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Two Essays on Investor Sentiment and the Profitability of Contrarian and Momentum Strategies

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TWO ESSAYS ON INVESTOR SENTIMENT AND THE PROFITABILITY OF CONTRARIAN AND MOMENTUM STRATEGIES

by

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ABSTRACT

TWO ESSAYS ON INVESTOR SENTIMENT AND
THE PROFITABILITY OF CONTRARIAN AND MOMENTUM STRATEGIES

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This dissertation, by employing different trading strategies, addresses the trading profitability issue in a broad scope of different markets.

In the equity market, I construct a group of *BUY-SELL* portfolios based on prior stock returns, and find that contrarian and momentum strategies are both significantly profitable. Investor sentiment, in addition to firm-specific risks, provides behavioral explanations to the profitability. Three popular sentiment measures are used for the purpose of study: two reduced-formed sentiment indexes that are constructed by Baker and Wurgler (2006) and the survey-based University of Michigan Consumer Sentiment Index. Several interesting findings are revealed: 1) extreme sentiment levels (either optimistic or pessimistic) tend to be followed by higher contrarian profits; 2) momentum profits appear to be negatively related with the lagged average 6-month sentiment levels; 3) former loser stocks are more important in determining the average contrarian profits, while momentum profits largely result from former winner stocks. The results are robust for all three sentiment proxies, and are consistent with the core implications of behavioral models. Specifically, contrarian profits are consistent with the overreaction hypothesis, and momentum profits can be explained by investor overconfidence and self-attribution.

In the foreign exchange market, I employ a different Weighted Relative Strength Strategy (a.k.a. WRSS). The WRSS strategies uncover similar profitability: eighteen among sixty-four basic strategies generate significant trading profits, and all of them are momentum. Contrarian profits mostly emerge in the second subperiod from 1999-2007, but none of them is statistically significant. Due to the difficulty of generalizing investor sentiment in the global context, the underlying autocorrelation structure of currency returns and the cross sectional dispersion in mean returns of individual currencies are responsible for the abnormal returns. It is found that the time serial predictability plays a critical role in determining trading profits and accounting for market inefficiency. The profits remain significant even when transaction costs come into effect.

This dissertation is dedicated to my mother, Yuanshu Zhang.

She gave me the surname, and helped me understand the importance of being an independent woman. Her love, wisdom, and positive attitude have sustained me throughout my life.

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INTRODUCTION

Many studies have documented that certain stock selection strategies can generate significant abnormal returns. The most famous ones are contrarian strategies (De Bondt and Thaler, 1985) and momentum strategies (Jegadeesh and Titman, 1993). De Bondt and Thaler (1985) find that stocks with extreme capital losses in the past (so-called "losers") will outperform those with extreme capital gains (so-called "winners") in the future 3-5 years. On the other hand, Jegadeesh and Titman (1993) suggest that stocks that perform the best (worst) over a 3 to 12 month period tend to continue to perform well (poorly) over the subsequent 3 to 12 months.

These financial anomalies, in general, cannot be explained by traditional asset pricing theories that are built upon the Efficient Market Hypothesis (EMH). According to the EMH, investors are assumed to be rational and follow the Bayes' rule to react to new information. Any mispricing should be corrected promptly so that there is no chance for excess returns.

Kahneman and Tversky (1979, 1982), the founders of behavioral finance, provide a different perspective on the anomalies. Their prospect theory challenges the underlying assumptions of the Efficient Market Hypothesis. They argue that people seem to make predictions based upon a simple matching rule: "The predicted value is selected so that the standing of the case in the distribution of outcomes matches its standing in the distribution of impressions (Kahneman and Tversky, 1982, 416)." In other words, to react to new available information, investors tend to put more weight on the most recent information and less on the prior data.

Based on Kahneman and Tversky's proposition, many behavioral theories have emerged since late 1990's. The limit of arbitrage is one of the most prominent. In this theory, Shleifer and Vishny (1997) suggest that the irrationality of investors causes mispricing and generates arbitrage profits in the market. However, due to transaction costs and/or the noise trader risk[1], arbitrageurs fail to correct the mispricing. Therefore abnormal returns become possible.

Other researchers build their theories upon investors' psychological biases. Several behavioral models fall into this category. Lakonishok, Shleifer and Vishny (1994) stand by their extrapolation theory. They believe that value strategies yield higher returns because typical investors *extrapolate* past performance too far into the future. To be specific, when average investors believe that the underperforming stocks (value stocks) will continue performing poorly in the future, speculators who employ contrarian strategies can earn extra profits because they are the only ones who buy the soon-to-be-corrected underpriced stocks.

Barberis, Shleifer and Vishny (1998) present a parsimonious model of investor sentiment based on representativeness and conservatism. The two psychological biases mislead investors to translate market information into irrational beliefs. For instance, if investors receive a series of positive (negative) shocks, they believe that a higher (lower) return will follow. Actually, the upcoming shock is random. The noisy information

[1] As opposed to rational arbitrageurs, noise traders have irrational beliefs on stock prices. They work against the arbitrageurs and cause the prices to diverge further away from the fundamental values.

processing causes underreaction and/or overreaction and therefore generates abnormal returns.

Hong and Stein (1999) divide the spectrum of investors into two types: newswatchers and momentum traders. They assume that both agents are partially rational. Newswatchers observe private information and slowly incorporate it into prices, causing underreaction in the short run. Momentum traders, on the other hand, try to capture the underreaction and chase the price drifts to make profits, leading to overreaction in the long run.

Daniel, Hirshleifer and Subramanyam (1998) suggest that investors tend to overreact to private information signals. Even after public information signals arrive, the self-attributed investors only partially correct their misjudgment. Especially, if their initial judgment is confirmed by the investment outcome, they become more confident and the overreaction phase will last longer. Overall, the reaction pattern is consistent with short-run positive autocorrelation and long-run negative autocorrelation.

In spite of their success in explaining the financial anomalies, behavioral models that rely on specific biases in individual investor psychology are often difficult to generalize. Fama (1998) points out that, not surprisingly, behavioral models work well on the anomalies they are designed to explain, but the real test is how well they can explain the big picture. Baker and Wurgler (2007) also realize that "real investors and markets are too complicated to be neatly summarized by a few selected biases and trading frictions." Instead they suggest that researchers focus on the measurement of reduced form, aggregate investor sentiment and trace its effects on market returns and individuals stocks.

Many candidates fall into the view of behavioral finance as being the representative of aggregate investor sentiment. Two categories of proxies are drawn from the literature: analytical indexes and survey-based indexes.

A. Analytical sentiment indexes. This group of proxies tends to capture the individual investor psychology from their trading behavior and their reaction to events.

a. Individual trading. Odean (1998), based upon a study of more than 10,000 randomly selected individual accounts, finds that investors are overconfident and they tend to trade excessively. More recently, Kaniel, Saar, and Titman (2005) suggest that individuals trade as if they are contrarians. The stocks that contrarian traders buy constantly show positive excess returns in the future. Therefore, net individual buying will predict a lower market return in the following months and *vice versa*.

b. Liquidity. Captured by the market turnover rate, liquidity is a reliable predictor of market returns. High liquidity implies that the market is full of irrational investors and that stocks prices tend to be overvalued. As a result, high turnover rate is more likely to lead to low future returns. Baker and Stein (2004) provide support to this argument. They find that conservative investors underreact to the information in the order flows and thereby they trade more frequently, adding liquidity to the market.

c. IPO volume and first-day IPO returns. IPO volume is said to be extremely sensitive to investor sentiment. Investment bankers speak of "windows of opportunity" for an IPO that capriciously opens and closes. An IPO's underpriced offer is also an unsolved puzzle. Investor sentiment might be the only reasonable explanation we know so far, in so much as average first-day IPO returns are highly correlated with the IPO volume, and that the latter is negatively related with future market returns.

d. Close-end fund discount. Similar to the IPO's trading volume, the close-end fund discount is widely accepted as a sentiment index. Lee, Shleifer, and Thaler (1991) and Neal and Wheatley (1998) both document that the discount increases when investors are bearish. Qiu and Welch (2005), however, point out that CEFD is not highly correlated with the consumer confidence index, a historically reliable proxy for investor sentiment. Their study casts doubts on the issue of whether CEFD has the ability to explain a variety of financial puzzles.

e. Dividend premium. This proxy is created by Baker and Wurgler (2004) in their catering model. This premium reflects investor sentiment in terms of investors' demand for dividends. Specifically, Baker and Wurgler (2004) assume that management tends to rationally cater the time-varying investor demand by paying dividends when investors prefer payers, and not paying when investors prefer non-payers.

B. Survey-based consumer confidence indexes. These indexes survey a large number of individual investors, and report their reaction to the macroeconomic situation and/or the capital market situation. Two consumer confidence measures are prominent: the Michigan Consumer Confidence Index and the Conference Board Consumer Confidence Index.

a. The University of Michigan Consumer Sentiment Index. This index is run by the Michigan Consumer Research Center. It focuses on the individual's economic conditions, and has become a major determinant of consumer confidence since 1958.

b. The Conference Board Consumer Confidence Index. This index is run by Greenwich, CT based NFO Research Inc. on the behalf of Conference Board. It mainly focuses on macroeconomic conditions (Qiu and Welch, 2005).

c. Other well-known survey-based sentiment indexes include UBS/Gallup Index of Investor Optimism, AAII (American Association of Individual Investors) Index, and VIX (The Market Implied Volatility Index). Each has its own strength and weakness in nature. UBS/Gallup conducts interviews among (random) investors with more than $10,000 in wealth, and therefore filters out relatively poor investors. AAII Index collects responses from registered members only, and therefore it is subject to potential self-selecting biases. The Market Implied Volatility Index (VIX) measures the implied volatility of options on the S&P 100 stock index. It is a relatively unbiased index and often called the "investor fear gauge". But VIX's short history since 1990 has limited power to represent investor sentiment in the long run.

Although none of the above-mentioned sentiment indexes is uniquely reliable, when aggregated, these proxies lead to a similar pattern of sentiment variation over time, which can help make predictions about patterns in market-wide investor sentiment and stock prices.

A breakthrough is provided by Baker and Wurgler (2006), in which they combine six principal proxies and create a reduced form of aggregate investor sentiment. Thanks to their ingenious work, I am able to directly test the relationship between investor sentiment and the profitability of various trading strategies. More importantly, this should help clarify the on-going debate among financial economists regarding the exact sources of momentum and contrarian profits.

Besides the financial anomalies found in the equity market, trading profitability is also observed in other capital markets such as the currency market. Sweeney (1986) finds that, using filter rules, investors can earn abnormal profits when trading from a risk-free Dollar asset to a risk-free Deutsche Mark asset. Kho (1996) also reports significant excess returns to the buy-and-hold strategy. Okunev and White (2003) re-examine momentum profits and find that the well-documented profitability holds for currencies throughout 1990's. Bianchi et al. (2004) report similar results using a sample of G7 countries.

However, in the context of the global economy, it is difficult to summarize investor sentiment into one single proxy. Instead, the fundamental characteristics such as the autocorrelation structure for currency returns and the cross sectional dispersion across currencies are plausible explanations for the trading profits.

In the literature, it is well-documented that the time serial autocorrelation in currency returns plays an important role in generating abnormal returns. Prior studies that employ either filter rules or moving average rules almost exclusively rely on the belief that the autocorrelation is the determinant of currency trading profits (Sweeney, 1986; Okunev and White, 2003; Bianchi et al., 2004). Taylor (1992) explicitly suggests that the exchange rates do not follow random walks but possess some degree of serial correlation.

Okune and White (2003) also find abnormal returns from the autocorrelation structure of currency returns.

In contrast, Conrad and Kaul (1998), Lehmann (1990), and Lo and MacKinlay (1990) argue that trading profitability should be explained by both the time serial component and the cross sectional mean return dispersion component. To understand the underlying principle, Conrad and Kaul (1998) suggest considering a benchmark return-generating process that follows a random walk:

$$R_{it}(k) = \mu_i(k) + \varepsilon_{it}(k), i = 1, 2, \dots N, \qquad (1)$$

where

$$E[\varepsilon_{it}(k)] = 0 \; \forall i, k \text{ and } E[\varepsilon_{it}(k)\varepsilon_{j,t-1}(k)] = 0 \; \forall \; i, j, k.$$

Also by construction,

$$Cov[R_{it}(k), R_{j,t-1}(k)] = 0 \; \forall \; i, j, k.$$

As suggested above, there should be no time serial autocorrelation or mean return dispersion in the benchmark model. Therefore, all profit potentials should be ruled out. However, when combined with the Weighted Relative Strength Strategy, the return-generating process shows that momentum (contrarian) strategies can still be profitable even under the assumption of random walks. In this case, even though the autocorrelation has been completely removed, trading profits are solely determined by the cross-sectional difference in mean returns.

Take momentum strategies as an example. When investors buy winners and sell losers, they are taking long positions in high mean-return assets and short positions in low mean-return assets simultaneously. Even when the market is following a random walk, meaning there are no abnormal returns generated from the autocorrelation, the dispersion in mean returns still contribute positive excess returns to momentum strategies. As reported in Conrad and Kaul (1998): "… the role of $\sigma^2[\mu(k)]$ has a small effect on profits to trading strategies that use weekly returns."

Inspired by Conrad and Kaul (1998), I conduct a decomposition of the currency trading profits (Lehmann, 1990; Lo and MacKinlay, 1990; Conrad and Kaul, 1998). This exercise not only provides insight into the components of trading profits, but also sheds light on the candidate explanations for market inefficiency.

The remainder of this dissertation is organized as follows. In the second section, I focus on the relationship between investor sentiment and trading profits in the equity market. In the third section I switch attention to the foreign exchange market, in which I re-examine the trading profitability, and investigate the potential sources of market inefficiency. The last section concludes and provides suggestions for future study on this subject.

SENTIMENT, CONTRARIAN, AND MOMENTUM PROFITS

I. Purpose of Study

For almost two decades, some simple trading strategies where portfolio holdings are based upon past relative return strength have drawn much interest in the literature. These return-based trading strategies can generally be classified into two categories: (a) the contrarian strategy that buys past losers and sells past winners; and (b) the momentum strategy that buys past winners and sells past losers. It is well known that contrarian strategies work in the short horizon from one week to one month, and momentum strategies generate positive returns in a longer horizon ranging from three to twelve months[2].

This dissertation first explores the relationship between investor sentiment, contrarian, and momentum trading profits. The profitability of these return-based trading strategies appears at odds with the traditional finance paradigm that is built upon the pivotal assumptions of rational investors and efficient markets. Research activities in this area have largely followed two paths. On one hand, some researchers attempt to reconcile investor rationality with the profitability of return-based trading strategies. For example, Lo and MacKinlay (1990) argue that the lead-lag effect between large and small stocks could be an important source of contrarian profits. Conrad and Kaul (1998) note that momentum strategy could potentially be consistent with rational asset pricing models if it takes long positions in high-mean-return stocks and short positions in low-mean-return stocks. On the other hand, many studies have endeavored to provide some interesting

[2] DeBondt and Thaler (1985) document that contrarian strategies are also profitable in the long run (i.e. three to five years). In this disseratation, we do not focus on this type of long-run contrarian profits and leave it for future research.

alternative explanations that are based on investor psychology and behavioral biases. For instance, Lehmann (1990), and Jegadeesh and Titman (1995) show that contrarian profits are likely induced by investors' overreaction to news. In the momentum literature, Barberis, Shleifer and Vishny (1998) discuss how conservatism bias might cause investors to underreact to information, which in turn gives rise to momentum profits. Daniel, Hirshleifer and Subrahmanyam (1998) show that self-attribution bias can induce overconfidence and consequently push stock prices to deviate from their fundamental values. In the model of Hong and Stein (1999), momentum stems from the gradual diffusion of information and hence underreaction to news.

In spite of their apparent success in explaining certain asset pricing anomalies, behavioral models that rely on specific biases in individual investor psychology are often difficult to generalize. Fama (1998) argues that, not surprisingly, behavioral models work well on the anomalies they are designed to explain, but the real test is how well they can explain the big picture. Baker and Wurgler (2007) point out that "real investors and markets are too complicated to be neatly summarized by a few selected biases and trading frictions." Instead they suggest that researchers focus on the measurement of reduced form, aggregate investor sentiment and tracing its effects on market returns and individuals stocks. Baker and Wurgler (2006) theorize that investor sentiment has cross-sectional effects when arbitrage constraints vary across stocks. They show that when sentiment is low (high), subsequent returns are relatively high (low) for small stocks, young stocks, high volatility stocks, and distressed stocks. Lemmon and Portniaguina (2006) also explore the time-series relationship between sentiment and the small-stock premium and find that consumer confidence can forecast small stock returns.

This dissertation is interested in the relationship between investor sentiment and returns to both short-term contrarian and long-term momentum trading strategies. The reasons are twofold.

First, unlike prior studies that almost exclusively focus on either a market index or decile portfolios sorted by size and/or book market ratio, this study extends the literature by exploring the relationship between sentiment and returns to contrarian and momentum trading strategies. Such a relationship should deepen the understanding of the interaction between sentiment and the limits of arbitrage, two pillars of behavioral finance.

To illustrate, consider the results from Hong, Lim, and Stein (2000).They find that stocks with low analyst coverage earn higher momentum profits because these stocks are more difficult to arbitrage. Baker and Wurgler (2006, 2007) also suggest that the (mis)valuation of stocks is more likely to be influenced by investor sentiment. In general, when investor sentiment drifts toward extreme levels, profiles of stocks that contribute to contrarian or momentum profits (namely small stocks, young stocks, highly volatility stocks, extreme growth stocks, and distressed stocks) appear to match stocks that are hard to arbitrage.

These observations confirm my intuition that there should be a linkage between investor sentiment and the profitability of contrarian and momentum strategies. To clarify the relationship, I suppose investors are subject to sentimental biases. The biases lead to irrational investment activities such as overbuying in an up-swing sentiment state and/or overselling in a down-swing sentiment state, and therefore cause stock mispricing. If the mispricing cannot be immediately corrected due to the limits of arbitrage, contrarian and momentum strategies are most likely to generate significant profits.

Second, Baker and Wurgler (2007) point out that none of the empirical results that are built upon specific sentiment proxies (such as close-end fund discount, IPO volume and price, new stock issues and dividend premium) is uniquely reliable. However, when aggregated, these proxies lead to a similar reduced form of sentiment variation over time, which help make predictions about patterns in market-wide investor sentiment and stock prices. Thus by studying the relationship between the waves of sentiment and the profitability of contrarian and momentum strategies, I am able to directly test the core implications of behavioral hypotheses. This should shed light on the on-going debate among financial economists regarding the exact sources of momentum and contrarian profits.

To be specific, in the context of contrarian strategies, if the hypothesis that investor overreaction is the main source of contrarian profits is true, there should be a causal relationship between the degree of investor pessimism or optimism and subsequent contrarian profits. For example, if investors are extremely pessimistic (optimistic) in month $t-1$, they tend to overreact to news and engage irrational activities such as overselling (overbuying), causing stocks to be undervalued (overvalued). With the presence of limits of arbitrage, the mispricing cannot be corrected promptly. Therefore, when in month t investor sentiment swings back to the mean, a contrarian strategy that buys losers and sells winners will appear to be profitable.

Likewise, speaking of momentum strategies, when investor sentiment is at extreme levels, investors who are subject to overconfidence and/or self-attribution biases tend to extrapolate their current beliefs too far into the future. Their (mis)valuation of stocks is likely to lead to lower returns in the long run. In contrast, staying in a modest sentiment state helps investors make rational decisions. As a result, a momentum strategy that buys winners (i.e. high mean-return stocks) and sells losers (i.e. low mean-return stocks) is likely to be profitable in the long term. Thus, one should expect to see higher momentum profits following a relatively mild level of investor sentiment.

Overall, investor sentiment should be the primary explanation for both contrarian and momentum profits. To test on the hypotheses, I construct a one-month-ranking-and-one-month-holding buy-losers-and-sell-winners strategy for contrarian profits, and a six-month-ranking-and-six-month-holding buy-winners-and-sell-losers strategy for momentum profits. Investor sentiment is indexed as 1 and 0 to capture extreme and modest levels respectively. Both the lagged level of investor sentiment and changes in the sentiment states are used to evaluate their effect on contrarian and momentum profits. Three proxies of investor sentiment are used for the purpose of study: two reduced-formed sentiment indexes that are constructed by Baker and Wurgler (2006) and the survey-based University of Michigan Consumer Sentiment Index. The results point to several interesting findings.

First, there is a clear pattern between investor sentiment and contrarian profits. When lagged investor sentiment is at extreme levels (either optimistic or pessimistic), subsequent contrarian profits are approximately twice as high as the case when prior sentiment levels are modest. The difference in the mean profits is statistically significant.

Also, contrarian profits are high when investor sentiment shifts from extreme to modest levels. These results are robust for all three sentiment proxies, and are consistent with the overreaction hypothesis.

Second, contrarian profits are mostly generated from buying former loser stocks but not from selling former winner stocks. It is found that loser portfolios provide larger and more significant returns to the contrarian profits, whereas the contributions of winner portfolios are not statistically different from zero. This suggests that the loser and winner stocks have asymmetrical responses to the extreme sentiment levels, providing further support to the overreaction hypothesis.

Third, momentum profits appear to be negatively related with the lagged average 6-month sentiment levels. In other words, the extreme sentiment levels are expected to be followed by lower subsequent momentum profits. This finding helps clarify the core implications of several behavioral models, such as investor overconfidence and self-attribution. The expected relationship persists even after controlling for three Fama-French factors.

Fourth, in contrast to contrarian profits, momentum profits largely result from buying and holding past winners for the long run. Selling former loser stocks only makes marginal contribution. The evidence is particularly strong under the bullish sentiment reading. Again, this can be explained by the theory that winner and loser stocks respond to extreme sentiment levels asymmetrically.

II. Analysis of the Data

A. Sentiment

This dissertation relies on two popular measures for investor sentiment. The first measure is the sentiment index constructed by Baker and Wurgler (2006). This index (henceforth *BW1*) is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount (*CEFD*), NYSE share turnover (*TURN*), the number of IPOs (*NIPO*), the average first-day returns on IPOs (*RIPO*), the equity share in new issues (*S*), and the dividend premium ($P_{D\text{-}ND}$). The index is constructed by applying principal component analysis of the six proxies and its final form is as follows:

$$SENTIMENT = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t$$
$$+0.257RIPO_{t-1} + 0.112S_t - 0.283P_{t-1}^{D-ND}$$

To isolate the effect of business cycles, Baker and Wurgler also put forward another sentiment index (henceforth *BW2*), which by construction is orthogonal to various macroeconomic variables. Specifically, Baker and Wurgler regress each of the six raw proxies on growth in industrial production, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions. The residuals from these regressions are then used to form the index *BW2*. Both *BW1* and *BW2* are available in monthly frequencies from January 1966 to December 2007[3].

The second sentiment measure is the University of Michigan Consumer Confidence Index (henceforth *UM*), a monthly survey index run by the Michigan Consumer Research Center. This index is calculated based on survey questions that poll respondents' current and expected future personal financial situations, business conditions, and intent to purchase major household items. Although the survey questions are not directly related to financial markets, Qiu and Welch (2006) find that this index

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[3] I would like to thank Jeffrey Wurgler for providing the data on his web site.

has a strong correlation with a more direct (but unfortunately much shorter) proxy for investor sentiment from UBS/Gallup. Furthermore, both Qiu and Welch (2006) and Lemmon and Portniaguina (2006) show that *UM* can forecast small stock returns. Prior to 1978, the index is available only in quarterly frequency. Starting from January 1978 *UM* is released on a monthly basis. To be consistent with *BW1* and *BW2*, I focus on the monthly *UM* data, which are obtained from FRED database at St. Louis Federal Reserve Bank web site.

Table 1 reports the summary statistics for all three investor sentiment proxies. Note that by construction *BW1* and *BW2* are mean zero with unit variance. Interestingly, whereas the correlation between *BW1* and *BW2* is very high (0.94), the correlation between *UM* and the two Baker-Wurgler sentiment proxies is quite low (0.23 for *BW1* and 0.06 for *BW2* respectively). This result is consistent with the findings in Qiu and Welch (2006), and it suggests that *UM* probably captures some unique aspects of investors' sentiment that are absent from the two Baker-Wurgler sentiment proxies. All three sentiment proxies are plotted in Figure 1 as well.

[Insert Table 1 here]

[Insert Figure 1 here]

B. Contrarian and Momentum Profits

Contrarian trading strategies usually have shorter holding periods, typically ranging from one week to a few weeks. Lehmann (1990) examines the profitability of contrarian strategies using weekly stock returns data. Jegadeesh (1990) finds that the same strategy works on monthly data as well. In this dissertation, I construct short-term contrarian strategies based on one-month-ranking and one-month-holding. Each month the portfolio is rebalanced by buying the top 10% loser stocks and selling the bottom 10% winner stocks based on the ranking from the previous month.

Momentum strategies, on the other hand, have longer holding periods, ranging from three to twelve months (Jegadeesh and Titman, 1993, 2001). The relatively longer-term momentum strategies are constructed based on six-month-ranking and six-month-holding. The portfolio buys the top 10% winner stocks and sells the bottom 10% loser stocks. This equally-weighted decile portfolio approach is comparable to the one used in Jegadeesh and Titman (1993). Following the convention in the literature, I also skip one month between the ranking and holding period to minimize microstructure issues related to illiquid stocks.

To synchronize with the sentiment data, I focus on monthly returns of all the stocks listed in the NYSE and AMEX from January 1966 to December 2007. The stock return data are obtained from the Center for Research in Security Prices database (CRSP). The use of monthly data also helps alleviate market microstructure related issues.

III. Sentiment and Contrarian Strategy Profits

Throughout this dissertation I rely on a critical assumption that investor sentiment can influence investors' buying- and selling-decisions. If this assumption is valid, I expect investor sentiment to be correlated with profits in contrarian and momentum strategies. Specifically, if investors are excessively optimistic (pessimistic), sentiment-driven buying (selling) forces could push stock prices go above (below) their fundamental values. A contrarian strategy that buys past losers and sells past winners will therefore be profitable. With the presence of limits of arbitrage, the profitability will remain until the (mis)valuation is subsequently corrected when sentiment swings back to the mean.

This explanation appears to be consistent with the overreaction hypothesis put forward by Lehmann (1990), among others, regarding the sources of contrarian profits. Hence I expect to see a positive relationship between extreme levels of investor sentiment and subsequent contrarian profits. In other words, when investors are overly optimistic or pessimistic in month t, the contrarian profits in month $t + 1$ should be higher, and *vice versa*. To test this hypothesis, I use an indicator variable I_t to define extreme and modest sentiment levels at time t. $I_t = 1$ if the current sentiment reading is extreme (larger than 75th percentile or less than 25th percentile), and $I_t = 0$ if the sentiment reading is modest (larger than 25th percentile but less than 75th percentile).

The evidence from Table 2 is consistent with the overreaction hypothesis.

[Insert Table 2 here]

First, the full sample results in Panel A show that unconditionally, short-term contrarian profits are statistically and economically significant. The average monthly return is 1.95% with a t-statistic of 8.03.

Second, when conditioning on lagged investor sentiment proxies, contrarian profits exhibit patterns that are consistent with the overreaction hypothesis. For example, when *BW1* in the prior month is above the 75th percentile or below the 25th percentile ($I_{t-1} = 1$, i.e. investor sentiment is in an extreme level), the average contrarian profit in the following month is about 2.72% with a t-statistic of 6.96. In contrast, when the lagged

BW1 proxy is between 25th and 75th percentiles ($I_{t-1} = 0$), the average contrarian profit shrinks to approximately 1.18%. The results are similar when using the *BW2* sentiment proxy. The average monthly profit is 2.61% conditional on an extreme sentiment reading, and 1.29% conditional on a modest reading. The results based on the *UM* proxy are also very similar (1.78% vs. 1.10%). I formally test if the conditional mean profits are statistically different when sentiment is in either extreme or modest setting. I find that the p-values of the spreads are statistically significant at 1% level for all three sentiment proxies.

Third, I consider separately the impact of loser and winner portfolios on the contrarian profits under either bullish or bearish sentiments. It is found that contrarian profits are mostly generated by buying former loser stocks but not by selling former winner stocks.

In Panel B of Table 2, I define bearish sentiment as the case when the sentiment indexes are below 25th percentile and bullish sentiment as the case when the indexes are above 75th percentile. The unconditional mean return for loser stocks is about 2.21% and appears much larger than that of winner stocks (0.25%). When conditional on bearish or bullish lagged investor sentiment, the results are even more striking – the average returns on loser portfolios are much stronger than those of winner portfolios. For example, when *BW1* is bullish, buying loser stocks generates an average profit of 1.81% to contrarian strategies, in contrast to the profit of 0.08% from selling winner stocks. When *BW1* is bearish, the loser portfolio brings in a profit of 4.13%, whereas the winner portfolio earns positive returns. Since contrarian strategies take short positions on winners, this subtracts away 0.58% from the profits. The patterns are also true for *BW2* and *UM* proxies.

This suggests that loser and winner stocks have asymmetrical responses to the extreme sentiment levels. When investors are overly pessimistic or optimistic, they are particularly sensitive to bad news. As a result of overreaction, they tend to oversell loser stocks. In the short run, the overselling leads to stock undervaluation and creates chances for contrarian profits in the following period. On the other hand, average investors have less incentive to keep buying winner stocks even with the presence of good news. Thus, the overvaluation of winner stocks is likely to be smaller than the undervaluation of loser stocks in terms of magnitude. Therefore, it is expected that, following a bullish or bearish month, buying the past losers will generate higher contrarian profits than selling the past winners.

If sentiment has a contemporaneous effect on investment decisions, then it is reasonable to assume that there should be a relationship between changes in investor sentiment (from the ranking period to the holding period) and contrarian profits. Specifically, if sentiment level is extreme in month t - 1 and swings back to a modest level in the following month t, according to the overreaction hypothesis, this shift in sentiment should be accompanied by a relatively higher contrarian profit, and *vice versa*. It can be seen that the first order difference of the dummy variable I_t, $\Delta I_t \equiv I_t - I_{t-1}$, should be negatively correlated to contrarian profits. To illustrate, $\Delta I_t = -1$ means that investor sentiment shifts from a state of extreme optimism or pessimism to a state of relatively mild emotions. Contrarian profits should be higher since the sentiment-driven undervalued/overvalued stocks tend to revert back to mean in this case. Likewise $\Delta I_t = 1$ indicates that investor sentiment has gone wild, and therefore contrarian profits should be low or even negative. $\Delta I_t = 0$ means there is no discernable change in investor sentiment.

The contrarian profits associated with the three different values of ΔI_t are reported in Table 3.

[Insert Table 3 here]

First of all, I find that the relationship between ΔI_t and contrarian profits is consistent with the prediction from the overreaction hypothesis. It is particularly noticeable in the case of *UM*. Profits are at their highest level when $\Delta I_t = -1$, and lowest when $\Delta I_t = 1$. The difference of the mean profits for the two cases where $\Delta I_t = -1$ and $\Delta I_t = 1$ is statistically significant at 1% level with a *t*-statistic of 4.65. Unfortunately, *BW1* and *BW2* proxies only provide limited support to the findings of *UM* because too many observations fall into the group of $\Delta I_t = 0$ (e.g. *BW1* has 470 observations for $\Delta I_t = 0$ and *BW2* has 450).

Second, Panel B of Table 3 examines the relationship between the mean returns of winner and loser portfolios and changes in investor sentiment in the following four cases. Case 1: Sentiment is bullish (greater than 75th percentile) in both month *t*-1 and month *t*. Case 2: Sentiment is bullish (greater than 75th percentile) in month *t*-1 and but not bullish (less than 75th percentile) in month *t*. Case 3: Sentiment is bearish (less than 25th percentile) in both month *t*-1 and month *t*. Case 4: Sentiment is bearish (less than 25th percentile) in month *t*-1 but not bearish (greater than 25th percentile) in month *t*. I find that the returns of loser portfolios appear to be bigger and more significant than that of winner portfolios, especially in Case 3. In terms of contrarian profits, the loser minus winner spread also appears to be the biggest in Case 3. This suggests that contrarian strategies work better when investors are generally bearish, which provides further evidence to support the overreaction hypothesis. Results from Case 1 and Case 2 are harder to interpret due to the limited number of observations.

Finally I investigate the relationship between contrarian profits and investor sentiment in a regression setting. I consider the following regression models:

$$CP_t = \beta_0 + \beta_1 I_{t-1} + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (2)$$

$$CP_t = \beta_0 + \beta_1 \Delta I_t + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (3)$$

where CP_t denotes contrarian profits at time t, I_{t-1}, as defined earlier, is a dummy variable to capture extreme and modest sentiment levels, and $\Delta I_t \equiv I_t - I_{t-1}$ measures the change in sentiment. RM_t, SMB_t, and HML_t are three Fama-French factors[4]. I run these regressions using all three sentiment proxies: *BW1*, *BW2*, and *UM*.

[Insert Table 4 here]

Panel A of Table 4 reports the regression results from Equation (2). As expected, the estimated coefficients for I_{t-1} are positive, which suggests that higher lagged investor sentiment level will increase subsequent contrarian profits. Moreover they are statistically significant for *BW1* and *BW2*, with or without Fama-French factors. The coefficient of *UM* proxy shows weak significance. Among the results, the lagged sentiment based on *BW1* appears most significant with a *t*-statistic of 3.19.

Panel B of Table 4 reports the regression results from Equation (3). In this case, the estimated coefficients for ΔI_t, changes in sentiment, are always negative, which is

[4] I would like to thank Ken French for making the data available on his website.

consistent with the overreaction hypothesis explained earlier. However, none of them are significant.

By using the dummy variable I_t, I could have potentially lost some useful information. Thus I also consider an alternative continuous variable $D_t \equiv |S^t - \mu^S|$, where S^t is the sentiment value at time t and μ^S is the sample mean of sentiment proxies. D_t is a measure of distance between the sentiment reading at t and its mean value. A large D_t indicates a relatively extreme level of sentiment. Likewise, I also define the change in D_t, $\Delta D_t \equiv D_t - D_{t-1}$. Panel C and Panel D report the results for the following regressions.

$$CP_t = \beta_0 + \beta_1 D_{t-1} + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (4)$$

$$CP_t = \beta_0 + \beta_1 \Delta D_t + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (5)$$

where I simply replace I_{t-1} and ΔI_t with D_{t-1} and ΔD_t respectively. The results from Panel C are consistent with the results from Panel A. There is a positive relationship between contrarian profits and D_{t-1}, which is supportive of the overreaction story. The estimated coefficients of D_{t-1} are significant for *BW1* and *BW2* but not *UM*. Like Panel B, Panel D shows a negative but insignificant relationship between ΔD_t and contrarian profits.

Overall, the collective evidence supports the notion that contrarian profits are linked to investor sentiment. When lagged sentiment proxies are at extreme (modest) levels, subsequent contrarian profits are higher (lower). In addition, when investor sentiment swings from extreme to modest levels, contrarian profits tend to be bigger, and *vice versa*.

IV. Sentiment and Momentum Strategy Profits

If profits to momentum trading strategies are results of investor psychological biases, as many behavioral models have suggested, one of the core implications is that investor sentiment should be related to momentum profits. To date, however, very few papers have directly addressed this linkage. Cooper et al. (2004) conjecture that investor optimism will be higher following periods of market gains as investors in general hold long positions in stocks. They define market states according to the overall market return during the past one to three years. If past market return is positive, then the market is in an "up" state, and *vice versa* for a "down" state. It is found that positive momentum profits tend to follow exclusively an "up" state, which is consistent with the theory of Daniel, Hirshleifer and Subrahmanyam (1998). In an "up" market state, investor optimism is high and consequently investor overconfidence can exacerbate the self-attribution bias. While Cooper et al. (2004) provide some very interesting empirical results, the use of market state as a measure of investor sentiment is non-standard. In fact, the market state is not a direct measure of investor sentiment. In particular, while market state may be a necessary condition for investor overconfidence, it is not sufficient. For example, an alternative explanation for the "market state" phenomenon could be the changes in real macroeconomic activities or business cycle regimes, where positive momentum profits also follow an "up" market state. In my view, a less ambiguous way to test the core implications is to directly examine the linkage between investor sentiment and momentum profits.

Similar to the previous section, I focus on three sentiment proxies: *BW1*, *BW2*, and *UM*. Since the momentum strategies are constructed with a six-month-ranking and a six-month-holding method, I use a sentiment dummy variable I_t^6 to capture the average sentiment level over the six-month period. $I_t^6 = 1$ if the average 6-month sentiment reading is extreme (larger than the 75th percentile or less than the 25th percentile), and $I_t^6 = 0$ if the average 6-month sentiment reading is modest (larger than the 25th percentile but less than the 75th percentile).

[Insert Table 5 here]

Panel A of Table 5 reports the average monthly returns as momentum trading profits. The unconditional full sample profit is 0.91% with a *t*-statistic of 3.38, and the skip-one-month return is even larger and more significant (1.14% with a *t*-statistic of 4.57). These results are comparable to other momentum studies.

When conditional on investor sentiment, there shows a negative relationship between momentum profits and average investor sentiment over the 6-month ranking period. To illustrate, when $I_{t-1}^6 = 1$, namely the lagged 6-month sentiment reading is extreme, the subsequent momentum profits are lower and less significant than in the case where $I_{t-1}^6 = 0$. For example, when the lagged *BW2* reading is extreme, the average momentum profit is only 0.43% and insignificant. In contrast, with a modest reading, *BW2* reports a higher and significant profit of 1.40% (t = 4.33). The difference of the mean profits is significant at 10% level. The results of *BW1* and *UM* are similar but the differences in mean returns are insignificant.

These findings can be explained by investor overconfidence and self-attribution bias. To be specific, when investors are in extreme sentiment levels, they tend to be overconfident in making investment decisions. Even after the public information arrives, they only partially correct their misjudgment. Especially when the investment outcome confirms their initial judgment, they become more confident and harder to correct. These biased behaviors will result in lower returns in the long run. On the other hand, when the sentiment state is modest, it helps investors make rational decisions. Therefore it is more likely to see a higher momentum profits following a modest sentiment level in the long term. In short, the psychological explanation provides support to the hypothesis that the momentum profits are negatively related with the lagged investor sentiment.

In Panel B of Table 5 I examine separately the average returns to loser and winner portfolios under lagged bullish (sentiment indexes above 75th percentile) or bearish (sentiment indexes below 25th percentile) readings. The unconditional average 6-month momentum profit for winner stocks is 1.64% and significant (t = 6.01), higher than that of loser stocks (0.73% and t = 1.84). When conditioning on the sentiment proxies, I find that the momentum profits largely result from buying former winner stocks, and that selling former loser stocks only makes marginal contribution. The evidence is particularly strong under the bullish sentiment setting: the winner minus loser spread in the case of bullish reading is much larger than the case of bearish reading.

Again, this provides support to the story that winner and loser stocks respond to extreme sentiment levels differently. Specifically, over the long run, the overreaction that generates short-term contrarian profits slowly fades away. Investors return to their rationality and expect to buy high mean-return stocks (i.e. winners) and sell low mean-return stocks (i.e. losers). Winner stocks therefore become more popular than loser stocks. As a result, they tend to be overvalued, which creates the opportunity for profitable momentum strategies in the following period. Thus, past winner stocks seem to be more important in determining the momentum profits in a long run.

In Table 6 I look at the change in investor sentiment from the ranking period to the holding period. $\Delta I_t^6 \equiv I_t^6 - I_{t-1}^6$ is defined as the first order difference of I_t^6. Note that in this case *t*-1 is the 6-month ranking period and *t* is the 6-month holding period. $\Delta I_t^6 = 1$ indicates that investor sentiment is at modest levels during the ranking period and at extreme levels during the holding period. In other words, sentiment is swinging to the extremes. Likewise, $\Delta I_t^6 = -1$ means that average investor sentiment has waned from the ranking period to the holding period. $\Delta I_t^6 = 0$ shows no discernable change in investor sentiment.

[Insert Table 6 here]

The results in Panel A of Table 6 reveal several findings. First, momentum profits are much higher when investor sentiment shifts from extreme to modest (i.e. $\Delta I_t^6 = -1$). In fact, momentum profits when $\Delta I_t^6 = -1$ more than double the profits when $\Delta I_t^6 = 0$. This is consistent for all three sentiment proxies. Second, the difference of mean profits between $\Delta I_t^6 = -1$ and $\Delta I_t^6 = 1$ is weakly significant for *BW1* but insignificant for *BW2* and *UM*. These findings suggest that the prior extreme sentiment levels are associated with higher subsequent momentum profits. However, this is inconsistent with my prediction.

Panel B of Table 6 reports the mean returns of loser and winner portfolios in the following four cases. Case 1: Sentiment is bullish (greater than 75th percentile) in both month *t*-1 and month *t*. Case 2: Sentiment is bullish (greater than 75th percentile) in month t-1 and but not bullish (less than 75th percentile) in month t. Case 3: Sentiment is bearish (less than 25th percentile) in both month t-1 and month t. Case 4: Sentiment is bearish (less than 25th percentile) in month t-1 but not bearish (greater than 25th percentile) in month t. In contrast to the results of contrarian profits, I find that the returns of winner portfolios are bigger and more significant than that of loser portfolios in most scenarios. This again suggests that winner portfolios are the major determinant to momentum profits. Among all results, the winner minus loser spread is more substantial in Case 1 and 2.

In Table 7 I run the following two regressions.

$$MP_t = \beta_0 + \beta_1 I_{t-1}^6 + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (6)$$

$$MP_t = \beta_0 + \beta_1 \Delta I_t^6 + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t, \qquad (7)$$

where MP_t denotes momentum profits at time t, I_{t-1}^6 and ΔI_t^6 are the same as previously defined. RM_t, SMB_t, and HML_t are three Fama-French factors.

[Insert Table 7 here]

In Panel A, the estimated coefficients of I_{t-1}^6 show expected negative signs. This suggests that the lagged extreme sentiment readings are associated with lower subsequent momentum profits. However, none of the estimates are statistically significant. In Panel B, the changes in sentiment (ΔI_t^6) also report expected negative signs, but again, the results are not significant. In Panel C and D I replace I_{t-1}^6 and ΔI_t^6 with D_{t-1}^6 and ΔD_t^6, where $D_t^6 \equiv |S_t^6 - \mu^S|$ and S_t^6 is the sentiment value at time t and μ^S is the sample mean. The results are similar to those of Panel A and B. Overall, the regression results suggest that there is a negative relationship between the lagged extreme sentiment levels and momentum profits. In other words, one should expect to see an extreme sentiment reading followed by lower subsequent momentum profits. Unfortunately, the findings lack statistical significance.

V. Further Discussion

Investor sentiment is an important cornerstone of behavioral finance. Many studies in the literature focus on the relationship between investor sentiment, market index, and a few size or book market ratio sorted portfolios. Very few have formally explored the relationship between investor sentiment and return-based portfolio trading strategies. However, understanding this relationship is important because it provides a refutable hypothesis for many theoretical models that are built upon investors' behavioral biases.

In this study, I find that both contrarian and momentum strategies are strongly influenced by investor sentiment. It helps deepen the understanding of the core implications in many behavioral models, and also provides indirect support to rational based explanations as offered by Johnson (2004) and Liu and Zhang (2008).

THE PROFITABILITY OF MOMENTUM AND CONTRARIAN STRATEGIES IN THE FOREIGN EXCHANGE MARKET

I. Background of Study

Abnormal trading profits have been documented in the equity market for years. Similar evidence is also found in the foreign exchange market. For example, Sweeney (1986), using filter rules, finds that investors can earn abnormal profits when trading from a risk-free Dollar asset to a risk-free Deutsche Mark asset. Kho (1996) also reports significant excess returns to the buy-and-hold strategy. Okunev and White (2003) re-examine momentum profits and find that the well-documented profitability holds for currencies throughout 1990's. Bianchi et al. (2004) report similar results using a sample of G7 countries.

These findings cast doubt on the Efficient Market Hypothesis (Fama, 1970) and raise the question of what has caused these financial anomalies. According to the EMH, prices follow a random walk. Therefore no abnormal profits should exist in the market. However, in reality, two underlying assumptions of the EMH are evidently violated: 1) arbitrageurs fail to correct the mispricing promptly because of transaction costs and/or noise trading; and 2) investors hold heterogeneous beliefs on equity prices (Barberis & Thaler, 2003; Shleifer & Vishny, 1997; De Long et al., 1990a).

In fact, it is found that the foreign exchange rates do not truly reflect all the currently available information on domestic and international economic and political environments (Fama, 1965). Instead the exchange rates possess some degree of serial correlation (Taylor, 1992). Okune and White (2003) also suggest that the abnormal returns result from the autocorrelation structure of currency returns.

In this section, I re-examine the profitability of various trading strategies in the foreign exchange market, and investigate the sources of trading profits. The results also clarify the underlying attributes to market inefficiency.

Weekly currency returns are used for the purpose of the study. The literature largely relies on either daily or monthly returns for convenience of data availability. However, daily data contain a large amount of trading noise. Monthly data seem to be more informative but rather impractical in the real world. To reconcile the difficulty of obtaining sufficient information and avoiding unnecessary noise, I construct a series of weekly currency returns. Seven exchange rates are examined. They are the rates of G7 countries (namely, Canada, France, Germany, Italy, Japan, the U.K., and the U.S.) and the European Union. U.S. dollars are used as the base currency. The full sample period ranges from January 1st, 1971 to December 31st, 2007, and is divided into two subperiods: the pre-Euro subperiod (1/1/1971 – 12/31/1998) and the post-Euro subperiod (1/1/1999 – 12/31/2007).

Momentum and contrarian trading strategies are both constructed using a past-performance-based Weighted Relative Strength Strategy (a.k.a. WRSS, Lehmann, 1990; Lo and MacKinlay, 1990; Conrad and Kaul, 1998). This method builds zero-cost long-short portfolios by buying winners and selling losers (momentum) or buying losers and selling winners (contrarian) based on their past performance. Average portfolio profits are calculated as trading profits.

Several interesting findings are revealed. First, it shows that momentum strategies are dominantly profitable in the foreign exchange market. Among sixty-four formed strategies, eighteen are significantly profitable and all of them are momentums. Contrarian profits mostly emerge in the second subperiod, but none are statistically significant. The results appear to be stronger when using the interest-adjusted returns.

Second, among the profitable momentum strategies, eight are *one*-week-ranking-and-k-week-holding strategies, and ten are k-week-ranking-and-k-week-holding strategies. The latter reports lower but more significant profits. This implies that longer ranking period eliminates noisy information and therefore provides more reliable trading profits.

Third, based on the *one*-week-ranking-and-k-week-holding method, I conduct a decomposition analysis of the trading profits. It is found that both the autocorrelation structure for currency returns and the cross sectional dispersion in mean returns of individual currencies are responsible for the abnormal returns. More importantly, the autocorrelation accounts for majority part of the profits. It is also the determining factor for market inefficiency.

Fourth and lastly, the trading profits remain significant even when transaction costs come into effect. Transaction cost in this case is defined as the sum of commissions and bid-ask spreads. It is shown that on average, the break-even transaction costs are twice as big as the trading profits. In other words, a one-way transaction cost $c = 0.0001$ (or a round-trip $c = 0.0002$) does not rule out the profitability in currency trading.

This study extends the literature in several ways. First, unlike most prior studies that almost exclusively use filter rules or moving average rules to explore the currency trading profits (Sweeney, 1986; Okunev and White, 2003; Bianchi et al., 2004), I employ a different Weighted Relative Strength Strategy. By using the WRSS method, I do not presume that the excess returns are solely generated from the autocorrelation in currency returns. Instead, I test the impact of both autocorrelation and cross-sectional difference in mean returns on trading profits.

Second, the WRSS construction also enables a further decomposition analysis (Lehmann, 1990; Lo and MacKinlay, 1990; Conrad and Kaul, 1998). This exercise not only provides insight into the components of trading profits, but also sheds light on the candidate explanations for market inefficiency. To preview the results, the time-series autocorrelation makes approximately a 90% contribution to the abnormal returns in most cases. Thus it is safe to suggest that autocorrelation is the determining source of market inefficiency.

Third, weekly returns are more appropriate for the purpose of the study than monthly or daily returns. Monthly evaluation seems to be more informative, but it is impractical in reality. According to Taylor and Allen (1992), in which they survey on chief foreign exchange dealers, about 90% of respondents report that their trading rules are evaluated in the horizons ranging from intraday to one week. Daily returns, on the other hand, contain too much noise from massive transactions. Moreover, prior studies show that the use of moving average rules or filter rules on a daily basis often suffers from the limited number of selected trading rules (Okunev and White, 2003). Weekly returns not only provide a substantial number of observations to form trading strategies (N = 1931), but also minimize unnecessary noise. It is believed the best proxy of currency returns for the study topic of trading profitability.

II. Data Description

Seven major exchange rates are studied in this dissertation, including the rates of G7 countries (namely Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) and the European Union. U.S. dollars are used as the base currency. The exchange rates of the Canadian Dollar, Deutsche Mark, Japanese Yen, Pound Sterling and Euro are obtained from the Federal Reserve Bank of St. Louis. The rates of French Franc and Italian Lira are downloaded from the International Monetary Fund (IMF) archives.

The sample period ranges from January 1st, 1971 to December 31st, 2007, and consists of a total of 1931 trading weeks. Choosing the specific period is based on two considerations. First, the world-wide fixed exchange rate regime (a.k.a. the Bretton Woods System) was removed in 1971. Since then foreign currencies were no longer directly correlated with gold and/or Dollars. Foreign governments had the freedom to choose their own exchange rate systems, and most of them settled with floating exchange rate regimes. This provides substantial liquidity to the global currency market and makes this study possible. Second, choosing December 2007 as the end of the sample period is intended to minimize the disturbing impact of the 2008-2009 U.S. financial turmoil on the global economy and the foreign exchange market.

As we all know, the European Union launched the Euro as a "single currency" for all European Union Member States on January 1st, 1999. Due to the major effect of this event, I divide the sample into two subperiods: the pre-Euro era from January 1971 to December 1998, and the post-Euro era from January 1999 to December 2007. The Euro is excluded in the first subperiod, and the Deutsche Mark, French Franc, and Italian Lira are substituted by the Euro in the second subperiod.

The continuously compounded weekly returns are computed based on daily exchange rates from Wednesday to Wednesday. Whenever the daily rate is missing on Wednesday, it is replaced with Tuesday rates. The replacement ensures the construction of a continuous weekly return data set.

Another interest-adjusted weekly return series is constructed based on the covered interest rate parity. Choosing the risk free rates is the key in this exercise. For Canada, France, Germany, the U.S., and the U.K., I use three-month government bond interest rates as their risk-free rates. For France, Italy, and Japan, since their short-term government bond rates are not available, I use comparable alternatives as their risk-free rates: three-month interbank interest rates for Italy and the European Union, and bank discount rates for Japan. All interest rates are obtained from the Standard & Poor DRI database.

A. Returns

The base currency returns from week *t*-1 to *t* are computed as follows:

$$R_t = \frac{S_t}{S_{t-1}} - 1, \qquad (8)$$

where R_t is the weekly return, S_t is the spot exchange rate at week *t*, and S_{t-1} is the spot rate at week *t*-1. All exchange rates are the ratio of foreign currencies to the U.S. Dollar.

The interest-adjusted currency returns are also computed. The rationale is based on the covered interest rate parity. To understand the relationship, consider investors that borrow money from foreign countries and invest in the United States, or *vice versa*, they would actually experience these returns. The interest-adjusted returns from week t-1 to t are as follows:

$$R_{I,t} = \frac{S_t}{F_{t-1}} - 1, \qquad (9)$$

where

$$F_{t-1} = S_{t-1} Exp\left[\left(r - r_f\right)_t\right]$$

$R_{I,t}$ is the interest-adjusted return, r is the domestic interest rate, r_f is the foreign interest rate, F_{t-1} is the forward rate in week t-1, and t is the current week. Approximately, the equation can be written as follows:

$$R_{I,t} = \frac{1}{52}(r_f - r_d) + \frac{S_t}{S_{t-1}} - 1. \qquad (10)$$

where $R_{I,t}$ is again the interest-adjusted return, $\frac{1}{52}(r_f - r_d)$ is the weekly interest rate differential between the U.S. (i.e. domestic country) and foreign countries, and $\frac{S_t}{S_{t-1}} - 1$ is the currency return shown in Equation (8).

B. Summary statistics

Table 8 reports the summary statistics of the base returns and the interest-adjusted returns for the full sample period.

[Insert Table 8 here]

Panel A is for the base returns. It is noticeable that Italy experiences the greatest depreciation across the sample period. The Italian Lira has a mean return of 6.21%. In contrast, Japan and the European Union experience the greatest appreciation. The mean returns of Japanese Yen and the Euro are -2.49% and -1.54%, respectively.

The first-order autocorrelation is positive and significant for all currency returns. This indicates strong linear dependence among returns over time. In other words, positive (negative) changes in returns are expected to be followed by positive (negative) changes. The Jarque-Bera tests are highly rejected for all currencies, meaning that returns are not normally distributed. Therefore, the independently identically distribution assumption is not plausible in this analysis.

Panel B reports the interest-adjusted returns. The results are similar: the Japanese Yen experiences the greatest appreciation (-7.43%), while the Italian Lira has the greatest depreciation (16.44%). The first order autocorrelation is significantly positive, and the normality hypothesis is rejected in all cases.

It is noticed that most interest-adjusted returns are larger in magnitude than the base returns. Moreover, five out of seven interest-adjusted returns are significantly different from zero (the exceptions are the Euro and the Deutsche Mark), whereas in the case of base returns, only the Italian Lira has significant non-zero mean returns. The fact that most of currencies have zero mean return in base version but non-zero mean return in interest-adjusted version implies a violation of the interest rate parity. In theory, the gain (loss) of currency appreciation (depreciation) should be compensated by the interest rate differentials. For example, the profits of holding the appreciated Japanese Yen should be offset by the negative interest rate differentials between Japan and the U.S. Similarly, the loss of investing in the depreciated Italian Lira is supposed to be offset by the positive interest rate differentials between Italy and the U.S. However, the evidence in Table 8 suggests that the interest rate parity does not hold for most currencies. In other words, arbitrageurs fail to correct the mispricing in currency transactions, leaving room for trading profits.

III. Trading Strategies and Trading Profits

In this section, momentum (contrarian) strategies are constructed as zero-cost portfolios that buy winners and sell losers (buy losers and sells winner) based on their past performance. This approach is also known as Weighted Relative Strength Strategy (a.k.a. WRSS, Lehmann, 1990; Lo and MacKinlay, 1990; Conrad and Kaul, 1998).

Specifically, the past performance is computed relative to the market performance of an equal-weighted portfolio that contains all N currencies during the time interval $\{t-1, t\}$. A currency that outperforms the market portfolio will be labeled as a "winner", whereas a currency that underperforms the market portfolio will be labeled as a "loser." A momentum (contrarian) strategy is designed to buy winner (loser) currencies at time t based on their performance in $\{t-1, t\}$, and hold them until time $t+1$.

To follow the convention of return-based trading strategies, I define the time interval $\{t-1, t\}$ as ranking period, and $\{t, t+1\}$ as holding period. By construction, the ranking and holding periods can have equal or unequal length. In this exercise, I use both to test the trading profitability. The strategies with unequal ranking and holding periods are designed based on *one* week performance (i.e. $\{t-1, t\}$ = 1) and held for *k* weeks (i.e. $\{t, t+1\}$ = 1, 2, 3, 4, 8, 13, 26, and 52 weeks). The strategies with equal ranking and holding periods are constructed based on the average *k*-week performance (i.e. $\{t-1, t\}$ = 1, 2, 3, 4, 8, 13, 26, and 52 weeks) and held for a matching *k*-week (i.e. $\{t, t+1\}$ = 1, 2, 3, 4, 8, 13, 26, and 52 weeks). A total of thirty-two basic strategies are implemented with the unequal ranking-holding design, sixteen for base returns, and sixteen for interest-adjusted returns. Similarly, another thirty-two strategies are constructed using the equal ranking-holding design.

The average returns of the performance-based portfolios are calculated as trading profits. The expected profits are the sum of the product of the return of each currency at time $t+1$ and the weight $w_{it}(k)$ that is put on each currency. Specifically, the weights are computed as follows:

$$w_{it}(k) = \pm\frac{1}{N}[R_{it}(k) - R_{mt}(k)], \qquad (11)$$

where $w_{it}(k)$ denotes the faction of the portfolio devoted to currency *i* at time *t*, $R_{it}(k)$ is the return on currency *i* at time *t*, *t* = 1, 2, 3 ...N, $R_{mt}(k)$ is the mean return of the equal-weighted portfolio of all *N* currencies ($R_{mt} = \frac{1}{N}\sum_{i=1}^{N} R_{it}$), and *k* is the length of time interval $\{t, t+1\}$.

The expected profits are then calculated as follows:

$$\pi_{t+1}(k) = \sum_{i=1}^{N} w_{it}(k) R_{i,t+1}. \qquad (12)$$

where $\pi_{t+1}(k)$ denotes the dollar profits and $R_{it+1}(k)$ is the return on currency i at time $t+1$. Note that the dollar profits can be arbitrarily scaled by any number. The positive or negative sign of $\pi_{t+1}(k)$ refers to a momentum or contrarian strategy. Inherently, the gain (loss) of a momentum strategy is equivalent to the loss (gain) of a contrarian strategy. This feature allows me to rely on the sign and statistical significance of the average $\pi_{t+1}(k)$ rather than the numeric figures.

The expression of dollar profits essentially captures the universal nature of all trading strategies. First, the positive or negative sign preceding the weights reflects an investor's belief. If the investor believes in price reversal and follows a contrarian strategy, a negative weight will be assigned to the strategies; if he believes in price continuation and follows a momentum strategy, a positive weight will be assigned to the strategies.

Second, the past performance of a currency relative to the market performance (i.e. the average return of all *N* currencies) is supposed to be informative about the future pattern in returns. In other words, no matter if a strategy is contrarian or momentum, its success is based on the time-series behavior of currency returns.

Third, by construction, the dollar weights in Equation (11) lead to an arbitrage (zero-cost) portfolio. The investment in dollars is given by

$$I_t(k) = \frac{1}{2}\sum_{i=1}^{N}|w_{it}(k)|, \qquad (13)$$

where long and short (currencies) are completely offset as follows:

$$\sum_{i=1}^{N} w_{it}(k) = 0 \ \forall k$$

Finally, and most importantly, this method allows me to decompose the trading profits into two components: the time serial autocorrelation of currency returns and the cross sectional difference in mean returns of individual currencies.

Table 9 reports the expected trading profits. Panel A shows the results for pre-Euro subperiod (1971-1998), and Panel B shows the results for post-Euro subperiod (1999-2007).

[Insert Table 9 here]

Many interesting results are found in Table 9. In Panel A, based on *one* week performance and held for *k* weeks (*k* = 1, 2, 3, 4, 8, 13, 26, and 52 weeks), momentum strategies appear to be dominantly profitable. Among thirty-two strategies, eight are statistically significant and all of them are momentum. The significant profits hold up to 13 weeks. The profits from interest-adjusted returns are higher and more significant.

The highest profit is found with the interest-adjusted returns based on a 1-on-3 ranking-holding strategy in the pre-Euro subperiod. The profit is $3.55 for a one-million-dollar contract. Given the huge trading volume, high margin level, and large trade unit of currency contracts, this figure can lead to a reasonable return in the currency market. For example, when buying a typical $125,000 EUR futures contract, if an investor is allowed to use 5% margin (i.e. he only pays $6,250 of his own money for the full contract and loans the rest of 95% from banks or brokers), he will be able to ensure himself an approximate 0.01% monthly return.

Another observation from the Panel A is the profitable momentum strategies only emerge in the first subperiod. With fewer currencies and shorter sample period, the same strategies turn to be contrarian and insignificant in the second subperiod. The pattern is consistent for both base returns and interest-adjusted returns.

In Panel B, the trading strategies are constructed based on *k*-week ranking and held for another *k* weeks ($k = 1, 2, 3, 4, 8, 13, 26, 52$ weeks). More strategies (ten out of thirty-two) appear to be significantly profitable, but the magnitude of profits becomes smaller. Again, the second subperiod only reports insignificant contrarian profits due to the limited sample size. Most momentum profits can hold up to 13 weeks.

Overall, the results suggest that 1) momentum strategies are more likely to be profitable in the foreign exchange market, while contrarian strategies play little role in generating abnormal returns; 2) base returns and interest-adjusted returns report similar patterns of profitability, but profits are higher and more significant when conditional on the interest rate differentials; 3) the past-performance-based strategies are likely to generate significant profits in the short- to medium-run, and the trading profits can hold up to 13 weeks.

IV. Sources of the Trading Profits

The above findings provide supportive evidence to my hypothesis that the Efficient Market Hypothesis is violated in the foreign exchange market. To further understand the sources of market inefficiency, I conduct a decomposition based on the trading profits. Due to the limitation of the strategy construction, I can only decompose the *one*-week-ranking-and-*k*-week-holding strategies. Two components are found to be responsible for the abnormal returns: the time series autocorrelation of currency returns and the cross sectional variation in mean returns.

The decomposition of the expected profits is computed as follows below (Conrad and Kaul, 1998; Lehmann, 1990; Lo and MacKinlay, 1990). Note that a key assumption is that both the mean return of each individual currency and the mean return of the market portfolio must be time invariant.

$$E[\pi_{t+1}(k)] = -Cov\left[R_{m,t+1}(k), R_{mt}(k)\right] + \frac{1}{N}\sum_{i=1}^{N} Cov\left[R_{i,t+1}(k), R_{it}(k)\right]$$

$$+\frac{1}{N}\sum_{i=1}^{N}[\mu_{it}(k) - \mu_{mi}(k)]^2$$

$$= -C_k + O_k + \sigma^2[\mu(k)]$$

$$= P(k) + \sigma^2[\mu(k)] \qquad (14)$$

where $P(k) = -C_k + O_k$ is the predictability – profitability index, $\mu_{it}(k)$ is the unconditional mean return of currency i, and $\mu_{mi}(k) = \frac{1}{N}\sum_{i=1}^{N} \mu_{it}(k)$ is the unconditional mean return of the equal-weighted market portfolio at time t.

Equation (14) shows that the total expected profits result from two parts: the time-series predictability in currency returns, $P(k)$, and the cross-sectional variance in mean returns, $\sigma^2[\mu(k)]$. The former consists of two components: C_k is the negative of kth-order autocovariance of the equal-weighted market portfolio return, and O_k is the average kth-order autocovariance of all N currencies. More specifically,

$$C_k = R_{m,t+1}(k)R_{mt}(k) - \hat{\mu}_{mt}^2(k) - \frac{1}{N^2}\sum_{i=1}^{N}[R_{i,t+1}(k)R_{it}(k) - \hat{\mu}_{it}^2(k)] \qquad (15)$$

$$O_k = \frac{N-1}{N^2}\sum_{i=1}^{N}[R_{i,t+1}(k)R_{it}(k) - \hat{\mu}_{it}^2(k)] \qquad (16)$$

and

$$\sigma^2[\mu(k)] = \frac{1}{N}\sum_{i=1}^{N}[\hat{\mu}_{it}(k) - \hat{\mu}_{mt}(k)]^2. \qquad (17)$$

Again, the key in this decomposition is to assume that individual currency returns are mean stationary, so that each individual currency has a constant mean return of $\hat{\mu}_{it}(k)$. The mean return of the market portfolio (i.e. the portfolio that contains all N currencies), $\hat{\mu}_{mt}(k)$, by definition is also mean stationary.

Table 10 reports the decomposition results for base returns. Panel A shows the first subperiod (1971-1998) and Panel B shows the second subperiod (1999-2007). The first striking finding is that the contribution of $\sigma^2[\mu(k)]$ to the profits is not constantly equal to 100%. This implies that currency returns do not follow a random walk. Therefore, the Efficient Market Hypothesis is evidently violated in the foreign exchange market.

To understand the rationale, consider a benchmark return-generating process (Conrad and Kaul, 1998). Assume that all currency returns follow a random walk:

$$R_{it}(k) = \mu_i(k) + \varepsilon_{it}(k), i = 1, 2, \dots N, \qquad (18)$$

where

$$E[\varepsilon_{it}(k)] = 0 \; \forall i, k \text{ and } E[\varepsilon_{it}(k)\varepsilon_{j,t-1}(k)] = 0 \; \forall \; i, j, k.$$

Also by construction,

$$Cov[R_{it}(k), R_{j,t-1}(k)] = 0 \; \forall \; i, j, k.$$

Therefore, there is no time serial autocorrelation of currency returns or mean return dispersion across different currencies when a random walk prevails. All profit potentials should be ruled out. However, when combined with Equation (14), momentum (contrarian) strategies can still be profitable. In this case, $P(k)$ is equal to zero under the assumption of random walks, and the expected profits are exclusively determined by the cross-sectional dispersion, $\sigma^2[\mu(k)]$. More specifically,

$$E[\pi_{t+1}(k)] = \frac{1}{N}\sum_{i=1}^{N}[\mu_{it}(k) - \mu_{mi}(k)]^2 = \sigma^2[\mu(k)], \qquad (19)$$

To illustrate, take momentum strategies as example. When investors buy winners and simultaneously sell losers, they are longing high mean-return assets and shorting low mean-return assets. Even when the market follows a random walk, meaning there is no profits from autocorrelation, the discrepancy in mean returns can still generate positive excess returns to momentum strategies.

However, the decomposition result in Table 10 shows that the cross-sectional variation does not fully explain the expected profits. Interestingly, the autocorrelation structure accounts for majority part of trading profits and thus market inefficiency. In most cases, the contribution of $P(k)$ exceeds 90%. Some are even greater than 100% because of the reversed effect of mean return variance. The results suggest that the trading profitability is primarily determined by the time-series pattern in returns. This finding is in line with Conrad and Kaul (1998): "... the role of $\sigma^2[\mu(k)]$ has a small effect on profits to trading strategies."

The results of interest-adjusted returns (Table 11) are similar and the reverse effect of mean return variance is even stronger. Again, the time serial predictability dominates the trading profits, while the cross-sectional mean returns variance makes marginal contribution. In general, the findings are consistent with Okunev and White (2003) and Bianchi et al. (2004).

V. Transaction Costs Consideration

It is argued that transaction costs can virtually eliminate any profit potential from trading strategies. Conrad, Gultekin, and Kaul (1997) suggest that a typical 0.2% level of transaction costs is enough to remove any extra profit in the stock market. In the foreign exchange market, Neely and Weller (1999) find that there will be no positive excess returns once a reasonable transaction cost (e.g. one-way transaction cost $c = 0.0001$ or 0.0002) is taken into account on a daily basis. In this section, I examine the effect of transaction costs on the trading profits.

Transaction costs in the over-the-counter foreign exchange market are far less explicit than in the equity or commodity market. Most of the time, currency traders place their orders through a broker, who in turn routes the orders to a market maker (dealer) or an exchange where the orders are actually executed. Within the process, two parties charge fees: the broker charges a commission, and the market maker who executes the orders on the exchange charges a spread. The spread is always a round-trip transaction cost. For instance, assume that a dealer has a EUR/USD spread of 1.2173/75 quoted from a bank. If the dealer widens the spread to 1.2170/78 for his customers, he has marked up the spread by 0.0003 on each side. The spread accounts for a major part of transaction costs in the currency market.

Following the framework of Lehmann (1990), I calculate the transaction costs per currency per week as

$$tc = 2c\left|w_{it} - w_{i,t-1}\right|, \qquad (20)$$

where c is the one-way transaction cost per dollar transaction (c = 0.0001), w_{it} is the number of dollars invested in currency i at time t, and $w_{i,t-1}$ is the number of dollars invested in currency i at time t-1. Using the multiplier 2 preceding c is because the transaction cost in the foreign exchange market is usually a round-trip cost.

The break-even percentage of transaction costs is computed by dividing the total average profits by the respective transaction costs. The results are reported in the leftmost columns in Table 10 and Table 11. In most cases, the percentages of transaction costs that are required to eliminate the profits are twice as big as the profit figures. Sometime the coverage extends to 5 or 6 times bigger.

The results are plausible in reality. Typically, a large institutional trader faces a 2 to 3 basis points spread charge per one-way in currency trading (Neely and Weller, 1999). In addition to the spread, a commission fee of 1 to 2 basis points per transaction would be a reasonable charge. In total the transaction costs will be no more than 5 basis points per transaction one-way. If the institutional trader implements the trading strategies specified earlier, by holding the portfolio for a certain period of time (k = 1, 2, 3, 4, 8, 13, 26, and 52 weeks), he is entitled to a one-time round-trip transaction cost for each currency. The sum of transaction costs for holding all N currencies is still not large enough to eliminate the trading profitability. It is theoretically possible because the designated trading strategies commit merely one transaction for each currency, and fewer transactions help the strategies remain profitable. Overall, the results suggest that the trading profits cannot be ruled out by transaction costs.

CONCLUSIONS

This dissertation, by employing different trading strategies, addresses the trading profitability issue in a broad scope of different markets. In the equity market, I construct a group of decile portfolios that buy (sell) the top 10% winner stocks and sell (buy) the bottom 10% loser stocks based on their prior returns. The former is known as momentum strategies, and the latter is known as contrarian strategies. In the foreign exchange market, I employ a different past-performance-based Weighted Relative Strength Strategy. In this method, the winners and losers are determined by their weights relative to the market performance of an equal-weighted market portfolio, and trading profits are computed as the sum of the product of the weights and future returns.

Both methods reveal significant trading profits in respective markets. By trading the *BUY-SELL* decile portfolios, I find that both contrarian and momentum strategies are significantly profitable. Unconditionally, the contrarian strategies report a 1.95% monthly return ($t = 8.03$), and the momentum strategies have a monthly return of 0.91% ($t = 3.38$). The WRSS strategies uncover similar profitability in the foreign exchange market. Eighteen out of a total of sixty-four basic strategies generate significant trading profits, and all of them are momentum.

Further efforts are made to investigate the sources of the profitability. In the equity market, there shows a clear pattern between investor sentiment and trading profits. Three popular investor sentiment proxies are used to test the relationship: 1) a reduced-formed sentiment index *BW1* that is constructed by Baker and Wurgler (2006); 2) a similar but orthogonized index *BW2*; and 3) the survey-based University of Michigan Consumer Confidence Index *UM*.

Several findings are revealed on the relationship between investor sentiment and trading profits. First, the extreme sentiment levels (either optimistic or pessimistic) tend to be followed by higher contrarian profits. Specifically, when the previous sentiment is at extreme levels, subsequent contrarian profits are approximately twice as high as the case where prior sentiment levels are modest. The difference in the mean profits is statistically significant. Also, contrarian profits are high when investor sentiment shifts from extreme to modest levels. These results are robust for all three sentiment proxies, and are consistent with the overreaction hypothesis.

Second, the past loser stocks are more important in determining the average contrarian profits. It is found that loser portfolios contribute significant returns to the contrarian profits, whereas winner portfolio returns are not statistically different from zero. This suggests that loser and winner stocks have asymmetrical responses to the extreme sentiment levels. It provides further support to the overreaction hypothesis.

Third, in terms of momentum strategies, the profits appear to be negatively related with the lagged average 6-month sentiment levels. In other words, the extreme sentiment levels are expected to be followed by lower subsequent momentum profits. The negative relationship between the extreme sentiment levels and momentum profits persists even after controlling for Fama-French factors. This finding helps clarify the core implications of several behavioral models, such as investor overconfidence and self-attribution bias.

Fourth and lastly, in contrast to contrarian profits, momentum profits largely result from buying former winner stocks. Selling former loser stocks only makes marginal contribution. The evidence is particularly strong under the bullish sentiment reading. Again, this can be explained by the theory that loser and winner stocks respond asymmetrically to the extreme sentiment levels.

Although investor sentiment seems to be a reliable explanation for the abnormal trading profits, it only works well in the domestic environment. In the context of global economy, it is difficult to summarize an index to represent the general sentiment among investors across the world. Therefore, in the context of currency transactions, it is more plausible to investigate the sources of trading profits based on the underlying characteristics of currency returns.

In the foreign exchange market, I look into two possible candidate explanations for the trading profitability: the autocorrelation structure of currency returns and the cross sectional difference in mean returns of individual currencies.

Some interesting results are discovered. First, it is shown that momentum strategies are dominantly profitable in the foreign exchange market. Among sixty-four formed strategies, eighteen are significantly profitable and all of them are momentum. Contrarian profits mostly appear in the post-Euro era (1999-2007), but none of them are statistically significant. When using the interest-adjusted returns, more momentum strategies turn out to be profitable and the momentum profits can hold up to 13 weeks.

Second, after decomposing the trading profits, I find that both the autocorrelation structure for the currency returns and the cross-sectional difference in mean returns are responsible for the abnormal returns. Moreover, the autocorrelation accounts for the majority part of the profits. Therefore, it is safe to suggest that the time serial autocorrelation is the determining source for market inefficiency.

Third and lastly, the profits remain significant even when transaction costs come into effect. Transaction cost in this case is defined as the sum of commissions and bid-ask spreads. It is shown that on average, the break-even transaction costs are twice as big as the trading profits. A one-way transaction cost $c = 0.0001$ (or a round-trip $c = 0.0002$) does not cancel out the profitability.

Overall, the empirical findings in both the stock market and the foreign exchange market suggest that 1) by following certain trading rules, investors can indeed achieve abnormal returns; 2) investor sentiment, in addition to firm-specific risks, provides behavioral explanations to the profitability in the equity market; 3) due to the difficulty of generalizing investor sentiment in the global context, the underlying autocorrelation structure of currency returns and the cross sectional dispersion in mean returns of individual currencies are responsible to for the trading profits in the foreign exchange market. More importantly, the time serial autocorrelation plays a critical role in determining trading profits and accounting for market inefficiency.

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Table 1 Summary Statistics: Sentiment Proxies

Panel A reports the summary statistics for three sentiment proxies. *BW1* stands for a sentiment index compiled by Baker and Wurgler (2006). *BW2* is similar to *BW1* but is orthogonal to macroeconomic variables. Both are standardized to have unit mean and standard deviation. *UM* is the University of Michigan Consumer Sentiment Index. *BW1* and *BW2* range from January 1966 to December 2007. *UM* ranges from January 1978 to December 2007. Panel B reports the correlation matrix of the three sentiment proxies.

Panel A: Summary Statistics

	N	*Mean*	*Std Dev*	*Min*	*Max*
*BW*1	504	0.00	1.00	-2.50	2.33
*BW*2	504	0.00	1.00	-2.39	2.93
UM	360	88.00	12.07	51.70	112.00

Panel B: Correlation Matrix

*BW*1	*BW2*	*UM*
1		
0.94261	1	
0.23417	0.06124	1

Table 2 Sentiment and Contrarian Profits

Panel A reports the contrarian profits conditioning on three sentiment proxies. *BW1* stands for a sentiment index compiled by Baker and Wurgler (2006). *BW2* is similar to *BW1* but is orthogonal to macroeconomic variables. *UM* is the University of Michigan Consumer Sentiment Index. *BW1* and *BW2* range from January 1966 to December 2007. *UM* is from January 1978 to December 2007. Contrarian strategies are constructed by buying past loser stocks and selling past winner stocks based on *one*-month lagged returns and held for another month (Jegadeesh and Titman, 1993). Average monthly returns are reported as trading profits. Skip-one-month results are also included. The conditional profits are reported in the cases where lagged sentiment levels are either extreme or modest. Specifically, $I_{t-1} = 1$ when the lagged sentiment reading is extreme (above 75^{th} percentile or below 25^{th} percentile); $I_{t-1} = 0$ when the lagged sentiment reading is modest (between 25^{th} percentile and 75^{th} percentile). The *t*-statistics of the mean contrarian profit spread between extreme and modest investor sentiment levels are reported. Panel B reports the returns on winner and loser portfolios conditional on whether lagged sentiment values are bullish (larger than 75^{th} percentile) or bearish (less than 25^{th} percentile). The *t*-statistics are reported in the parentheses.

Table 2 (Continued)

Panel A: Sentiment and Contrarian Profits							
		Ranking-Holding: 1-on-1			*Skip-one-month*		
Full Sample		N	π		N	π	
		503	0.0195		502	-0.0016	
			(8.03)			(-0.82)	
Sentiment Proxies		N	π	Spread *t-stat*	N	π	Spread *t-stat*
BW1	$I_{t-1} = 1$	252	0.0272	3.02	251	-0.0025	-0.49
			(6.96)			(-0.87)	
	$I_{t-1} = 0$	251	0.0118		251	-0.0006	
			(4.21)			(0.26)	
BW2	$I_{t-1} = 1$	252	0.0261	2.60	251	-0.0010	0.30
			(6.52)			(-0.32)	
	$I_{t-1} = 0$	251	0.0129		251	-0.0021	
			(4.80)			(-1.00)	
UM	$I_{t-1} = 1$	179	0.0178	2.69	179	0.0006	1.06
			(3.87)			(0.16)	
	$I_{t-1} = 0$	180	0.0110		180	-0.0027	
			(4.04)			(-1.19)	

Table 2 (Continued)

Panel B: Sentiment and Winner and Loser Portfolio Returns				
Full Sample			*Bullish Sentiment*	*Bearish Sentiment*
	Loser	0.0221		
		(5.74)		
	Winner	0.0025		
		(0.95)		
Sentiment Proxies			*Bullish Sentiment*	*Bearish Sentiment*
BW1	Loser		0.0181	0.0413
			(2.35)	(4.44)
	Winner		-0.0008	0.0058
			(-0.16)	(0.93)
BW2	Loser		0.0176	0.0420
			(2.21)	(4.50)
	Winner		-0.0021	0.0094
			(-0.40)	(1.53)
UM	Loser		0.0127	0.0329
			(1.40)	(3.28)
	Winner		0.0007	0.0092
			(0.14)	(1.28)

Table 3 Contrarian Profits and Changes in Sentiment

Panel A reports the average contrarian profits conditional on the changes in investor sentiment. A dummy variable I_t is used to define the sentiment reading. $I_t = 1$ if sentiment reading is larger than 75th percentile or less than 25th percentile. $I_t = 0$ if sentiment reading is between 25th percentile and 75th percentile. $\Delta I_t \equiv I_t - I_{t-1}$ is the first order difference of I_t. $\Delta I_t = 1$ when investor sentiment swings up to extremes, and $\Delta I_t = -1$ when investor sentiment swings back to modest. $\Delta I_t = 0$ means there is no discernable change in investor sentiment. *BW1*, *BW2*, and *UM* are three sentiment proxies. Average monthly returns are reported as trading profits when $\Delta I_t = -1$, 0, and 1. The *t*-statistics of the mean contrarian profit spread between $\Delta I_t = -1$ and $\Delta I_t = 1$ are also reported. The rightmost columns are skip-one-month results. Panel B presents the mean returns of losers and winners portfolios in the following four cases. Case 1: Sentiment is bullish (greater than 75th percentile) in both month *t*-1 and month *t*. Case 2: Sentiment is bullish (greater than 75th percentile) in month *t*-1 and but not bullish (less than 75th percentile) in month *t*. Case 3: Sentiment is bearish (less than 25th percentile) in both month *t*-1 and month *t*. Case 4: Sentiment is bearish (less than 25th percentile) in month *t*-1 but not bearish (greater than 25th percentile) in month *t*. The *t*-statistics are reported in the parentheses.

Table 3 (Continued)

Panel A: Changes in Sentiment and Contrarian Profits							
		Ranking-Holding: 1-on-1			*Skip-one-month*		
Sentiment Proxies		N	π	Spread *t-stat*	N	π	Spread *t-stat*
BW1	$\Delta I_t = -1$	17	0.0140		17	0.0040	
			(1.65)			(0.51)	
	$\Delta I_t = 0$	470	0.0204	1.06	469	-0.0019	0.21
			(7.95)			(-0.94)	
	$\Delta I_t = 1$	16	0.0009		16	0.0012	
			(0.10)			(0.10)	
BW2	$\Delta I_t = -1$	27	0.0162		27	0.0034	
			(1.19)			(0.39)	
	$\Delta I_t = 0$	450	0.0203	0.44	449	-0.0016	0.85
			(7.93)			(-0.79)	
	$\Delta I_t = 1$	26	0.0100		26	-0.0064	
			(1.34)			(-0.84)	
UM	$\Delta I_t = -1$	34	0.0197		34	0.0094	
			(1.37)			(0.71)	
	$\Delta I_t = 0$	290	0.0139	4.65	290	-0.0028	0.90
			(5.10)			(-1.23)	
	$\Delta I_t = 1$	35	0.0125		35	0.0030	
			(1.91)			(0.63)	

Table 3 (Continued)

Panel B: Changes in Sentiment and Winner and Loser Portfolio Returns					
Sentiment Proxies		*Case 1*	*Case 2*	*Case 3*	*Case 4*
BW1	Loser	0.0188	0.0075	0.0411	0.0439
		(2.33)	(0.33)	(4.15)	(2.06)
	Winner	-0.0012	0.0047	0.0047	0.0199
		(-0.23)	(0.28)	(0.71)	(1.44)
BW2	Loser	0.0173	0.0200	0.0409	0.0523
		(2.00)	(1.04)	(4.16)	(1.67)
	Winner	-0.0039	0.0124	0.0074	0.0268
		(-0.70)	(0.85)	(1.10)	(2.26)
UM	Loser	0.0071	0.0299	0.0283	0.0626
		(0.80)	(1.20)	(2.53)	(3.31)
	Winner	-0.0016	0.0078	0.0033	0.0471
		(-0.24)	(1.06)	(0.43)	(3.16)

Table 4 Contrarian Profits, Sentiment, and Fama-French Factors

Panel A reports the results from the following OLS regression:

$$CP_t = \beta_0 + \beta_1 I_{t-1} + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t.$$

Panel B reports the results from the following OLS regression:

$$CP_t = \beta_0 + \beta_1 \Delta I_t + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t.$$

CP_t denotes contrarian profits at time t based on *one*-month lagged returns and held for *one* month. I_{t-1} is a dummy variable. $I_{t-1} = 1$ if the sentiment reading is above 75^{th} percentile or below 25^{th} percentile; $I_{t-1} = 0$ if the sentiment reading is between 25^{th} percentile and 75^{th} percentile. $\Delta I_t \equiv I_t - I_{t-1}$ measures the change in sentiment. RM_t, SMB_t, and HML_t are the Fama-French factors. I use three sentiment proxies, *BW1*, *BW2*, and *UM* to calculate I_{t-1} and ΔI_t. In Panel C and Panel D, I rerun the same regressions except that I replace I_{t-1} and ΔI_t with D_{t-1} and ΔD_t, where $D_t \equiv |S^t - \mu^S|$ and S^t is the sentiment value at time t and μ^S is the sample mean. The t-statistics are reported in the parentheses.

Table 4 (Continued)

Panel A: Lagged Sentiment Levels					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.01182	0.01537			
	(3.47)	(3.19)			
	0.01053	0.01320	0.00238	0.00536	0.00136
	(3.34)	(2.95)	(4.29)	(7.44)	(1.61)
BW2	0.01289	0.01324			
	(3.77)	(2.74)			
	0.01181	0.01050	0.00243	0.00535	0.00147
	(3.72)	(2.34)	(4.35)	(7.38)	(1.74)
UM	0.01096	0.00680			
	(2.92)	(1.28)			
	0.00930	0.00720	0.00194	0.00414	-0.00005
	(2.58)	(1.44)	(2.95)	(4.91)	(-0.05)

Table 4 (Continued)

Panel B: Changes in Sentiment					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.01951	-0.00616			
	(8.02)	(-0.65)			
	0.01696	-0.00037	0.00240	0.00554	0.00168
	(7.38)	(-0.04)	(4.26)	(7.64)	(1.99)
BW2	0.01952	-0.00311			
	(8.02)	(-0.41)			
	0.01696	-0.00179	0.00239	0.00554	0.00169
	(7.38)	(-0.26)	(4.26)	(7.65)	(2.00)
UM	0.01435	-0.00357			
	(5.39)	(-0.59)			
	0.01289	-0.00231	0.00197	0.00408	-0.00006
	(4.93)	(-0.40)	(2.98)	(4.83)	(-0.06)

Table 4 (Continued)

Panel C: Lagged Sentiment Levels Based on Deviation from the Mean					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.00744	0.01613			
	(2.01)	(4.32)			
	0.00476	0.01647	0.00257	0.00536	0.00134
	(1.39)	(4.78)	(4.68)	(7.54)	(1.62)
BW2	0.01047	0.01244			
	(2.89)	(3.40)			
	0.00860	0.01166	0.00252	0.00534	0.00143
	(2.56)	(3.43)	(4.55)	(7.40)	(1.71)
UM	0.00944	0.00051			
	(2.17)	(1.42)			
	0.00872	0.00044	0.00191	0.00408	-0.00012
	(2.11)	(1.30)	(2.90)	(4.84)	(-0.12)

Table 4 (Continued)

Panel D: Changes in Sentiment Based on Deviation from the Mean					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.01958	-0.02792			
	(8.06)	(-1.38)			
	0.01710	-0.01586	0.00231	0.00564	0.00171
	(7.45)	(-0.84)	(4.09)	(7.78)	(2.03)
BW2	0.01962	-0.00998			
	(8.06)	(-0.79)			
	0.01709	-0.00949	0.00235	0.00564	0.00172
	(7.45)	(-0.82)	(4.20)	(7.78)	(2.04)
UM	0.01434	0.00018			
	(5.38)	(0.26)			
	0.01281	0.00062	0.00204	0.00411	-0.00003
	(4.90)	(0.90)	(3.07)	(4.87)	(-0.03)

Table 5 Sentiment and Momentum Profits

Panel A reports average 6-month momentum profits conditioning on three sentiment proxies. *BW1* stands for a sentiment index compiled by Baker and Wurgler (2006). *BW2* is similar to *BW1* but is orthogonal to macroeconomic variables. *UM* is the University of Michigan Consumer Sentiment Index. *BW1* and *BW2* range from January 1966 to December 2007. *UM* is from January 1978 to December 2007. Momentum strategies are constructed by buying past winner stocks and selling past loser stocks based on *six*-month lagged returns and held for another *six* months (Jegadeesh and Titman, 1993). Average monthly returns are reported as trading profits. Skip-one-month results are also included. The conditional profits are reported in the cases where lagged sentiment levels are either extreme or modest. Specifically, $I_{t-1}^{6} = 1$ when lagged 6-month average sentiment reading is extreme (above 75th percentile or below 25th percentile); $I_{t-1}^{6} = 0$ when lagged 6-month average sentiment reading is modest (between 25th percentile and 75th percentile). The *t*-statistics of the difference in the means of momentum profits under extreme and modest investor sentiment readings are also reported. Panel B reports the returns on winner and loser portfolios conditional on whether lagged 6-month average sentiment values are bullish (larger than 75th percentile) or bearish (less than 25th percentile). The *t*-statistics are reported in the parentheses.

Table 5 (Continued)

Panel A: Sentiment and Momentum Profits							
		Ranking-Holding: 6-on-6			*Skip-one-month*		
Full Sample		N	π		N	π	
		498	0.0091		497	0.0114	
			(3.38)			(4.57)	
Sentiment Proxies		N	π	Spread *t-stat*	N	π	Spread *t-stat*
BW1	$I_{t-1}^{6} = 1$	249	0.0078		248	0.0102	
			(1.89)	-0.47		(2.72)	-0.47
	$I_{t-1}^{6} = 0$	249	0.0104		249	0.0126	
			(3.00)			(3.82)	
BW2	$I_{t-1}^{6} = 1$	249	0.0043		248	0.0065	
			(0.99)	-1.79		(1.65)	-1.93
	$I_{t-1}^{6} = 0$	249	0.0140		249	0.0162	
			(4.33)			(5.37)	
UM	$I_{t-1}^{6} = 1$	176	0.0095		176	0.0124	
			(1.78)	-0.47		(2.51)	-0.12
	$I_{t-1}^{6} = 0$	178	0.0123		178	0.0129	
			(4.18)			(4.45)	

Table 5 (Continued)

Panel B: Sentiment and Winner and Loser Portfolio Returns				
Full Sample			*Bullish Sentiment*	*Bearish Sentiment*
	Winner	0.0164		
		(6.01)		
	Loser	0.0073		
		(1.84)		
Sentiment Proxies			*Bullish Sentiment*	*Bearish Sentiment*
BW1	Winner		0.0164	0.0214
			(3.05)	(3.49)
	Loser		0.0025	0.0197
			(0.30)	(2.22)
BW2	Winner		0.0110	0.0222
			(2.01)	(3.72)
	Loser		-0.0006	0.0253
			(-0.07)	(2.73)
UM	Winner		0.0142	0.0275
			(2.49)	(3.64)
	Loser		-0.0018	0.0245
			(-0.20)	(2.37)

Table 6 Momentum Profits and Changes in Sentiment

Panel A reports the average momentum profits conditional on the changes in investor sentiment. A dummy variable I_t^6 is used to define the sentiment reading. $I_t^6 = 1$ if average 6-month sentiment reading is larger than 75th percentile or less than 25th percentile. $I_t^6 = 0$ if average 6-month sentiment reading is between 25th percentile and 75th percentile. $\Delta I_t^6 \equiv I_t^6 - I_{t-1}^6$ is the first order difference of I_t^6. Note that *t*-1 is the 6-month ranking period and *t* is the 6-month holding period. $\Delta I_t^6 = 1$ when investor sentiment swings up to extremes, and $\Delta I_t^6 = -1$ when investor sentiment swings back to modest. $\Delta I_t^6 = 0$ means there is no discernable change in investor sentiment. *BW1*, *BW2*, and *UM* are three sentiment proxies. Average monthly returns are reported as trading profits when $\Delta I_t^6 = -1$, 0, and 1. The *t*-statistics of the mean contrarian profit spread between $\Delta I_t^6 = -1$ and $\Delta I_t^6 = 1$ are also reported. The rightmost columns are skip-one-month results. Panel B presents the mean returns of losers and winners portfolios in the following four cases. Case 1: Sentiment is bullish (greater than 75th percentile) in both month *t*-1 and month *t*. Case 2: Sentiment is bullish (greater than 75th percentile) in month *t*-1 and but not bullish (less than 75th percentile) in month *t*. Case 3: Sentiment is bearish (less than 25th percentile) in both month *t*-1 and month *t*. Case 4: Sentiment is bearish (less than 25th percentile) in month *t*-1 but not bearish (greater than 25th percentile) in month *t*. The *t*-statistics are reported in the parentheses.

Table 6 (Continued)

Panel A: Changes in Sentiment and Momentum Profits							
		Ranking-Holding: 6-on-6			*Skip-one-month*		
Sentiment Proxies		*N*	π	Spread *t-stat*	*N*	π	Spread *t-stat*
BW1	$\Delta I_t^6 = -1$	11	0.0241		11	0.0249	
			(2.17)			(2.15)	
	$\Delta I_t^6 = 0$	477	0.0093	1.94	476	0.0116	1.81
			(3.35)			(4.57)	
	$\Delta I_t^6 = 1$	10	-0.0156		10	-0.0151	
			(-0.84)			(-0.74)	
BW2	$\Delta I_t^6 = -1$	10	0.0246		10	0.0259	
			(2.56)			(2.74)	
	$\Delta I_t^6 = 0$	479	0.0089	1.37	478	0.0111	0.90
			(3.20)			(4.30)	
	$\Delta I_t^6 = 1$	9	0.0033		9	0.0125	
			(0.26)			(1.03)	
UM	$\Delta I_t^6 = -1$	11	0.0193		11	0.0198	
			(2.21)			(2.56)	
	$\Delta I_t^6 = 0$	332	0.0104	0.13	332	0.0122	0.12
			(3.26)			(4.07)	
	$\Delta I_t^6 = 1$	11	0.0165		11	0.0169	
			(1.51)			(1.58)	

Table 6 (Continued)

Panel B: Changes in Sentiment and Winner and Loser Portfolio Returns					
Sentiment Proxies		*Case 1*	*Case 2*	*Case 3*	*Case 4*
BW1	Winner	0.0170	0.0051	0.0210	0.0311
		(3.10)	(0.17)	(3.38)	(0.78)
	Loser	0.0036	-0.0195	0.0202	0.0077
		(0.42)	(-0.57)	(2.20)	(0.34)
BW2	Winner	0.0105	0.0236	0.0228	0.0079
		(1.90)	(0.62)	(3.68)	(1.01)
	Loser	0.0003	-0.0212	0.0263	0.0033
		(0.03)	(-0.61)	(2.72)	(0.20)
UM	Winner	0.0133	0.0249	0.0263	0.0517
		(2.21)	(1.43)	(3.34)	(5.68)
	Loser	-0.0015	-0.0060	0.0231	0.0527
		(-0.15)	(-0.36)	(2.15)	(2.47)

Table 7 Momentum Profits, Sentiment, and Fama-French Factors

Panel A reports the results from the following OLS regression:

$$MP_t = \beta_0 + \beta_1 I^6_{t-1} + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t.$$

Panel B reports the results from the following OLS regression:

$$MP_t = \beta_0 + \beta_1 \Delta I^6_t + \beta_2 RM_t + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_t.$$

MP_t denotes momentum profits at time t based on *six*-month lagged returns and held for *six* months. I^6_{t-1} is a dummy variable. I^6_{t-1}= 1 if the sentiment reading is above 75th percentile or below 25th percentile; I^6_{t-1}= 0 if the sentiment reading is between 25th percentile and 75th percentile. $\Delta I^6_t \equiv I^6_t - I^6_{t-1}$ measures the change in sentiment. RM_t, SMB_t, and HML_t are the Fama-French factors. I use three sentiment proxies, *BW1*, *BW2*, and *UM* to calculate I^6_{t-1} and ΔI^6_t. In Panel C and Panel D, I rerun the same regressions except that I replace I^6_{t-1} and ΔI^6_t with D^6_{t-1} and ΔD^6_t, where $D^6_t \equiv |S^6_t - \mu^S|$ and S^6_t is the sentiment value at time t and μ^S is the sample mean. The t-statistics are reported in the parentheses.

Table 7 (Continued)

Panel A: Lagged Sentiment Levels					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.01041	-0.00258			
	(2.73)	(-0.48)			
	0.01072	0.00345	-0.00182	-0.00637	-0.00360
	(2.98)	(0.68)	(-2.90)	(-7.72)	(-3.79)
BW2	0.01397	-0.00970			
	(3.67)	(-1.80)			
	0.01421	-0.00365	-0.00186	-0.00619	-0.00348
	(3.96)	(-0.72)	(-2.95)	(-7.51)	(-3.65)
UM	0.01225	-0.00273			
	(2.86)	(-0.45)			
	0.01316	-0.00189	-0.00118	-0.00371	-0.00122
	(3.10)	(-0.32)	(-1.52)	(-3.70)	(-1.03)

Table 7 (Continued)

Panel B: Changes in Sentiment					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.00908	-0.01958			
	(3.37)	(-1.49)			
	0.01232	-0.01606	-0.00182	-0.00627	-0.00345
	(4.77)	(-1.31)	(-2.89)	(-7.70)	(-3.62)
BW2	0.00909	-0.01093			
	(3.37)	(-0.79)			
	0.01239	-0.01002	-0.00186	-0.00626	-0.00352
	(4.79)	(-0.78)	(-2.96)	(-7.69)	(-3.71)
UM	0.01090	-0.00142			
	(3.59)	(-0.12)			
	0.01226	-0.00339	-0.00120	-0.00373	-0.00128
	(3.96)	(-0.28)	(-1.54)	(-3.72)	(-1.08)

Table 7 (Continued)

Panel C: Lagged Sentiment Levels Based on Deviation from the Mean					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.01404	-0.00656			
	(3.35)	(-1.53)			
	0.01550	-0.00414	-0.00188	-0.00620	-0.00347
	(3.93)	(-1.03)	(-2.98)	(-7.57)	(-3.64)
BW2	0.01430	-0.00713			
	(3.52)	(-1.70)			
	0.01507	-0.00368	-0.00188	-0.00618	-0.00347
	(3.92)	(-0.93)	(-2.98)	(-7.51)	(-3.64)
UM	0.01090	0.00000			
	(2.19)	(0.00)			
	0.01164	0.00007	-0.00120	-0.00372	-0.00125
	(2.37)	(0.16)	(-1.54)	(-3.71)	(-1.06)

Table 7 (Continued)

Panel D: Changes in Sentiment Based on Deviation from the Mean					
Sentiment Proxies	β_0	β_1	β_2	β_3	β_4
BW1	0.00915	0.01294			
	(3.38)	(0.34)			
	0.01244	-0.00080	-0.00184	-0.00628	-0.00355
	(4.79)	(-0.02)	(-2.92)	(-7.70)	(-3.73)
BW2	0.00910	-0.01071			
	(3.36)	(-0.33)			
	0.01240	-0.01225	-0.00185	-0.00628	-0.00353
	(4.78)	(-0.41)	(-2.93)	(-7.70)	(-3.72)
UM	0.01090	-0.00040			
	(3.59)	(-0.17)			
	0.01224	-0.00061	-0.00119	-0.00372	-0.00124
	(3.96)	(-0.26)	(-1.53)	(-3.72)	(-1.05)

Table 8 Summary Statistics of Currency Returns

This table reports the weekly currency returns that are continuously compounded from Wednesday to Wednesday based on daily exchange rates. Seven returns are reported. They are for G7 countries (namely, Canada, France, Germany, Italy, Japan, the U.K., and the U.S.) and the European Union. U.S. dollars are used as the base currency. The sample period ranges from January 1st, 1971 to December 31st, 2007. Panel A shows the descriptive statistics of the base returns. The base returns are computed as $R_t = \frac{S_t}{S_{t-1}} - 1$. Panel B shows the descriptive statistics of the interest-adjusted returns. The interest-adjusted returns are computed as $R_{I,t} = \frac{1}{52}(r_f - r_d) + \frac{S_t}{S_{t-1}} - 1$. The Jarque-Bera test of normality is computed based on skewness and excess kurtosis with Chi-square distributed with two degrees of freedom.

Table 8 (Continued)

Panel A: Base Returns							
	Canada	*European Union*	*France*	*Germany*	*Italy*	*Japan*	*UK*
N	1931	470	1460	1461	1461	1929	1931
Mean (%)	0.70	-1.54	3.35	1.86	6.21	-2.49	3.51
Median (%)	0.99	-4.78	0.00	-1.77	1.46	2.64	-0.54
Std Dev	0.0067	0.0122	0.0143	0.0137	0.0096	0.0134	0.0128
t-stat	0.46	-0.27	0.90	0.52	2.48	-0.82	1.21
Skewness	0.18	0.26	0.47	0.24	1.94	-0.39	0.52
Kurtosis	3.78	0.31	3.89	3.98	20.92	3.62	4.09
Auto-correlation							
1	0.0178	0.0121	0.0093	0.0216	0.2051	0.0509	0.0453
2	0.0719	-0.0111	0.0311	0.0837	0.2440	0.0580	0.0147
3	-0.0175	0.0433	0.0474	0.0207	0.2269	0.0492	0.0307
4	-0.0017	0.0320	0.0116	-0.0441	0.0451	0.0123	0.0161
5	-0.0417	0.0661	-0.0186	0.0256	0.0903	0.0175	0.0566
6	0.0294	-0.0220	-0.0290	-0.0226	0.0385	-0.0306	0.0038
7	0.0065	-0.0216	0.0129	0.0118	0.0345	0.0018	-0.0065
8	-0.0402	-0.0151	0.0612	0.0445	0.0510	0.0148	0.0154
9	0.0222	-0.0074	0.0080	0.0218	-0.0040	-0.0390	-0.0086
10	-0.0197	0.0624	-0.0135	0.0483	0.0617	0.0038	-0.0086
Jarque-Bera	1160.13	7.25	976.09	978.36	27572.31	1100.90	1433.94
	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 8 (Continued)

Panel B: Interest-adjusted Returns							
	Canada	*European Union*	*France*	*Germany*	*Italy*	*Japan*	*UK*
N	1931	470	1460	1461	1461	1929	1931
Mean (%)	3.92	-1.81	9.66	1.14	16.44	-7.43	8.08
Median (%)	3.58	-7.09	7.11	-0.74	11.37	0.69	2.73
Std Dev	0.0068	0.0122	0.0143	0.0136	0.0096	0.0133	0.0128
t-stat	2.55	-0.32	2.59	0.32	6.54	-2.45	2.78
Skewness	0.17	0.27	0.47	0.24	2.03	-0.42	0.54
Kurtosis	3.83	0.33	3.92	4.04	21.40	3.69	4.19
Auto-correlation							
1	0.0189	0.0079	0.0081	0.0180	0.2127	0.0471	0.0432
2	0.0728	-0.0154	0.0301	0.0804	0.2511	0.0540	0.0122
3	-0.0167	0.0392	0.0466	0.0175	0.2338	0.0455	0.0285
4	-0.0011	0.0278	0.0111	-0.0473	0.0534	0.0087	0.0139
5	-0.0411	0.0622	-0.0188	0.0228	0.0984	0.0138	0.0544
6	0.0305	-0.0264	-0.0294	-0.0254	0.0469	-0.0344	0.0021
7	0.0081	-0.02589	0.0127	0.0091	0.0432	-0.0020	-0.0081
8	-0.0387	-0.0193	0.0612	0.0419	0.0596	0.0112	0.0139
9	0.0236	-0.0115	0.0081	0.0193	0.0054	-0.0428	-0.0099
10	-0.0184	0.0586	-0.0135	0.04583	0.0709	0.0002	-0.0100
Jarque-Bera	1191.70	7.72	987.80	1007.01	28871.47	1148.63	1509.09
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 9 Average Profits to Past Performance-Based Trading Strategies

This table reports average profits to zero-cost trading strategies that buy winners and sell losers based on their past performance. The past performance is computed relative to the performance of an equal-weighted index of all *N* currencies. Eight basic strategies are implemented in each of the two subperiods, respectively. The first subperiod ranges from January 1st, 1971 to December 31st, 1998, and the second subperiod ranges from January 1st, 1999 to December 31st, 2007. The dollar profits are computed as $\pi_{t+1}(k) = \sum_{i=1}^{N} w_{it}(k) R_{i,t+1}, i = 1, 2, 3, \ldots N$, where $w_{it}(k) = \pm\frac{1}{N}[R_{it}(k) - R_{mt}(k)]$ denotes the faction of the portfolio devoted to currency *i* at time *t*, $R_{it}(k)$ is the return on currency *i* at time *t*, $R_{mt}(k)$ is the return on the equal-weighted portfolio of all *N* currencies ($R_{mt} = \frac{1}{N}\sum_{i=1}^{N} R_{it}$), and *k* is the length of ranking/holding time interval. The positive (negative) sign of $\pi_{t+1}(k)$ refers to a momentum (contrarian) strategy. Panel A reports the trading strategies that are constructed based on *one*-week ranking and held for *k* weeks (*k* = 1, 2, 3, 4, 8, 13, 26, and 52 weeks). Panel B reports the trading strategies that are constructed based on *k*-week ranking and held for another *k* weeks (*k* = 1, 2, 3, 4, 8, 13, 26, and 52 weeks). The first two columns are for base returns; the last two columns are for interest-adjusted returns. *t*-statistics are shown in the parentheses. All profits are multiplied by 10^6.

Table 9 (Continued)

Panel A: *one*-week-ranking-and-*k*-week-holding Strategies				
	Base Returns		*Interest-adjusted Returns*	
Ranking-Holding	*1971-1998*	*1999-2007*	*1971-1998*	*1999-2007*
1 – 1	0.24	1.10	0.77	1.04
	(0.16)	(0.59)	(0.51)	(0.56)
1 – 2	2.96**	-0.81	3.48***	-0.86
	(2.23)	(-0.44)	(2.61)	(-0.48)
1 – 3	3.03***	-0.84	3.55***	-0.90
	(2.33)	(-0.45)	(2.70)	(-0.48)
1 – 4	1.19	-1.02	1.72	-1.06
	(0.99)	(-0.54)	(1.42)	(-0.57)
1 – 8	2.53**	-2.41	3.08***	-2.45
	(2.25)	(-1.46)	(2.72)	(-1.49)
1 – 13	2.95***	1.11	3.52***	1.07
	(2.65)	(0.61)	(3.14)	(0.59)
1 – 26	-0.86	0.33	-0.25	0.27
	(-0.85)	(0.19)	(-0.25)	(0.15)
1 – 52	-0.04	1.99	0.56	1.90
	(-0.04)	(1.04)	(0.54)	(0.99)

*** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level
* indicates statistical significance at the 10% level

Table 9 (Continued)

Panel B: *k*-week-ranking-and-*k*-week-holding Strategies				
	Base Returns		*Interest-adjusted Returns*	
Ranking-Holding	*1971-1998*	*1999-2007*	*1971-1998*	*1999-2007*
1 – 1	0.24	1.10	0.77	1.04
	(0.16)	(0.59)	(0.51)	(0.56)
2 – 2	2.99***	-0.83	3.51***	-0.88
	(2.88)	(-0.60)	(3.33)	(-0.65)
3 – 3	1.91***	-1.34	2.43***	-1.39
	(2.56)	(-1.15)	(3.23)	(-1.19)
4 – 4	0.69	-0.72	1.22*	-0.76
	(1.08)	(-0.78)	(1.90)	(-0.81)
8 – 8	1.26***	0.53	1.83***	0.48
	(2.94)	(0.80)	(4.17)	(0.73)
13 – 13	0.70**	-0.23	1.30***	-0.26
	(2.01)	(-0.41)	(3.55)	(-0.47)
26 – 26	0.12	0.06	0.73***	-0.01
	(0.46)	(0.18)	(2.75)	(-0.04)
52 – 52	-0.14	-0.23	0.50	-0.32
	(-0.78)	(-1.00)	(0.58)	(-1.38)

*** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level
* indicates statistical significance at the 10% level

Table 10 Decomposition of Trading Profits: Base Returns

This table reports the components of trading profits based on base returns. All trading strategies are constructed as zero-cost portfolios that buy winners and sell losers based on their past performance. Each strategy has equal ranking and holding periods. The dollar profits are computed by $\pi_{t+1}(k) = -C_k + O_k + \sigma^2[\mu(k)] = P(k) + \sigma^2[\mu(k)]$, where $P(k) = -C_k + O_k$ is the index of predictability-profitability, C_k is the negative of *k*th-order autocovariance of the equal-weighted market portfolio return, O_k is the average *k*th-order autocovariance of all *N* currencies, and $\sigma^2[\mu(k)]$ is the cross-sectional variance in mean returns. Round-trip break-even transaction costs are calculated by dividing the total average profits by the respective transaction costs tc, where $tc = 2c|w_{it} - w_{i,t-1}|, c = 0.0001$. Panel A reports the results for the first subperiod from 1971 to 1998. Panel B reports the results for the second subperiod from 1999 to 2007. *t*-statistics are shown in the parentheses. All profits are multiplied by 10^6.

Table 10 (Continued)

Panel A: 1971-1998							
Ranking-Holding	$E[\pi_{t+1}(k)]$	C_k	O_k	$\sigma^2[\mu(k)]$	$\%P(k)$	$\%\sigma^2[\mu(k)]$	*BE tc*
1 – 1	0.24	-5.80	5.94	0.10	57.79	41.94	6.87
	(0.16)	(-2.89)	(1.93)	(1272.66)			
1 – 2	2.96**	-6.10	8.96	0.10	96.52	3.42	0.56
	(2.23)	(-3.17)	(3.12)	(1125.35)			
1 – 3	3.03***	-4.01	6.93	0.10	96.65	3.35	0.55
	(2.33)	(-2.10)	(2.44)	(1157.78)			
1 – 4	1.19	-0.11	1.20	0.10	91.50	8.48	1.41
	(0.99)	(-0.06)	(0.47)	(1170.83)			
1 – 8	2.53**	-2.15	4.58	0.10	95.92	4.00	0.66
	(2.25)	(-1.15)	(1.75)	(1182.79)			
1 – 13	2.95***	-1.97	4.82	0.10	96.56	3.43	0.57
	(2.65)	(-1.15)	(1.92)	(1182.23)			
1 – 26	-0.86	1.82	-2.78	0.10	111.84	-11.84	-2.04
	(-0.85)	(1.09)	(-1.18)	(1173.29)			
1 – 52	-0.04	-0.36	0.21	0.10	344.73	-242.81	-41.49
	(-0.04)	(-0.22)	(0.09)	(1610.45)			

Table 10 (Continued)

Panel B: 1999-2007							
Ranking-Holding	$E[\pi_{t+1}(k)]$	C_k	O_k	$\sigma^2[\mu(k)]$	$\%P(k)$	$\%\sigma^2[\mu(k)]$	*BE tc*
$1-1$	1.10	-5.59	5.74	0.62	19.90	80.02	2.15
	(0.59)	(-2.77)	(1.84)	(1636.62)			
$1-2$	-0.81	-5.88	8.74	0.62	82.18	17.78	0.47
	(-0.44)	(-3.06)	(3.04)	(1447.91)			
$1-3$	-0.84	-3.81	6.74	0.62	82.57	17.43	0.47
	(-0.45)	(-2.00)	(2.36)	(1489.52)			
$1-4$	-1.02	-5.59	5.74	0.62	19.90	80.02	2.15
	(-0.54)	(-2.77)	(1.84)	(1636.62)			
$1-8$	-2.41	-2.00	4.46	0.62	79.84	20.09	0.55
	(-1.46)	(-1.06)	(1.69)	(1521.62)			
$1-13$	1.11	-1.84	4.74	0.62	82.41	17.57	0.48
	(0.61)	(-1.07)	(1.89)	(1520.89)			
$1-26$	0.33	1.84	-2.71	0.62	346.26	-246.12	-6.92
	(0.19)	(1.10)	(-1.16)	(1509.40)			
$1-52$	1.99	-0.32	0.26	0.62	-10.06	109.96	3.08
	(1.04)	(-0.20)	(0.12)	(2068.15)			

Table 11 Decomposition of Trading Profits: Interest-Adjusted Returns

This table reports the components of trading profits based on interest-adjusted returns. All trading strategies are constructed as zero-cost portfolios that buy winners and sell losers based on their past performance. Each strategy has equal ranking and holding periods. The dollar profits are computed by $\pi_{t+1}(k) = -C_k + O_k + \sigma^2[\mu(k)] = P(k) + \sigma^2[\mu(k)]$, where $P(k) = -C_k + O_k$ is the index of predictability-profitability, C_k is the negative of *k*th-order autocovariance of the equal-weighted market portfolio return, O_k is the average *k*th-order autocovariance of all *N* currencies, and $\sigma^2[\mu(k)]$ is the cross-sectional variance in mean returns. Round-trip break-even transaction costs are calculated by dividing the total average profits by the respective transaction costs tc, where $tc = 2c|w_{it} - w_{i,t-1}|, c = 0.0001$. Panel A reports the results for the first subperiod from 1971 to 1998. Panel B reports the results for the second subperiod from 1999 to 2007. *t*-statistics are shown in the parentheses. All profits are multiplied by 10^6.

Table 11 (Continued)

Panel A: 1971-1998							
Ranking-Holding	$E[\pi_{t+1}(k)]$	C_k	O_k	$\sigma^2[\mu(k)]$	$\%P(k)$	$\%\sigma^2[\mu(k)]$	*BE tc*
$1-1$	0.77	-1.79	2.80	0.10	91.12	8.88	1.50
	(0.51)	(-0.82)	(1.06)	(99999.99)			
$1-2$	3.48***	-1.00	0.09	0.10	112.13	-12.13	-2.08
	(2.61)	(-0.41)	(0.03)	(99999.99)			
$1-3$	3.55***	-2.64	1.70	0.10	111.64	-11.64	-2.00
	(2.70)	(-1.21)	(0.61)	(99999.99)			
$1-4$	1.72	0.58	-1.70	0.10	109.62	-9.62	-1.66
	(1.42)	(0.25)	(-0.60)	(99999.99)			
$1-8$	3.08***	-0.84	-1.66	0.10	104.07	-4.07	-0.71
	(2.72)	(-0.34)	(-0.58)	(99999.99)			
$1-13$	3.52***	3.28	-2.27	0.10	91.19	8.81	1.49
	(3.14)	(1.28)	(-0.76)	(99999.99)			
$1-26$	-0.25	-3.48	3.72	0.10	70.37	29.63	5.09
	(-0.25)	(-1.42)	(1.26)	(99999.99)			
$1-52$	0.56	1.94	-0.04	0.10	95.09	4.91	0.84
	(0.54)	(0.81)	(-0.02)	(99999.99)			

Table 11 (Continued)

Panel B: 1999-2007							
Ranking-Holding	$E[\pi_{t+1}(k)]$	C_k	O_k	$\sigma^2[\mu(k)]$	$\%P(k)$	$\%\sigma^2[\mu(k)]$	$BE\ tc$
1 – 1	1.04	-1.60	2.58	0.07	93.56	6.44	1.58
	(0.56)	(-0.74)	(0.98)	(99999.99)			
1 – 2	-0.86	-0.81	-0.12	0.07	107.77	-7.77	-1.94
	(-0.48)	(-0.34)	(-0.04)	(99999.99)			
1 – 3	-0.90	-2.44	1.48	0.07	107.50	-7.50	-1.88
	(-0.48)	(-1.12)	(0.53)	(99999.99)			
1 – 4	-1.06	0.78	-1.91	0.07	106.31	-6.31	-1.59
	(-0.57)	(0.33)	(-0.68)	(99999.99)			
1 – 8	-2.45	-0.66	-1.86	0.07	102.74	-2.74	-0.70
	(-1.49)	(-0.27)	(-0.65)	(99999.99)			
1 – 13	1.07	3.45	-2.45	0.07	93.70	6.30	1.55
	(0.59)	(1.35)	(-0.83)	(99999.99)			
1 – 26	0.27	-3.33	3.53	0.07	75.43	24.57	6.15
	(0.15)	(-1.36)	(1.20)	(99999.99)			
1 – 52	1.90	2.04	-0.21	0.07	96.46	3.54	0.89
	(0.99)	(0.85)	(-0.08)	(99999.99)			

Figure 1 Investor Sentiment Proxies

This figure plots the time series of three investor sentiment proxies. *BW1* (top panel) is a sentiment index compiled by Baker and Wurgler (2006). *BW2* (middle panel) is similar to *BW1* but is orthogonal to macroeconomic variables. *UM* (bottom panel) is the University of Michigan Consumer Sentiment Index. *BW1* and *BW2* range from January 1966 to December 2007. *UM* ranges from January 1978 to December 2007.