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Fibonacci Retracements and Self-Fulfilling Prophecy

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Introduction

Technical analysis is a market analysis technique that explicitly seeks to exploit trends in past prices, whether through visual analysis of graphs or more quantitative measures (e.g. moving averages), to develop a trading strategy that will earn profit. Technical trading tools provide signals to traders that can broadly be classified into four categories: buy, sell, exit the market, and enter the market. One tool prominently featured in technical trading strategies are support and resistance levels, a tool that predicts trend interruptions and one that generally is used to signal market entry. Broadly speaking, a support is a price level under the current market price where a decline is halted and prices turn back again. Resistance is the opposite of support [Osler (2000)].

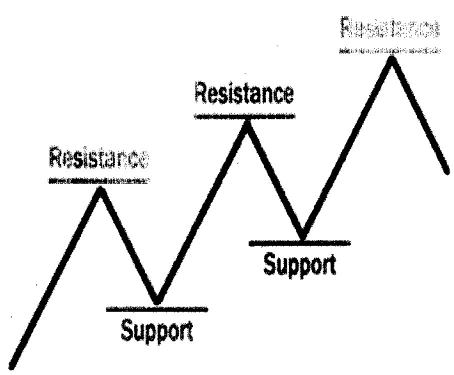

Figure 1: Graphical representation of Support and Resistance Levels. Figure courtesy babypips.com.

Figure 1 depicts a graphical representation of support and resistance levels during a market with an upward trend. If one starts at the very left of the figure, that is, at the first price point, one sees that the next marked resistance is a price level above the current market price where the price stops moving upward. Similarly, once at the resistance, one sees that the subsequent support is a price level below the current market price where prices cease their downward movement. In trending markets, certain support and resistance levels are termed retracements. During uptrends, retracements are support levels where temporary downward price movements within the uptrend are halted. During downtrends retracements are resistance levels where temporary upward price movements within the downtrend are reversed. For example, in Figure 1, the three price levels marked with "supports" would all be considered retracements. Some traders believe that Fibonacci ratios, a sequence of numbers generated by taking ratios of terms in the Fibonacci sequence, can be used to predict future retracements.[1] There are five Fibonacci ratios used by traders to predict retracements: 0.236, 0.382, 0.500. 0.618, and 0.764. Figure 2 provides a graphical illustration of how a Fibonacci retracement based upon the Fibonacci ratio 0.382 is calculated.

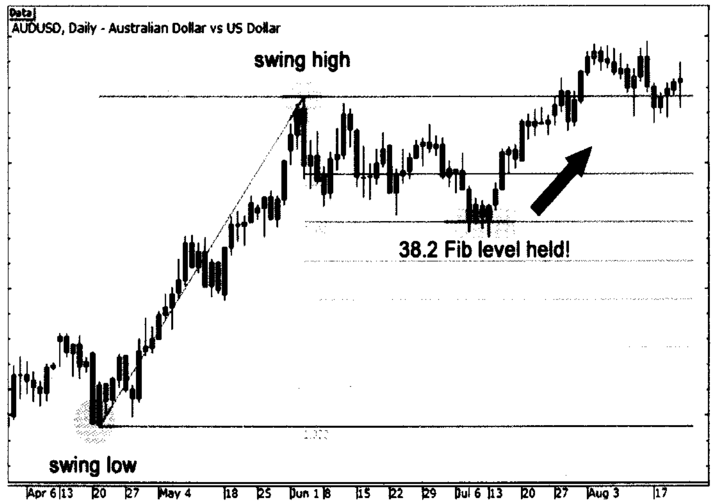

Figure 2: Graphical representation of Fibonacci Retracement. Figure courtesy babypips.com.

Figure 2 depicts a small portion of a broader uptrend. The swing high and swing low points are simply two local extrema in the exchange rate selected because they delineate the extent of a short-term upward spike in prices during this broader uptrend. One can view them as analogous to the portion of the prices in Figure 1 between the initial price and the first resistance level. As in Figure 1, prices begin a downward spike after the swing high, halting at a support level marked in Figure 2 with the term "Fib level." This terminology is used because the ratio of the distance between the swing high and the support level and the swing high and swing low is equal to the Fibonacci ratio 0.382. Explicitly,

$$\frac{\text{Swing High} - \text{Support Level}}{\text{Swing High} - \text{Swing Low}} = 0.382$$

As this ratio equals a Fibonacci ratio, this retracement is termed a Fibonacci retracement. The goal of the trader is to utilize the swing high and swing low with the Fibonacci ratios to predict the trend interruption that occurred in Figure 2, and use this prediction as a signal to enter the market. Use of Fibonacci ratios are ubiquitous in technical trading, particularly in the foreign exchange market: almost every guide to technical trading includes a section on Fibonacci retracements and all online platforms used for technical trading in the foreign exchange market have built in tools to construct potential Fibonacci retracements. Despite this ubiquity regarding the use of Fibonacci retracements, there has yet to be any academic inquiry of Fibonacci retracements, as we will discuss in our literature review.

[1]Indeed, veritably every technical trading guide includes a section on Fibonacci retracements, indicating the ubiquity of the technique. See Murphy (1986) for a typical example.

Technical analysis of all forms has long been a curiosity for academia because it violates our beliefs of financial market efficiency.[2] In a *weak-form* efficient market, the price of an asset fully reflects all past prices of (returns to) the asset [Fama (1970)]. Belief in weak-form efficient financial markets results in academic skepticism of technical traders: if the foreign exchange market were weak-form efficient, it would be impossible to create a strategy using only past prices as inputs that generates sustained economic (i.e. risk-adjusted) profits. Consequently, the effort expended using technical analysis would be futile; only irrational traders would utilize technical analysis and they would quickly be driven out of the market by rational market agents.

A caveat is worth mentioning at this point. The Efficient Markets Hypothesis (EMH) was originally formulated in terms of US financial markets. The foreign exchange market has some structural differences from US financial markets (i.e. the presence of market makers, the lack of an easily identifiable risk-free asset, ambiguity concerning what constitutes insider information, etc.) that necessitates justifying application of the EMH to the foreign exchange market. The essence of the EMH concerns how a given set of information is reflected in the market price through the assumption of No Arbitrage – the assumption that any and all arbitrage opportunities are quickly exploited and removed by market agents. It is customary when examining US financial markets to consider three information sets when speaking of market efficiency: the set of all past price data, the set of all publicly available information, and the set of all relevant information (including private information). This last category includes what the popular press terms insider information. Only the first of these three information sets transfers to the foreign exchange market, as the only insider traders in the foreign exchange market would be central bankers. However, different market agents are privy to different information sets in the foreign exchange market as well. For example, foreign exchange dealers have access to private information in the form of order flow (the flow of buy and sell order placed by customers with their dealers) that is not accessible to other market participants and can give dealers an advantage over other market participants. Moreover, the assumption of No Arbitrage certainly extends to the foreign exchange market, the largest financial market in the world in terms of volume of trades and number of participants [Menkhoff and Taylor (2007)], and one of the only financial markets with continuous trading and no restrictions on short-selling. In light of this discussion, the assumption that weak-form efficiency holds in the foreign exchange market is eminently reasonable, and the aforementioned implications of the EMH to be expected.

Contrary to these expectations of the EMH, technical analysis is widely used throughout the foreign exchange market. In the past two decades, questionnaire surveys sent to chief foreign exchange dealers found that upwards of 85% of respondents in London, Germany, and Hong Kong placed some weight upon technical analysis [Taylor and Allen (1992), Menkhoff (1997), Lui and Mole (1998), and Gehrig and Menkhoff (2004, 2006)]. The surveys find that technical analysis has emerged as the dominant forecasting tool used by professionals, particularly for forecasting horizons of a few days, and that traders utilizing technical analysis

[2] See Menkhoff and Taylor (2007) and Park and Irwin (2004) for detailed surveys of the technical trading literature.

are not the irrational market participants predicted by the EMH.[3] More specifically, Gehrig and Menkhoff (2004, 2006) were able to characterize traders into three categories based upon the techniques they use in trading: fundamentalists, technical traders, and flowtists. Fundamentalists assert that the most important determinant of exchange rates is fundamental information about the underlying health of the country's economy (i.e. interest rates, jobs created, etc.). Technical traders primarily use technical analysis to try to predict and profit from short-term exchange rate movements, while flowtists base their analysis on order flow data. Gehrig and Menkhoff (2006) establishes that flow analysis dominates intradaily investor horizons, technical trading dominates investor horizons of a few days, and fundamental analysis dominates time horizons of a month or longer.

Realizing that technical analysis is widespread, academic inquiry turned to whether technical analysis can generate significant risk-adjusted returns and, if so, what accounts for this seeming market inefficiency. The evidence concerning risk-adjusted profitability of technical analysis is ambiguous [Menkhoff and Taylor (2007)]. This ambiguity stems in part because of difficulties in identifying meaningful risk-adjusted returns for foreign currency assets, and in part because of the sensitivity of the results to time period and frequency of data used. The literature can broadly be divided by methodology into older, pre-1990s, testing of technical analysis profitability and more recent approaches that utilize the technique of bootstrapping. This paper more closely follows modern studies, and the following literature review focuses on more recent developments. For a survey of older studies, see Park and Irwin (2004).

Literature Review

Technical analysis profitability tests can be categorized along two dimensions: investor time horizon and trading strategy. Profitability is sensitive upon investment time horizon and testing period, but not upon choice of strategy tested. Trading rules are profitable net transaction costs over market indices and buy-and-hold strategies when using exchange rate data at the daily frequency or higher [Neely, Weller and Dittmar (1997), LeBaron (1999), Neely (2002), and Okunev and White (2003)]. Intraday technical trading, though still having substantial predictive power on exchange rate movements, has not been shown to generate excess returns [Curcio et al. (1997), Osler (2000) and Neely and Weller (2003)]. Evidence suggests that technical trading rules have declined in profitability during the 1990s [Olson (2004), Qi and Wu (2005), and Neely, Weller and Ulrich (2009)]. Tested trading strategies include filter rules [Sweeney (1986)], trading band or channel strategies [Curcio et al (1997)], simple moving average rules [LeBaron (1999) and Neely (2002)], genetic algorithms [Neely, Weller, and Dittmar (1997) and Neely, and Weller (2003)], momentum strategies [Okunev and White (2003)], and support and resistance levels [Osler (2000)]. Of these tested strategies, support and resistance levels have been explored the least. Furthermore, Osler, while finding that support and resistance levels had statistically significant explanatory power in identifying intra-daily trend interruptions, only explores support and resistance levels pro-

[3] t-tests conducted in more than one of the surveys find no evidence for the hypotheses that professionals who preferred technical analysis were younger, less educated, less likely to reach senior positions, and more likely to work in smaller institutions than other market participants.

vided by six brokerage firms to paying clients. Other methods of determining these levels (i.e. Fibonacci ratios) have yet to be explored.

The literature identifies three possible explanations for the continued use of technical trading analysis: the EMH, the Adaptive Markets Hypothesis (AMH), and self-fulfilling prophecy. As the literature on technical trading analysis has yet to identify time-varying risk premiums for currency assets [Menkhoff and Taylor (2007)], it is impossible to determine whether any returns generated by a trading strategy are significant over their risk component, and the central assertion of the Efficient Markets Hypothesis remains unchallenged. However, as mentioned earlier, the EMH would also suggest that the traders who used such a suboptimal strategy would be driven quickly out of the market, a prediction that does not survive the available survey evidence [Menkhoff (1997), Gehrig and Menkhoff (2004, 2006)].

The Adaptive Markets Hypothesis suggests that market participants learn – while inefficiencies exist, they are eroded over time as market participants identify and exploit them. Evidence for this hypothesis is only recently emerging, as testing the AMH requires data over a lengthy period of time. However, new literature suggests that technical trading rules have declined in profitability during the 1990s [Olson (2004), Qi and Wu (2005), and Neely, Weller and Ulrich (2009)]. The authors in question believe this phenomenon to be the result of sufficiently many market agents learning about and, subsequently, exploiting inefficiencies in the foreign exchange market. This explanation, however, suffers from difficulties in demonstrating that market inefficiencies existed in the first place, as any such demonstration would necessitate identifying meaningful risk premiums for currencies.

The final proposed explanation for the prevalence of technical trading analysis in the foreign exchange market concerns self-fulfilling prophecy – traders use technical trading analysis because this analysis influences short term exchange rate movements in a self-fulfilling way.

Figure 3: Technical trading driving exchange rate movements through herd mentality? Figure courtesy *The Economist*

Research in this area has focused upon order flow. More specifically, order flow is said to be clustered when large numbers of orders are located in the same small price range. A cluster of buy orders will drive the price up, and a cluster of sell orders will drive the price down. Osler (2000, 2002, 2003) find that two common predictions of technical trading analysis[4] can

[4]The predictions are: 1) trends reverse course at predictable support and resistance levels; and 2) trends

be explained by the fact that sufficiently many traders believe in these predictions, resulting in order flow clustering in predictable locations. This clustering then drives the exchange rate to reify the predictions. In a similar study, Schulmeister (2006) finds that several types of technical trading analysis[5] suggest holding the same position in the foreign exchange market at the same time. Again, technical analysis is driving order flow, and contributing to small exchange rate trends in a self-fulfilling fashion, humorously depicted in Figure 3 (if one supposes the man initially on the phone is using technical analysis to determine which stocks to invest in).

Overall, the literature has yet to reach consensus as to whether there is sufficient evidence to reject the EMH in currency markets. Two major reasons explain this inconclusiveness. First, the failure of international finance research to identify meaningful time-varying risk premiums for currency assets makes it impossible to establish the existence of risk-adjusted profitability to technical trading strategies.[6] Second, insufficient effort has been made to conceptualize alternate models that can replace market efficiency, largely because only a handful of the above papers provide reasons for how technical trading could generate excess returns. Of the two alternate explanations mentioned above – the Adaptive Markets Hypothesis and self-fulfilling prophecy – the latter has yet to be systematically explored by the literature [Menkhoff and Taylor (2007)].

This paper will contribute to the literature by examining a technical trading tool used to predict the location of future support levels known as Fibonacci retracements, a hitherto unexamined trading strategy, and by exploring whether the predictive power of this tool, if such power exists, arises due to self-fulfilling prophecy. The decision to ascribe potential predictive power of Fibonacci ratios to prophecy is grounded in both the literature and the particular nature of the tool investigated. Other papers to examine support and resistance levels [Osler (2000) and Osler (2003)] posit that the predictive power of these elements has a self-fulfilling component. Furthermore, Fibonacci retracements arise from Elliott Wave Theory, a trading strategy predicated upon the belief that mass psychology (i.e. herd mentality) drives prices in predictable waves, resulting in retracements at Fibonacci levels.[7] Finally, surprisingly few of the above papers conduct their analysis at multiple data frequencies, a troubling omission given that different types of traders operate at different time horizons. In contrast, this paper will examine the predictive power of Fibonacci retracements over multiple investment horizons, ranging from intradaily to monthly.

are unusually rapid once they have broken through these levels.

[5]In his study, the types of technical trading analysis tested are moving average rules and momentum strategies.

[6]The author of this paper cannot stress this point enough. Unless one can identify time-varying risk premiums for currency assets, it will be impossible to make any statement in rejection of the EMH.

[7]Indeed, the reason that Elliot Wave Theory believes retracements occur at Fibonacci ratios is simply because Fibonacci numbers are ubiquitous in nature. The only way such a tool, entirely unconnected to financial markets, could exert predictive power on the exchange rate is if sufficiently many market participants used the tool so as to make its effects self-fulfilling.

Theory

The economic theory underlying tests of technical trading profitability is the Efficient Markets Hypothesis. Under its classic formulation, an efficient market is one in which "prices incorporate all of the relevant information," [Ross (2005)]. The set of relevant information is generally taken to be either all past price data, or all publicly available information, in which case the market is labeled as weak-form or semi-strong form efficient respectively. Technical traders share a similar belief. A prominent technical analysis manual writes that the cornerstone of technical analysis is the "statement 'market action discounts everything.' The technician believes that anything that can possibly affect the price ... is actually reflected in the price of that market," [Murphy (1999)]. Clearly proponents of market efficiency and technical traders do not believe in the same implications of this shared original belief. The difference arises because a fundamental belief of finance theory is the assumption of No Arbitrage (NA), that is, the assumption that any ability to earn profits from the information incorporated into prices without paying some cost quickly disappears. Traders disagree with this statement for one of two reasons: they believe that information is incorporated into profits long before individuals realize it, and, therefore, technical analysis is crucial in its ability to reveal information about fundamentals, or they do not believe technical analysis has any intrinsic value but because everyone in the market uses it, market participants beliefs become self-fulfilling. Gehrig and Menkhoff (2006) indicates that the two opposing viewpoints have comparable numbers of adherents.

These two opposing beliefs by traders can be identified with the Adaptive Markets Hypothesis (AMH) and self-fulfilling prophecy respectively. The first belief, that fundamental information in prices is incorporated into prices but that market agents need time to process the information and eliminate inefficiencies, is the essence of the AMH. The second belief creates a mechanism by which the predictive power of Fibonacci retracements is self-fulfilling. The mechanism begins with a group of heterogenous traders all wanting to maximize profits (i.e. minimize costs subject to revenue constraints). To profit from exchange rate fluctuations, a trader needs to be able to anticipate trend interruptions – the trader needs some ability to predict when the price will stop rising (falling) and reverse direction. Under the EMH, the traders have no information beyond what is already available to the market to predict these turning points. Having to select a point from a uniform distribution of potential turning points is costlier than using a rule of thumb to predict said points, even if from the perspective of economic theory the rule of thumb is arbitrary. One plausible rule of thumb is Fibonacci retracements. Suppose a subset of the traders begin to use Fibonacci retracements to predict trend interruption points. Then, prices will face increasing resistance as they move through Fibonacci retracement values. As other traders witness more trend interruptions at Fibonacci retracements, they are more likely to use Fibonacci retracements to predict trend reversals, thus resulting in a self-reinforcing mechanism for the predictive power of Fibonacci retracements.[8]

[8]Note the similarity in the stylized model we present above with the works of Osler and Schulmeister. In all three, technical analysis drives order flow and, through sufficiently many market participants either observing said order flow or observing the effects of this order flow on the price, eventually influences small exchange rate movements in a self-fulfilling fashion.

To derive testable hypotheses we find statements implied or required by the stylized model that contradicts the EMH and the AMH, thus allowing us to distinguish between these three models. First, our stylized model requires that Fibonacci retracements exert some predictive power over the exchange rate, else the self-fulfilling mechanism has not transpired. Second, the stylized model suggests that Fibonacci retracements can be incorporated into a trading strategy with significant risk-adjusted returns; otherwise profit-maximizing traders would never include them in their trading strategies. Third, Fibonacci retracements should exhibit greater predictive power over time as more traders begin to use them. Lastly, given that fewer traders operating at intradaily and monthly time horizons use technical trading analysis,[9] the predictive power of Fibonacci retracements under the stylized model should be lower at the shortest and longest data frequencies than at data frequencies corresponding to investment horizons of a few days. Essentially, under the stylized model, the predictive power of Fibonacci retracements, when plotted against investor time horizon, should follow an upside down U-curve.

To see that these four hypothesis are suitable for our tasks, consider the following. While the EMH does not preclude Fibonacci retracements from having predictive power (e.g. Fibonacci retracements could have limited predictive power over exchange rates that would be impossible to exploit profitably due to transaction costs), if Fibonacci retracements have no power over the exchange rate, then market prices have clearly incorporated all, if there was any to begin with, of the information contained by Fibonacci retracements. The second assertion directly contradicts the essence of the EMH – that it is impossible for any investment strategy utilizing only past prices as inputs to have a risk-adjusted expected return larger than the risk-free interest rate . The final two hypotheses are used to differentiate whether the predictive power of Fibonacci retracements (if any) arises due to the stylized model or the AMH. Under the AMH, the predictive power of Fibonacci retracements will decrease over time (as the market learns) and increase as time horizon increases (fewer market participants using technical analysis will result in more of the inefficiencies corrected by technical trading remaining). These are opposite the predictions of the stylized model.

All four of the following hypotheses are stated under the assumption that the EMH holds.

- <u>Testable Hypothesis 1:</u> Fibonacci retracements do not exert predictive power over the exchange rate.
- <u>Testable Hypothesis 2:</u> One cannot construct a trading strategy utilizing Fibonacci retracements with risk-adjusted returns greater than the risk-free interest rate.
- <u>Testable Hypothesis 3:</u> The predictive power of Fibonacci retracements is invariant over time.
- <u>Testable Hypothesis 4:</u> The predictive power of Fibonacci retracements is invariant as data freqency changes.

The most important of these hypothesis is TH2. However, this hypothesis is the most difficult

[9] Gehrig and Menkhoff (2004, 2006)

to test as it is a statement about existence.[10] Instead, we note that rejecting TH2 implies rejecting TH1. Thus, if we cannot reject TH1, then we cannot reject TH2. Below, we discuss the data, methodology and results.

Data, Methodology, & Results

This paper uses exchange rate data at the tick-by-tick frequency from GAIN Capital, a major provider of online trading services for the foreign exchange market, for five major currency pairs: AUD/USD, EUR/USD, USD/CAD, USD/CHF, and USD/JPY from 2003 - 2008. For the tests in this paper, we extract rate data at one-minute frequency, five-minute frequency, and 15-minute frequency.[11] These data frequencies correspond (roughly) to investor time horizons of a few hours, a few days, and a month,[12] and, using the results of Gehrig and Menkhoff (2006) discussed previously, allows us to differentiate between the three different types of traders. The methodological approach to test the predictive power of Fibonacci retracements used in this paper, following Osler (2000), identifies 'bounce frequencies' as the measure of the predictive power of Fibonacci retracements. Define an exchange rate as 'hitting' a given Fibonacci retracement level if, during a pre-identified period of time τ (i.e. a trend), the exchange rate comes within a given percentage α of that value. Define an exchange rate as 'bouncing' off a given support (resistance) level if it remains above (below) that level for some subset of the period τ.[13] Then the 'bounce frequency' of a Fibonacci retracement level f during time period T_i, B_{f,T_i}, is the ratio of the number of bounces to the number of hits:

$$B_{f,T_i}(\alpha, \tau) = \frac{\text{\# of bounces in } T_i}{\text{\# of hits in } T_i} \tag{1}$$

[10]Moreover, Fibonacci retracements are used only to signal entry into the market. They are usually part of a broader trading strategy that is determined by the individual trader and, hence, is unknowable.

[11]Note that during periods of very low trading (e.g. when none of the three major markets are open, or on Friday nights) high frequency data does not exist. If data is missing for a given minute at a certain frequency, it is customary to use the last available price for the missing missing minute.

[12]To see why this mapping between data frequency and investor time horizon makes sense, consider the number of data points a trader would have using each of these frequencies during a normal trading day of 8 hours. Using 1-minute frequency data, s/he would have access to roughly 480 data points. The corresponding figures for the 5-minute and 15-minute data frequencies are about 90 and 20. It is implausible for a trader to make multiple trades during a trading day if they only had access to 90 or 20 data points. If one uses the standard of having at least 350 data points to execute multiple trades, the mapping follows.

[13]The criterion for 'bouncing' in this paper is stricter than that of Osler (2000). In Osler (2000), a rate bounces off a given support (resistance) level if 15 minutes after hitting the level, the exchange rate is above (below) that value. The author believes that Osler's definition of a bounce is too broad. For example, suppose that during a downtrend the GBP/USD exchange rate had a previous high of 2.0000 before falling to 1.0000 and beginning to rise. Using Fibonacci retracements, a trader predicts that the upward trend will be reversed at 1.5000. If the price spikes upwards to 3.0000 before falling back below 1.5000 in a highly volatile 15 minutes of trading, Osler's methodology will label the exchange rate has having bounced at 1.5000 and the trader's prediction as being correct. Moreover, in the current example, Osler's methodology will label the exchange rate as bouncing at any value between 1.5000 and 3.0000, and any trader who predicted a trend interruption at any value between 1.5000 and 3.0000 will have made a correct prediction. Such a broad definition of a bounce is, in this author's view, essentially meaningless

Note that T_i refers to a longer time period than τ. For example, T_i may refer to the period of a month, whereas τ may refer to a trend that occurs for a few hours during that month. Bounce frequencies are a very intuitive measure for the predictive power of Fibonacci retracements; it is the fraction of times we guess correctly where the next trend interruption will occur. Thus, in order to conduct tests upon the predictive power of Fibonacci retracements, we first need to extract bounce frequencies from the data. We begin with an abstract discussion of the process, before turning to a more concrete example.

Extracting Bounce Frequencies

The first step to identifying bounce frequencies is to note that Fibonacci retracements are only used during trending markets – when the market is very volatile, traders do not use retracements as a tool for entering trades. As there has yet to be any identification of an *ex ante* methodology for trend identification in financial markets, this paper uses an *ad hoc* approach to identify trends. We will first outline our trend identification procedure in an abstract setting, before turning to a specific example. The first task is to find all the local maxima and minima of a given set of rate data. To determine the collection of local maxima of a set of rate data, calculate the first difference of the rate data and identify a point (x_i) as a local maxima if the previous difference is positive $(x_i - x_{i-1} > 0)$ and the subsequent difference is negative $(x_{i+1} - x_i < 0)$. Local minima are defined analogously. Price trends begin at local extrema: a downtrend (uptrend) begins at a local maxima (minima). Without loss of generality, assume we are trying to identify an uptrend, and the first local minima is denoted by l_0. Consider the sequence of local extrema $\{h_1, l_1, h_2, l_2, h_3, l_3, \ldots\}$ where h_i denotes the *ith* local maxima after l_0 and l_i denotes the ith local minima after l_0. If $l_2 > h_1$, we denote the prices between l_1 and h_3 as part of an uptrend. If $l_2 \not> h_1$, consider the pair (l_3, h_2), and repeat the above identification process. Inductively, proceed through the entire sequence of local extrema in this fashion, denoting portions of the price data as an uptrend where appropriate. Note that this identification process is intuitive: it identifies a price movement as an uptrend if in the sequence of local extrema one is finding that subsequent local minima are higher than previous local maxima, a phenomenon that could only occur if prices were rising. A downtrend is identified analogously.

Having identified points within a trend in the previous paragraph, we must now find the starting and ending points of the trend. Consider as example one of the uptrends identified in the preceding paragraph and suppose, without loss of generality, that $l_6 > h_5$ so that the prices between l_5 and h_6 were denoted as part of an uptrend. To identify the start of the uptrend, examine the sequence of local minima $\{l_5, l_4, l_3, \ldots, l_0\}$ that occur before l_6. The local minima with the smallest subscript $n, n \in \mathbb{Z}^+$ for which $l_{n+1} - l_n > 0$ marks the start of the uptrend. Again, such an identification criterion is intuitive: if $l_5 - l_4 > 0$, then l_4 is a 'lower' local minima than l_5 and, hence, a better candidate for the start of this uptrend. Similarly, to find the end of the uptrend, consider the sequence of highs that occur after h_6: $\{h_7, h_8, \ldots\}$. The local maxima with the highest subscript $n, n \in \mathbb{Z}^+$ for which $h_n - h_{n-1} > 0$ marks the end of the uptrend. Intuitively, this is the 'highest' local maxima occurring in a consecutive sequence after the end of the portion of data we had already identified as belonging to an uptrend. This procedure is conducted for all the pairs of local extrema identified in the previous paragraph as belonging to an uptrend. An analogous process is used to identify the start and end of a downtrend.

To eliminate noise in our trend identification process, for rate data at a given frequency, we identify trends with the above methodology for a 50-period exponential moving average of higher frequency rate data, before mapping those trends back onto the original data. Such a methodology is commonly used by technical traders. Indeed, many prominent technical trading guides recommend traders examine rate data at frequencies longer than their trading horizons in order to understand trends in the market.[14]

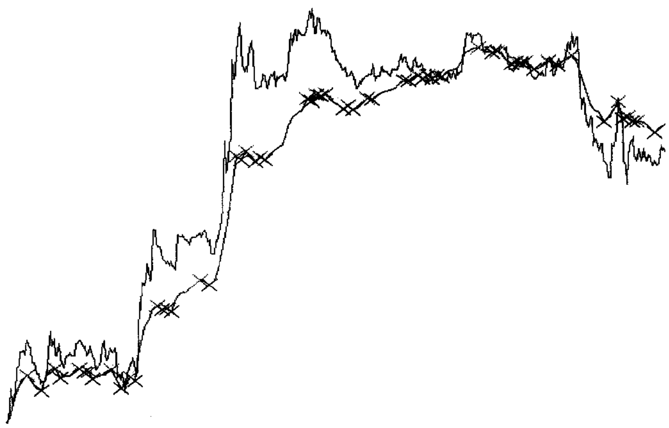

Figure 4: Trend Identification Example, pt 1. EUR/USD, December 2005, 5-minute data frequency.

Figure 4 depicts the first stages of the trend identification process. The black line is the 5-minute frequency exchange rate data for a period in December 2005 for the EUR/USD exchange rate. The red line is a 50-period exponential moving average of the corresponding 15-minute frequency exchange rate data. The green and blue crosses represent local maxima and minima respectively (the sequence of $\{h_i, l_i, \ldots\}$ from the above paragraph). Using the methodology from above, we examine the sequence of green and blue crosses, looking for a blue cross that is higher in value than the green cross preceding the green cross immediately before the blue cross. Examining Figure 4, there are several such instances, indicating that this portion of the exchange rate data falls into an uptrend. The methodology developed above then simply tries to find the largest possible uptrend that includes the portions of the price identified by the procedure. Figure 5, on the next page, shows the price data for a larger portion of the December 2005 EUR/USD 5-minute data frequency exchange rate. Again, the black line denotes the 5-minute frequency exchange rate data for a period in December 2005 for the EUR/USD exchange rate. The red stars denote the beginning and ending of our trends (thus, the portion of code between red stars is either an uptrend or a downtrend). One can identify the portion of the exchange rate examined in Figure 4 towards the middle of Figure 5, encompassed within a large uptrend.

[14]See Murphy (1986) or babypips.com for two such examples.

Figure 5: Trend Identification Example, pt 2. EUR/USD, December 2005, 5-minute data frequency.

While not perfect, the trend identification procedure we utilize is certainly adept at establishing uptrends and downtrends and will be more than sufficient for our purposes.

Once we have identified periods of trending price (e.g. between the second and third red stars in Figure 5), we next need to identify bounce frequencies for Fibonacci retracements. In our discussion of the methodology used to identify bounce frequencies for Fibonacci retracements, we again begin in an abstract setting before turning to a more concrete example. Recall that when prices are falling, a retracement level will be a region above the current price where short and temporary upward price movements within this downtrend are halted. In contrast, when prices are rising, a retracement level will be a region below the current price where short and temporary downward price movements within this uptrend are halted. Retracements are calculated based upon swing highs and swing lows. A swing high, h_s, is defined as a local maxima that is higher in value than its immediate predecessor and immediate successor in the sequence of local maxima: $h_s > h_{s-1}; h_s > h_{s+1}$. Swing lows are defined analogous. Without loss of generality, suppose we are examining a downtrend. Consider the sequence of swing highs and swing lows for this downtrend: $\{h_{s1}, l_{s1}, h_{s2}, h_{s3}, l_{s2}, h_{s4}, \ldots\}$ and label this sequence as swing points.[15] Recall that during a downtrend, retracements are

[15]Note that this sequence does not necessarily follow a pattern of high, low, high, low, ...

resistance levels that follow a consecutive pair of swing points that occur in the order swing high, swing low. Fibonacci retracements occur when the retracement occurs at a Fibonacci ratio multiplied by the magnitude of the difference between the swing high and the swing low. There are five Fibonacci ratios used for calculating Fibonacci retracements: 0.236, 0.382, 0.500, 0.618, and 0.764.

When calculating bounce frequencies we set $\alpha = 0.05$ in equation (1). Suppose during a downtrend that $\{h_{s1}, l_{s1}, h_{s2}, h_{s3}, l_{s2}, h_{s4}, \ldots\}$ is a sequence of swing highs and swing lows. The first set of Fibonacci retracements will be predicted using rate data between h_{s1} and l_{s1}, and rate data between l_{s1} and h_{s3} will be used to calculate bounce frequencies for these predictions. Thus, τ in equation (1) denotes the time between pairs of the form (h_{si}, l_{sj}) or (l_{sk}, h_{sm}) depending upon whether we are examining an uptrend or a downtrend.

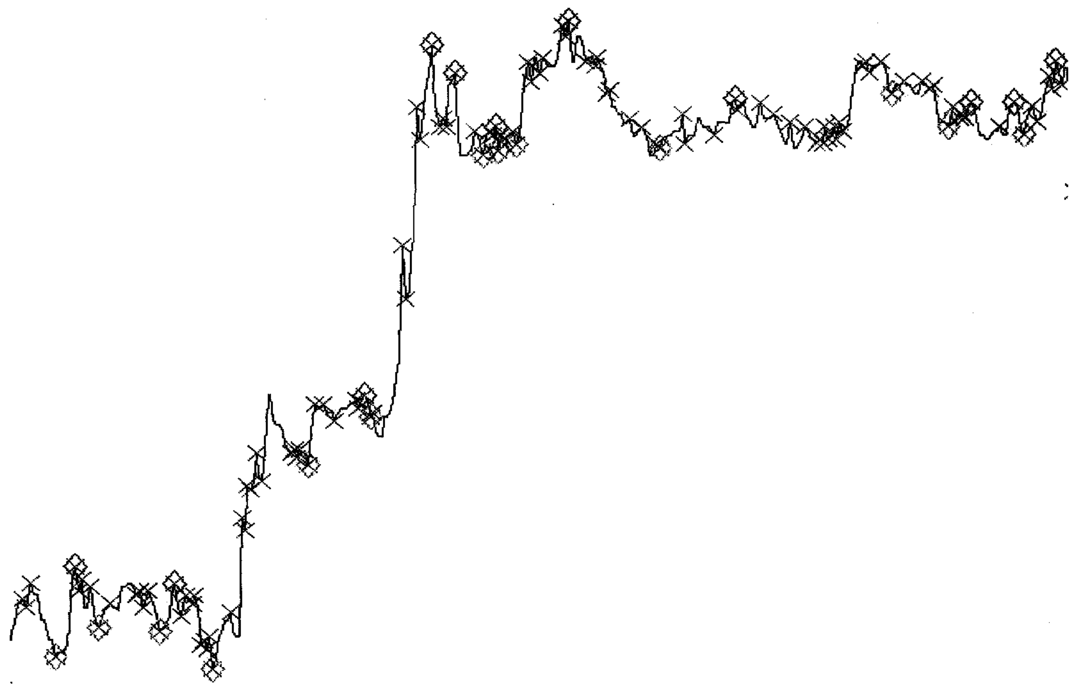

Figure 6: Bounce Frequency Calculation Example, EUR/USD, December 2005, 5-minute data frequency.

Figure 6 provides an example of calculating bounce frequencies for the same portion of the EUR/USD December 2005 exchange rate depicted in Figure 4. The black line is the exchange rate itself (at the 5-minute data frequency), the red crosses denote local extrema, while the blue diamonds and green diamonds represent swing highs and swing lows respectively. Following the algorithm described above, we look at the sequence of all the diamonds, and find pairs of diamonds in the order green diamond, blue diamond (as this is an uptrend). Between one identified pair of diamonds and the next identified pair, we draw hypothetical bands around each potential Fibonacci retracement level, and see whether the exchange rate hits or bounces for these levels. We iterate through the entire uptrend, and then through all the trends in the month of December 2005 for the EUR/USD exchange rate, arriving at a monthly bounce frequency for each Fibonacci ratio.

To determine statistical significance, we will need a control with which to compare the bounce frequencies from the Fibonacci ratios. Following Osler (2000) we use random simulation to empirically estimate the true distribution of retracement ratios. Thus, for each pair of swing points identified above, we randomly generate five numbers from a uniform distribution on [0,1], rank them smallest to largest, and compute the associated bounce frequencies. The smallest of the five simulated ratios corresponds to the smallest Fibonacci ratio, etc. This randomization procedure is repeated 100 times for every Fibonacci bounce frequency we calculate, and the averages of these hundred simulations are taken as the simulated bounce frequency for a given month.

Data

Bounce frequency data for the five currency pairs and five Fibonacci ratios are summarized in Tables 1-2. There are 72 months in our sample; for each currency pair and each Fibonnaci ratio there are 72 monthly bounce frequencies. Simulated bounce frequencies are reported in parentheses.

Table 1:
Average Monthly Bounce Frequencies for Fibonacci Retracement Levels for Five Currency Pairs 2003-2008

Fibonacci Retracement Level	Data Frequency (min)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	1	0.0145 (0.0077)	0.0151 (0.0079)	0.0166 (0.0093)	0.0173 (0.0086)	0.0141 (0.0076)
	5	0.0136 (0.0079)	0.0141 (0.0081)	0.0146 (0.0086)	0.0139 (0.0087)	0.0141 (0.0080)
	15	0.0165 (0.0141)	0.0334 (0.0189)	0.0265 (0.0141)	0.0322 (0.0133)	0.0155 (0.0121)
0.382	1	0.0211 (0.0136)	0.0198 (0.0135)	0.0175 (0.0146)	0.0184 (0.0141)	0.0194 (0.0132)
	5	0.0202 (0.0134)	0.0170 (0.0136)	0.0197 (0.0142)	0.0171 (0.0141)	0.0216 (0.0139)
	15	0.0203 (0.0213)	0.0314 (0.0250)	0.0275 (0.0220)	0.0268 (0.0201)	0.0464 (0.0225)
0.500	1	0.0181 (0.0149)	0.015 (0.0135)	0.0175 (0.0149)	0.0169 (0.0145)	0.0168 (0.0142)
	5	0.0146 (0.0146)	0.0154 (0.0154)	0.0154 (0.0158)	0.0153 (0.0151)	0.0170 (0.0154)
	15	0.0203 (0.0229)	0.0175 (0.0218)	0.0255 (0.0225)	0.0221 (0.0197)	0.0248 (0.0267)
0.618	1	0.0153 (0.0123)	0.0154 (0.0122)	0.0153 (0.0124)	0.0144 (0.0119)	0.0147 (0.0119)
	5	0.0151 (0.0130)	0.0163 (0.0141)	0.0181 (0.0143)	0.0155 (0.0136)	0.0170 (0.0140)
	15	0.0221 (0.0205)	0.0269 (0.0180)	0.0252 (0.0197)	0.0175 (0.0174)	0.0159 (0.0215)
0.764	1	0.0092 (0.0095)	0.0092 (0.0098)	0.0107 (0.0101)	0.0095 (0.0100)	0.0100 (0.0101)
	5	0.0130 (0.0117)	0.0128 (0.0126)	0.0096 (0.0131)	0.0103 (0.0119)	0.0139 (0.0123)
	15	0.0140 (0.0190)	0.0112 (0.0143)	0.0089 (0.0172)	0.0131 (0.0173)	0.0259 (0.0181)

There are 72 monthly bounce frequencies per fibonacci level, currency pair, and data frequency.
The numbers in parentheses are the average of the 72 monthly simulated bounce frequencies corresponding to each Fibonacci ratio, currency pair, and data frequency triple.

The most important conclusion from Tables 1 and 2 are that Fibonacci retracements cannot meaningfully predict short-term exchange rates. Most of the average monthly bounce frequencies for all currency pairs and all time horizons fail to exceed 3%. The largest average monthly bounce frequency is only 4.6%. Thus, on average, a trader using Fibonacci retracements will successfully predict future trend interruptions about 3-4% of the time. Such predictive power is meager, at best. Indeed, the maximum monthly bounce frequency over six years for all five currency pairs at either the 1-minute or 5-minute data frequency is only 7%. Such small predictive power is economically meaningless. Given the high percentage of false signals any use of Fibonacci retracements would generate, the author finds it highly doubtful that a trader could utilize these predictions to construct a trading strategy with significant risk-adjusted returns.

A caveat must be mentioned when interpreting the maximum monthly bounce frequencies at the 15-minute data frequency. At this higher data frequency, there are only 1-2 trends per month from which we extract bounce frequencies. Thus, when examining the raw results for the 15-minute frequency data, one finds many months where the bounce frequencies are zero, and a few months with high bounce frequencies owing to a small number of total trends examined. It should be noted, however, that this does not contribute upward bias to the measure of bounce frequency.

Table 2:
Maximum Monthly Bounce Frequencies for Fibonacci Retracement Levels for Five Currency Pairs 2003-2008

Fibonacci Retracement Level	Data Frequency (min)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	1	0.0455 (0.0125)	0.0408 (0.0144)	0.0423 (0.0147)	0.0427 (0.0134)	0.0377 (0.013)
	5	0.0513 (0.0159)	0.0424 (0.0151)	0.0531 (0.015)	0.0405 (0.0149)	0.0439(0.0142)
	15	0.25 (0.14)	0.3333 (0.17)	0.2 (0.06)	0.5 (0.12)	0.0909 (0.0625)
0.382	1	0.0667 (0.022)	0.0392 (0.0208)	0.0556 (0.0227)	0.0414 (0.0207)	0.0476 (0.0209)
	5	0.061 (0.0216)	0.0526 (0.0244)	0.0531 (0.0236)	0.042 (0.0222)	0.0556 (0.0216)
	15	0.1818 (0.095)	1 (0.12)	0.25 (0.14)	0.5 (0.09)	1 (0.105)
0.500	1	0.055 (0.0267)	0.0363 (0.0213)	0.0536 (0.0233)	0.0419 (0.0224)	0.0504 (0.0222)
	5	0.0519 (0.0223)	0.0449 (0.029)	0.0641 (0.0258)	0.0405 (0.0248)	0.0437 (0.0242)
	15	0.25 (0.1)	0.1667 (0.08)	0.25 (0.11)	0.1429 (0.065)	0.5 (0.16)
0.618	1	0.0448 (0.0238)	0.0458 (0.0188)	0.0331 (0.0213)	0.0319 (0.0171)	0.0404 (0.02)
	5	0.0541 (0.0219)	0.0458 (0.0291)	0.045 (0.0253)	0.0376 (0.0246)	0.0615 (0.0263)
	15	0.25 (0.0775)	0.25 (0.0775)	0.3333 (0.0567)	0.1818 (0.07)	0.1333 (0.1)
0.764	1	0.038 (0.0182)	0.0246 (0.0153)	0.0561 (0.0263)	0.0306(0.0188)	0.0476 (0.0214)
	5	0.0476 (0.0294)	0.0562 (0.0347)	0.0408 (0.0282)	0.0327 (0.0233)	0.0667 (0.0312)
	15	0.125 (0.12)	0.2 (0.04)	0.1176 (0.0772)	0.1111 (0.09)	0.5 (0.06)

There are 72 monthly bounce frequencies per fibonacci level, currency pair, and data frequency.
The numbers in parentheses are the maximum of the 72 monthly simulated bounce frequencies corresponding to each Fibonacci ratio, currency pair, and data frequency triple.

Evaluating the Four Testable Hypotheses

Recall the first testable hypothesis: Fibonacci retracements do not exert predictive power over exchange rates. Table 1 indicates that the predictive power attributable to Fibonacci retracements is small – about 1-4%. In order to test whether such predictive power is significant, we compare the average monthly bounce frequencies from Fibonacci ratios to the average monthly bounce frequencies from the simulated ratios. If the Fibonacci ratios consistently outperform the randomized trials, then we can conclude that Fibonacci ratios do exert meaningful predictive power over the exchange rate, and that there is some value for a trader to use these ratios. To compare simulated versus Fibonacci bounce frequencies, we first use the methodology advanced in Osler (2000). View each month as an independent trial, where the probability of the Fibonacci bounce frequency exceeding the random bounce frequency equals one-half. Then, over 72 months, one can calculate the probability that the Fibonacci bounce frequency exceeded the random bounce frequency n times using a binomial distribution:

$$P(X > n) = 1 - \sum_{i=1}^{n} \binom{72}{i} \left(\frac{1}{2}\right)^{i} \left(\frac{1}{2}\right)^{72-i} \tag{2}$$

where X is a Binomial random variable taking integer values between 0 and 72. This probability, following the notation of Osler (2000), is dubbed the *marginal significance*, and when the marginal significance is less than 0.05, the result is viewed as statistically significant. Table 3 contains, for each currency pair and each Fibonacci ratio, the number of months that the Fibonacci bounce frequency exceeds (is strictly greater than) the corresponding simulated frequency, with the accompanying marginal significance included in parentheses.

For clarity of exposition, we provide a sample calculation. Taking as example the 0.618 Fibonacci ratio for the AUD/USD exchange rate at the 5-minute frequency, Table 3 shows that out of the 72 month sample, the average monthly Fibonacci bounce frequency exceeded the average monthly simulated bounce frequency for 34 months. The associated probability with this event, then, is:

$$P(X > 34) = 1 - P(X < 34) = 1 - \sum_{i=1}^{34} \binom{72}{34} \left(\frac{1}{2}\right)^{34} \left(\frac{1}{2}\right)^{38} = 0.63$$

These computations can be easily performed on most statistical computer software.

Table 3:

Number of Months Fibonacci Bounce Frequencies Exceed Randomized Bounce Frequencies for Five Currency Pairs 2003-2008

Fibonacci Retracement Level	Data Frequency (min.)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	1	58 (0.00)	61 (0.00)	51 (0.00)	65 (0.00)	58 (0.00)
	5	50 (0.00)	52 (0.00)	50 (0.00)	50 (0.00)	54 (0.00)
	15	23 (0.99)	36 (0.45)	40 (0.14)	36 (0.45)	29 (0.94)
0.382	1	54 (0.00)	56 (0.00)	44 (0.02)	48 (0.00)	59 (0.00)
	5	53 (0.00)	45 (0.01)	43 (0.04)	46 (0.01)	55 (0.00)
	15	29 (0.94)	25 (0.99)	33 (0.72)	30 (0.90)	31 (0.85)
0.500	1	42 (0.06)	33 (0.72)	43 (0.04)	40 (0.14)	42 (0.06)
	5	32 (0.79)	39 (0.20)	28 (0.96)	35 (0.55)	39 (0.20)
	15	25 (0.99)	24 (0.99)	28 (0.96)	31 (0.85)	23 (0.99)
0.618	1	41 (0.10)	47 (0.00)	45 (0.01)	42 (0.06)	53 (0.00)
	5	34 (0.63)	38 (0.28)	40 (0.14)	41 (0.10)	45 (0.01)
	15	30 (0.90)	28 (0.96)	28 (0.96)	20 (1)	26 (0.99)
0.764	1	30 (0.90)	32 (0.80)	36 (0.45)	29 (0.94)	33 (0.77)
	5	35 (0.55)	30 (0.90)	20 (1)	29 (0.94)	35 (0.55)
	15	23 (0.99)	19 (1)	15 (1)	23 (0.99)	31 (0.85)

There are 72 months of bounce frequencies per currency pair, data frequency and Fibonacci ratio.
The numbers in parentheses are the probabilities that the monthly Fibonacci bounce frequencies exceeded the monthly randomized bounce frequencies the stated number of times under a Binomial test with parameter $n = 72$.

The standout feature from Table 3 is that for all currencies at the one and five minute data frequencies, average monthly bounce frequencies for the Fibonacci ratios 0.236 and 0.318 exceed the average monthly simulated bounce frequencies significantly. Equally important is that none of the average differences are significant at the 15-minute data frequency for all currency pairs, and most of the average differences are not statistically significant for all currency pairs over all time horizons for the largest three Fibonacci ratios. Note that the test just conducted does not take into account the magnitude of the difference between Fibonacci and simulated monthly bounce frequencies. If the monthly bounce frequency for the Fibonacci ratio 0.236 exceeds the corresponding simulated bounce frequency by a fraction of a percent, in economic terms, the difference in performance is meaningless.

Table 4 presents the differences between Fibonacci and simulated average monthly bounce frequencies, and includes p-values for a two-sample t-test under the null hypothesis that the difference is equal to zero. The p-values are for a one-sided alternative hypothesis that the average of the differences between Fibonacci and simulated average monthly bounce frequencies is strictly positive. The two-sample t-test assumes equal variances between the distribution of Fibonacci ratios and the randomized distribution, consistent with a null hypothesis that the two distributions are identical. This test has a sample size of 144 and has 142 degrees of freedom.

Again, we find statistically significant results for Fibonacci ratios 0.236 and 0.382, across all currency pairs for one and five minute data frequencies. However, far more important than statistical significance are the magnitude of the differences. Note that except in two instances, the differences are a fraction of a percentage point. For example, a trader operating in the AUD/USD market using Fibonnaci ratios outperforms random guessing by about 0.6% on average. While these results may be statistically significant, they are economically meaningless. Despite the statistical significance, it is highly doubtful that a trader could use these ratios, which outperform random guessing by less than a percentage point, to design a trading strategy that would earn significant risk-adjusted returns net transaction costs and overnight interest rate adjustments.

Table 4:
Average Difference Between Fibonacci and Simulated Monthly Bounce Frequencies for Five Currency Pairs 2003-2008

Fibonacci Retracement Level	Data Frequency (min.)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	1	0.0068 (0.00)	0.0071 (0.00)	0.0073 (0.00)	0.0087 (0.00)	0.0065 (0.00)
	5	0.0057 (0.00)	0.0060 (0.00)	0.0060 (0.00)	0.0052(0.00)	0.0061 (0.00)
	15	0.0025	0.0145 (0.04)	0.0124 (0.00)	0.0189 (0.01)	0.0034
0.382	1	0.0075 (0.00)	0.0062 (0.00)	0.0029 (0.01)	0.0044 (0.00)	0.0062 (0.00)
	5	0.0068 (0.00)	0.0034 (0.01)	0.0055 (0.00)	0.0030(0.01)	0.0077 (0.00)
	15	-0.0010	0.0065	0.0055	0.0067	0.0240
0.500	1	0.0033 (0.01)	0.0007	0.0027 (0.02)	0.0023 (0.02)	0.0026 (0.02)
	5	-0.0001	0.0000	-0.0004	0.0002	0.0015 (0.09)
	15	-0.0026	-0.0043	0.0030	0.0024	-0.0019
0.618	1	0.0031 (0.01)	0.0032 (0.00)	0.0029 (0.00)	0.0024(0.01)	0.0028 (0.00)
	5	0.0022 (0.09)	0.0021 (0.06)	0.0038 (0.01)	0.0019 (0.04)	0.0031 (0.02)
	15	0.0016	0.0089 (0.09)	0.0055	0.0001	-0.0056
0.764	1	-0.0003	-0.0006	0.0006	-0.0005	-0.0001
	5	0.0013	0.0002	-0.0035	-0.0016	0.0016
	15	-0.0049	-0.0031	-0.0083	-0.0042	0.0078

The numbers in parentheses are the p-values associated with two-sample one-sided t-tests that the average difference between Fibonacci and simulated monthly bounce frequencies is strictly positive. p-values above 0.1 are not shown. The t-tests have a sample size of 144 and 142 degrees of freedom.

Thus, while there is mixed evidence both for and against Testable Hypothesis 1, there is no where near sufficient evidence to reject Testable Hypothesis 2. As such, regardless of the subsequent analysis in this paper, we will not be able to reject the EMH as a plausible explanation for the observed phenomenon.

There are two remaining hypothesis to be tested. Testable Hypothesis 3 asserts that the predictive power of Fibonacci ratios does not increase over time. Again, given the miniscule magnitudes of the predictive powers of the Fibonacci ratios, any observed differences over time will still be economically meaningless. We will use two two-sample t-tests to examine this hypothesis. The data period will be divided into two 3-year periods: 2003-2005 and 2006-2008. The relevant variable is the difference of the average Fibonacci monthly bounce frequencies between periods one and two. The first hypothesis test will be conducted under the null hypothesis that the mean difference of the average Fibonacci monthly bounce frequencies between period 1 and period 2 is equal to zero and the alternate hypothesis that the aforementioned difference is positive. The second hypothesis test will be conducted under the same null hypothesis, but with an alternate hypothesis that the difference of the average monthly bounce frequencies between the two periods is negative. The first test is used to determine support for the stylized model, while the second test measures support for the AMH. As there are 36 observations per period, these tests will have a sample size of 72 and will have 70 degrees of freedom. Both hypothesis tests assume equal variances between the distributions of the Fibonacci ratios across the two time periods, an assumption in perfect accord with the two null hypotheses. Table 5 shows the differences (p-values) between the two-periods for all five currency pairs.

A cursory examination of Table 5 reveals no clear pattern. Out of the 75 entries in the table, 34 are positive and 41 are negative. There is no clear pattern as to which results are significant with 5% confidence (in either the positive or negative direction). Indeed, such evidence suggests that in both the hypothesis tests mentioned above, one cannot reject the null hypothesis. Economically, there is no indication that the predictive power of Fibonacci ratios increases or decreases with time. Thus, this test lends no support for either the AMH or the stylized model over the EMH (which is in accord with the null hypotheses above).

Table 5:

Average Difference of Fibonacci Monthly Bounce Frequencies
Between Periods 2003-2005 and 2006-2008 for Five Currency Pairs

Fibonacci Retracement Level	Data Frequency (min.)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	1	0.0028 (0.06)	0.0013	0.0013	0.0003	-0.0001
	5	0.0055 (0.02)	0.0025	0.0017	0.0030	-0.0022
	15	-0.0112	-0.0228 (0.06)	-0.0009	-0.0236 (0.06)*	-0.0013
0.382	1	-0.0035	0.0018	-0.0011	-0.0012	0.0045 (0.02)
	5	-0.0007	-0.0021	0.0061 (0.03)	0.0005	-0.0035
	15	-0.0043	-0.0333	-0.0022	-0.0132	-0.0673 (0.04)*
0.500	1	0.0006	-0.0007	0.0022	-0.0039 (0.03)*	-0.0015
	5	-0.0044	-0.0054 (0.00)*	0.0008	0.0022	0.0000
	15	0.0054 (0.03)*	0.0085	0.0070	-0.0135 (0.03)*	0.0024
0.618	1	-0.0009	-0.0009	0.0018	-0.0028 (0.06)*	0.0013
	5	-0.0026	-0.0005	-0.0020	0.0017	0.0028
	15	-0.0036	0.0069	-0.0100	-0.0033	-0.0004
0.764	1	0.0007	-0.0007	-0.0005	0.0013	0.0021
	5	-0.0064	-0.0019	0.0006	0.0006	0.0047 (0.03)
	15	-0.0010 (0.00)*	-0.0046	-0.0027	-0.0033	0.0096

Values in parentheses are p-values corresponding to one of two two-sample one-sided t-tests on the stated mean difference. p-values associated with positive (negative) mean differences are associated with the first (second) hypothesis test that the average mean difference between the two periods is positive (negative). p-values above 0.1 are not shown. * denotes significance vis-a-vis second hypothesis test. Each test has a sample size of 36 with 34 degrees of freedom.

The final testable hypothesis asserts that the predictive power of Fibonacci retracemenets is invariant over investor time horizon. As discussed previously, there are two alternate claims: 1) the AMH implies that the predictive power of Fibonacci retracements will increase linearly over time; 2) the stylized model implies that the predictive power of Fibonacci retracements will be highest at the 5-minute data frequency. We must conduct two hypotheses tests to evaluate these claims. Both tests will be two-sample t-tests. The first test will examine the difference of average Fibonacci monthly bounce frequencies between the 15-minute and 1-minute frequency data for all currency pairs and all Fibonacci ratios. The null hypothesis for this test will be that the mean of the aforementioned differences is equal to zero; the alternative hypothesis will be that said mean is positive. This first test provides evidence for choosing between the EMH and the AMH: if we reject the null hypothesis, then the predictive power of Fibonacci ratios is higher at longer data frequencies where there are fewer investors using Fibonacci ratios, providing some evidence for the AMH.

The second test examines the difference of average Fibonacci monthly bounce frequencies between the 5-minute and 1-minute frequency data for all currency pairs and all Fibonacci ratios. The null hypothesis for this test will be that the mean of the aforementioned differences is equal to zero; the alternative hypothesis will be that said mean is positive. This test provides evidence for choosing between the EMH and the stylized model. If we cannot reject the null hypothesis for this test, then the assertion that the predictive power of Fibonacci retracements is highest for the 5-minute frequency data, implied by the stylized model, cannot hold true.

Table 6 presents the results for these tests. The top row of each cell corresponds to the average of the differences of mean monthly bounce frequencies between the 15-minute frequency and 1-minute frequency data sets, while the bottom row corresponds to the analogous average when comparing the 5-minute and 1-minute frequency data sets. Numbers in parentheses are the corresponding p-values. Both tests have a sample size of 144 and 142 degrees of freedom, and both tests (reasonably) assume equal variances for the distributions of the Fibonacci ratios across time horizons.

As with Table 5, no clear pattern emerges for either of the tests. Of the 25 cases of the first hypothesis test in the above table, 23 have positive average differences, but only five have statistically significant mean differences at 5% confidence. Of the 25 cases of the second hypothesis test, thirteen have positive average differences, with only four being statistically significant at 5% confidence. Moreover, the magnitude of these differences is, as expected, miniscule.

Table 6:
Average Difference of Fibonacci Monthly Bounce Frequencies Between Different Data Frequencies for Five Currency Pairs

Fibonacci Retracement Level	Data Frequencies Used for Calculation (min., min.)	AUD/USD	EUR/USD	USD/CAD	USD/CHF	USD/JPY
0.236	(15,1)	0.0020	0.0183 (0.01)	0.0099 (0.02)	0.0149 (0.03)	0.0014
	(5,1)	-0.0010	-0.0009	-0.0020	-0.0034	0.0000
0.382	(15,1)	-0.0008	0.0117	0.0100 (0.02)	0.0083	0.0270 (0.08)
	(5,1)	-0.0009	-0.0027	0.0022	-0.0013	0.0022
0.500	(15,1)	0.0022	0.0025 (0.08)	0.0080 (0.08)	0.0052	0.0080
	(5,1)	-0.0035	0.0004	-0.0021	-0.0016	0.0002
0.618	(15,1)	0.0068 (0.08)	0.0115 (0.04)	0.0100 (0.05)	0.0031	0.0012
	(5,1)	-0.0002	0.0008	0.0028 (0.05)	0.0012	0.0023 (0.08)
0.764	(15,1)	0.0048 (0.07)	0.0020	-0.0018	0.0036 (0.09)	0.0159
	(5,1)	0.0038 (0.01)	0.0036 (0.01)	-0.0011	0.0009	0.0039 (0.01)

Numbers in parentheses are p-values for the two-sample t-test that the average difference between the listed data frequencies is strictly positive. p-values above 0.1 are not shown. Each test has a sample size of 144 and 142 degrees of freedom.

All of the average differences in the above table are less than 2%, with most less than 1% (particularly for the second test). The evidence presented in Table 6 is insufficient to reject the null hypothesis of either of the hypotheses tests just conducted. In words, there is no evidence to suggest that the predictive power of Fibonacci ratios increases with investor time horizon, or peaks at a time horizon of roughly five days (5-minute frequency data). Thus, this test provides no support for either the AMH or the stylized model developed in this paper over the EMH.

Summary and Economic Implications of Results

The results found for all four Testable Hypotheses do not permit us to reject the EMH. Indeed, the EMH is the only model that our data appear to confirm. While there was limited evidence that Fibonacci retracements exerted predictive power over exchange rates, the magnitude of this power was minimal (at most 4%). Noting that statistical significance does not confer economic relevance, the author of this paper is extremely skeptical that Fibonacci ratios can be used to generate significant risk-adjusted returns in currency markets (it is doubtful that outperforming random guessing by a few fractions of a percent will even offset transaction costs). Indeed, the bounce frequencies we obtain are in accord with how Fibonacci retracements are used – traders acknowledge that tools that signal market entry are often erroneous, and seek to capitalize on the few occasions (i.e. 1-4% of the time) when the signals make accurate predictions. Additional tests found no evidence to suggest that the limited predictive power of Fibonacci ratios varied over time period considered or over investor time horizon, both in accord with the EMH.

That the results of this paper are not as strong as those in Osler (2000) comes as no surprise. Osler examined support and resistance levels predicted by six private brokerage firms. These levels were not publicly available information; they were costly information provided only to paying clients. Moreover, the brokerage firms that provided these levels most likely used proprietary information (i.e. the firm's order flow) in calculating these levels, information inaccessible to the general trader. As such, markets can be weak-form efficient and not reflect the information in the support and resistance levels studied by Osler (2000). By contrast, Fibonacci retracements are calculated using solely past price data, and a weak-form efficient market must account for all the information captured by these retracements.

While no evidence was presented in this paper that directly supported the AMH, the author would like to stress that no evidence was presented against this model either. Given that Fibonacci ratios have been well known for at least thirty years and are mentioned in veritably every technical trading manual, it is entirely plausible that any inefficiencies in the market that could have been exposed by Fibonacci ratios have been arbitraged away long ago. To truly be able to differentiate between the AMH and the EMH would require examining the predictive power of Fibonacci ratios over, perhaps, a thirty year time span to fully consider whether or not the market adapted over time. Finally, though there is insufficient evidence to reject the AMH from our results, there is sufficient evidence to reject our stylized model, as virtually every test performed in this paper either provided results contradictory to the stylized model (i.e. the invariance of the predictive power of Fibonacci ratios over time and investor time horizon) or did not provide sufficient supporting evidence for the model (i.e. the extremely low overall predictive power of the Fibonacci ratios).

Concluding Remarks

Technical trading analysis remains enigmatic to the Academy, as no consensus has been reached as to whether the continued existence of technical analysis provides sufficient evidence to reject the EMH. This paper examined a hitherto unexplored technical trading tool, Fibonacci retracements, and sought to explain these retracements using one of three models: the EMH, the AMH, or a stylized model based upon self-fulfillment. After examining retracements for five currency pairs from 2003-2008 at three different data frequencies, the evidence suggests that Fibonacci retracements exert little to no predictive power over exchange rates, and that, at least for this trading phenomenon, the EMH remains the best explanation of the data observed.

Obvious extensions of this work concern expanding the time span considered in the data and the number of currencies examined. More meaningful extensions of this work would explore other technical trading tools that may also be explained by a stylized model similar to the one posited in this paper. Such tools may include, but are not limited to, trading strategies based upon Elliot Wave Theory, analysis of candlestick patterns, or analysis of market sentiments. A final possible extension would be to devise broader trading strategies that incorporate Fibonacci ratios in addition to other technical tools, perhaps through the use of genetic algorithms, to test whether trading strategies based upon Fibonacci ratios can earn significant risk-adjusted returns.

The study of technical trading continues to be a rich field in the finance literature. With my limited knowledge of finance, the author of this paper is hesitant to offer suggestions for future research in such a well-trodden area. However, in my eyes, there are two critical issues that need to be addressed by this sub-field before meaningful progress can be made. The first concerns the identification of time-varying risk-premiums in currency markets. Until this task is accomplished, it is unclear that anything accomplished by this subfield is more than data mining, for no results will be able to dislodge the EMH from its current lofty position in academic discourse. The second concerns identifying viable alternatives to replace the EMH. The standards of scientific rigor demand that one model can only be replaced by a newer model, better able to withstand empirical scrutiny. Throwing the stones of data anomalies at the castle of the EMH will not result in its demise; a new castle must be built in its place.

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