2004 to September 2009. It reports the top five currency pairs traded, 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

Exhibit 2 Descriptive Statistics for Dependent and Independent Variables

This exhibit reports descriptive statistics for accountholders, and 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	Maximum	Minimum	Std Dev	Skewness
Net Daily Excess Returns	0.0576	43.1505	-12.8813	2.2197	6.1793
BB Index	-0.0288	8.2200	-5.1900	0.9460	-0.1489
MACD Index	0.0019	3.5500	-4.2700	0.7147	0.1666
RSI Index	-0.0185	8.5400	-5.3900	0.9486	-0.1328
MA Index	0.0192	3.2900	-4.4400	0.6889	0.1780

Panel B - Correlation Coefficients

	Net Daily Excess Returns	BB Index	MACD Index	RSI Index	MA Index
Net Daily Excess Returns	1				
BB Index	-0.0650	1			
MACD Index	0.0231	-0.0444	1		
RSI Index	-0.0729	0.5062	0.0227	1	
MA Index	0.0446	-0.5861	0.4273	-0.3086	1

Exhibit 3 - Coefficient Summary for Technical Currency Model Regressions for Individual Accounts

This exhibit 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 Significant Coefficients	percent	Number of Significant Coefficients	percent	Total Number of Significant Coefficients	Percent (neg and pos)
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

Exhibit 4. Regression Results for Technical Analysis as a Determinant of Performance

This exhibit reports regression results for $alpha_i = \alpha + \beta_{1i} R_i^2 + \varepsilon_t$, where alpha and R_i^2 are obtained from the technical currency model in equation (1). Accounts are ranked on performance and then placed into portfolios with quartile 1 (4) containing the best (worst) performing individual currency traders. *t*-statistics are in parentheses and significant values are in bold. ** denotes statistical significance at the 5% level and * at the 10% level.

Quartile Ranks on Performance				
Variable	1 (best)	2	3	4 (worst)
R^2 (explanatory variable)	1.15	-0.23	-0.63	-1.46
	(0.85)	(-0.90)	**(-2.19)****	**(-2.48)****
R^2	0.007	0.007	0.031	0.014
Observations	107	107	107	107