Temporal Patterns in Foreign Exchange Returns And Options*

First Version: August, 2004
Current Version: January 16, 2006

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Abstract:

Although the foreign exchange market is believed to be one of the most efficient financial markets in the world, there is significant evidence that technical analysis is profitable in this market. In this study we investigate the ability of information from the options market to supplement the commonly used information on past prices to predict temporal patterns in foreign exchange returns. We find that information from the options market improves the performance of technical trading strategies. Strategies using information from at-the-money options were more consistently profitable than the most commonly used strategies based on only historical spot exchange rates (past prices). Our results hold out-of-sample as well as in the late nineties, a period when few sources of information have proven reliable. Consequently options appear to contain valuable information regarding future spot exchange rate movements.

JEL Codes: G0, G14
Keywords: Technical analysis, exchange rates, derivatives

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1. Introduction:

Despite the fact that the foreign exchange market is the largest financial market in the world and the majority of traders in this market are large, professional, institutional investors, tests of the weak form of market efficiency in this market are often rejected. In a market that is weak form efficient, traders should not be able to generate significant excess returns by trading purely on the basis of past, publicly available information, but studies starting with Poole (1967) and Dooley and Shafer (1976) have documented profitability for technical analysis in the foreign exchange market. More recently, studies such as Levich and Thomas (1993), Neely, Weller, and Dittmar (1997), LeBaron (1998, 1999), Gençay (1999), and Okunev and White (2003) have gone to great lengths to demonstrate the robustness of the profitability of technical analysis in the foreign exchange market using only information on past prices. The results consistently find that such strategies are profitable, especially before 1995, and thus appear to reject weak form market efficiency for the foreign exchange market.

We extend these studies by investigating the predictive power of another source of information for the foreign exchange market – options. Specifically we investigate whether information on options can help to predict large exchange rate movements and we compare this to the predictions one would have obtained from just using past exchange rates as in standard studies of technical trading rule profitability. We accomplish this by comparing the characteristics of the returns from standard trading strategies to the returns from strategies including information from options. We evaluate these technical trading strategies based on their ability to earn economically and statistically significant excess risk-adjusted returns.

Despite the potential information that can be obtained from the options market, we are one of the first studies to investigate the information content of more than the implied volatility from options. Studies such as Easley, O'Hara, and Srinivas (1998), for example, demonstrate that the options market contains valuable information regarding the value of the underlying asset. In a related fashion, studies such as Schachter (1988), Levy and Yoder (1993), Arnold, Erwin, Nail, and

Bos (2000), and Jayaraman, Frye, and Sabherwal (2001) document that the options market reacts to information around key events. More directly related to our study, are Bonser-Neale and Tanner (1996), Chaboud and LeBaron (2001), and Sapp (2004) who have considered how different features of derivative securities can be useful in predicting future exchange rate fluctuations thereby motivating our investigation of the value of options.

Although we use several methods to study the value of the information in options data, our analysis focuses on its ability to improve the profitability of technical analysis in the foreign exchange market. Focusing on technical analysis allows us to test both the economic and statistical significance of the predictive ability of options. As such the methodology employed in this paper can be viewed as an extension of Neely and Weller (2001). Neely and Weller, for example, investigate whether information about central bank interventions can be used to supplement past exchange rates in deriving profitable technical trading strategies. We use the open interest[1] of foreign exchange options contracts to complement past exchange rates in deriving technical trading strategies. Beyond considering a theoretically motivated source of information which has not been considered in previous work, another advantage of using options-based information is that it is publicly available. Consequently the information for our technical trading strategies is all publicly available. This ensures we are truly studying the weak form of market efficiency.

Recognizing the potential concerns related to data mining in this type of analysis, we employ extensive out-of-sample testing and methods designed for such multiple testing environments. Our out-of-sample tests rank moving average trading rules based on their historical performance and considers how they perform in the future. This offers a simple, objective way of selecting rules that could have been used and implemented by investors. We do this using daily data for the US dollar-Deutsche Mark spot exchange rate and characteristics of options on the Deutsche Mark over the period from January 1, 1988 to December 31, 1999

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[1] The open interest on call (put) options is the cumulative value in dollars of all the call (put) contracts that have not been closed and are still active on a given day. This is not to be confounded with volume, which is defined as the number of contracts traded on a given day.

Consistent with previous studies, we find that technical analysis is able to generate statistically significant profits in the foreign exchange market over our 1988 to 1999 sample period. Further, rules using information on the open interest differential (Call – Put) for at-the-money options ("ATM rules") fared better and were more consistently profitable than rules based on only the historical spot exchange rates ("SPOT rules") – the data used in previous studies.

Overall our out-of-sample tests for the ATM rules outperformed the SPOT rules with an average annualized excess return (Sharpe ratio) of 3.42% (0.36) compared to 1.16% (0.14) for the SPOT rules. We also found that the profitability of the rules using the ATM options were more robust. Three times more rules using ATM options provided returns statistically significant at the 5% level and the best ATM strategy earned almost twice as much as the best SPOT strategy with annualized excess returns (Sharpe ratios) of 10.73% (1.63) and 5.47% (0.71) respectively. To put this into perspective, the S&P500 index earned 8.34% (0.62) in annualized excess return (Sharpe ratio) between 1988 and 1999, a period of unprecedented growth in the United States.

Additionally, combining signals from both ATM options and historical spot exchange rates improves the annualized mean excess return in the late nineties and tightens the overall distribution of returns thereby making the investment strategies less risky. The rules using information from both the spot exchange rates and ATM options are the most profitable rules after 1994, a period during which few variables have been found to be successful at predicting exchange rates, with a mean annualized excess return (Sharpe ratio) of 2.59% (0.41). The ATM rules ranked second with an average annualized excess return (Sharpe ratio) of 1.70% (0.21). Consistent with Olson (2004) and Sapp (2004), we do not find the SPOT rules to be profitable during that period with an average annualized excess return (Sharpe ratio) of -0.62% (-0.12).

As a result, the differential in open interest for ATM put and call options appears to carry more consistent information about future price movements than historical spot exchange rates. These findings are confirmed using simple regression analysis where we find significant predictive ability from changes in the open interest differential for changes in exchange rates. In light of our results, we interpret the differential in open interest as a valuable source of information regarding the future value of currencies which has not been considered before. Our results add empirical support to the model proposed by Easley, O'Hara, and Srinivas (1998) in which option trades carry information about future spot prices. It also supports the idea that the options market may actually lead the spot market (e.g., Manaster and Rendleman (1982), Bhattacharya (1987), and Anthony (1988)). Consequently the differential in open interest for ATM options carries valuable information that can be used by investors to better time the foreign exchange market, even in the late nineties. This is an important contribution because few variables or structural models have proven successful at predicting future spot exchange rates (Meese and Rogoff (1983)).

The paper is organized as follows. Section 2 provides a review of the literature relevant for our study. Section 3 discusses the data used in our analysis. The fourth section presents our methodology and describes our hypotheses. Results are presented in section 5. Finally, conclusions are presented in section 6.

2. Literature Review:

In this section we discuss some of the most relevant literature to our study.

2.1 Technical Analysis:

Even though practitioners support technical analysis, academics have been reluctant to accept its value. Surveys of foreign exchange traders such as Taylor and Allen (1992) report that more than 90% of the firms surveyed use some form of technical analysis in determining their short-term investment strategies in the foreign exchange market. In a survey of US-based foreign exchange traders, Cheung and Chinn (2001) report that almost 30% (the most popular answer) of the respondents answered "technical analysis" as best describing their trading practices. In Hong Kong, Lui and Mole (1998) find technical analysis to be almost twice as important as fundamental analysis for short-term investments. Despite the extensive use of technical analysis in practice, relatively few academic studies have investigated the source of this value.

Though the use of technical analysis by practitioners can be traced back to the writings of Charles Dow[2], it was not until the work of Alexander (1961, 1964) and Fama and Blume (1966) that the first uses of technical analysis are found in the academic literature. Subsequent academic work in this area provides mixed results. For example, studies of technical analysis in the stock market such as Brock, Lakonishok and LeBaron (1992) and Sullivan, Timmerman and White (1999) find that trading strategies can be profitable, but the results of studies such as Allen and Karjalainen (1999) do not. The results are clearer in the foreign exchange market where studies starting with Poole (1967), and Dooley and Shafer (1976, 1983) consistently document profitability for technical analysis.

The controversial nature of this apparent rejection of weak-form market efficiency in the foreign exchange market has led many researchers to examine the robustness of this profitability. Studies have considered the performance of a variety of technical trading strategies ranging from the most basic filter rules (e.g., Sweeney (1986)) or moving average rules (e.g., Levich and Thomas (1993), LeBaron (1999)) to more elaborate rules such as head-and-shoulder rules (Chang and Osler (1999), Lucke (2003)). One of the most extensive tests is Neely, Weller, and Dittmar (1997) who use genetic programming to optimally select among a wide variety of technical trading rules. Investigating the robustness of technical trading profits, Levich and Thomas (1993) use a bootstrap approach to show that none of the conventional time-series models could explain the profitability of technical analysis. Qi and Wu (2001) apply White (2000)'s Reality Check bootstrap to ensure that these profits were not simply due to chance or collective data-mining. The key result emerging from all of these studies is that simple technical trading rules using only past information on exchange rates can be used by investors in the foreign exchange market to earn economically and statistically significant returns.

In light of these results, researchers have proposed various explanations to elucidate the source of this apparent inefficiency. For example, Kho (1996) investigates whether the unusually

[2] A nice synthesis of the works of Dow and his followers can be found in Rhea (1932).

high technical trading rules' returns could be compensation for bearing risk. Using a conditional asset pricing model he tests whether the profitability of technical analysis in the foreign exchange market could be explained by time-varying risk premiums and finds the profits of simple MA rules to be insignificant after controlling for these risk premiums. This suggests that the returns in the foreign exchange market may be compensation for bearing risk.

Other studies such as Szakamary and Mathur (1997) have hypothesized that central bank interventions may be the source of the apparent inefficiency. They postulate that central banks in their effort to stabilize the foreign exchange market may slow down the process by which exchange rates reach their true equilibrium value and thereby provide trend chasers an opportunity to earn abnormal profits. Using monthly changes in foreign currency reserves as a proxy for interventions, they find a significant correlation between the profitability of technical analysis and interventions. Using official Federal Reserve interventions, LeBaron (1999) corroborates Szakamary and Mathur (1997)'s findings and shows that the technical trading returns are insignificant once the days of intervention are removed from the return series. Saacke (2002) extends LeBaron's results using official Bundesbank intervention data and shows that technical analysis is unusually profitable around the interventions but that Central Banks profit from these interventions in the long-run. Sapp (2004) shows that the profitability of the rules varies with the type of interventions – i.e. announced, unannounced, unilateral, or coordinated.

Using higher frequency data, Neely (2002) shows that the majority of the returns are earned before the interventions occurred. Consequently the central banks appear to have intervened to counter a force that was already at play. This is consistent with the inability of Neely and Weller (2001) to find a significant increase in the technical trading profitability when adding interventions to the traders' information set.

We extend this literature by investigating whether information from the options market contains valuable information. Since options offer investors many advantages which may encourage informed investors to migrate to this market, abnormal activities in the options market may provide valuable information on where the currencies are heading. Aside from Neely and Weller (2001) who combine past foreign exchange rates and central bank interventions to obtain buy and sell signals, most of the existing studies focus on a single series, the past exchange rates. By considering the options data as well, we add to this literature by investigating whether another source of information can shed light on the apparent inefficiency of the foreign exchange market.

2.2 Value of Options

Options have always been a source of interest for traders and researchers (e.g., Kairys and Valerio (1997)). Initially scholars focused on how to price options using increasingly complex option pricing models. More recently, however, researchers have started to look at options as a source of information on the future state of financial markets. In a Black-Scholes world without transaction costs and information asymmetries, options are redundant securities so they contain no new information. In the real world, however, it is possible that options may contain information either unavailable or difficult to obtain from the spot market. This information is available because options help expand the investment feasibility set (e.g., Ross (1976) and Kumar, Sarin, and Shastri (1998)) and make it easier for informed investors to hide their trades (e.g., Easley, O'Hara, and Srinivas (1998)) [3].

Many researchers have investigated the potential feedback between the spot market and the options market for equities. For example, Fedenia and Grammatikos (1992), Kumar, Sarin, and Shastri (1998), and Danielsen and Sorescu (2001), among others, find that the listing of new options are usually associated with significant changes in the bid-ask spread, transaction size, trading volume, and trading frequency in the spot market. Studies which try to assess where new information is incorporated first have come to mixed conclusions. Manaster and Rendleman (1982), Bhattacharya (1987), and Anthony (1988) find that the options market leads the spot

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[3] See Coughenour and Shastri (1999) for a thorough review and discussion of the advantages and disadvantages of trading options.

market by as much as one day for equities. Using intraday data, Stephan and Whaley (1990) came to the opposite conclusion. However after controlling for microstructure inefficiencies, Chan, Chung, and Johnson (1993) reject Stephan and Whaley (1990)'s conclusion.

There does, however, appear to be some consensus that options contain valuable information. For example, Levy and Yoder (1993), Arnold, Erwin, Nail, and Bos (2000), and Jayaraman, Frye, and Sabherwal (2001) look at trading activities in the options market around mergers and acquisitions, Kumar, Sarin and Shastri (1992) around large block trades and Schachter (1988) around quarterly earnings announcements and they all report abnormal activities in the open interest, volume, or implied volatility in the options market before these events. These results are consistent with informed trading taking place in this market. Moreover, Bates (1991) documents that out-of-the-money put options were overpriced before the crash of 1987 suggesting that options may also contain valuable information on overall market conditions.

From a theoretical perspective, Easley, O'Hara, and Srinivas (1998) propose a model where informed and uninformed investors choose between investing in the stock market or the options market. Investors make their decision based on the relative levels of trading activity in each market, and their information. Easley et al. show that, under reasonable assumptions, some informed investors choose to invest in options rather than the underlying asset so option trades may contain valuable information regarding future prices. Specifically, they show that buyer initiated trades (i.e. purchases of calls or sales of puts), what they label as "positive volume", and seller initiated trades (i.e. purchases of puts or sales of calls), what they label "negative volume" were statistically significant in predicting future stock prices.

All told, technical analysis provides apparent evidence of inefficiency in the foreign exchange market, but the source of this inefficiency is unclear. We investigate the information in the options market to try to provide insight into these issues.

3. Data:

We consider the spot exchange rate and options data for the US dollar-Deutsche Mark (US$/DM) over the period from January 1, 1988 to December 31, 1999 for a total of 3,131 business days. We restrict our analysis to this sample period because trading in currency options was relatively light and the data unreliable before the end of 1987 and options on the US$/DM gradually ceased to be traded following the introduction of the Euro in January 1999. The options data on the US$/DM are from the Chicago Board of Options Exchange (CBOE) obtained from the Futures Industry Institute. The historical exchange rates are the noon buying rates from the Federal Reserve Bank of New York.

There are several distinct trends in the value of the US dollar-Deutsche Mark exchange rate over this period as illustrated in Figure 1. Between 1988 and 1995 the DM appreciated against the US dollar peaking at 0.74 US$/DM in April 1995. The trend reversed in the latter years with the US$/DM spot exchange rate closing at 0.51 by the end of 1999, well below the 0.63 recorded at the start of our sample in 1987. These patterns suggest that the ability to time the market could have led to significant profits from trading in the foreign exchange market.

For our options data we concentrate on the open interest differential[4]. The open interest is the number of option contracts outstanding at the end of the day and the open interest differential is defined as the difference in open interest between call and put options. We restrict our analysis to options with a time to maturity of greater than 30 calendar days but less than 90 calendar days as these are the most actively traded options in our sample. Although we impose a minimum of 30 calendar days to maturity to avoid false signals triggered by the disappearance of option contracts, our results are similar if we allow very short-term options to be included[5]. We group these options into nine categories (see Table 1), ranging from deep in-the-money (ITM) options (category 1 for

[4] We discuss our motivation for focusing on the open interest differential below.

[5] The minimum of 30 calendar days is only an issue for in-the-money and out-of-the-money options due to their thinner trading. Qualitatively, however, the results are unaffected if we relax the bounds to include options with less than 30 days to maturity and/or more than 90 days.

calls and category 9 for puts) to deep out-of-the-money (OTM) options (category 9 for calls and category 1 for puts). The ATM options (category 5) are defined as options with strike prices within 3% of the current spot exchange rate. The other categories are defined in increments of 4%, so that category 4 (6) contains options with strike prices below (above) the spot exchange rate by 3% to 7%, and category 3 (7) as options with strike prices below (above) the spot exchange rate by 7% to 11%, and so on.

Because of the different characteristics of the options in each category, they may contain different information so they are considered separately. For example, informed investors may be tempted to invest in deep OTM options to leverage their position or they may choose to invest in ATM options because they are more liquid and thus better for concealing trading activity. Since fully informed investors would benefit from leveraging their position using OTM options, most researchers have focused on the informational content of deep OTM options (e.g., Bates (1991), Easley, O'Hara, and Srinivas (1998)). Although this makes sense for stocks, where insiders may have a clear informational advantage regarding pending news such as earnings disclosure (e.g., Schachter (1988)) or mergers announcements (e.g., Levy and Yoder (1993), Arnold, Erwin, Nail, and Bos (2000) and Jayaraman, Frye, and Sabherwal (2001)), it is not clear that such an investor exists in the foreign exchange market. Therefore, in this market ATM options may offer a better liquidity/leverage trade-off that enables investors to benefit from the advantages of a leveraged position while making it relatively easy for investors to liquidate their position.

Figure 2 plots the open interest on all of the call and put options over the entire sample period. Investors were particularly active in the options market between 1991 and 1995 with contracts outstanding frequently exceeding 100,000 for both call and put options. This is not surprising given the turmoil in the European Monetary System (EMS) at this time which suggests that investors use options at times of market uncertainty. The average number of contracts outstanding on a daily basis for each category can be found in Table 1. As expected, the open interest varies considerably with the moneyness of the options. On average, more contracts are outstanding for ATM options with 15,921 and 15,228 contracts for call and put options respectively. As the strike price gets further away from the current spot exchange rate, we see the number of open contracts falling with the decrease being more severe for in-the-money (ITM) options. Deep ITM options (the first two intervals) have less than a thousand contracts outstanding for call and put options. In comparison, the number of OTM call (put) option contracts (intervals 6 to 9) outstanding ranges from 8,084 (10,288) to 2,332 (1,895)[6].

To ensure we have enough data to implement our technical trading strategies, we aggregate the open interest for i) all the options traded, ii) for the ATM options (category 5) and iii) for the OTM options (categories 6 to 9 for call options and categories 1 to 4 for put options).

3.1 Why Open Interest?

We focus on open interest for a few reasons. First, open interest has been used for years by technical traders because it gauges the strength and type of information present in the market. An increase in open interest along with an increase (decrease) in price is said to confirm an upward (downward) trend, while a decrease in open interest often points to a trend reversal. The underlying idea is illustrated by the following quote from Pring (2002 p. 399):

> *"A new high in price that is not confirmed by volume should be regarded as a red flag, warning that the prevailing trend may be about to reverse"*

Both volume and open interest are interpreted as measures of the strength of a trend. We believe the open interest differential is more informative than volume because it is closer to the concept of "positive volume" and "negative volume" put forward in Easley, O'Hara, and Srinivas (1998). Since the quantity of buyer or seller initiated trades may be informative in their model, the number of call contracts outstanding relative to the number of put contracts (the open interest differential)

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[6] There are four annual spikes in open interest related to the expiration of the most liquid contracts March, June, September and December. Because we focus on ATM options where the spikes are less noticeable and we study the differences in open interest between puts and calls where these differences cancel each other out, they do not significantly impact our results. We do, however, perform several robustness tests to ensure that there is no significant impact of this seasonality in the option market on our conclusions.

may also be informative. Buying an option is substantially different from selling one, so investors having more information would be better off taking long positions in option contracts (i.e., puts or calls) that match their views. Consequently having more (less) call options outstanding than put options may be interpreted as a bullish (bearish) signal.

Finally Schachter (1988) and Jayaraman, Frye, and Sabherwal (2001)'s event-studies for US firms around mergers and quarterly earning announcements, respectively, support the idea that open interest is one of the most important variables around key events. We confirm this using our own quasi-event study[7]. We analyze the behavior of the option contracts before and after the 50 largest positive and 50 largest negative daily movements in exchange rates. The average daily returns on the event dates range from 2% to 3% as illustrated in Panel A of Figure 3. Panel B illustrates the behavior of the open interest differential around the days with the extreme daily returns on the US$/DM[8]. Two striking results emerge from these figures. First, in Panel A, no pattern could be identified from the spot market in the days preceding the days with extreme returns. On average, the standardized exchange rates were relatively flat and oscillated around one. Second, in Panel B, the average open interest differential was positive (negative) and increasing (decreasing) in the days leading up to positive (negative) jumps in the US$/DM. This suggests that investors may have been able to forecast changes in the spot market by looking at the changes in the number of call and put contracts outstanding. On average, momentum seems to be building in the options market before large changes in the spot market.

In sum, the open interest differential appears to be a valuable source of information regarding future extreme returns. In the next few sections we investigate whether investors can benefit from this information.

[7] We use the term "quasi" to emphasize the fact that we do not require that a real event actually took place. The events are defined by selecting the days having the most extreme daily returns.

[8] The same conclusions hold when considering periods with the most extreme returns over 3-day and 5-day periods but are not reported here for brevity.

4. Methodology:

In this section we discuss our different technical trading rules and tests. A trading rule is a systematic method for determining when to hold (0), go long (+1) or go short (-1) the asset. The series of exchange rates we consider is expressed as US$/DM so going long means buying DM, while going short means buying US$. Our trading strategies are based on simple moving average (MA) rules. We select these rules because they are easy to use, simple to interpret, widely popular among practitioners, and the most commonly tested in academic research.

4.1 The Trading Rules

Formally, the *n-day* moving average at time *t* on the asset with price *s* is defined as:

$$MA_{n,t} = \sum_{i=t-n+1}^{t} \frac{s_i}{n} \tag{1}$$

The objective of MA trading rules is to profit from momentum or trends in asset prices. Many variants exist but the most common is to hold a long (short) position while the short *m*-day moving average is above (below) the long *n*-day moving average where (*n* is greater than *m*)[9]. The idea is that changes in these moving averages may signal the start of a new trend. In this study we consider two types of strategies: (1) variable-length strategies where the investment is held until the opposite signal is received (see Panel A of Figure 4) and (2) fixed-length strategies where the investment is held for a fixed number of days before going neutral and waiting for the next signal (see Panel B of Figure 4). In either case, a position can only be initiated when the two moving averages cross.

Each trading rule is fully defined by three parameters. The number of days used to compute the short and long MAs and the "holding period" parameter. The choice of parameters is problematic since there are virtually an infinite number of combinations. To decrease the risk of data mining, we use some of the most common values. When a single series is used to derive the

[9] See Pring (2002) for a detailed discussion.

signals we chose {1,2,5,10} as the length of our short MAs, {25,50,75,100} as long MAs, and {0,5,15,25}[10] as holding periods. There are therefore 64 different rules if we use every combination of parameters – four short MAs times four long MAs times four holding periods. When combining signals from two series, we reduced the set of short MAs to {1,5,10}, long MAs to {25,50,75,100}, and holding periods to {0,15}. This results in 24 x 24 or 576 different trading rules.

Formally if we hold a long or short position at time *t* but have to wait to unwind our position because we are within the holding period, the signal at time t is the last signal:

$$Signal_t = Signal_{t-1} \tag{2}$$

Otherwise the signal is determined as follows:

$$Buy\ Signal_t = \left[MA_{m,t-1} \leq MA_{n,t-1}\right] \times \left[MA_{m,t} > MA_{n,t}\right] \qquad (2)'$$

$$Sell\ Signal_t = -\left[MA_{m,t-1} \geq MA_{n,t-1}\right] \times \left[MA_{m,t} < MA_{n,t}\right] \qquad (2)''$$

Equation (2) ensures that we hold our position as long as we have to (i.e., for the holding period). Equations (2)' and (2)'' indicate new signals based on the crossing of the long MA by the short MA. The first portion of the equations ensures that the crossing has not already taken place.

The trading rules are applied to four individual data series: (i) the series of historical spot exchange rates, and the differential in open interest for (ii) all the options that are traded (ALLOI), (iii) ATM options and (iv) OTM options. Although we use both past spot exchange rates and the open interest differential to obtain the buy and sell signals, we only invest in the currencies and not the options because Coval and Shumway (2001) found that the underlying asset offers a superior risk-return trade-off than the options. This also avoids potential complications related to having to roll over positions in options around maturity.

[10] A holding period of "0" is the "variable-length strategy". This means we hold our position until the moving averages cross again sending the opposite signal. When the value is greater than zero we hold our position for that number of days, regardless of further signals during that time.

As mentioned before, we derive the signals for our technical trading strategies from each series separately but also together to benefit from the information in both series. Few studies have considered whether using more than one series can improve the results from technical analysis. One exception is Neely and Weller (2001) who combine the information from historical exchange rates and central bank interventions to build trading strategies to invest in the foreign exchange market. Even though the Neely and Weller results are inconclusive (central bank interventions seem to provide little additional information for generating excess out-of-sample risk-adjusted returns), their study is a first step in making the technical trading strategies more similar to what investors use. There are many ways to combine the information. For simplicity we adopt an approach similar to that used in Neely and Weller (2001) by combining the signals from multiple series using the "and" operator. This means we go long when both series send a buy signal, go short when both send a sell signal, and stay out of the market otherwise.

4.2 The Returns

To investigate the magnitude of the returns from our trading strategies, we compute the mean excess return[11]and the Sharpe ratio. We use these as our two main measures because they are intuitive and widely used in the field. The annual excess return serves as a useful benchmark since this should be close to zero if technical analysis has no value. We also consider the Sharpe ratio because returns alone do not take into account the riskiness of an investment. We study the returns from three cases: the overall strategy, long positions exclusively, and short positions exclusively. The overall strategy includes the returns for days on which we go long, go short, as well as days where we hold no position at all.

[11] As in Neely and Weller (2001) we assume investors borrow the currency they sell so that the strategies are self-financing and the returns are excess returns. The "excess return" should not be interpreted as the return over a "buy-and-hold" strategy. They argue, and we agree, that it does not apply to the foreign exchange market since a "buy-and-hold" strategy is not well defined for a global investor. Moreover, currencies, unlike market indices, fluctuate and revert back to a long term mean so the expected long-run return is zero. Therefore, the "excess return" can be interpreted as the return from being active rather than passive in the market.

The continuously compounded daily excess return at time t+1 is given by[12]:

$$r_{t+1} = \ln\left(\frac{S_{t+1}}{S_t}\right) \times I_t = I_t \ln(S_{t+1}) - I_t \ln(S_t) \tag{3}$$

Where S_t is the US$/DM exchange rate at time t, and I_t is the signal from the trading strategy {-1, 0, 1} at time t. Assuming a year to have 250 trading days, the annualized excess returns and Sharpe ratios are computed as follows:

$$R_{Annualized} = E[r_i] \times 250 \text{, i } \epsilon \text{ \{all, long, short\}} \tag{4}$$

and

$$Sharpe_{Annualized} = \frac{E[r_i]}{\sigma[r_i]} \times \sqrt{250} \text{, i } \epsilon \text{ \{all, long, short\}} \tag{5}$$

Where $E[r_i]$ is the average daily excess return and $\sigma[r_i]$ is the standard deviation of these returns.

To assess the statistical significance of our results we use a bootstrap approach similar to Brock, Lakonishok, and LeBaron (1992). We did so to ensure our results would not be biased by assumptions about the asymptotic distribution of returns. First, we fitted an AR(1)[13] process to the series of spot exchange rates covering three in-sample periods – the entire sample, 1988 to 1999, as well as two sub-periods 1988 to 1993 and 1994 to 1999. Using the estimated coefficients and randomly selecting the estimated residuals with replacement we simulated 5,000 series of spot exchange rates over each of the periods. We apply each of the technical trading rules to the simulated series to obtain the empirical distribution of the returns and Sharpe ratios of each rule individually. The significance levels are determined by comparing the observed value to the empirical distribution[14].

[12] For completeness, the interest rate differential and the bid-ask spread should have been taken into account. However, previous studies such as LeBaron (1999), Neely and Weller (2001), and Sapp (2004) have documented that these factors have a marginal impact on the results and were therefore omitted.

[13] We use the AR(1) process because this is consistent with one of the simplest forms of the random walk model.

[14] Because of the potentially complex distribution for the returns generated by such a procedure, the bootstrap methodology allows us to empirically estimate the level of statistical significance.

4.3 Out-of-sample tests

Since investors are most concerned about being able to use currently available information to select rules that will allow them to make money going forward, we want to identify rules that perform well both in- and out-of-sample. To investigate this we perform a series of tests using various combinations of training and testing periods. This extends the common approach of splitting the sample in two with the first half of the sample being the training period to determine the best strategy and the second half being the testing period where the significance of this strategy is tested out-of-sample. By using a wider variety of training and testing periods, we reduce the risk of data-mining and improve our ability to determine how dynamic rule selection can impact the profitability of the trading rules. We arbitrarily select {2, 3, 4, 5} years as training periods[15] and {1, 2, 3, 4, 5} years as testing periods. This gives a total of 20 out-of-sample tests. We also added four more tests, which consist of using the first 2, 3, 4, and 5 years as the training periods and employing the best rules from that time for the rest of the sample period. This provides us with a total of 24 out-of-sample tests.

We tested the 10 (50) best-performing rules out of the 64 (576) rules derived using one (two) data series. We used the annualized mean excess returns from the training period to rank the rules. Our test consists of six steps outlined below and summarized in Figure 5.

1. We apply the 64 (576) MA rules to the series of US$/DM spot exchange rates to obtain 64 (576) series of buy/sell signals between 1988 and 1999.

2. We divide the sample period into training and testing periods for each of the 24 window combinations. A simple example using 2-year training periods and 3-year testing periods is illustrated in Figure 5. In this example, we have four 2-year training periods (1988-1989, 1991-

[15] We imposed a minimum of two years on training periods to ensure that we have enough data points to rank the rules appropriately. This is particularly important for longer MA rules where, in some cases, a hundred days are required before the first signal can be obtained.

1992, 1994-1995, and 1997-1998) and four 3-year testing periods {1990-1992, 1993-1995, 1996-1998, and 1999-1999[16]).

3. We compute the annualized mean excess return for each of the 64 (576) MA rules over each of the training periods using the buy/sell signals from Step 1 and the corresponding daily exchange rate returns.

4. We rank the 64 (576) rules to identify the 10 (50) best rules over each training period. These rules are used to generate buy/sell signals in the testing periods.

5. We combine the 10 (50) streams of buy/sell signals from Step 4 to obtain series of buy/sell signals that cover the whole sample period, excluding the first training period.

6. We compute the overall annualized mean excess return and Sharpe ratios for the 10 (50) strategies from Step 5.

5. Results:

The average summary statistics for the out-of-sample tests for each series are reported in Table 2. The results are striking. Overall the strategies using information from ATM options outperformed every other series. In Panel A of Table 2 we see the ATM rules earning on average 3.42% (0.36) in excess annual returns (Sharpe ratio) and the rules using information from both the SPOT and ATM data earning 2.88% (0.37). Furthermore, the ATM rules were profitable in all 24 out-of-sample tests with average annualized excess returns (Sharpe ratios) ranging from 1.52% (0.16) to 4.74% (0.48) as can be seen in Figure 6. The best strategy in each out-of-sample test earned between 4.63% (0.49) and 10.73% (1.03) in annualized excess return (Sharpe ratio). Moreover, the ATM rules outperformed the SPOT rules in every out-of-sample test. They also performed well when taking long (short) positions beating the SPOT rules in all but two (five) of the 24 out-of-sample tests. These results are even more impressive since buying and holding the

[16] Note: the last testing period only covers one year of data.

S&P500 index between 1988 and 1999, a period of unprecedented growth in the United States, would have only generated a mean annualized excess return (Sharpe ratio) of 8.34% (0.62).

The results for the strategies using information from ATM options are robust and much more consistent than those obtained using other series with 61% of the ATM rules and 51% of the rules using information from both the SPOT and ATM earning statistically significant excess returns at the 5% level, compared to only 21% of the SPOT rules. The statistics for the ATM rules show that the best performing rules tend to remain profitable for extended periods of time. Clearly technical analysts would benefit from incorporating the differential in open interest for ATM options into their strategies.

The results are less impressive for the rules using the aggregated data from all three types of options (ALLOI rules) and very poor for those using only out-of-the-money options (OTM rules). Overall, only 18% of the ALLOI rules and 13% of the OTM rules generated statistically significant returns at the 5% level between 1988 and 1999 with average excess returns (Sharpe ratios) of 0.83% (0.10) and 0.14% (0.02) respectively.

The poor performance of the OTM rules is somewhat surprising since many studies have found that these options carry valuable information around key events (e.g., Bates (1991), and Easley, O'Hara, and Srinivas (1998)). Informed investors are often hypothesized to prefer OTM options because of the leverage advantage they provide. Nevertheless it appears these options contain very little information useful for predicting future spot exchange rates. Since the level of private information may be lower in the foreign exchange market than in equity markets, informed investors may prefer to invest in the more liquid ATM options to facilitate the liquidation of their positions. Our results suggest that informed investors prefer liquidity (ATM options) rather than leverage (OTM options). Therefore, we focus on ATM rules below.

The series of historical spot exchange rates seems to carry little information not already captured by the differential in open interest for ATM options with, in most tests, the SPOT-ATM rules performing no better than the ATM rules. However, the two series complement each other very well when going long as illustrated in Panel B of Table 2. The SPOT-ATM rules outperformed each series of rules on their own in all 24 out-of-sample test, beating the ATM (SPOT) rules by a mean annualized excess return of 2.28% (5.40%). Moreover, combining signals from both series more than doubled the percentage of rules significant at the 5% level to 56% following long signals, resulting in a tighter distribution of returns and mean annualized excess returns (Sharpe ratios) ranging from 2.26% (0.29) to 3.93% (0.48) compared to 1.52% (0.16) to 4.74% (0.48) for the ATM rules. The same complementarities in signals do not seem to exist when going short. The ATM rules outperformed the other rules, including the SPOT-ATM rules, by more than 1% annually with a mean annualized excess return (Sharpe ratio) of 6.68% (0.65) and a standard deviation in returns of 1.08% - the lowest of all rules (see Panel C of Table 2). Furthermore, 90% of the ATM rules were statistically significant at the 5% level compared to 81% and 65% for the SPOT-ATM and SPOT rules respectively. The differential in open interest for ATM options is clearly the best momentum indicator when going short. Nevertheless, most rules did a reasonable job of timing appreciation of the US-dollar against the Deutsche-Mark with a mean annualized excess return exceeding 3.50%.

The added value of combining signals from both series is more apparent when comparing the out-of-sample results across sub-periods as can be seen in Panels B and C of Table 3. To maximize the number of out-of-sample days in each sub-period, we only report the out-of-sample results from using 500-day training periods[17]. First, in both sub-periods the ATM and SPOT-ATM rules outperformed the SPOT rules by more than 2%. Combining signals from both series clearly improves the out-of-sample results in the second half of the sample with a mean annualized excess return (Sharpe ratio) of 2.59% (0.41) for the SPOT-ATM rules, of -0.62% (-0.12) for the SPOT rules, and of 1.70% (0.21) for the ATM rules. Some of the SPOT-ATM rules performed very well in the late nineties with annualized excess returns (Sharpe ratios) exceeding 6% (1.00). The strategies based on combining information from both series were therefore more consistent, less

[17] The results are similar for the other periods.

risky and performed especially well in the late nineties where few strategies have proven successful.

In sum, the rules using information from the ATM options performed better than any other set of rules – they were more consistently profitable and performed well both on days when we held a long position and on days we held a short position. Combining signals from both the ATM options and spot exchange rates does an especially good job of timing the appreciation of the Deutsche Mark against the US dollar and tightening the distribution of returns. Overall we find that the options appear to contain at least as much and generally more information than the spot exchange rates that have been used in earlier studies.

5.2 Discussion

Using technical analysis we have seen that the series of open interest differentials for ATM options has predictive power regarding future fluctuations of the spot exchange rates. These results support the idea that unusual option trading activity may indicate the presence of informed investors in the market. However, the apparent profitability of the ATM rules could potentially be the result of increased risk at that time as suggested by Kho (1996). If we assume that investors are using options to hedge risky positions or speculate when the risk of large price movements is increasing, significant trading profits may simply be compensation for increased risk at these times. A simple somewhat ad-hoc way to investigate this issue is to recompute the out-of-sample results after removing the days with the 50 most positive and negative returns from the analysis as they represent the days with potentially the most risk (similar to LeBaron (1999)). A priori, if the open interest differential coincides with periods of greater risk we would expect our rules to largely benefit from these extreme returns. As expected, the ATM rules were the most affected with a decline in profitability of 1.33% and half the rules no longer being statistically significant at the 5% level. These results support the idea that the rules at least partially benefited from increased risk but they do not tell the whole story as the ATM rules remain highly profitable with an annual average excess return (Sharpe ratio) of 2.09% (0.25). These results suggest the differential in open interest for ATM options is a good predictor of extreme changes in the spot market.

Studies such as LeBaron (1999), Saacke (2002), and Sapp (2004) have tried to explain these apparent market inefficiencies by looking at central bank interventions. They find technical analysis to be most profitable around interventions and that large, persistent changes in the foreign exchange market often lead to interventions. Interestingly, Neely and Weller (2001) did not find that seeking signals from these interventions improves the profitability of the technical rules as most of the profits were earned before or on days of interventions rather than after. It could well be that the series of open interest differentials are a leading indicator of these interventions. If the ATM rules profit from anticipating these interventions, we would expect our rules to send a bullish (bearish) signal on days prior to the purchase of Deutsche Marks (US dollars) by the central banks.

We investigate this possibility using an event-study considering the open interest differentials for ATM options around interventions made by the Federal Reserve or the Deutsche Bundesbank. A positive (negative) event is defined here as the purchase of US dollars (Deutsche Marks) by the Fed or the Bundesbank. The results are illustrated in Figure 7. It appears that the investors had strong beliefs on the days preceding the interventions – the number of call contracts outstanding for ATM options outnumbered put contracts prior to positive interventions while the opposite was true prior to negative interventions. On average both the Fed and the Bundesbank intervened to reverse the direction of exchange rate movements by purchasing the declining currency and the open interest differentials for ATM options were bullish (bearish) before bearish (bullish) interventions. To confirm the role of interventions in our results we recomputed the out-of-sample returns after removing days of interventions. The results are summarized in Panel D of Table 3. We find that the interventions had a marginal impact on the profitability of the ATM rules; the overall average annualized excess return (Sharpe ratio) remains almost the same at 3.37% (0.36). In light of these results, we have to reject the hypothesis that the profitability of our technical trading rules using options was due to interventions.

Once again, these findings are consistent with the model of Easley, O'Hara, and Srinivas (1998) who suggest that options convey information about informed investors' beliefs and therefore serve as an indicator of where the currencies are heading. On the rare occasions when investors go too far and push the currency away from what is considered acceptable by the central banks, the options market recognizes this and the differential in open interest becomes bullish (bearish) before bearish (bullish) interventions by the central banks.

To ensure that our results are not biased by potential non-synchronicity in the data and to investigate how sensitive the results are to the precise timing of the buying and selling required by the rules, we repeat the analysis lagging the signals by one day. Overall, the results (Panel E of Table 3) hold. The ATM rules were the most affected with a decrease in profitability of 0.27%. Nevertheless, the ATM rules remain highly profitable with an average annualized excess return (Sharpe ratio) of 3.15% (0.33).

We also regressed the daily exchange rate returns on five lags of the standardized differential in open interest for ATM options. We standardize the series of open interest differentials by dividing the open interest by the mean open interest differential over the previous 50 days to ensure consistency over our sample as options trading volume ebbs and flows. We restricted our regression analysis to the returns from days on which we held a long or a short position to specifically test the significance of our rules. If the signals are meaningful the coefficients in the regression should be statistically significant. We ran a total of 240 (24 out-of-sample tests × ten best rules) regressions. Approximately 60% of the time, the first two lags are significant and positive while the third and fifth coefficients are significant and negative (results not presented). This is consistent with MA rules identifying trend reversals. On average, our rules benefited from quick reversals in the open interest differential from negative to positive (bullish), or positive to negative (bearish), in a relatively short period of time.

Consequently, the differential in open interest for ATM options appears to be a robust variable that can be used by investors to time the foreign exchange market and obtain economically and statistically significant profits.

6. Conclusions:

Over the years, researchers have presented new evidence that the foreign exchange market might not be as efficient as the theory would suggest. However, most researchers have focused their attention on the series of historical spot exchange rates without attempting to explore other potentially useful sources of information. We contribute to this literature by finding strong evidence that another source of information, options and more specifically open interest on options, add value when investing in the underlying asset. Our set of rules was fairly basic and was limited to moving average strategies. Nevertheless, all of our strategies based on at-the-money options were profitable out-of-sample and managed to earn an average mean annualized excess return of 3.42%. Moreover, we find that combining signals from both at-the-money options and historical spot exchange rates greatly improves the results from using either one of them on their own to time appreciation of the Deutsche-Mark against the US dollar with an average annualized excess return of 3.71%. A priori, if the foreign exchange market was weak efficient one should not expect to systematically earn a positive profit.

We also find evidence that the ATM rules benefited on days of extreme returns, days of potentially great changes and greater risk, consistent with a time-varying risk premium explanation. However, we interpret our results as being more consistent with the study by Easley, O'Hara, and Srinivas (1998), where option trades convey information about the informed investors' views. Overall, our results suggest that the foreign exchange market and especially the series of US$/DM does not appear to be as efficient as the theory would suggest, not so much because of historical spot rates but rather because of another source of information, the option market.

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FIGURE 1

The level of the US dollar – Deutsche Mark spot exchange rates between January 1988 and December 1999.

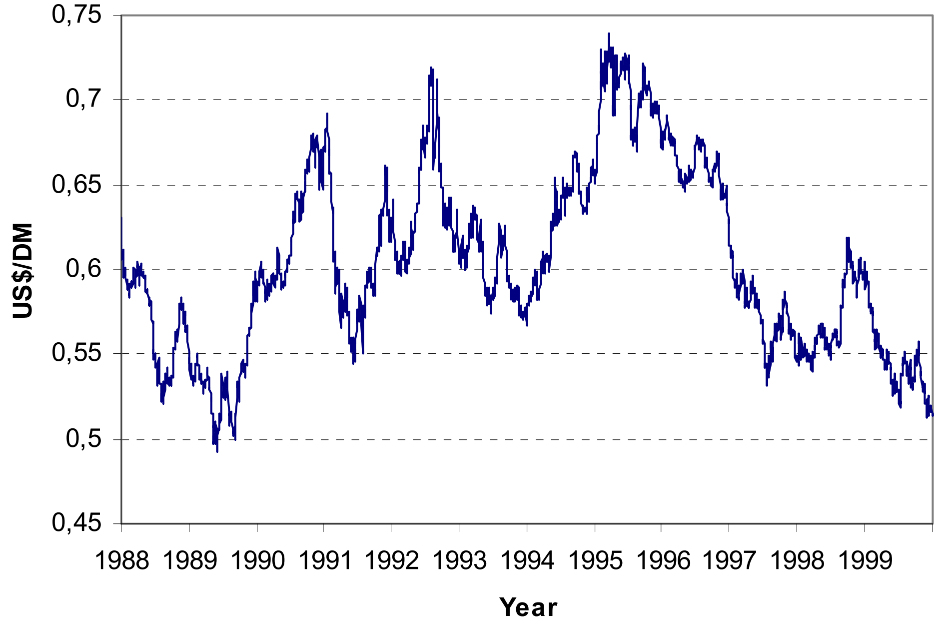
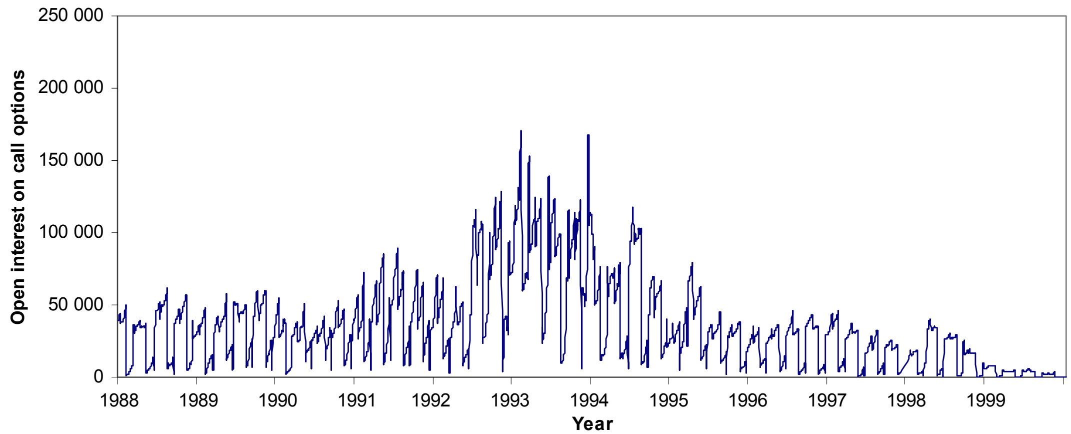


FIGURE 2

Total open interest on call and put options, including ITM, ATM, and OTM options, between January 1988 and December 1999.

Total open interest on call options between 1988 and 1999



Total open interest on put options between 1988 and 1999

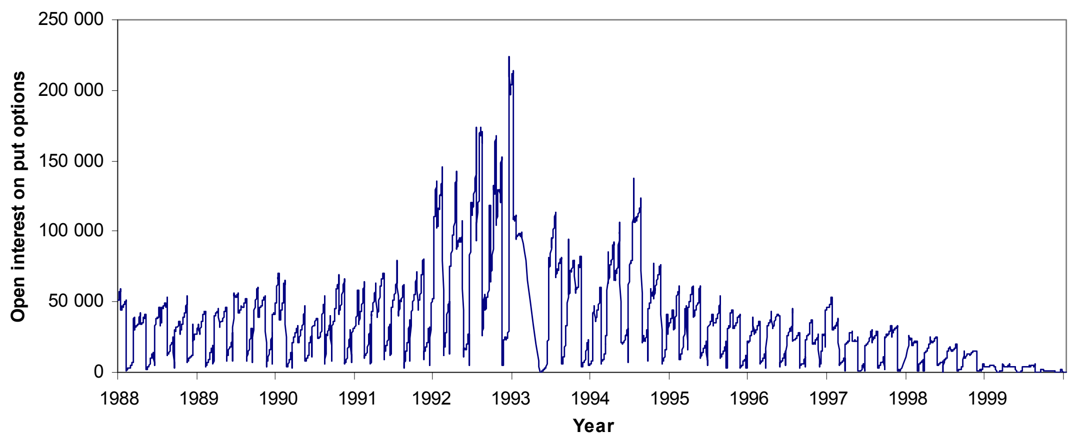
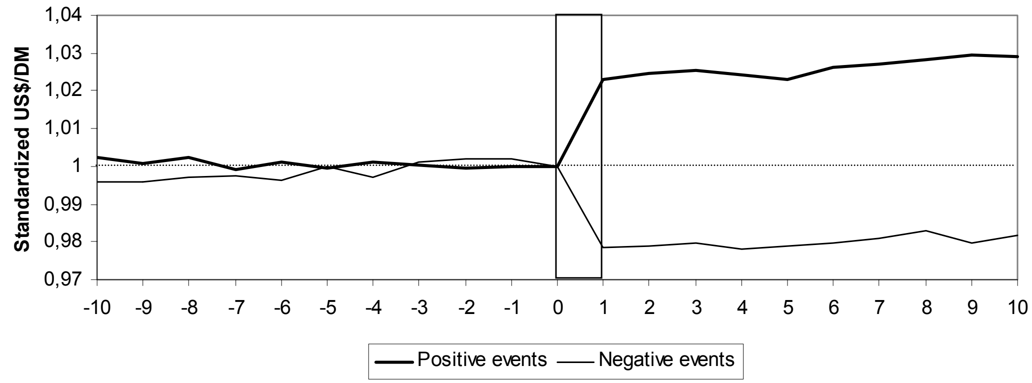


FIGURE 3

The average standardized US$/DM exchange rate and the average open interest differential (calls – puts) around the 50 days (t =0) with the most extreme positive and 50 most negative daily returns. In Panel A, we plot the average standardized US$/DM exchange rate standardized by dividing by the spot exchange over the window by the rate at t = 0. In Panel B, we consider the average differential for all of the short-term option contracts – ITM, ATM, and OTM.

Panel A



Panel B

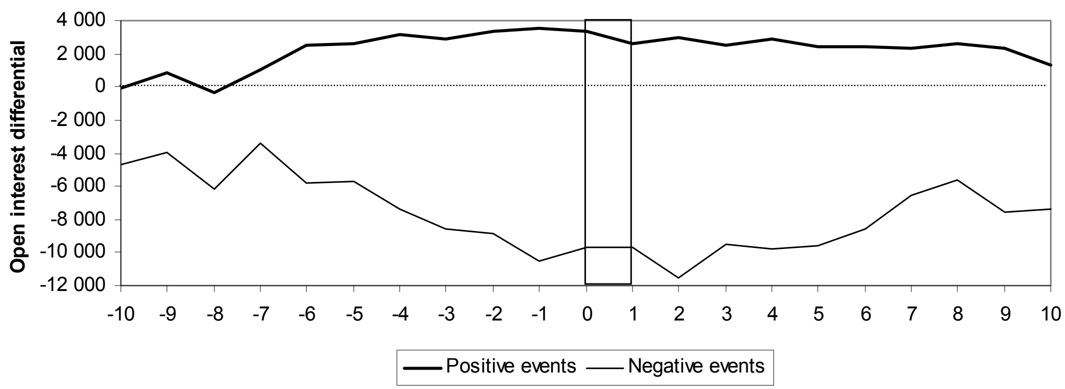
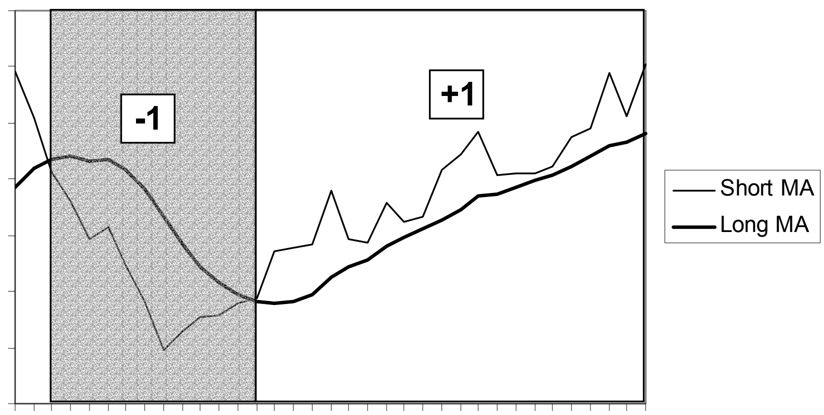


FIGURE 4

Illustration of the variable-length strategy (i.e., a zero day holding period) and a five-day fixed-length strategy (i.e., a five day holding period). The signal is set to (-1) when going short the asset, to (+1) when going long the asset, and to (0) when holding no position.

Panel A – Variable-Length Strategy



Panel B – 5-day Fixed-Length Strategy

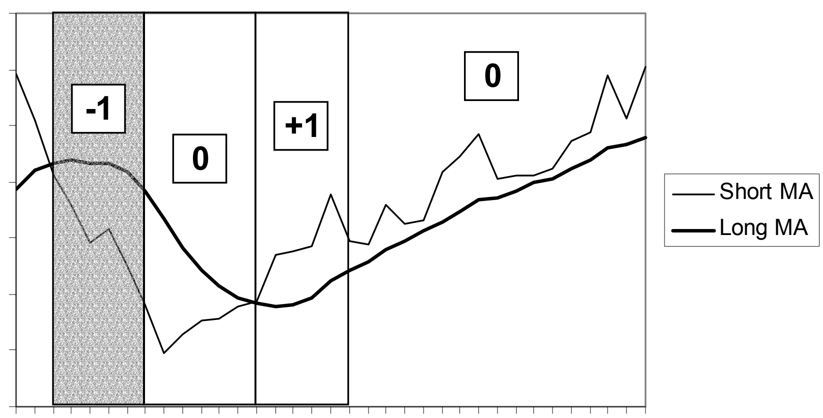


FIGURE 5

The six steps involved in computing the overall statistics of the ten best performing rules.

1

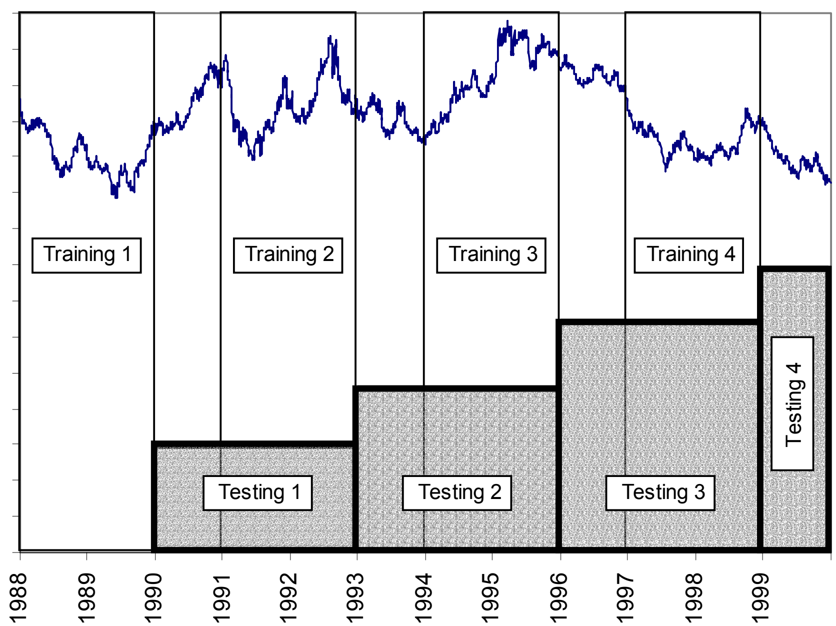
Apply the 64 MA rules to the series of US$/DM spot exchange rates to obtain 64 streams of buy/sell signals between 1988 and 1999.

2

Divide the sample period into training and testing periods for each of the 24 window combinations considered in this study. (See below for an example of 2-year training periods and 3-year testing periods.)

3

Compute the annualized mean excess return of each of the 64 MA rules over each of the training periods using the buy/sell signals from Step 1 and the daily exchange rate returns.



4

Rank the 64 rules to identify the 10 best rules in terms of excess returns over each of the training periods. Keep the 10 corresponding streams of buy/sell signals in the testing periods.

5

Combine the 10 streams of buy/sell signals from Step 4 to obtain 10 complete streams of buy/sell signals that cover, excluding the first training period, the whole sample period.

6

Compute the overall annualized mean excess return and Sharpe ratios of the 10 strategies using the buy/sell signals from Step 5 and the daily exchange rate returns.

FIGURE 6

The out-of-sample mean annualized excess returns of the overall strategies for the 10 best SPOT and ATM rules and the 50 best SPOT-ATM rules over the 1988-1999 period for our complete set of 24 training/testing combinations. We used {500, 750, 1000, 1250} trading days as training periods and {250, 500, 750, 1000, 1250} trading days as well as the remaining of the sample period as testing periods. "SPOT" summarizes the results for strategies based on signals obtained from the series of spot exchange rates, "ATM" for strategies based on signals obtained from the differential in open interest for at-the-money options, and "SPOT-ATM" summarizes the results for strategies that combine signals from both series using the "and" operator.

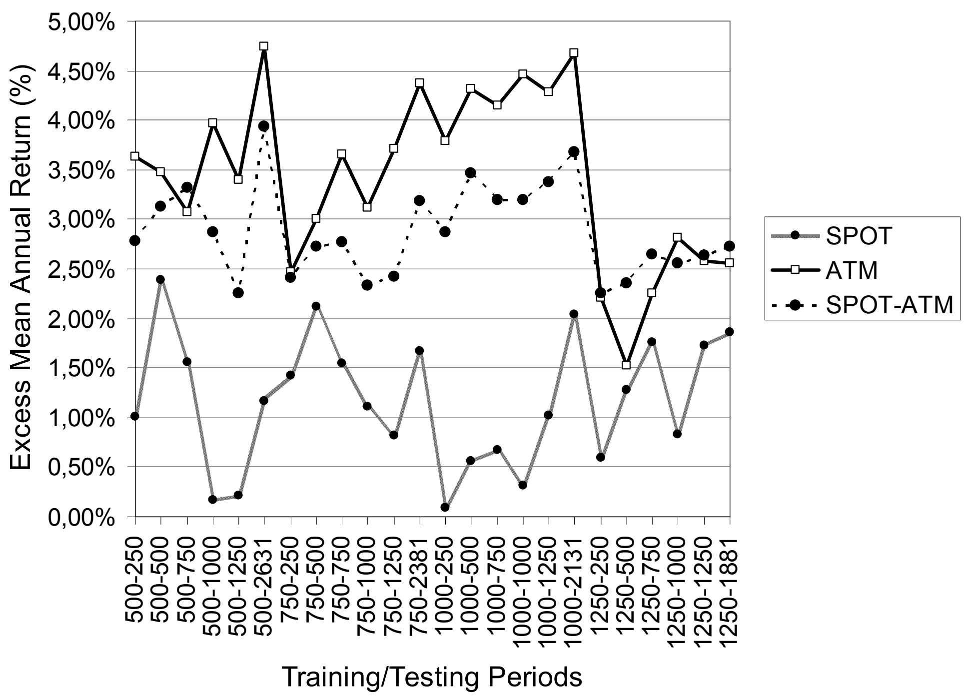
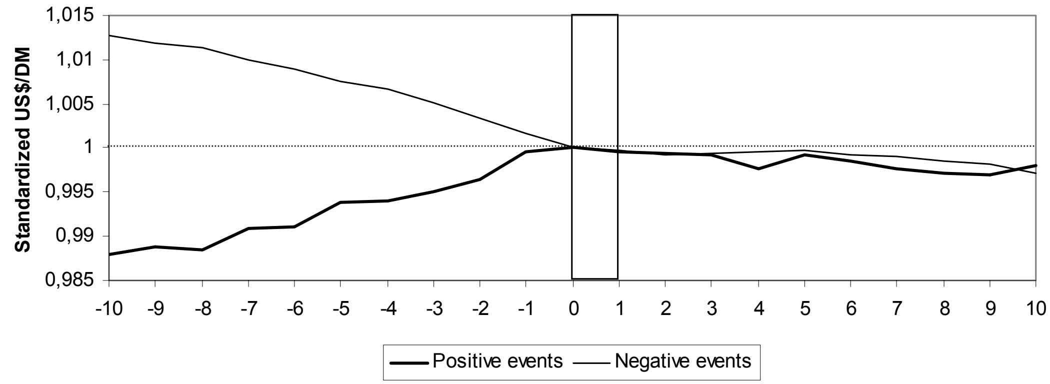


FIGURE 7

Panel A plots the average standardized US$/DM exchange rate while Panel B plots the average open interest differential (calls – puts) for ATM options around days (t =0) of interventions made by the Federal Reserve or the Bundesbank. A positive event is defined here as the purchase of US dollars while a negative event is defined as the purchase of Deutsche Marks. In Panel A, we standardized the series of US$/DM by dividing by the spot exchange rates at t = 0.

Panel A



Panel B

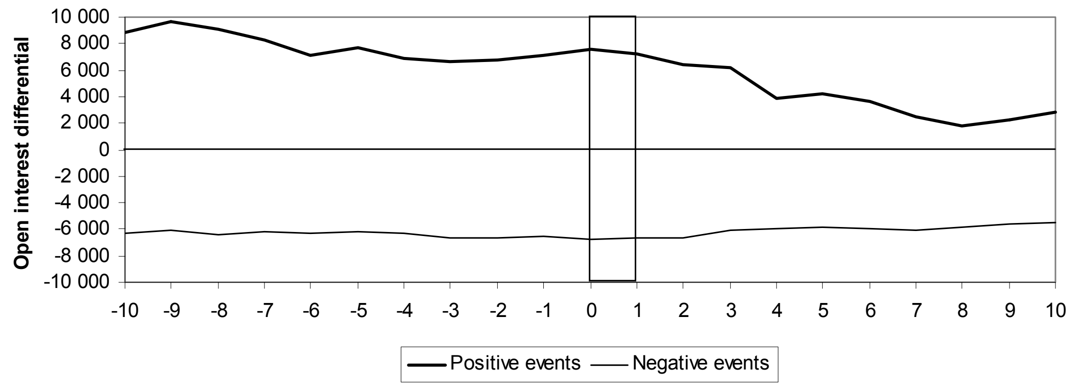


TABLE 1

The average number of call and put contracts outstanding on a daily basis based on the moneyness of options.

OPEN INTEREST ON CALL OPTIONS

	In-the-money (ITM)				ATM	Out-of-the-money (OTM)				
	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	Category 9	
(Strike - Spot)/Spot	-100% to -15%	-15% to -11%	-11% to -7%	-7% to -3%	-3% to 3%	3% to 7%	7% to 11%	11% to 15%	15% to +inf.	Sum of ALL OI
Mean	103	689	2476	4312	15921	8084	4118	2343	2332	35066
Stdev	328	2114	5002	6291	14370	9025	5451	3740	4460	29639
% -25%	0	0	35	196	4836	2125	570	256	54	12004
% - 50%	0	47	420	1471	12377	6049	2244	913	439	30188
% - 75%	29	348	2483	6410	22918	10694	5588	2848	2066	46255
Min	0	0	0	0	1	1	0	0	0	1
Max	2588	18515	33515	50292	88089	85838	58773	34353	25374	170650

OPEN INTEREST ON PUT OPTIONS

	In-the-money (ITM)				ATM	Out-of-the-money (OTM)				
	Category 9	Category 8	Category 7	Category 6	Category 5	Category 4	Category 3	Category 2	Category 1	
(Strike - Spot)/Spot	15% to +inf.	11% to 15%	7% to 11%	3% to 7%	-3% to 3%	-7% to -3%	-11% to -7%	-15% to -11%	-100% to -15%	Sum of ALL OI
Mean	200	445	1033	2995	15228	10288	5127	2775	1895	35093
Stdev	425	1107	2200	4666	13710	12129	7643	4233	2681	32883
% -25%	0	2	14	156	5418	1937	395	58	81	10556
% - 50%	1	30	186	919	12345	6900	1892	1326	883	27938
% - 75%	156	272	734	3965	20147	14245	7148	3666	2448	46664
Min	0	0	0	0	2	1	0	0	0	1
Max	3385	10213	16292	35394	103700	101640	70456	31643	23598	222990

TABLE 2

The out-of-sample statistics for the 10 (50) best trading rules derived using a single (two) series of data over the 1988-1999 period for the 24 training/testing combinations. We used {2, 3, 4, 5} years as training periods and {1, 2, 3, 4, 5} years as well as the remaining of the sample period as testing periods. Panel A summarizes the overall strategy statistics, which include the returns for days on which we go long, go short, as well as days where we hold no position at all. Panel B and C summarize the results for days on which we go long and short the asset respectively. "SPOT" summarizes the results for strategies based on signals obtained from the series of spot exchange rates, "ATM" for strategies based on signals obtained from the differential in open interest for at-the-money options, "ALLOI" for strategies based on signals obtained from the differential in open interest for all categories of options, "OTM" for strategies based on signals obtained from the differential in open interest for out-of-the-money options. "SPOT-ATM", "SPOT-ALLOI", and "SPOT-OTM" summarize the results for strategies that combine signals from more than one series using the "and" operator. "ER" is the annualized excess return, "Sharpe" is the annualized Sharpe ratio, "% Significant" is the percentage of rules with annualized excess returns (Sharpe ratios) significant at the 5% level, and "#Rules" is the number of technical rules considered in each analysis..

Panel A – The overall positions

	SPOT		ATM		ALLOI		OTM		SPOT-ATM		SPOT-ALLOI		SPOT-OTM	
	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe
Mean	1,16%	0,14	3,42%	0,36	0,83%	0,10	0,14%	0,02	2,88%	0,37	0,36%	0,05	0,37%	0,08
Stdev	0,66%	0,08	0,87%	0,09	0,91%	0,11	0,65%	0,09	0,46%	0,05	0,53%	0,08	0,41%	0,08
% Significant	21%	26%	61%	67%	18%	25%	13%	20%	51%	72%	6%	16%	7%	24%
#Rules	240		240		240		240		1200		1200		1200	

Panel B – The long positions

	SPOT		ATM		ALLOI		OTM		SPOT-ATM		SPOT-ALLOI		SPOT-OTM	
	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe
Mean	-1,69%	-0,16	1,42%	0,13	-1,73%	-0,18	-3,09%	-0,31	3,71%	0,35	-4,49%	-0,41	0,21%	0,01
Stdev	1,21%	0,12	2,29%	0,22	2,03%	0,21	1,85%	0,19	2,98%	0,28	2,75%	0,24	2,42%	0,22
% Significant	5%	3%	28%	28%	11%	11%	9%	9%	56%	55%	12%	11%	37%	36%
#Rules	240		240		240		240		1200		1200		1200	

Panel C – The short positions

	SPOT		ATM		ALLOI		OTM		SPOT-ATM		SPOT-ALLOI		SPOT-OTM	
	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe	ER	Sharpe
Mean	4,53%	0,45	6,68%	0,65	4,28%	0,43	3,90%	0,38	5,68%	0,58	4,76%	0,47	3,50%	0,34
Stdev	1,96%	0,20	1,08%	0,10	2,29%	0,23	1,85%	0,18	1,26%	0,15	2,41%	0,23	2,32%	0,22
% Significant	65%	67%	90%	90%	58%	59%	55%	55%	81%	82%	66%	66%	50%	50%
#Rules	240		240		240		240		1200		1200		1200	

TABLE 3

In Panel A are listed some of the statistics from Table 2 to facilitate the comparison of the results. Panel B and C summarize the results over the sub-periods 1988-1993 and 1994-1999 (* We only consider tests that use 500-day training periods because of the short length of the sub-periods). Panel D summarizes the results from removing days of intervention by the Federal Reserve and/or the Bundesbank. Finally, Panel E summarizes the results from lagging the signals by one day. "ER" is the mean annualized excess return, "Sharpe" is the mean annualized Sharpe ratio, "% Significant" is the percentage of rules with annualized excess returns (Sharpe ratios) significant at the 5% level, and "#Rules" is the number of technical rules considered in each analysis.

	SPOT		ATM		SPOT-ATM	
	ER	Sharpe	ER	Sharpe	ER	Sharpe
Panel A						
1988-1999	1.16%	0.14	3.42%	0.36	2.88%	0.37
% Significant	21%	26%	61%	67%	51%	72%
#Rules	240		240		1200	
Panel B*						
1988-1993	2.26%	0.21	5.71%	0.53	5.52%	0.62
% Significant	26%	24%	64%	64%	70%	79%
#Rules	50		50		250	
Panel C*						
1994-1999	-0.62%	-0.12	1.70%	0.21	2.59%	0.41
% Significant	0%	2%	18%	30%	21%	62%
#Rules	50		50		250	
Panel D						
No intervention	0.86%	0.10	3.37%	0.36	2.60%	0.34
% Significant	19%	25%	62%	65%	44%	65%
#Rules	240		240		1200	
Panel E						
1-day lag	0.97%	0.11	3.15%	0.33	2.60%	0.33
% Significant	18%	23%	56%	59%	42%	63%
#Rules	240		240		1200	