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SPECULATION IN THE FOREIGN EXCHANGE MARKETS USING INTERTEMPORAL EMPIRICAL MODELS

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ABSTRACT

Due to recent asset bubbles, behavioral economics has gained popularity among some economists to explain market phenomena where traditional economics breaks down. Behavioral economics predicts that market inefficiencies due to irrational behavior in the short run creates speculative opportunities in order to return assets to fundamental levels in the long run. Using two intertemporal empirical models, moving average convergence divergence (MACD) and relative strength index (RSI), in the foreign exchange markets, EUR/USD, GBP/USD, USD/CHF, and USD/JPY, over three time periods, 5 minute, hourly, and daily, the models are fitted to 2000-2009 data and applied to 2010-2012 data to test the models' robustness. It is found that six combinations achieve excess returns of 5% or more while having essentially a zero probability of randomly occurring. Also, it is shown that asset returns are partially dependent upon previous returns as predicted by the non-random walk theory.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

Throughout history, there have been asset bubbles which had catastrophic effects on economic markets in the short run. Two recent bubbles, the dot com and real estate bubbles, have made some economist question their unwavering belief in traditional economics. Behavioral economics in particular has gained popularity in explaining market phenomena where traditional economics breaks down. Behavioral economics studies the effects that psychology has on agents making economic decisions.

A classic example of traditional vs. behavioral economics is the random walk vs. non-random walk theories. The random walk theory which comes out of traditional economic theory states that future asset returns randomly deviate from an average return. It has been shown that the random walk theory holds in the long run in open markets. The non-random walk theory states that the random deviations in the short term are time dependent and thus can be predicted using past returns. Almost all of the compelling explanations for the non-random walk theory result from behavioral economics. At the core of the debate is whether inefficiencies or "frictions" in the market are caused by irrational behavior.

In order to test the time dependency of asset returns, two intertemporal empirical models, the moving average convergence divergence (MACD) and relative strength index (RSI) models, will be applied to four foreign exchange pairs, EUR/USD, GBP/USD, USD/CHF, and USD/JPY, over three time periods, five minute, hourly, and daily. The models are fitted to 2000-2009 data and later applied to 2010-2012 data to determine the robustness of the models. In order for the non-random walk theory to hold, the models must obtain significant excess returns over the average asset returns for that period, and the returns achieved by the models must have a minimal probability of randomly occurring.

This paper is divided into five primary sections: literature review and theoretical framework, data and methods, results, discussion, and conclusion.

The literature review and theoretical framework begin with a brief overview on foreign exchange and technical analysis which are needed as background information for the remainder of this paper. The literature review is focused on the explanations offered by economists for the results predicted by the non-random walk theory. The theoretical framework discusses the random walk and non-random walk theories in depth, as well as mean reversion and momentum.

In the data and methods section, the two intertemporal empirical models used in this analysis and the input parameters of these models are described in detail. The software package, MetaTrader 5, and data sources, Metaquotes, are introduced to understand the testing process employed. The evaluation criteria used to select model parameters are defined to clearly identify the rationale for selecting certain parameters. Lastly, the analysis techniques that are used to compute the excess returns are thoroughly described.

The results begin with a commentary on the return distributions in general and how these distributions relate back to the non-random walk and random walk theories. Then the probability weighted returns and annualized returns for both models are presented for all 24 combinations of model, currency pair, and time period. The 2000-2009 results are presented first, followed by the 2010-2012 data, with each date range having a brief discussion of the results. The results for the two date ranges are analyzed and compared with each other to gain further insights into the behavior of the models.

After the results are presented, the discussion section dives into analyzing the rates of return and probabilities of random occurrence for six specific models. Then this analysis is reframed from the perspective of the random vs. non-random walk theories.

Finally, the conclusion sums up the primary findings of this paper and introduces some interesting ideas for future work related to this topic. Based upon previous literature, the conclusion speculates about possible causes for the observed results. Lastly, the implications that result from this paper are discussed, in particular how the results impact random and non-random walk theories, and behavioral and traditional economics.

Chapter 2

Literature Review and Theoretical Framework

Background

Foreign Exchange

Foreign exchange has become one of the most popular assets among technical analysts for a few reasons. The primary reason is that the major foreign exchange pairs are extremely liquid with large volumes of trades. According to the Bank of International Settlements, the foreign exchange market has an estimated daily turnover of $4 trillion. This high volume limits the effect that a single large actor can have on the price of the assets. Also, the foreign exchange markets are open 24 hours a day for 5 days a week. These extended hours when compared with most asset exchanges minimize discontinuities in prices from after hour trading which results in smoother price movements. Finally, relatively high leverage is available for forex trades which amplifies profits from trading strategies. Most technical analysis strategies rely on leverage since the strategies do not generate large profits but instead many profitable transactions. (Feenstra & Taylor, 2012)

Technical Analysis

Technical analysis attempts to forecasts future asset prices using historical data, primarily historical prices and volume. Although many of the technical analysis techniques were developed in the early 19th century, technical analysis did not gain popularity until the late 19th century. There are multiple reasons for its slow adoption. Primarily, technical analysis relies heavily on running complicated computations over large sets of data, and this is almost impossible to do by hand. Until the modern computer was developed which allowed for these computations to occur more readily, only large investment firms had the manpower required for technical analysis. Also, the large data sets required to run the computations were not readily available. Although the data was published, it was difficult to find the information published in a compiled format. With the modern computer, especially with the development of the Internet, these large data sets became readily available. (Schill, 2009)

Technical analysis has a few primary principles. The first principle is that asset prices reflect all of the relevant information. Second, prices of those assets move in trends: either higher, lower, or sideways. Third, history tends to repeat itself; by understanding how prices moved in the past, it is possible to gain insight into how prices may move in the future. (Schill, 2009)

Technical analysis has two primary branches, chart patterns and chart indicators. Chart patterns rely on visually identifying certain patterns in an asset's prices that have occurred in the past. These patterns will precede a certain price action (either up, down, or sideways). Because chart patterns do not rely too heavily on mass computations, this type of technical analysis was more popular before modern computers were developed. Figure 1 shows a support line pattern used in technical analysis. A level that is repeatedly tested is a support or resistance level. When a support level is broken it becomes a resistance level and vice versa. (Schill, 2009)

Figure 1: Support and Resistance (MetaquotesSoftwareCorporation, 2013)

Chart indicators use empirical models and asset information, primarily prices and volume, to predict future price movements. These models are essentially algorithms that take the asset information as input, and outputs the predicted price action. Even very simple algorithms require massive amounts of computations to obtain actionable output data, which is why this type of technical analysis has gained popularity since the advent of the modern computer. Figure 2 shows the use of moving averages. Two moving averages, one slow (purple) and one fast (blue), are overlaid on the same chart. When the fast crosses below the slow, it is a sell signal because it indicates the previously uptrend has been broken and a new downtrend has been established, and when the fast crosses above the slow it is a buy signal because the previous downtrend has been broken and a new uptrend has been established. (Schill, 2009)

Figure 2: Moving Average Convergence Divergence (MACD) (MetaquotesSoftwareCorporation, 2013)

Literature Review

Park and Irwin in 2007 wrote "What Do We Know about the Profitability of Technical Analysis?" in which they examine 135 studies on technical analysis. Park and Irwin's paper is used in this thesis to explore previous analyses done using technical analysis and determine how this thesis fits into the existing literature. Of the 135 studies that Park and Irwin analyzed, only 20 were conducted in the foreign exchange markets since the European Union was formed. All of these studies were conducted on a much longer timeframe (months or years) than most technical traders use (hourly, daily, or weekly). (Park & Irwin, 2007)

There also have been no academic works on the most common technical indicators like the moving average convergence divergence (MACD) or relative strength index (RSI) for all of the major currency pairs (EUR/USD, USD/JPY, GBP/USD, USD/CHF). There have been some analyst reports surveyed by Park and Irwin which have done this, but these analyst reports only present the results and do not discuss what may be causing the results and the implications. Park and Irwin attempted to bring this perspective, but only compiled a survey of analyst results and did not specifically test any strategies.

Because this thesis looks to explore speculation for a typical technical trader in the foreign exchange markets, parameters such as the timeframe, indicator, and currency pair are selected to reflect a technician's perspective. Also, the results will be analyzed from an economic perspective to interpret the results and their implications. This thesis looks to build upon the work by Park and Irwin by testing specific technical trading strategies commonly used by technical traders. Park and Irwin's explanations for the market behavior will be applied to the results of this exercise to determine which explanations best describe the results found.

Theoretical Framework

Random Walk Theory

The random walk theory states that asset prices cannot be predicted based on past information (i.e. there is no time dependency in asset returns). The random walk theory states that asset returns follow Equation 1: (Goldman, 1976)

Equation 1

$$
\begin{aligned}
&r_t = \mu_t + \epsilon_t \\
&where: \\
&r_t: asset\ return \\
&\mu_t: mean\ of\ the\ asset\ return \\
&\epsilon_t \sim N(0, \sigma_x) \\
&\sigma_x: standard\ deviation\ of\ the\ asset\ return
\end{aligned}
$$

Equation 1 defines asset returns under the random walk theory. The asset's return at time t is r_t, μ_t is the asset's mean return, σ_x is the asset's standard deviation in returns, and ϵ_t is an error term which is normally distributed with a mean of zero and a standard deviation of σ_x. Simply, this equation states that the return of an assets is the average return plus an error term. This error term is the key part to the random walk theory. Because this error term is time independent, the autocorrelation between returns is zero, therefore the returns in previous periods have no effect on the returns in the current period. This means that the only way for technical analysis strategies to be profitable is to be lucky since the standard error term is random. (Goldman, 1976)

Non-Random Walk Theory

The non-random walk theory predicts that asset prices can be predicted using past information (i.e. there is time dependency in asset returns). The non-random walk theory states that asset returns follow Equation 2: (Goldman, 1976)

Equation 2

$$
\begin{aligned}
&r_t = \mu_t + \epsilon_t \\
&where: \\
&r_t: asset\ return \\
&\mu_t: mean\ of\ the\ asset\ return \\
&\epsilon_t = f(r_{t-1}, r_{t-2}, \ldots)
\end{aligned}
$$

Equation 2 defines asset returns under the non-random walk theory. The asset's return at time t is r_t, μ_t is the asset's mean return, and ϵ_t is an error term which is dependent upon $r_{t-1}, r_{t-2}, \ldots$, which are the previous returns of the asset, among other factors. Basically, the return of an asset is the average return of the asset plus an error term which varies over time based on the previous returns of the asset. The goal of a technical analysis indicator is to model the error term which is a function of past returns. By using the past returns as the input, the model predicts the error term and thus the returns of the asset. (Goldman, 1976)

Comparison

Because the random walk and non-random walk are two competing theories, it is important to compare the two. The primary difference between the two theories is the error term used to predict the future returns of the assets. The random walk theory uses an error term which depends only on the standard deviation of the returns of the asset. This error term is normally distributed such that the mean is zero and the standard deviation is the same as the standard deviation of the asset. A random draw from this normal distribution determines what this error term is. This distribution does not vary with time since the standard deviation is assumed to be constant. However in the non-random walk theory, the error term is a function of the previous returns of the asset. (Goldman, 1976)

Non-Random Walk Theory Explanation

Some theoretical explanations for the results predicted by the non-random walk theory are presented in Park and Irwin's paper. Park and Irwin described the results as "frictions" in the market that explain the inefficiency. The first explanation is noisy rational expectations where the market acts rationally but there is a small amount of noise in the asset's price due to unobserved supply of a risky asset or information quality. "Price shows a pattern of systematic slow adjustment to new information, thereby allowing the possibility of profitable trading opportunities." (Park & Irwin, 2007, p. 805)

Another explanation proposed by Park and Irwin is the impact of behavioral effects on an asset's prices. This explanation assumes there are two types of investors: speculators who form fully rational expectations about asset returns and noise traders who irrationally trade on noise as if it were information. There are two other assumptions made in this explanation. "First, noise traders' demand for risky assets is affected by irrational beliefs or sentiments that are not fully justified by news or fundamental factors. Second, speculation, defined as trading by fully rational investors not subject to sentiment, is risky and limited because speculators are likely to be risk-averse." In this scenario, "it may be optimal for speculators to jump on the 'bandwagon' themselves. Speculators optimally buy the asset that noise traders have purchased and sell much later when price rises even higher. Therefore, although speculators ultimately force prices to return to fundamental levels, in the short run they amplify the effect of noise traders." (Park & Irwin, 2007, p. 808)

The third explanation for the non-random walk theory is herding. "Informed traders who want to buy or sell in the near future can benefit from their information only if it is subsequently impounded into the price by the trades of similarly informed speculators. Therefore, traders having short horizons will make profits when they can coordinate their trading based on the same or similar information." (Park & Irwin, 2007, p. 809)

The final explanation proposed by Park and Irwin is chaos theory where technical analysis "may be equivalent to non-linear forecasting methods for high dimension (or chaotic) systems. Thus, technical analysis performs better on non-linear data than on random data and generates more profits than a random trading rule." (Park & Irwin, 2007, p. 810)

Park and Irwin also presented some empirical explanations for the non-random walk theory. The first empirical explanation is that technical trading profits are correlated with central bank intervention. Although central bank actions are correlated with technical trading returns, Park and Irwin are not able to show central bank actions directly cause technical trading returns. (Park & Irwin, 2007, p. 810)

Order flow around round numbers in prices is another empirical explanation presented by Park and Irwin. "Clustering of order flows at round numbers is possible because (1) the use of round numbers reduces the time and errors incurred in the transaction process, (2) round numbers may be easier to remember and to manipulate mentally and (3) people may simply prefer round numbers without any reasoning." Because order flows cluster at round numbers often around support and resistance levels, these limit orders contribute to price movement consistent with technical analysis. (Park & Irwin, 2007, p. 811)

Another explanation is that profits generated by technical trading are compensation for holding risk. This risk premium for technical analysis is paid because technical analysis in general holds higher risks than other strategies such as buy and hold. (Park & Irwin, 2007)

Mean Reversion

Mean reversion is one of the key principles of technical analysis. The principle states that an asset's price will tend to move to an average price over time. This average price is allowed to change over time. Fluctuations in asset price, either above or below the mean, will return back to the average price of the asset in the long run. Many technical models use mean reversion as one of their fundamental principles. These models attempt to calculate the mean price of an asset at some given period of time. Once the mean price of the asset is established, the model will determine how far away from the mean price the current price is. Most mean reversion strategies enter a trade when the current price is overextended, which is when the current price is significantly above or below the mean price. When the difference between the mean price and current price is large, investors expect the price to revert back to the mean price at some point in the future. The more overextended the current price, the higher the probability for a mean reversion. Also, the more overextend the current price, the greater the price action toward the mean which equates to higher profits. (Schill, 2009)

Figure 3 shows an example of mean reversion. The solid red line is a 100 period moving average of the asset price, and the red and green bars are the actual asset prices. As predicted by mean reversion, whenever the asset price overextends below the average asset price, it tends to revert back to the mean asset price. The red arrows indicate times when the current asset price was overextended when compared to the mean asset price of the past 100 periods. Figure 3 also illustrates how the more overextended the current price is, the more likely and more violently the price reverts back to the mean price.

Figure 3: Mean Reversion

Momentum

Momentum is another key principle of technical analysis. The principle simply states that when an asset price is moving up, the price tends to continue to move up, and when the asset price is moving down, the price tends to continue to move down. An uptrend in price is defined as a series of higher high prices and higher low prices, while a downtrend in price is defined as a series of lower lows and lower highs. (Schill, 2009)

Figure 4 illustrates the principle of momentum. Notice how the downtrend on the left has a series of lower highs and lower lows (indicated by the black bars). The uptrend on the right has a series of higher highs and higher lows (indicated by the black bars). At some point the momentum runs out, and the trend ends. The trend ends for an uptrend when a lower high or lower low is found (indicated by the blue bar), and a downtrend ends when a higher high or lower low is found (indicated by the blue bar).

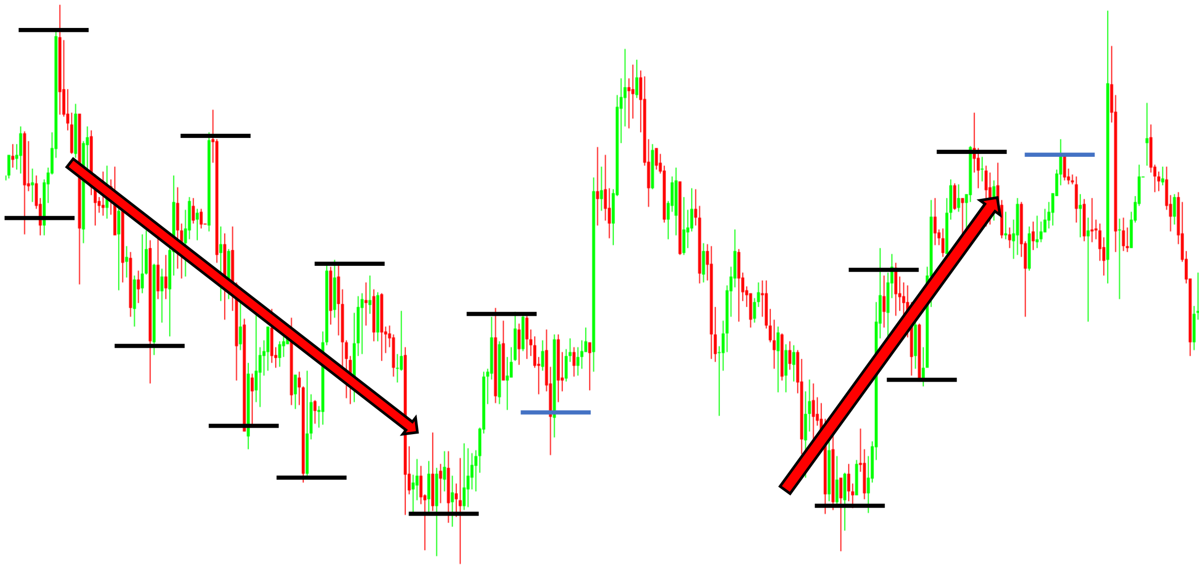


Figure 4: Momentum (MetaquotesSoftwareCorporation, 2013)

Combining Mean Reversion and Momentum

Mean reversion and momentum are often combined because the principles complement each other. Momentum predicts that trends in price movement are likely to continue, and mean reversion predicts that prices tend to revert back to the mean prices. By combining these two principles, prices tend to move in a trend until the current price becomes overextended relative to the mean price. When an asset reverts back to the mean, it often starts a new trend in the opposite direction as the previous trend. Also, when the current price reverts back to the mean, the price often overshoots the mean price because an uptrend or downtrend has been established. Frequently, the trend will continue until it is overextended on the other extreme. This is what leads to the oscillatory nature of asset price movements. (Schill, 2009)

Figure 5 illustrates how combining mean reversion and momentum complement one another. Notice how the uptrend on the left, which is defined by a series of higher highs and higher lows, begins when the current price is overextended below the mean. As the current price reverts back to the mean price, the uptrend is established. The price movement overshoot the mean price because an uptrend has been established. When the prices in the uptrend become overextended above the mean, the uptrend "loses momentum" and begins to revert back to the mean. This established the downtrend on the right. Again the prices revert back to the mean and overshot the moving average because a downtrend has been established.

Figure 5: Mean Reversion and Momentum (MetaquotesSoftwareCorporation, 2013)

Chapter 3

Data and Methods

Data

The MetaTrader 5 platform, which is owned by Metaquotes Software Corporation, uses foreign exchange data from the electronic communications networks (ECNs) which facilitates banks to trade financial assets (in this case currencies) outside of a typical exchange. Because the foreign exchange market lacks a central trading desk but instead uses the ECNs to stream quotes from top tier banks across the globe, foreign exchanges are decentralized and operate 24 hours a day for 5 days a week. These quotes are stored in a historical database by the ECNs. Metatrader 5 uses the historical database of quotes by the ECNs to generate price and volume data for all of the currency exchanges. (SEC, 2007)

Methods

Empirical Models

General Parameters

A stop loss is a limit order, which is an open order that is entered when a trade begins that does not execute until the market price reaches a specified price, at a price level which limits the losses on the transaction by exiting the trade, “stopping the loss,” once the price level is reached. A stop loss is used to limit the downside risk of a transaction by limiting the maximum loss that can occur on the transaction. This allows the trader to know the maximum loss, which translates to risk, on a trade even before enter it. By “tightening” the stop loss (reducing the distance between the price level at which the trade is entered and the price level of the stop loss), the risk of a trade is reduced because the maximum amount of money lost on a single trade is reduced. However, if a stop loss become too tight, a transaction that may be profitable is actually “stopped out” by the noisy fluctuations in the price movement. (Samuel, 2010)

A take profit is a limit order at a price level which limits the profits of the transaction by exiting the trade, “taking profit,” once the price level is reached. A take profit level is used to cash in unrealized profits. By setting a take profit level before entering a trade, the maximum profits for a trade are known. If a take profit is too tight, potential profits may be missed because the profits are being capped. However if a take profit is too loose, the price action may not reach the take profit level (even if the model accurately predicted the price action), so unrealized profits are lost. This is why both stop loss levels and take profit levels need to be carefully calibrated to match the price action predicted by the model used. (Samuel, 2010)

Figure 6 depicts a typical example of stop loss and take profit usage. Notice that the trade is a buy order, so the asset is expected to appreciate. In foreign exchange, a pip is a unit of measure which is equal to one percent of one percent or .0001 (the only exception is for the USD/JPY where a pip is just one percent or .01). The take profit level is located 500 pips above the purchase level and the stop loss is located 100 pips below the purchase price.

Figure 6: Stop Loss and Take Profit Example For a Buy Order (MetaquotesSoftwareCorporation, 2013)

The stop loss and take profit parameters are used in both the RSI and MACD models in this analysis. Stop loss and take profit allows a trader to determine the risk and reward before entering the trade, which essentially gives him information on both risk and return. Also, by having a ratio of take profit to stop loss greater than 1, it allows the trader to remain profitable even if his model is incorrect about the price movement more than it is correct. (Samuel, 2010)

Two other important parameters for foreign exchange models are the lot size and lot percentage. The lot percentage and lot size are two ways to measure the quantity of a currency in a transaction. Lot size is an absolute measure of the quantity of a currency, while the lot percentage is a relative measure of the quantity of a currency. In foreign exchange a lot is 10,000 units of the base currency, so a lot size of 1 is 10,000 units of the base currency. The lot percentage is the total value of the lot size purchased divided by the total value of the portfolio. Basically, the lot percentage indicates how much of the portfolio is being allocated for the transaction (and how much is at risk).

MACD

The moving average convergence-divergence (MACD) model is one of the most popular technical analysis tools. It uses two simple moving averages, one fast and one slow, to determine the future price direction of an asset. The signal simple moving average is a moving average of the difference between the fast and the slow moving averages. Using the signal line and threshold levels, buy and sell signals are established. These parameter are explained in more detail below. (Chong & Ng, 2008)

The slow moving average computes the moving average of a relatively long period of time (when compared to the fast moving average), so the slow moving average reacts slower to changes in the price. This slow moving average acts as the mean price of an asset for the MACD model. So at any period in time, the slow moving average is assumed to be the mean price of the asset. Although the mean price is not static since it adjusts to new prices, it is relatively static when compared to the fast moving average. (Chong & Ng, 2008)

The fast moving average computes the moving average of a relatively short period of time (when compared to the slow moving average), so the slow moving average reacts quicker to the changes in price. The fast moving average attempts to mirror the current price movements of the asset. In the MACD model, the fast moving average acts as a proxy for the current price. (Chong & Ng, 2008)

The MACD signal moving average computes the moving average of the difference between the fast moving average and the slow moving average. The signal moving average is a really short moving average (just a few periods) that smoothes the difference between the fast and slow moving averages. The signal moving average is the core of the MACD model since it triggers the trading rules. The MACD signal line is multiplied by the MACD signal weight to amplify or reduce the value of the signal line. (Chong & Ng, 2008)

Equation 3: MACD Equations

$$MACD\ Signal = MACD\ Weight \times SMA(Slow\ SMA(P, i) - Fast\ SMA(P, i), n)$$

$$where:$$

$$SMA: Simple\ Moving\ Average$$

$$P: Prices$$

$$i: Period\ of\ Slow\ SMA$$

$$j: Period\ of\ Fast\ SMA$$

$$n: Period\ of\ MACD\ Signal$$

The signal threshold is the level that the MACD signal line must reach to enter a trade. When the signal line crosses above the threshold and the fast moving average is above the slow moving average, the asset should be sold because the current price is overextend to the upside and will likely revert to the downside. When the signal line crosses below the threshold and the fast moving average is below the slow moving average, the asset should be bought because the current price is overextend to the downside and will likely revert to the upside. (Chong & Ng, 2008)

Figure 7 shows the MACD signal line with the threshold levels. Observe how the buy signal occurs when the signal line crosses below the lower threshold level, and the sell signal occurs when the signal line crosses above the upper threshold level.

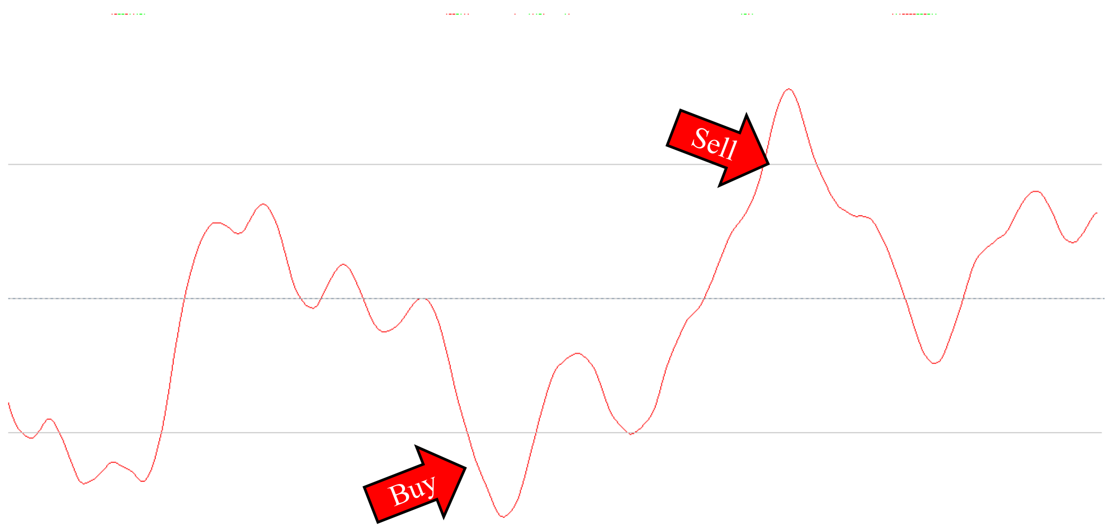


Figure 7: MACD Example

RSI

The relative strength index (RSI) is an indexed value between 0 and 100 and is used to determine if an asset price is likely to revert back to the mean. The number of periods used to compute the RSI and threshold levels for action are the parameters used in this model. Below is the derivation of the RSI. (Chong & Ng, 2008)

Equation 4: Period of Increasing Asset Prices

$$U = P_{now} - P_{previous}$$

$$D = 0$$

$$where:$$

$$U: up$$

$$D: down$$

$$P: price$$

Equation 5: Period of Decreasing Asset Prices

$$U = 0$$

$$D = P_{now} - P_{previous}$$

$$where:$$

$$U: up$$

$$D: down$$

$$P: price$$

Equation 6: Relative Strength

$$RS = \frac{EMA(U,n)}{EMA(D,n)}$$

$$where:$$

$$RS: Relative\ Strength$$

$$EMA: Exponential\ Moving\ Average$$

$$n: number\ of\ periods$$

Equation 7: Relative Strength Index

$$RSI = 100 - \frac{100}{1 + RS}$$

The number of periods used in the RSI model determines the number of periods that are used to calculate the RSI. Since an exponential moving average is used, the more recent periods are weighted more heavily than the older periods. The RSI is multiplied by the RSI weight to amplify or reduce the RSI value. The threshold levels are used to determine when action should be taken when using the RSI. (Chong & Ng, 2008)

Figure 8 shows how the RSI model determines when to take action. When the RSI line crosses below the bottom signal line, a buy signal is established, and when the RSI line crosses above the top signal line, a sell signal is established. (Chong & Ng, 2008)

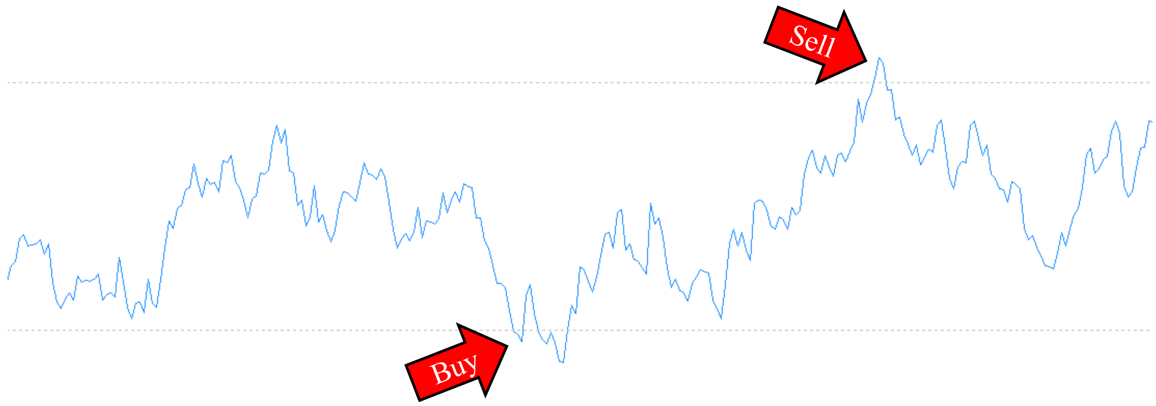


Figure 8: RSI

Software Package

MetaTrader 5 from Metaquotes Software Corporation is utilized to run the MACD and RSI models. The MACD and RSI models are coded into the program which can be run given parameter values as input over the desired currency pair, date range, and time period. MetaTrader 5 outputs the trading history of the model which can be analyzed. In order to understand the evaluation of the output data from MetaTrader 5, a few terms which are used by MetaTrader 5 need to be defined:

Profit — obtained profit/loss for this run;

Total trades — total number of trades (deals that resulted in fixing a profit or loss) executed for the run;

Profit factor — ratio of the total profit to the total loss in percentage. One means that the total of profits is equal to the total of losses;

Expected payoff — this is a statistically calculated value that reflects the average profitability/loss of one trade;

Drawdown — the relative drawdown of equity, the largest loss in percentage from the maximal value of equity. Withdrawal of assets by an Expert Advisor during optimization is taken into account when the drawdown is calculated;

Recovery factor — this value reflects the riskiness of the strategy - the amount of money risked by the Expert Advisor to make the profit it obtained. It is calculated as the ratio of a profit obtained to the maximal drawdown;

Sharpe Ratio — this ratio characterizes efficiency and stability of a strategy. It reflects the ratio of the arithmetical mean profit for the position holding time to the standard deviation from it. Also, it accounts for the risk-free rate which is the profit on a certain deposited amount of money.

(MetaquotesSoftwareCorporation, 2013)

Evaluation Criteria

Each model will use the basic parameters of stop loss, take profit, lot size, and lot percentage for portfolio management. The MACD model will use a fast moving average period, slow moving average period, signal moving average period, signal weight, and signal thresholds as parameters. The RSI model will use a signal period, signal weight, and signal thresholds as parameters. The MACD and RSI models are applied to the EUR/USD, GBP/USD, USD/CHF, and USD/JPY currency pairs on time periods of 5 minutes, hourly, and daily. The input parameters for the MACD and RSI models will be varied based on Table 1 and Table 2, respectively. The parameter range and step size are the default values recommended by the

MetaTrader 5 in order to balance computing time with accuracy. The models are fit to data from January 1, 2000 to December 31, 2009.

Table 1: MACD Parameters

	Start	Step	Stop
Signal Threshold (Open)	10	1	100
Signal Threshold (Close)	10	1	100
Stop Loss	50	5	500
Take Profit	50	5	500
Fast Period	12	1	120
Slow Period	24	1	240
Signal Period	9	1	90
Signal Weight	1	.1	10
Lot Percent	10	1	100
Lot Size	.1	.01	1

Table 2: RSI Parameters

	Start	Step	Stop
Signal Threshold (Open)	10	1	100
Signal Threshold (Close)	10	1	100
Stop Loss	50	5	500
Take Profit	50	5	500
Signal Period	8	1	80
Signal Weight	1	.1	10
Lot Percent	10	1	100
Lot Size	.1	.01	1

Once the data sets are completed for all 24 combinations of currency pair, time period, and model, the results are filtered and sorted using the following criteria:

- The profit, expected payoff, profit factor, recovery factor, and sharpe ratio must be above the average value for each factor
- The drawdown, total trades, and lot percentage must be below the average value of each factor
- The filtered data is then sorted in descending order of profit factor

The evaluation criteria used to select which set of parameters is used for each specific combination (note: a combination is a unique combination of currency pair, time period, and model) reflect the personal preferences of the investor. However, the filters selected are generally accepted as desirable; the filter primarily seeks to remove parameter sets where there is either high risk, low return, or both. Once filtered, the metric chosen to be maximized is purely arbitrary and dependent upon the investor’s preferences, however for this thesis the profit factor is maximized.

Once the set of parameters is selected, the trading histories for each combination are used to compare the two models (which stand in for the non-random walk) to the price histories (which stand in for the random walk baseline) for each currency pair and time period combination between 2000 and 2009. The non-random walk results will be compared to the random walk results in two ways: annualized rates of return and probability weighted rates of return. For the analysis, excess returns over the baseline will be used to compare the combinations from an equal starting point. Essentially, the baseline return will be subtracted from each combination. This eliminates any biases found in the baseline returns (i.e. EUR/USD appreciates 2% and GBP/USD depreciates 3.5% over the same period) which allows model returns to be compared directly. The annualized rates of return are calculated using Equation 8. Annualized rates of return are used to compare the aggregate or total return of the models.

Equation 8: Annualized Rate of Return

$$r = \sqrt[n]{\left(\frac{P_2}{P_1}\right)} - 1$$

$$where:$$

$$r: Rate\ of\ Return$$

$$n: Number\ of\ Years$$

$$P_1: Initial\ Asset\ Price$$

$$P_2: Final\ Asset\ Price$$

The probability weighted rates of return are calculated using Equation 9. The probability weighted rate of return is the expected rate of return for a single trade. In this analysis, a relative frequency histogram is constructed from the trade returns for each combination. The weighted rate of return is calculated as the net area (positive minus negative area) under the relative probability curve.

Equation 9: Probability Weighted Rate of Return

$$r = \sum_{i=1}^{n} P(r_n) * r_n$$

$$where:$$

$$r: Rate\ of\ Return$$

$$n: Number\ of\ Bins$$

$$r_n: Rate\ of\ Return\ for\ Bin\ n$$

$$P(r_n): Relative\ Probability\ of\ r_n$$

Figure 9 shows an example of a relative probability distribution used to calculate the probability weighted rate of return. The net area under the probability curve, which equates to the probability weighted return, is calculated for the baseline, MACD, and RSI. The excess returns are calculated by simply subtracting the probability weighted return of the baseline from both the MACD and RSI probability weighted returns.

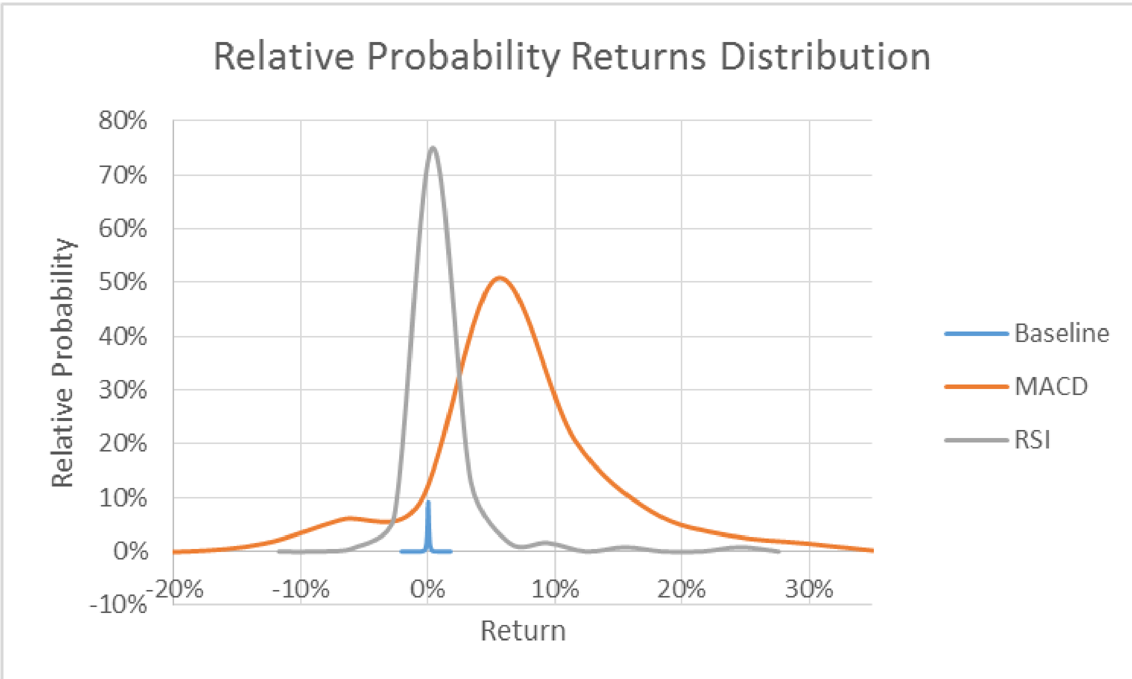


Figure 9: Relative Probability Distribution Example

In order to test the robustness of the models, the models will be applied to price data from January 1, 2010 to December 31, 2012. Because the each model's parameters are fit to 2000-2009 data, the model should perform well during that date range. However, if the model also performs well on 2010-2012 data which it is not fitted to, then the model is robust enough to perform well in other date ranges besides those the model is not fitted to. The evaluation process used on the 2000-2009 data is used to evaluate the 2010-2012 data.

Chapter 4

Results

Return Distributions

Before analyzing the returns of the combinations, an important discovery about the return distributions must first be discussed. In both the random walk and non-random walk theories, the rates of return are assumed to be normally distributed given a large enough sample size. In practice, this is commonly not the case given the relatively short time periods analyzed in this paper.

The normally distributed assumption typically begins to break down when the time period becomes smaller than a day. As the time period becomes smaller, the distribution becomes less and less normally distributed. This is displayed in both the baseline returns of the asset and the model returns. As the time period shrinks, the kurtosis (spikiness of the peak and fatness of the tails) increases. The shape of the baseline returns appears to look more like a normal distribution than the model returns. This is not surprising because the baseline returns are random (thus bell shaped) but the model returns are not random (i.e., the model returns should be irregularly shaped to increase profits over the baseline returns). Although the random walk theory assumes a normal distribution for returns, this assumption is primarily made to simplify the analysis, but the core distinction between the two theories (time dependency of the error term) remains. In order to confirm the non-random walk theory, the model returns must significantly outperform the baseline returns while also having a minimal probability of randomly occurring.

2000-2009 Results

Figure 10 and Figure 11 show the excess annualized rates of return and excess probability weighted rates of return, respectively. Again, by subtracting the baseline return from the MACD and RSI returns, the excess returns can be compared directly without any biases due to period, currency pair, etc. By looking first at the annualized rates of return, it is immediately clear that the RSI model performs relatively poorly (below 10%) on the 5 minute time period for all four currency pairs and the hourly time period for all currency pairs except for USD/JPY. Also, the MACD model performs well (above 10%) for every combination except for the USD/JPY – Hourly combination.

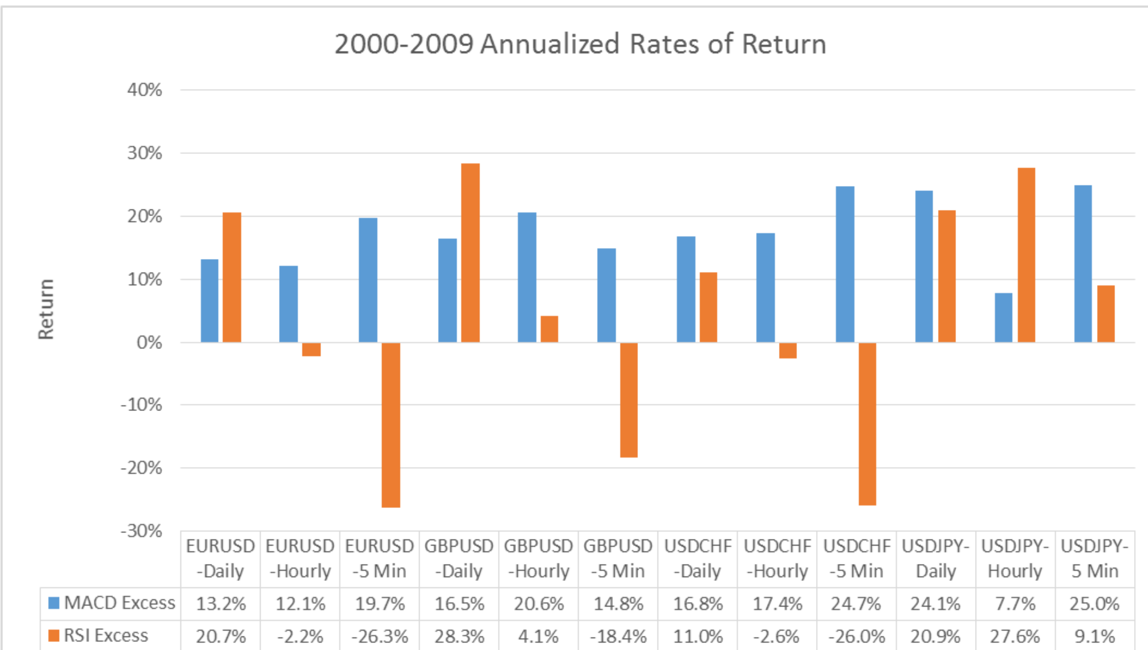


Figure 10: 2000-20009 Annualized Rates of Return

The probability weighted rates of return tell a similar story as the annualized rates of return. In fact, the correlation between the two sets of data is strongly positive (.5 or greater) for both the MACD and RSI excess returns. This makes sense because higher returns per trade result in higher total returns and vice versa. Surprisingly, not every combination performs well even when applied to the data the model is fitted to.

There is a divergence between some of the probability weighted returns and annualized returns. For example, the EUR/USD - 5 Minute – RSI combination has a probability weighted return of 2.4% yet an annualized return of -26.3%. This divergence is due to a couple of factors. Both the MACD and RSI models have a difficult time fitting to the 5 minute time period; the 5 minute time period is just too random and choppy to extract information about future returns. Also, the divergence occurs for combinations which did not have enough trades to produce a large enough sample size to approximate the probability weighted returns accurately. These two factors cause the different results between the probability weighted returns and the annualized returns. However, these differences occur almost exclusively with the poorer performing combinations which will not be used in the final analysis anyway.

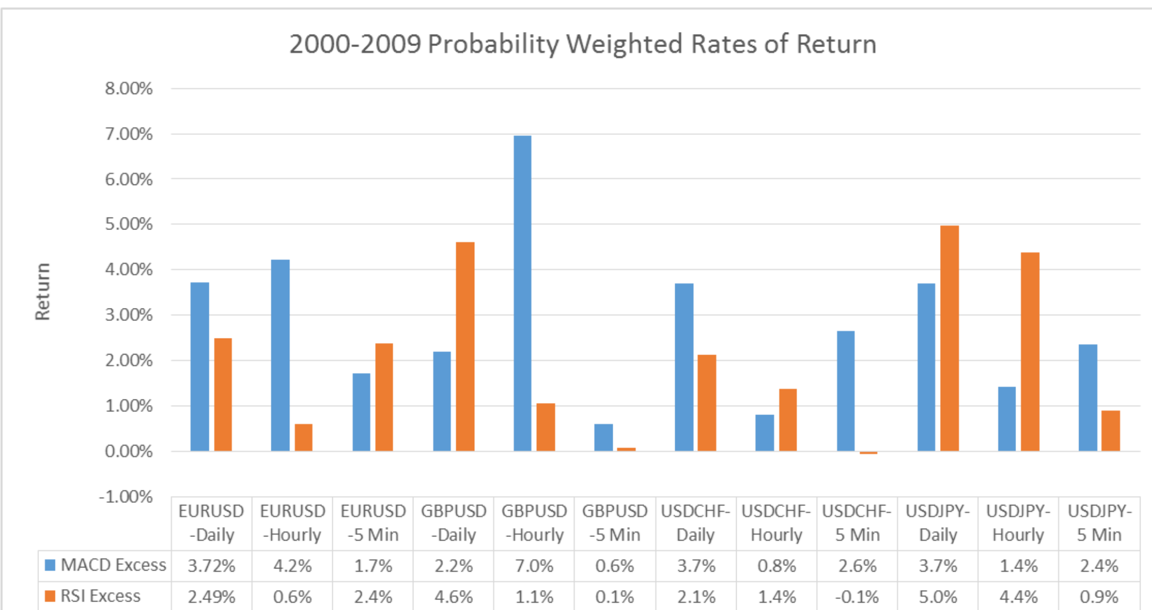
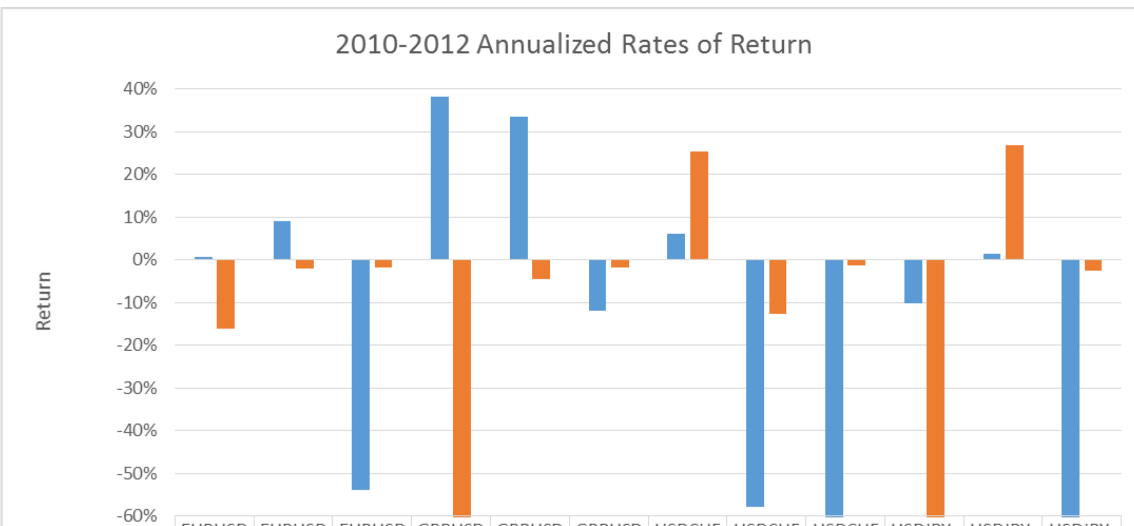


Figure 11: 2000-2009 Probability Weighted Rates of Return

2010-2012 Results

Figure 12 and Figure 13 show the excess annualized rates of return and excess probability weighted rates of return, respectively. Note that the return axis does not extend to the maximum negative value (but can be found in the table below chart) in order to more clearly display the smaller magnitude returns (i.e., do not care whether it lost 40% or 100% because both are extremely undesirable). By first looking at the annualized returns, it is clear that only 6 combinations performed relatively well (above 5%) while the rest either gained/lost fairly small returns or completely collapsed.



	EURUSD -Daily	EURUSD -Hourly	EURUSD -5 Min	GBPUSD -Daily	GBPUSD -Hourly	GBPUSD -5 Min	USDCHF -Daily	USDCHF -Hourly	USDCHF -5 Min	USDJPY-Daily	USDJPY-Hourly	USDJPY-5 Min
MACD Excess	0.7%	9.2%	-53.8%	38.1%	33.6%	-12.0%	6.2%	-57.8%	-66.6%	-10.2%	1.3%	-66.0%
RSI Excess	-16.2%	-2.1%	-1.7%	-70.6%	-4.5%	-1.9%	25.3%	-12.7%	-1.3%	-100.0%	27.0%	-2.5%

Figure 12: 2010-2012 Annualized Rates of Return

The probability weighted rates of return tell a similar story. Unfortunately, the errors found in the 2000-2009 date range due to using too small a sample size to calculate the probability weighted rates of return are amplified because the date range is only three years instead of ten years. However, strong positive correlations (greater than .5) still exist between the annualized rates of return and the probability weighted rates of return for both the MACD and RSI models.

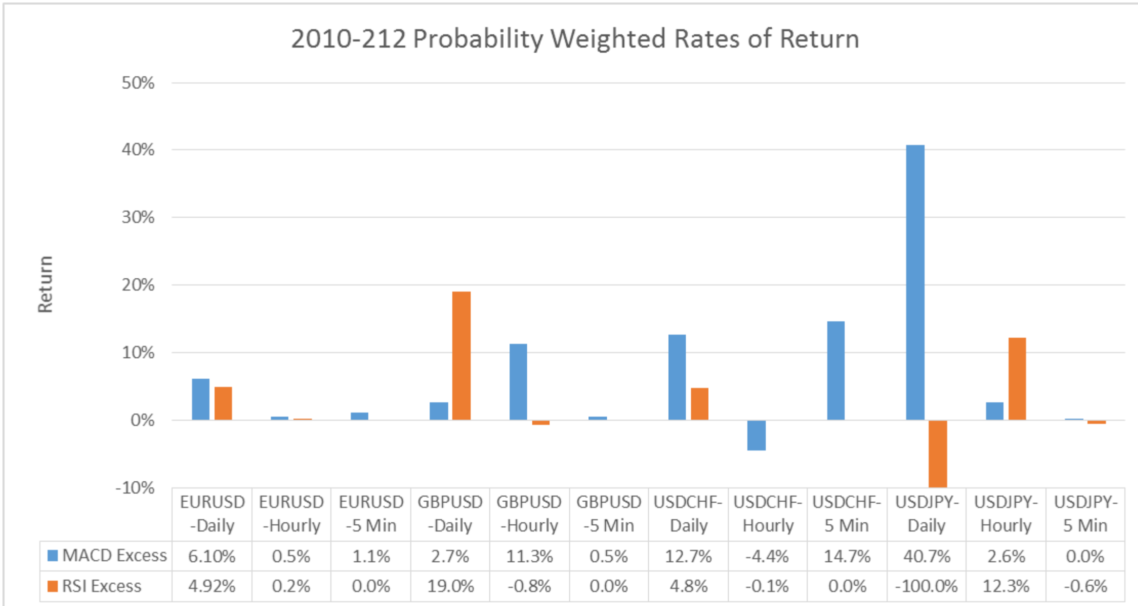


Figure 13: 2010-2012 Probability Weighted Rates of Return

Chapter 5

Discussion

The reason for applying the MACD and RSI models to both the 2000-2009 data and 2010-2012 data is to determine the robustness of the models. Since both models use parameters fitted to the 2000-2009 data, one would expect the models to perform relatively well on the data which it is fitted to, 2000-2009, and poorer on data which it isn't fitted to, 2010-2012. This is clearly seen when comparing the returns between these two date ranges. For the annualized returns, all but one combination produced positive returns during 2000-2009 (and even that only lost .1%), while only 6 combinations produced returns above 5% (and a large number of combinations resulted in catastrophic losses). When looking at the probability weighted returns, the same trend is revealed. Clearly, only those 6 combinations are robust enough to accurately model its respective currency pair and time period. Table 3 summarizes the excess rates of return for the 6 selected combinations.

Table 3: Excess Rates of Return for Selected Combinations

Excess Rates of Return	2000-2009		2010-2012	
	Annualized	Probability Weighted	Annualized	Probability Weighted
MACD-EUR/USD-Hourly	12.1%	4.2%	9.2%	0.5%
MACD-GBP/USD-Daily	16.5%	2.2%	38.1%	2.7%
MACD-GBP/USD-Hourly	20.6%	7.0%	33.6%	11.3%
MACD-USD/CHF-Daily	16.8%	3.7%	6.2%	12.7%
RSI-USD/CHF-Daily	11.0%	2.1%	25.3%	4.8%
RSI-USD/JPY-Hourly	27.6%	4.4%	27.0%	12.3%

All 6 combinations achieve significant excess rates of return in both the fitted, 2000-2009, and the unfitted, 2010-2012, date ranges. By earning significant excess returns in both date ranges, the robustness of these 6 combinations is confirmed. Because the 2010-2012 data only spans 3 years, the returns vary not insignificantly from the 2000-2009 returns, but these returns still have a reasonable probability of occurring based upon the return distributions for each combination. For example, the relative probability distribution for the MACD-GBP/USD-Daily combination during the 2000-2009 date range, shown in Figure 14, shows that it is not unreasonable for the probability weighted return to shift up from 2.2% in 2000-2009 to 2.7% in 2010-2012. The same can be shown for the other five combinations. Another interesting result that comes from analyzing the relative probability distributions is an additional explanation for the large jumps in returns either for probability weighted or annualized. Due to the extremely non-normal distributions, which can include multiple peaks as seen in Figure 14, the returns can "jump" from one peak to another peak.

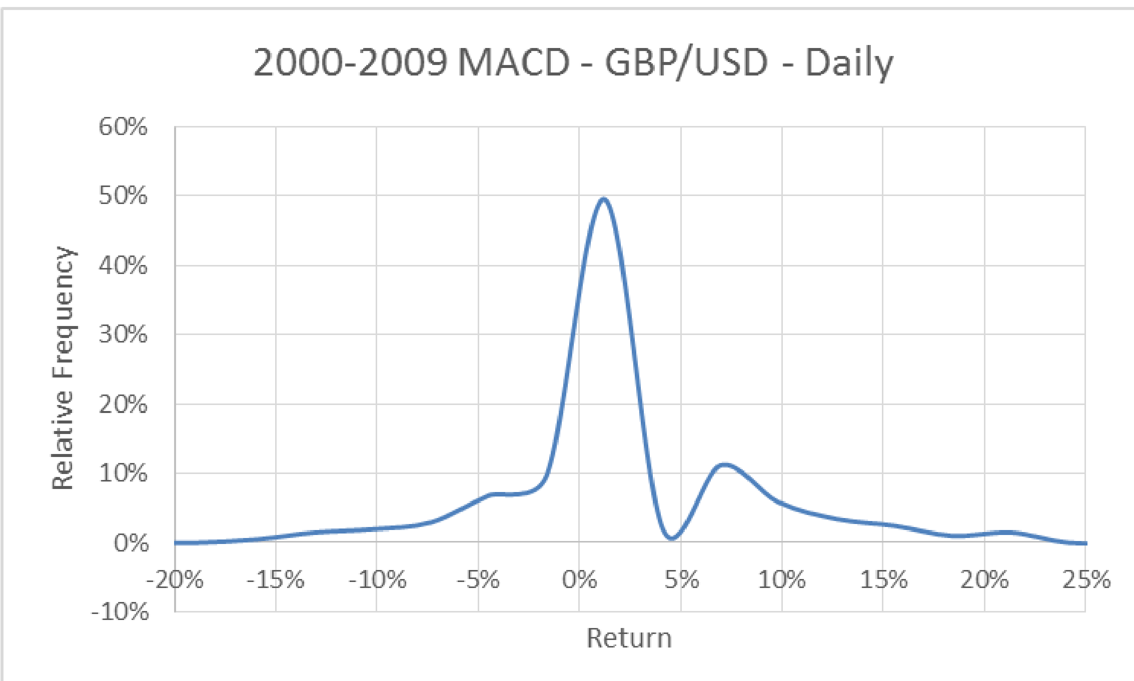


Figure 14: 2000-2009 MACD-GBP/USD-Daily Relative Probability Distribution

An important observation about the probability distributions is that the model return distributions are not only highly non-normal but are also not bell shaped. Often these return have multiple peaks and valleys with varying degrees of skewness. This is not surprising due to the fact that the model seeks to increase the probability weighted return. In order to do this, the model essentially deforms and distorts the bell shaped random return distribution, which are found in the baseline returns, to increase the probability of higher returns and decrease the probability of lower/negative returns.

In order to show that the models did not just get lucky, the probability of the returns is calculated (shown in Table 4). Using the baseline return distribution for each date range, the probability of the return achieved by the model can be determined. By multiplying the probability from each date range together, the combined probability of the two returns occurring is calculated. It is clear from the combined probability for each combination that it is extremely unlikely that the returns achieved by the model in both date ranges are random occurrences.

Table 4: Random Probability of Model Returns

	2000-2009	2010-2012	Combined
MACD-EURUSD-Hourly	0.000000%	0.004933%	0.000000%
MACD-GBPUSD-Daily	0.002317%	8.427191%	0.000195%
MACD-GBPUSD-Hourly	0.000000%	0.000000%	0.000000%
MACD-USDCHF-Daily	0.000000%	0.000000%	0.000000%
RSI-USDCHF-Daily	0.015615%	0.000013%	0.000000%
RSI-USDJPY-Hourly	0.000000%	0.000000%	0.000000%

Random Walk vs. Non-Random Walk Implications

Six combinations produced excess returns of 6% or more over two date ranges which have a probability of randomly occurring of essentially zero. Because of these excess returns and their minimal probability of randomly occurring, these six models effectively predict future asset prices by using past price information. The non-random walk theory states that the error or variable component of asset returns is a function of time (among other factors). Because the models used past price information to predict future returns, it proves that future returns are dependent upon past returns as predicted by the non-random walk theory.

Chapter 6

Conclusion

Overview

In order to validate the non-random walk theory, two intertemporal empirical models, MACD and RSI, are applied to the four major currency pairs, EUR/USD, GBP/USD, USD/CHF, and USD/JPY, on three different time periods, 5 minute, hourly, and daily. If the empirical models obtain significant excess returns with minimal probability of randomly occurring, then future returns are shown to be partially dependent on past returns thus confirming what is predicted by the non-random walk theory. After fitting the models to 2000-2009 data, the models are applied to 2010-2012 data to test the robustness of these models. Of the 24 models tested, 6 models achieved significant excess returns with essentially no probability of randomly occurring. This proves that time dependency exists in asset returns as predicted by the non-random walk theory.

There are a few interesting areas for future work connected with the results found in this paper. There are hundreds of technical analysis models, many more currency pairs (and assets in general), and time periods that were not tested in this analysis. It would be interesting to see the results produced by these other combinations using the same analysis techniques as applied in this paper. Another idea for future work came about while working through the analysis. It became clear that the optimal selection of model parameters depends almost entirely upon investor preferences. It would be interesting to see what would happen if advanced portfolio theory were applied to determine model parameters based on certain assumptions about investor preferences.

Implications

Although the random walk theory has been previously proven to hold true in the long run, the random walk theory breaks down in the short run. The results founds in this paper show that the non-random walk theory holds in the short run even over extended date ranges. Park and Irwin described this discontinuity in short run and long run behavior being due to “frictions” that create inefficiencies in the short-run which are corrected in the long run by speculation. Two “frictions” that Park and Irwin describe are especially applicable in explaining this market behavior.

The first explanation involves behavioral effects on market behavior. Behavioral economics is a new and growing part of economics, especially since the Great Recession’s housing bubble, which is being used to explain some of the market behaviors where traditional economics break down. By including human (irrational) behavior in economics, short term inefficiencies can be explained. Because investors may have different time horizons, short-term, irrational (noise) traders may benefit from long-term, rational (speculative) traders as described by Park and Irwin on page 808 of their article in the *Journal of Economic Surveys*. Although the speculative traders may temporarily benefit the noise traders by amplifying the noise traders’ effects, the speculative traders profit in the long run by returning the asset to the fundamental levels.

Another explanation provided by Park and Irwin which applies is herding which is also part of behavioral economics. Noise traders can only benefit when other noise traders make decisions based upon the same information. By trading with the same information, short term fluctuations in asset prices are unintentionally coordinated by traders using the same information and rationale. Essentially, noise traders create a self-fulfilling prophesy when enough noise traders coordinate their behaviors in the short run.

Clusters of limit orders around round numbers is another viable explanation offered by Park and Irwin especially with regard to stop loss levels. These clusters of order can act as a floor which prevents an asset price from dropping below that price level. Anytime the price does drop below, there is an immediate demand from these limit orders which boosts the asset's price. Effectively positioning a stop loss to coincide with these clusters reduces the chances that a trade will be "stopped out" for a loss.

This paper highlights the importance that irrational behavior has on markets especially in the short run. As long as humans are involved in markets, irrational behavior will continue to appear which also presents speculative opportunities to rational investors. Although these market inefficiencies appear to correct themselves in the long run, the short run impacts can be devastating as seen in any asset bubble.

REFERENCES

Chong, T., & Ng, W.-K. (2008). Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30. . *Applied Economics Letters*, 1111-1114.

Feenstra, R., & Taylor, A. (2012). *International Macroeconomics.* New York: Worth Publishers.

Goldman, B. (1976). Portfolio Reutrns and the Random Walk Theory: Comment. *The Journal of Finance*, 153-156.

MetaquotesSoftwareCorporation. (2013, March 13). MetaTrader 5. *Version 5.0 Build 778*.

Park, C.-H., & Irwin, S. H. (2007). What Do We Know about the Profitability of Technical Analysis? *Journal of Economic Surveys*, 786-826.

Samuel, J. (2010). Stopping the Losses: The Application of Stop-Loss Rules to Transactions Involving Foreign Affiliates. . *Canadian Tax Journal*, 897-925.

Schill, M. (2009). *An Introduction to Technical Analysis.* Charlottesville: University of Virginia - Darden Graduate School of Business Administration.

SEC. (2007, June 25). *Electronic Communication Networks (ECNs)*. Retrieved from SEC: http://www.sec.gov/answers/ecn.htm

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Education

The Pennsylvania State University, University Park, PA May 2013
Schreyer Honors College
Bachelor of Science in Aerospace Engineering
Minor in Business
Minor in Economics

Experience

Operations Management Leadership Program (July 2013) GE Transportation Erie, PA

Quality Systems Analyst, Intern (May 2010-Present) GE Transportation Erie, PA

Quality Management System (QMS) Documentation

- Manage Standard Work Practices (SWP) homepage and over 2500 process documents.
    - Created efficient standard work management process which maintained strict controls by overhauling document approval process using lean-six sigma techniques.
    - Developed metrics to track the quality of QMS documents and the timeliness of their approval.
    - Created QMS glossary and template to standardize terminology and formatting of documents.
- Proposed new Stop Shipment Risk Assessment Process to Quality Systems Leader.
- Decentralized 2000+ local documents by coordinating with quality leaders to implement the new process.
- Collaborated with Mfg. Quality to implement standard work template and establish local document controls.
- Established operating rhythms for global requirements' deployment by developing site quality plans, analyzing QMS sections, and identifying process gaps.
- Proposed and implemented new organizational structure for over 2500 process documents.
- Identified QMS gaps by comparing GE Energy, and GE Healthcare's QMS with Transportation's QMS.
- Updated document formatting and references to new quality standard for all 350+ HQ QMS documents.
- Designed global system to organize standard work.
- Inventoried over 2500 standard work documents and met with functional leaders to define document status.

Quality Communications

- Designed and now manage and maintain QMS homepage.
- Designed quality portals for quality organizations to communicate initiatives throughout GETS.
- Proposed QMS improvements to enhance One QMS focus by eliminating redundant systems.

Quality System Audits

- Earned Lead Auditor Certification
- Audited Erie and Grove City for Document Control, Security, and CTPAT
- Validated Corrective Action Requests (CARs) in Erie and Grove City

Activities

Co-Founder and Webmaster, Penn State Bike Share

- Working with the administration to deploy University-wide bike share program.
- Launched pilot program (Spring 2011).
    - 10 bikes available for use.
    - 50 participants from two residence halls.
- Designed a website to communicate group objectives to the public.
- Developed database to streamline the user experience and collect usage data.
- Appeared on 3 radio stations for donations.
- Raised over $2000 and collected 21 bikes.

2010 GE Student Leadership Conference
Team Leader and 2nd Place Team, 2012 GE Intern Business Case Competition
Team Leader and 1st Place Team, 2012 GE Quality Video Competition

Skills

Qualified Lead Auditor | Web Design | Excel 2013 | Access 2013 | MATLAB

Awards

6 Dean's List Awards
Academic Excellence Scholarship
Tau Beta Pi: Engineering Honors Society
Howard Waltemeyer Sr. Scholarship
Sigma Gamma Tau: Aerospace Engineering Honors Society