Remarks on the optimal trading horizon concerning the profitability of technical analysis on currency exchange rates: euro/US dollar 1999 - 2013

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Abstract

This paper examines the profitability regarding the application of technical trading models on data consisting of different observation lengths varying from daily data to data per second, applied to the euro/US dollar exchange rate. Excluding transaction costs, profitability concerning the application of technical trading models increases when the observation length decreases. However, once transaction costs are included, only the application of technical trading models on data consisting of daily or hourly observations remain profitable. Regarding shorter time spans, average gains from directly anticipating to a signal change do not offset the additional transaction costs, resulting in negative returns.

Keywords: technical analysis, moving averages, momentum, exchange rates

JEL classification: F31, G14, G15

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1. Introduction

Technical analysis is a popular method which is commonly used in order to predict future foreign exchange rates. The results of a survey, performed by Taylor and Allen (1992), indicate that 90% of their respondents, mainly consisting of foreign exchange dealers, make use of technical analysis in order to forecast future prices of assets. According to Cheung and Chinn (2001), investors believe exchange rates primarily fluctuate due to non-fundamental issues in the short-run. Therefore, technical analysis can be particularly useful in the determination of trading decisions in the short-term.

A large variety of studies examine whether asset prices follow exploitable patterns. Despite the fact that some studies, for example Fama (1970), conclude that markets follow a random walk and therefore price developments of assets are not exploitable, the majority of existing literature tends to adopt the view that time series contain forms of serial dependency which can be exploited. Schulmeister (2008a, 2008b) examines the profitability of both moving average models and momentum models in the spot foreign exchange market, and finds evidence for earnings potential. However, profitability with regard to technical trading rules based on daily data steadily declined over time. The decrease in profitability can be explained in two possible ways, according to Schulmeister (2008b). Firstly, profit opportunities lead to an increase in the amount of competitors which will lead to vanishing profits in the long run. Secondly, markets evolve over time, with a gradual increase in both the speed of trading and complexity of technical trading rules. Evidence in favor of the second explanation is available.

High frequency trading has grown rapidly in the 2000s to an annual trading volume of roughly $50 trillion in 2010, which is equivalent to approximately 50% of the total trading volume in the US equity markets (Kearns, Kulesza and Nevmyvaka, 2010). From the latter, one may wonder whether trading techniques can be accelerated indefinitely or whether limitations exist concerning the extent trading techniques can be accelerated.

This paper utilizes the technical trading models developed in Schulmeister (2008a, 2008b), in order to test the profitability of applying technical trading rules on the euro/US dollar exchange market regarding various observation lengths, varying from daily observations to observations per second. The main research question is ‘to what extent does the shortening of the observation length increases returns when technical trading rules are applied?’ This paper is an extension of Schulmeister (2008a, 2008b), in which multiple observation lengths, rather than one type of observations (i.e., daily observations), are investigated. Furthermore, a bootstrap approach, based on the methodology Levich and Thomas (1993) developed, is performed as a robustness check. To the extent the author knows, this paper is the first one with a focus on multiple observation lengths, varying from daily data to data consisting of observations per second.

The results demonstrate that shortening the observation length results to a limited extent in better performances, when applied to the euro/US dollar exchange rate. When transaction costs are excluded, profitability of the application of technical trading models increases when the timespan between observations is reduced. The application of technical trading models on data based on observations per second yield the largest profitability, followed by the application of technical trading models on data based on observations per minute, per hour and per day. However, when including transaction costs, only the application of technical trading models on data consisting of daily and hourly observations remain profitable. The latter is in contrast to findings from Schulmeister (2008a, 2008b) stating the profitability of the application of technical trading rules on daily observations disappeared. In short, transaction costs limit the extent to which trading decisions can be accelerated. When one is able to decrease the amount of transaction costs substantially, trading decisions potentially can be speeded up.

The structure of the paper is as follows. The next section discusses relevant literature concerning technical analysis. In addition, section 3 describes the data and section 4 the methodology. Furthermore, section 5 discusses empirical results. Lastly, section 6 concludes and provides limitations.

2. Literature review

This section explores relevant literature with regard to the profitability of the application of technical analysis. Section 2.1 describes different methods for analyzing asset prices. Section 2.2 discusses theories both contradicting and validating the utility of technical analysis. Section 2.3 and 2.4 provide evidence for profitability regarding the application of technical analysis on stock exchange markets and foreign exchange markets respectively. Section 2.5 discusses developments concerning technical trading systems, resulting in the establishment of a hypothesis.

2.1. Trading techniques

Two types of methods can be distinguished in order to forecast asset prices, namely fundamental analysis and technical analysis. A fundamental analyst is concerned with all factors potentially influencing the value of an asset. For example, by taking into account financial statements, market perspectives, threats of new entrants and governance, a stock price is evaluated (Edwards, Magee and Bassetti, 2007). In contrast to fundamental analysts, technical analysts are solely concerned with asset price developments. Edwards, Magee and Bassetti define technical analysis as follows:

"Technical analysis is the science of recording, usually in graphic form, the actual history of trading (price, changes, volume of transactions, etc.) in a certain stock or in 'the averages' and then deducing from that pictured history the probable future trend."

In short, technical analysts attempt to discover price trends which can be exploited. With regard to technical analysis, a wide variety of indicators is developed, mainly based on chart patterns. This paper investigates two of the most popular indicators, namely indicators based on momentum and indicators based on moving averages. According to Taylor and Allen (1992), approximately 90% of the foreign exchange dealers uses technical analysis. Moreover, roughly 64% makes use of moving average indicators and 40% uses momentum indicators in order to determine trading decisions. Both moving average and momentum rules indicate price trends, the former by comparing the price of a security at time t with the price at a chosen time in the past and the latter by comparing a short-term moving average with a long-term moving average.

2.2. Theories

Fama (1970) developed the efficient market hypothesis, which is a frequently used assumption in economic models. In an efficient market, all the information available is fully reflected in market prices. According to Fama (1970), the evidence that this assumption holds is comprehensive. From the assumption of efficient markets, it follows implicitly that achieving excess returns by making use of technical analysis in order to predict future stock prices is not possible. A theory consistent with the efficient market hypothesis is the assumption of asset prices following a random walk. Malkiel (2012) examines the random walk hypothesis and finds evidence in favor of this assumption. According to Malkiel (2012), stock prices are unpredictable and follow a random walk. Furthermore, technical analysis leads to inferior results in comparison with a buy and hold strategy.

Efficient markets assume no transaction costs, full accessibility of information to all investors and homogeneously beliefs (Fama, 1970). One may wonder what credibility can be given to the efficient market hypothesis in light of the formation of bubbles, like the dot.com bubble around the year 2000 and the real estate bubble in the recent years. From the latter, one may question in particular the assumption of homogeneously beliefs.

Lo and MacKinlay (2002) denounce the assumption of stock prices following a random walk and find evidence which is in contradiction to this assumption. Main findings are markets following trends and thus, predictable patterns exist concerning asset returns. De Long et al. (1987) developed a model in which the assumption of homogeneous beliefs is softened. This model assumes investors with non-optimal beliefs can influence market prices and consequently can outperform fully informed investors' returns. In particular, short-horizon trading may cause asset prices deviating from fundamental values. In the long run, however, asset prices converge to fundamental values, according to De Long et al. (1987).

Froot, Scharfstein and Stein (1992) investigate inefficiencies of asset prices in the short run. Contrary to classical models, which generally assume that one may benefit from information which is not widely available, they state that in the short run, investors may benefit by using information other investors utilize. It is the perception of other investors in the market which determines whether assets prices increase or decrease in the short run. In short, the more investors are aware of a certain part of information, the more homogeneously short-term investors act and the more excess returns can be achieved. When relating the foregoing to technical analysis, one may expect to benefit when applying information resulting from analyzing trends, assuming sufficient investors make use of the same information.

2.3. Evidence from stock exchange markets

Brock, Lakonishok and LeBaron (1992) define 10 simple moving average rules and analyze the returns during the first 10 days subsequent to a trend reversal. They use daily data of the Dow Jones Industrial Average for the period 1897 to 1986, in order to test the technical trading rules. The models consist of short and long periods of 1 and 50, 1 and 150, 5 and 150, 1 and 200, and 2 and 200 days respectively. Moreover, the moving average rules are tested both with and without a band. The concept behind the band is that the crossing of the two moving averages possibly creates a false signal. By using a one percent band, however, they minimize the chance the signal is not a permanent trend reversal. Brock, Lakonishok and LeBaron (1992) provide strong evidence of moving average rules containing predictive power. Fang and Xu (2002) test the trading rules developed by Brock, Lakonishok and LeBaron (1992) for an enlarged dataset. They use data from the Dow Jones Industrial Index, the Dow Jones Transportation Index and the Dow Jones Utilities Index, for the period 05/1896 to 05/1996. From Brock, Lakonishok and LeBaron, it can be concluded that the utilization of technical trading rules is particularly useful in order to determine when to take a long position in the market. Furthermore, the models including a 1% band outperform the models without a band.

Wong, Manzur and Chew (2003) examine whether technical analysis can lead to a better timing when to entry and when to exit the market. They test moving average rules and rules regarding the relative strength index on the Singapore Stock Exchange for the years 1974 to 1994. The relative strength index is a form of a momentum oscillator, which compares the ratio between the average positive return and the average negative return for a given time span. A high ratio reflects a positive momentum whereas a low ratio reflects a negative momentum (Edwards, Magee and Bassetti, 2007). Wong, Manzur and Chew find evidence for the achievement of excess returns when following signals obtained from the technical trading rules. Transaction costs, however, are excluded in the analysis.

Lin, Yang and Song (2011) use genetic algorithms in conjunction with technical trading rules. The technical trading rules include moving average rules. The model they developed outperforms the traditional buy and hold strategies. Marshall, Cahan and Cahan (2008) investigate moving averages on the Standard & Poor's Depository Receipt. The results from this study, however, do not indicate any signs of inefficiencies for the period 2002 to 2003. Vella and Ng (2013) use high frequency data in order to develop a model with a dynamic set of moving average signals. They investigate the performance of a trading model with holding periods from 10 minutes to 1 hour on the London Stock Exchange, for the period 06/2007 to 06/2008. By applying the model Vella and Ng developed, excess returns can be achieved in the short run.

2.4. Evidence from foreign currency markets

Numerous empirical studies regarding the application of technical trading rules on foreign currency markets are available. Dooley and Shafer (1986) test foreign exchange rates based on daily data for the period 03/1973 to 11/1981 and find evidence for foreign exchange rates following a non-random walk. Resulting from this, Dooley and Shafer conclude that the efficient market theory does not hold on the foreign exchange market. Furthermore, they find no evidence of a decline in profitability over time for the utilization of trading rules. Hsieh (1989) yields similar results. By analyzing the British pound, Canadian dollar, Deutsche mark, Japanese yen and the Swiss franc against the US dollar for the period 1974 to 1983, Hsieh finds evidence of interdependency between daily observations.

Neely, Weller and Dittmar (1997) use a given sample period in order to attain trading rules leading to excess returns. They analyze a variety of exchange rates against the dollar, as well as the yen/Deutsche mark and Swiss franc/pound. In order to avoid a potential bias by examine trading rules ex post, they use an out of sample period in order to test the trading rules obtained from the sample period. The trading rules attained from the sample period lead to excess returns in the out of sample period, transaction costs taken into account. The results from a bootstrap procedure support the findings.

Schulmeister (2009a) investigates 1024 moving average and momentum models. Schulmeister finds evidence of excess returns by using the technical trading rules in the yen/US dollar market, using daily data for the period 1976 to 2007. Schulmeister (2008a) investigates the profitability of momentum and moving average models on the Deutsche mark/US dollar market, for the period 1973 to 1999. The findings arising from this study are equivalent to the findings from Schulmeister (2009a). Moreover, in an out-of-sample period test, containing daily euro/US dollar returns for the period 2000 to 2004, above 90% of the trading models continues to be remunerative.

Previously discussed literature focuses on daily data. According to Schulmeister (2007), however, profit opportunities regarding the application of technical analysis on daily data are declining. Schulmeister (2007) analyzes the S&P 500 spot market and concludes that the profitability by using technical trading rules steadily declined from 8.6% in the period 1960 to 1971 to no profit at all in the 1990s. In the foreign exchange market, the profitability by using technical analysis on daily basis followed a similar pattern over time. Schulmeister (2008b) states the profitability with regard to currency trading based on technical analysis has vanished since 2000. In the yen/US dollar market, the average return of the investigated models yield an average return of 0.1% per year between 2000 and 2007. However, an out-of-sample test, performed on the euro/US dollar market in the period 2000 to 2004, yields an average return of 3.8%. Olson (2004) and Neely, Weller and Ulrich (2007) yield similar results.

In short, from the studies discussed above it can be concluded that initially, it was feasible to achieve significant excess returns by using technical trading rules based on daily data. However, this profitability declined gradually over time. Concerning technical trading rules based on intraday data, literature in which more advanced trading rules are applied is mainly available.

Gençay et al. (2002) examine the performance of a real-time trading model in which buy and sell signals are defined by using exponential moving averages. They use five-minute data of four exchange rates for the years 1990 to 1996, which totals a sample of over 500,000 observations. The real-time trading model they analyze yield excess returns in the sample period. Osler (2000) finds evidence for profitability based on a one-minute interval, using technical trading rules with regard to support and resistance levels. Neely and Weller (2001) use data with a time span of 30 minutes per observation for the year 1996 and find predictable patterns in the intraday exchange rates they investigate. However, once transaction costs are included, they achieve no significant excess returns. Kearns, Kulesza and Nevmyvaka (2010) and Schulmeister (2009b) provides evidence of profitability for the application of technical trading rules based on intraday data concerning the stock exchange market. Kearns, Kulesza and Nevmyvaka examine the application of technical trading rules on high frequencies, with holding periods varying from 10 milliseconds to 10 seconds, and find profits to be moderate. Schulmeister (2009b) finds evidence for profitability when technical trading models are applied to 30-minute data. Moreover, profitability remained stable between 1983 and 2007.

2.5. Development of technical trading systems

As can be derived from the literature above, it can be concluded that the profitability regarding the application of technical trading rules based on daily data has gradually declined. Moreover, evidence is available that profitability shifted to the application of technical trading rules on data with a shorter timeframe. Developments in computer software and internet resulted in the emergence of intraday pricing models. The focus on intraday data led to more irregular daily price changes and the subsequent decline in profit opportunities based on daily data, according to Schulmeister (2007).

Schulmeister (2008b) mentions two different explanations as possible causes for the disappearance of the profitability when applying technical trading rules based on daily data. Firstly, the decline in profitability can be explained by the adaptive market hypothesis, a theoretical concept developed by Lo (2004). Lo defines the adaptive market hypothesis as an extension of the efficient market hypothesis, in which the degree of efficiency depends on the market conditions and the amount and nature of market participants. In an initially inefficient market, competition will increase due to profit opportunities. As a result of increasing competition, profit opportunities will decline over time. Although an increase in competition is a plausible argument for a decline in profit opportunities in general, this is contrary to Froot, Scharfstein and Stein (1992), stating an increase in the number of well-informed market participants may lead to an increase in profit opportunities in the short run. Secondly, developments in the type of models and type of data traders use can explain the decline in profitability of simple technical trading rules based on daily data. Due to the fact that technical trading rules tend to focus on shorter time spans and/or trading rules become more advanced, profit opportunities using simple technical trading rules based on daily data are eroding.

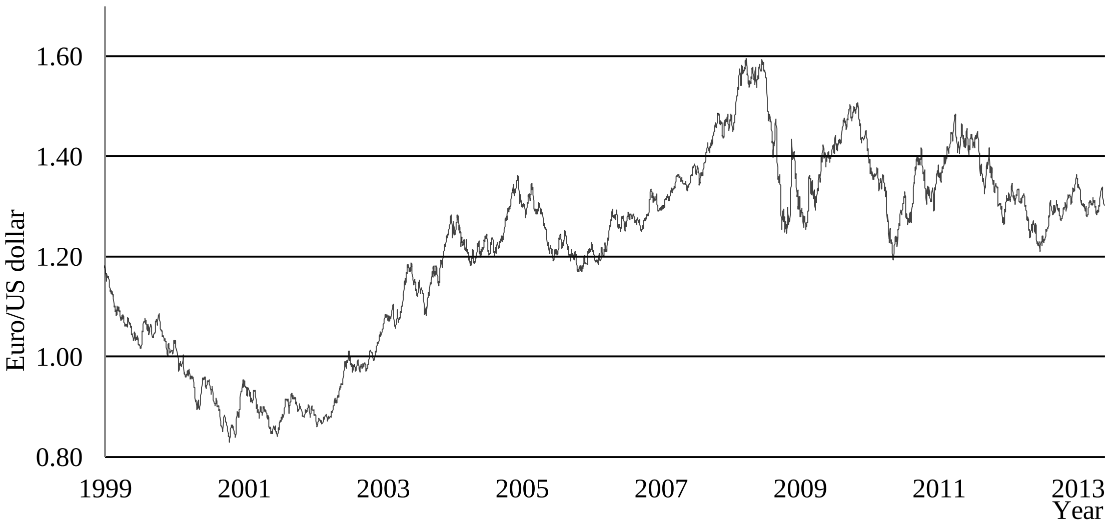
This paper investigates the profitability of the application of moving average models and momentum models on data regarding a range of timeframes, varying from daily observations to observations per second. Based on existing literature and explanations Schulmeister (2008b) provides, the following hypothesis can be drawn up: 'shortening the observation length results in increasing returns when technical trading rules are applied'. The next section describes the data this paper uses.

3. Data

This paper uses the euro/US dollar exchange rate in order to test the hypothesis stated above. Specifically, this paper uses data based on daily observations, hourly observations, as well as data based on observations per minute and observations per second.

Figure 3.1
Euro/US dollar exchange rate 1999-2013

Figure 3.1 displays the euro/US dollar exchange rate for the period 01/1999 to 06/2013.



The euro/US dollar exchange rates are obtained from Dukascopy[2], a Swiss Forex Bank and Marketplace. Daily returns for the period 01/1999 to 06/2013, hourly returns for the period 07/2003 to 06/2013, returns per minute for the period 01/2013 to 06/2013 and returns per second for the period 09-30-2013 to 10-02-2013 are collected. Due to the fact the foreign exchange market is closed between Friday 21.00 GMT and Sunday 21.00 GMT, data in-

[2] The euro/US dollar exchange rates are obtained from the following website: http://www.dukascopy.com/swiss/english/marketwatch/historical/

between this period is cleared out. Quotations are defined as the averages of hourly open and closing rates. From this, logarithmic returns (x_t) are calculated. The final sample consists of 4,304 daily logarithmic returns, 63,017 hourly logarithmic returns, 184,423 logarithmic returns for the data per minute and 259,196 logarithmic returns for the data per second.

Figure 3.1 shows the euro/US dollar exchange rate for the period 01/1999 to 06/2013. The euro/US dollar exchange rate declined in the period 1999 to 2001. In the subsequent years, the euro/US dollar exchange rate increased from 0.84 in 07/2001 to a peak of 1.59 in 04/2008. From the peak in 04/2008, a downward trend started. The euro/US dollar exchange rate amounted to 1.30 in 06/2013.

Table 3.1
Summary statistics for returns per day, hour, minute and second

This table provides summary statistics for the data used in this study. The sample period for the daily euro/US dollar returns is 01/1999 to 06-2013, for the hourly euro/US dollar returns is 07/2003 to 06/2013, 01/2013 to 06/2013 for the euro/US dollar returns per minute and 09-30-2013 to 10-02-2013 for the euro/US dollar returns per second. *N* is the number of logarithmic returns.

	Day	Hour	Minute	Second
Mean	0.0000233	0.0000019	-0.0000001	0.0000000
Median	0.0000221	0.0000000	0.0000000	0.0000000
Maximum	0.025273	0.013880	0.002049	0.000532
Minimum	-0.021778	-0.013002	-0.013141	-0.000801
Std. Dev.	0.004402	0.000946	0.000108	0.000012
Skewness	-0.0371	0.1216	-10.0344	-0.7594
Kurtosis	4.5567	12.8613	1,202.4140	244.2743
Sum	0.1002	0.1217	-0.0148	0.0066
N	4,304	63,017	184,423	259,196

Table 3.1 provides statistics for the data used in this study. Summary statistics for euro/US dollar returns per day, per hour, per minute and per second are reported. The mean return is small for all samples, with an average return of below 1% per year for the daily and hourly returns. The total return for the sample based on data per minute, with a sample period of half a year, equals -1.48% and the three day return for the sample based on returns per second is equally to 0.66%. The standard deviation per unit of time is the highest for the daily statistics and decreases when the timespan between observations decreases. A normal distribution is defined to have a skewness of 0 and a kurtosis of 3 (Brooks, 2008). The skewness for the daily data, hourly data as well as data per second is around zero. The distribution of the data per minute, however, is highly asymmetric, with a skewness of -10.03. The value of the kurtosis exceeds 3 in all samples, with very high values for the samples based on data per minute and data per second. The latter indicates the disturbances are non-normally distributed.

4. Methodology

This section provides a description of the models this paper uses in order to test the hypothesis. Furthermore, this section describes a bootstrap approach which serves as a robustness check.

4.1 Models

The methodology in this paper is based on Schulmeister (2008a, 2008b). Schulmeister investigates respectively the daily Deutsche mark/US dollar and the daily yen/US dollar exchange rates. Schulmeister examined the profitability of 1024 technical trading models, consisting of models based on simple moving averages as well as momentum models. Schulmeister tested a large number of models since investors generally use many different models. Furthermore, a large set of models is analyzed in order to avoid selection bias. In this paper, data based on daily returns, as well as returns per hour, minute and second will be analyzed. Schulmeister (2008b) selected the 25 best performing models and tested these models out-of-sample. These 25 models performed similar out-of-sample in comparison to the average in-sample performance. From this it can be concluded that model picking ex ante will not lead to abnormal returns on average. A sample consisting of 70 from the 1,024 technical trading models defined by Schulmeister will be analyzed in this paper.

The first type of models, used by Schulmeister, compares a short-term moving average with a long-term moving average. Moving average rules are defined as follows: take a long position when the short-term moving average intercepts with the long-term moving average from below and take a short position if the opposite occurs. The short-term moving average consists of respectively 1, 5, 10 or 15 hours, the long-term moving average consists of 5, 10, 15, 20, 25, 30, 35 or 40 hours. Furthermore, each model is performed with and without a one-hour lag. The reason for a one-hour lag is to prevent the models from providing wrong signals (Brock, Lakonishok and LeBaron, 1992). All combinations will be analyzed, with the requirement the long-term average exceeds the short-term moving average, which results in a quantity of 52 technical trading models. Transaction costs will be included in the analysis. According to Schulmeister (2008a, 2008b), transaction costs will amount to 0.02% per trade, in which the bid-ask spread is included. Thus, a conversion from a short to a long position or vice versa will result in transaction costs of 0.04%. When it is assumed that having a position is equivalent to borrowing in one currency and going long in the other currency, interest will be both paid and received. According to LeBaron (1999), this is equivalent to a zero cost strategy.

Therefore, net interest costs are assumed to be zero. The moving averages can be stated in formula as follows:

$$STMA_t = \left(\frac{\sum_{t-a+1}^{t} \cdot x_t}{a}\right) \text{ with } a \in \{1, 5, 10, 15\} \text{ and } a < b \tag{4.1}$$

$$LTMA_t = \left(\frac{\sum_{t-b+1}^{t} \cdot x_t}{b}\right) \text{ with } b \in \{5, 10, 15, 20, 25, 30, 35, 40\} \text{ and } a < b \tag{4.2}$$

Where:

$STMA_t$ = short-term moving average at time t

$LTMA_t$ = long-term moving average at time t

x_t = $ln\ (E_t) - ln\ (E_{t-1})$

E_t = euro/US dollar spot exchange rate at time t

From equations (4.1) and (4.2), the following trading rules can be defined:

Assuming a lag of zero:

$$S_t = \begin{cases} 1, if\ \ STMA_t > LTMA_t \\ -1, if\ \ STMA_t < LTMA_t \\ S_{t-1}, if\ \ STMA_t = LTMA_t \end{cases} \tag{4.3}$$

Assuming a one-period lag:

$$S_t = \begin{cases} 1, if\ STMA_t > LTMA_t\ \ and\ \ \ STMA_{t-1} > LTMA_{t-1} \\ -1, if\ STMA_t < LTMA_t\ \ and\ \ STMA_{t-1}\ <\ LTMA_{t-1} \\ S_{t-1}, if\ \ S_t \neq S_{t-1} \end{cases} \tag{4.4}$$

When the signal changes from positive to negative or vice versa, this has an effect on the return of the subsequent hour. From this, it follows that the return at time t can be defined as:

$$r_t = x_t \cdot S_{t-1} - (|S_t - S_{t-1}|) \cdot c \tag{4.5}$$

Where:

c = transaction costs

The average return, resulting from a trading model for a period with n returns, can be defined as:

$$\overline{R} = \frac{\sum_{t=1+b}^{n} S_{t-1} \cdot r_t}{n-b} \tag{4.6}$$

The second type of models, used by Schulmeister, is based on momentum. Momentum rules are defined as: take a long (short) position when an exchange rate at time t is increased (decreased) compared with h hours prior to time t, with h having a value of 3, 5, 10, 15, 20, 25, 30, 35 or 40. Equally to the models based on moving averages, the models based on momentum (M) will be performed both with and without a one-hour lag. In formula:

$$M \quad = E_t - E_{t-h}, \qquad \text{with } h \in \{3, 5, 10, 15, 20, 25, 30, 35, 40\} \tag{4.7}$$

Trading rules are defined as follows:

Assuming a lag of zero:

$$S_t \quad = \begin{cases} 1, if\ M_t > 0 \\ -1, if\ M_t < 0 \\ S_{t-1}, if\ M_t = 0 \end{cases} \tag{4.8}$$

Assuming a one-period lag:

$$S_t \quad = \begin{cases} 1, if\ M_t > 0\ and\ M_{t-1} > 0 \\ -1, if\ M_t < 0\ and\ M_{t-1} < 0 \\ S_{t-1}, if\ M_t \neq M_{t-1} \end{cases} \tag{4.9}$$

Returns can be calculated in a similar way as the returns from the moving average models:

$$r_t \quad = x_t \cdot S_{t-1} - (|S_t - S_{t-1}|) \cdot c \tag{4.10}$$

Average return equals to:

$$\overline{R} \quad = \frac{\sum_{t=1+h}^{n} S_{t-1} \cdot r_t}{n-h} \tag{4.11}$$

Tests will be performed concerning the mean returns. The null hypothesis can be defined as follows: the average return does not significantly differ from zero. Under the alternative hypothesis, average returns do significantly differ from zero. Tests regarding the average return of the moving average models, both with and without a lag, and the average return of the momentum models, both with and without a lag, are performed. Furthermore, the average return of all models combined is tested against the null hypothesis. The hypothesis is tested using t-statistics. T-statistics assume returns following a normal distribution. Secondly, error terms are assumed to have a constant variance, with a covariance and a mean of zero over time. Lastly, covariances between error terms and explanatory variables are assumed to be zero (Brooks, 2008). Time-series based on asset returns, however, typically do not satisfy these assumptions. According to Brooks, the disturbances of financial time series most likely follow a non-normal distribution. Financial time series are normally characterized by a leptokurtic distribution, a distribution which is more peaked at the mean and which has fatter tails. Due to the existence of non-normality, the results of test-statistics are of limited value. Therefore, in addition to the t-test, the Wilcoxon signed rank test will be performed. The Wilcoxon signed rank test tests whether median returns significantly differ from zero (Wilcoxon, 1945). Furthermore, a bootstrap analysis will be applied in order to check the robustness of the results.

4.2 Bootstrapping

Bootstrapping is a non-parametric application and is suitable to check the robustness of the results, due to several advantages. Firstly, normality and a constant variance is not necessary. Furthermore, determination of the distribution is not necessary and results are solely based upon many replications (Rochowicz Jr., 2010). Bootstrapping is a process in which data points from the original sample will be used. By simulating a large amount of random samples, using the original data as an input, the approximate distribution of the original sample can be determined. In this study, a bootstrap procedure, comparable to the bootstrap process of Levich and Thomas (1993), is applied. Logarithmic returns from the original data are used in the simulation process. 500 Random samples (with replacement) are generated from the logarithmic returns following from the original data. By randomly shuffling the original data, any dependency between observations in the original data are removed, allowing one to draw conclusions with regarding the actual data (Brooks, 2008). Each set of trading rules, specifically the set of moving average rules and the set of momentum rules (both with and without a one-period lag), are applied on the set of randomly simulated samples. Statistics with regard to the profits resulting from applying the technical trading rules on the simulated samples are provided. Furthermore, average profits from the application of technical trading rules on the original data are compared to the profits resulting from the application of technical trading rules on the simulated samples. Assuming the original sample contains a non-random walk which can be exploited by using technical trading model, one may expect the profitability from the application of technical trading rules on the original data exceeds the profitability from the application of technical trading rules on the simulated samples.

5. Results

This section contains an overview of the results. Firstly, section 5.1 contains results regarding the full set of models and subsets of models. Results regarding the profitability for each sample are provided, as well as test statistics regarding the comparison of samples and results regarding the sustainability of returns over time. In addition, section 5.2 contains results regarding the bootstrap approach. Finally, section 5.3 describes the best performing individual models.

5.1 Results sets of models

Table 5.1
Sample statistics of daily returns

This table provides an overview of the coefficients and test statistics with regard to daily returns on the euro/US dollar exchange market for the period 01/1999 to 06/2013. MA refers to the set of moving average models, without and with a one-period lag, respectively. MO refers to the set of momentum models, respectively without and with a one-period lag. *N* is the number of logarithmic returns. Transaction costs amount to 0.02% per trade.

Panel A: Transaction costs included					
	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	4,264	4,265	4,265	4,265	4,264
Mean	0.000329	0.000613	0.000098	0.000380	0.000126
Median	0.000021	0.000102	-0.000023	0.000116	0.000038
Std. dev.	0.002236	0.002605	0.002650	0.003229	0.003266
Skewness	1.41	1.30	0.50	0.63	0.31
Kurtosis	15.32	11.02	10.77	8.51	8.24
t-statistics					
Value	9.61	15.36	2.41	7.69	2.51
Probability	0.0000	0.0000	0.0159	0.0000	0.0120
Wilcoxon signed rank					
Value	6.95	12.11	1.22	6.38	1.93
Probability	0.0000	0.0000	0.2232	0.0000	0.0540
Panel B: Transaction costs excluded					
	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	4,264	4,265	4,265	4,265	4,264
Mean	0.000388	0.000695	0.000153	0.000416	0.000153
Median	0.000080	0.000185	0.000000	0.000149	0.000064
Std. dev.	0.002224	0.002575	0.002633	0.003216	0.003260
Skewness	1.41	1.33	0.51	0.63	0.30
Kurtosis	15.47	11.27	10.89	8.55	8.26
t-statistics					
Value	11.39	17.62	3.78	8.46	3.07
Probability	0.0000	0.0000	0.0002	0.0000	0.0022
Wilcoxon signed rank					
Value	9.88	15.74	3.35	7.40	2.75
Probability	0.0000	0.0000	0.0008	0.0000	0.0059

Tables 5.1 to 5.4 contain sample statistics for respectively returns based on data per day, per hour, per minute and per second. For each sample, an overview is provided both including transaction costs, amounting to 0.02%, and excluding transaction costs. Furthermore, each table shows the results for the subset of models with regard to moving average and momentum rules, both with and without a one-period lag.

From table 5.1, it follows that mean daily returns are positive for each set of models, when transaction costs are included. Mean returns are positive and significant at a 1% confidence interval, for both the set of moving averages and the set of momentum models without a lag. When a one-period lag is included, mean returns for both the set of moving average models and the set of momentum models are significant at a 5% confidence level. Median returns are positive and significant at a 1% confidence interval for both the set of moving average models and the set of momentum models without a lag. The moving average models and momentum models with a one-period lag yield no significant results at a 5% confidence interval. The average return for the full sample equals 0.0329% per observation, which is equivalent to an average return of 10.39% per year. The daily standard deviation is 0.22% for the full sample, and varies from 0.26% to 0.33% in the subsamples. The results, when transaction costs are excluded, are all significant at a 1% confidence level. The distribution is asymmetrical with a moderate skewness to the right and a positive kurtosis in all samples, reflecting a leptokurtic distribution.

Sample statistics concerning hourly returns, shown in table 5.2, yield mixed results. Transaction costs included, returns for the moving average models and the momentum models without a lag are positive and significant at a 1% confidence level. When a one-period lag is included, however, both set of models yield negative returns, significant at a 1% confidence level. Median returns are negative and significant at a 1% confidence level, when transaction costs are included. The mean return is 0.0013% per hour, which is equal to an average yearly return of approximately 8.19%. The hourly standard deviation averages 0.02%, which is slightly less than the daily standard deviation. Both skewness and kurtosis are slightly larger in comparison with the daily skewness and kurtosis. Assuming no transaction costs, all subsamples yield positive mean returns, significant at a 1% confidence level. The mean return for the full sample is 0.007% per observation, which is equal to a yearly return of over 44%. Median returns are positive and significant in all subsamples, except for the set of momentum models with a lag, which yields a negative and highly significant median return.

Table 5.2
Sample statistics of hourly returns

This table provides an overview of the coefficients and test statistics with regard to hourly returns on the euro/US dollar exchange market for the period 07/2003 to 06/2013. MA refers to the set of moving average models, without and with a one-period lag, respectively. MO refers to the set of momentum models, respectively without and with a one-period lag. *N* is the number of logarithmic returns. Transaction costs amount to 0.02% per trade.

Panel A: Transaction costs included					
	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	62,977	62,978	62,978	62,978	62,977
Mean	0.000013	0.000057	-0.000026	0.000033	-0.000023
Median	-0.000046	-0.000044	-0.000046	-0.000026	-0.000040
Std. dev.	0.001975	0.002882	0.002544	0.001887	0.002035
Skewness	1.72	2.11	0.45	1.26	0.35
Kurtosis	25.19	25.00	18.27	22.41	20.02
t-statistics					
Value	6.36	22.82	-11.09	11.49	-8.27
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Wilcoxon signed rank					
Value	31.31	12.45	35.52	9.72	24.81
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B: Transaction costs excluded					
	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	62,977	62,978	62,978	62,978	62,977
Mean	0.000070	0.000135	0.000027	0.000071	0.000007
Median	0.000007	0.000023	0.000000	0.000006	-0.000002
Std. dev.	0.000492	0.000596	0.000569	0.000696	0.000677
Skewness	1.79	2.35	0.50	1.38	0.36
Kurtosis	26.42	28.00	19.46	23.03	20.35
t-statistics					
Value	35.86	56.96	11.88	25.67	2.63
Probability	0.0000	0.0000	0.0000	0.0000	0.0086
Wilcoxon signed rank					
Value	27.28	51.58	6.13	15.52	3.85
Probability	0.0000	0.0000	0.0000	0.0000	0.0001

Contrary to the returns based on daily and hourly data, returns per minute yield no positive results when transaction costs are included. As shown in table 5.3, both mean returns and median returns are negative and highly significant in all subsets. The mean return for the full sample equals -0.0053% per minute, which is equivalent to a daily loss of 7.63%. The standard deviation amounts to 0.0072% per observation for the full sample. The distribution is moderately skewed and contains a high level of kurtosis. When excluding transaction costs, positive results can be achieved using technical trading models. All subsets, except from momentum models including a one-period lag, yield significant results on a 1% confidence level. The set of momentum models with a one-period lag yield significant positive returns on a 5% confidence level. In the absence of transaction costs, the full sample yields a profit of 0.0007% per minute on average, which is equivalent to 1.01% per day.

Table 5.3
Sample statistics of returns per minute

This table provides an overview of the coefficients and test statistics with regard to minute returns on the euro/US dollar exchange market for the period 01/2013 to 06/2013. MA refers to the set of moving average models, without and with a one-period lag, respectively. MO refers to the set of momentum models, respectively without and with a one-period lag. *N* is the number of logarithmic returns. Transaction costs amount to 0.02% per trade.

Panel A: Transaction costs included

	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	184,384	184,384	184,384	184,384	184,384
Mean	-0.000053	-0.000067	-0.000052	-0.000035	-0.000032
Median	-0.000059	-0.000064	-0.000043	-0.000036	-0.000033
Std. dev.	0.000072	0.000106	0.000092	0.000102	0.000092
Skewness	0.89	-0.21	0.19	-1.22	0.09
Kurtosis	93.23	84.38	17.91	190.19	55.10
t-statistics					
Value	-314.85	-272.72	-244.54	-147.85	-151.15
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Wilcoxon signed rank					
Value	294.20	263.45	250.52	190.68	192.72
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B: Transaction costs excluded

	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	184,384	184,384	184,384	184,384	184,384
Mean	0.000007	0.000014	0.000003	0.000006	0.000000
Median	0.000000	0.000002	0.000000	0.000000	-0.000001
Std. dev.	0.000058	0.000067	0.000064	0.000081	0.000078
Skewness	1.14	-0.56	1.40	-1.58	0.31
Kurtosis	199.67	433.70	55.45	412.31	98.62
t-statistics					
Value	50.40	88.89	17.11	31.03	-2.28
Probability	0.0000	0.0000	0.0000	0.0000	0.0225
Wilcoxon signed rank					
Value	40.18	91.84	8.70	12.13	22.07
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Sample statistics based on data per second yield results similar to the statistics based on data per minute. As shown in table 5.4, all sets of models yield significant negative returns when transaction costs are included. The positive amounts of kurtosis indicate a leptokurtic distribution. Contrary to the datasets previously discussed, the distribution for the data per second is skewed to the left for the full sample. The standard deviation varies from 0.0036% for the full sample to 0.0070% for the set of moving average models without a lag. When transaction costs are excluded, all sets of technical trading models yield positive returns, significant at a 1% confidence level. Mean returns are 0.00004% in the sample analyzed, which is equivalent to a net return of 3.46% per day on average.

Table 5.4
Sample statistics of returns per second

This table provides an overview of the coefficients and test statistics with regard to second returns on the euro/US dollar exchange market for the period 09-30-2013 to 10-02-2013. MA refers to the set of moving average models, without and with a one-period lag, respectively. MO refers to the set of momentum models, respectively without and with a one-period lag. *N* is the number of logarithmic returns. Transaction costs amount to 0.02% per trade.

Panel A: Transaction costs included

	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	259,157	259,157	259,157	259,157	259,157
Mean	-0.000041	-0.000060	-0.000035	-0.000023	-0.000020
Median	-0.000035	-0.000031	-0.000015	0.000000	0.000000
Std. dev.	0.000036	0.000070	0.000050	0.000051	0.000046
Skewness	-0.86	-1.35	-1.88	-3.34	-3.59
Kurtosis	3.99	5.29	8.27	19.84	22.94
t-statistics					
Value	-582.83	-435.22	-358.76	-230.54	-218.94
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Wilcoxon signed rank					
Value	397.35	361.47	340.43	248.64	240.09
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B: Transaction costs excluded

	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
N	259,157	259,157	259,157	259,157	259,157
Mean	0.0000004	0.0000006	0.0000002	0.0000005	0.0000002
Median	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000
Std. dev.	0.0000061	0.0000075	0.0000071	0.0000094	0.0000093
Skewness	2.09	2.56	0.60	1.19	1.41
Kurtosis	299.01	323.63	260.01	475.56	542.44
t-statistics					
Value	31.75	40.05	12.99	26.38	12.74
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Wilcoxon signed rank					
Value	27.66	35.80	11.02	19.95	7.60
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5.5 provides test statistics regarding the comparison of mean returns between different samples, given a fixed period. The samples based on daily observations, hourly observations and observations per minute are compared on a daily basis. Since the sample for returns based on observations per second consists of sample observations totaling three days, the sample regarding observations per second is compared with the sample regarding observations per minute, based on returns per minute. Tests for the equality of means are performed using a Welch F-test. The existence of heteroscedasticity causes standard t-tests and ANOVA F-test being less appropriate, since these tests assume a constant variance. The Welch F-test overcomes the latter issue, by allowing inequality variances (Welch, 1951).

Table 5.5
Comparison of mean returns

This table provides category statistics of sample returns based on returns per day, for the daily data, hourly data and data per minute. In addition, category statistics of sample returns based on returns per minute for both the minute data and second data are provided. Furthermore, test statistics regarding the equality of means are provided. *N* is the number of logarithmic returns.

Panel A: Category statistics

		Including transaction costs		Excluding transaction costs	
	N	Mean	Std. dev.	Mean	Std. dev.
Daily returns (day)	4,265	0.000329	0.002235	0.000388	0.002224
Hourly returns (day)	2,609	0.000326	0.003250	0.001705	0.003094
Minute returns (day)	155	-0.063169	0.025722	0.008082	0.004507
Minute (minute)	184,421	-0.000053	0.000072	0.000007	0.000058
Second (minute)	4,320	-0.002453	0.000943	0.000023	0.000062

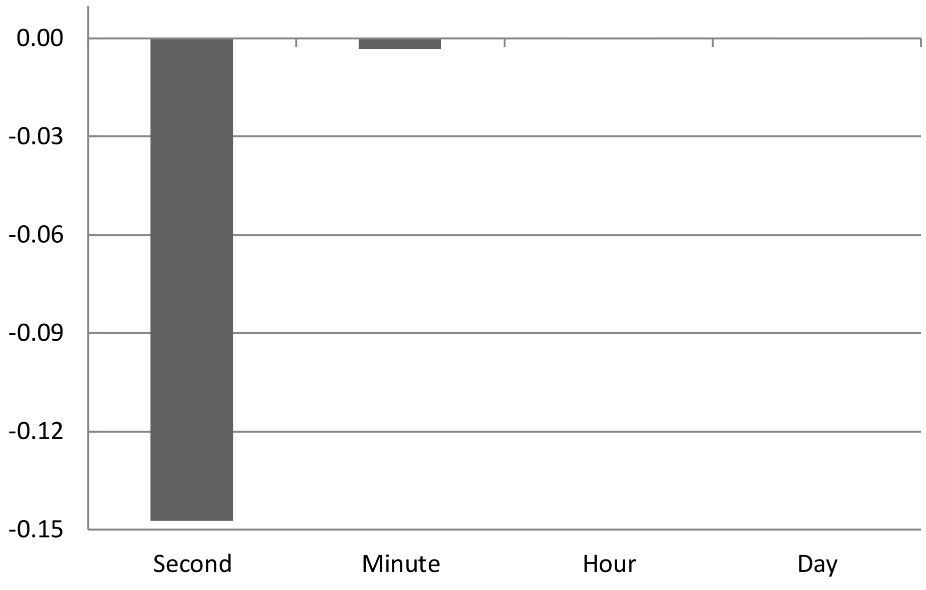
Panel B: Test for equality of means

	Difference	Welch F-test	
Including transaction costs	mean return	Value	Probability
Day – hour (day)	0.000003	0.0020	0.9641
Day – minute (day)	0.063498	944.3154	0.0000
Hour – minute (day)	0.063495	943.5828	0.0000
Minute – second (minute)	0.002400	27,973.2100	0.0000
Excluding transaction costs			
Day – Hour (day)	-0.001317	359.2474	0.0000
Day – minute (day)	-0.007694	447.7018	0.0000
Hour – minute (day)	-0.006377	301.8006	0.0000
Minute – second (minute)	-0.000016	274.1287	0.0000

Following from table 5.5, no significant differences exist between the mean of returns based on daily observations and hourly observations on a daily basis, transaction costs included. In addition, both the sample based on daily observations and the sample based on hourly observations outperform the sample based on observations per minute. Both results are highly significant. Furthermore, the sample based on observations per minute outperforms the sample consisting of observations per second, significant on a 1% confidence level. From the latter, it can be concluded both the sample consisting of observations per day and the sample consisting of observations per hour outperforms the sample consisting of observations per second. The results, when excluding transaction costs, are entirely different compared to the results including transaction costs. The sample based on hourly observations outperforms the sample based on daily observations, when comparing returns on a daily basis. In addition, the sample consisting of observations per minute outperforms both the sample consisting observations per hour and the sample consisting observations per day. Lastly, the sample comprising of observations per second outperforms the sample comprising of observations per minute, when comparing returns on a minute basis. From the latter, it can be concluded the sample consisting of observations per second outperforms both the sample based on daily data and the sample based on hourly data as well. All results regarding the comparison of mean returns, transaction costs excluded, are significant on a 1% confidence level.

Figure 5.1
Returns per hour based on 0.02% transaction costs

This figure displays mean returns based on returns per hour for the application of the technical trading models on daily data, hourly data, data per minute and data per second. Transaction costs of 0.02% per trade are included.

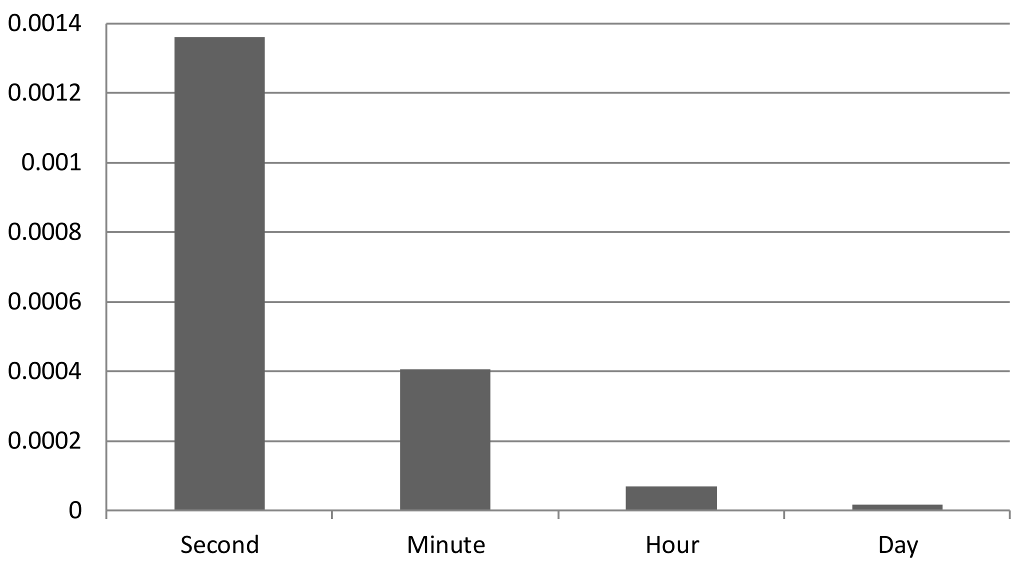


Figures 5.1 and 5.2 show the mean returns graphically. Mean returns are displayed based on returns per hour. From figure 5.1 and 5.2, it can be concluded that transaction costs are the primary cause for the underperformance of the models based on observations per minute and observations per second. Without transaction costs, models based on observations per second

outperform the models based on large timeframes, with an average return of 0.14%. However, when transaction costs of 0.02% per trade are included, profitability disappears, resulting in a negative return of 14.72% per hour. The effect of transactions costs on the profitability concerning daily and hourly observations is moderate compared to the effects on the profitability regarding observations per minute and per second. Profitability of the application of technical trading models on hourly data declines from 0.007% to 0.00012% per hour, which is equivalent to a decline of 0.003% per basis point increase in transaction costs. Profitability of the application of technical trading models on daily data amounts to 0.0016% per hour when transaction costs are excluded and 0.0014% when transaction costs amount to 0.002%. The latter equates to a decline in profitability of 0.0001% per basis point increase in transaction costs. For comparison, a 1 basis point increase in transaction costs results in a decrease of 0.18% for the application of the technical trading models on data per minute and 7.43% concerning data per second.

Figure 5.2
Returns per hour, transaction costs excluded

This figure displays mean returns based on returns per hour for the application of the technical trading models on daily data, hourly data, data per minute and data per second. Transaction costs are excluded.



In order to check for fluctuations in profitability during the sample period, table 5.6 provides an overview of the yearly results for the daily and hourly data, including transaction costs of 0.02%. Since no significant profits can be achieved by applying technical trading rules concerning both moving averages and momentum models on data per minute and data per second, no overview of the results per sub-period regarding data per minute and data per second is incorporated. Daily statistics for the year 2013 and hourly statistics for the years 2003 and 2013 contain statistics based on half a year, which are not taken into account in the following discussion.

Table 5.6
Returns per year

This table provides an overview of the profitability per annum, based on the application of the full set of technical trading models on both daily and hourly data. A summary of the yearly statistics for the period 1999 to 2013 is provided based on daily data and for the hourly data, yearly statistics are provided for the period 2004 to 2013. *N* is the number of logarithmic returns. Years denoted with a * contain statistics based on semi-annual returns. Wilcoxon test

Panel A: Daily returns

						t-statistics		*Wilcoxon signed rank*	
Year	*N*	Mean	Median	Std. Dev.	Sum	Value	Prob.	Value	Prob.
1999	251	0.000166	-0.000009	0.001975	0.042	1.33	0.1843	1.05	0.2943
2000	252	0.000696	0.000173	0.002882	0.175	3.83	0.0002	3.15	0.0016
2001	255	0.000227	-0.000057	0.002544	0.058	1.42	0.1556	0.67	0.5025
2002	260	0.000300	0.000009	0.001887	0.078	2.56	0.0110	1.43	0.1537
2003	307	0.000467	0.000091	0.002035	0.143	4.02	0.0001	3.45	0.0006
2004	314	0.000148	-0.000018	0.001981	0.047	1.32	0.1862	0.51	0.6118
2005	314	0.000208	-0.000043	0.001645	0.065	2.24	0.0257	0.92	0.3570
2006	313	0.000207	-0.000017	0.001503	0.065	2.43	0.0155	1.52	0.1297
2007	313	0.000202	-0.000007	0.001188	0.063	3.00	0.0029	2.07	0.0380
2008	314	0.000656	0.000082	0.003562	0.206	3.26	0.0012	2.61	0.0090
2009	314	0.000413	0.000009	0.002618	0.130	2.80	0.0055	1.53	0.1255
2010	313	0.000418	0.000057	0.002589	0.131	2.85	0.0046	2.28	0.0229
2011	313	0.000231	0.000043	0.002327	0.072	1.76	0.0801	1.31	0.1906
2012	314	0.000279	0.000030	0.001746	0.087	2.83	0.0050	2.27	0.0230
2013*	155	0.000294	0.000092	0.001499	0.046	2.45	0.0156	2.06	0.0398

Panel B: Hourly returns

						t-statistics		*Wilcoxon signed rank*	
Year	*N*	Mean	Median	Std. Dev.	Sum	Value	Prob.	Value	Prob.
2003*	3213	0.000007	-0.000051	0.000503	0.023	0.82	0.4102	8.24	0.0000
2004	6339	0.000017	-0.000046	0.000506	0.110	2.72	0.0065	9.32	0.0000
2005	6305	0.000000	-0.000050	0.000431	-0.002	-0.07	0.9477	12.64	0.0000
2006	6318	-0.000006	-0.000048	0.000375	-0.040	-1.36	0.1754	15.42	0.0000
2007	6182	-0.000012	-0.000050	0.000317	-0.071	-2.85	0.0044	17.62	0.0000
2008	6079	0.000040	-0.000045	0.000706	0.242	4.39	0.0000	6.09	0.0000
2009	6342	0.000032	-0.000045	0.000614	0.204	4.17	0.0000	5.40	0.0000
2010	6197	0.000032	-0.000040	0.000546	0.198	4.61	0.0000	4.39	0.0000
2011	6484	0.000012	-0.000046	0.000547	0.078	1.78	0.0748	7.54	0.0000
2012	6472	0.000009	-0.000044	0.000398	0.059	1.85	0.0651	10.95	0.0000
2013*	3084	-0.000001	-0.000046	0.000421	-0.002	-0.08	0.9346	9.12	0.0000

Applying technical trading rules on daily data results in a net profit each single year. 7 out of 14 years yield significant mean returns at a confidence level of 1% and based on a confidence level of 5%, 10 out of 14 years yield significant positive results. The daily standard deviation varies from 0.119% in the year 2007 to 0.3562% in 2008. However, concerning median returns, only 2 out of 14 years are significant and positive, based on a confidence level of 1%. From table 3.1 it follows that between 07/2001 and 04/2008 the price movement of the euro/US dollar exchange rate was directed upwards, followed by a downtrend from 05/2008 to 06/2013. The results stated in table 5.6 indicate no erosion of profit opportunities using technical trading rules based on daily data. Furthermore, profitability remained fairly stable during the downtrend of the euro/US dollar exchange rate starting in 2008. From the last five years, three years yielded an above average net profit, whereas the years 2011 and 2012 yielded a profit marginally under average.

The yearly profits based on hourly data varies from -7.10% to 24.17%, indicating more variance in the results. The latter can be confirmed when reviewing the standard deviation. The average hourly standard deviation is 0.049%, equaling a daily standard deviation of 0.242%, in comparison with an average daily standard deviation of 0.218% for the results based on daily data. 3 out of 9 years produce a negative return. 4 out of 9 years result in a significant net profit, based on both a confidence level of 5% and a confidence level of 1%. All median returns are negative and highly significant. The average net return equals 7.78%, compared to an average net return of 9.73% when applying the set of technical trading models to daily data.

5.2 Bootstrap results

The statistics concerning skewness and kurtosis in table 5.1 to table 5.4 indicate a non-normal distribution. Therefore, the approximate distribution of the original sample is determined using a bootstrap approach. Table 5.7 contains sample statistics with regard to the profitability of the application of technical trading rules on 500 simulated samples. The results of the 500 randomly simulated samples are unambiguous. Average mean returns per data point are negative in all cases. The average mean return is around -0.007% for the daily, hourly and returns per minute. The return per second equals -0.005%.

The full sets of models based on data per day, per hour, per minute and per second, outperform 99% of the simulated models. 2 out of 16 subsamples do not outperform the 5% best performing simulated models and 2 out of 16 subsamples perform worse than the 1% best performing models from the simulated samples.

Table 5.7
Sample statistics regarding the profitability of the technical trading models of 500 simulated samples

This table provides an overview of the statistics for both the moving average models as well as the momentum models, regarding 500 simulated samples. MA refers to the set of moving average models, with a zero-period lag and a 1-period lag, respectively. MO refers to the set of momentum models, with a zero-period and a one-period lag, respectively. In all samples, a transaction cost of 0.02% per trade is incorporated. average top 5% and 1% is the threshold value for the average returns for respectively the top 5% and top 1% of the simulated samples.

	Full sample	MA (lag=0)	MA (lag=1)	MO (lag=0)	MO (lag=1)
Panel A: Daily returns					
Average	-0.000070	-0.000110	-0.000050	-0.000051	-0.000030
Median	-0.000073	-0.000113	-0.000054	-0.000045	-0.000040
St. dev	0.002751	0.002598	0.002611	0.003171	0.003179
Average top 5%	0.000002	-0.000041	0.000020	0.000029	0.000048
Average top 1%	0.000035	-0.000013	0.000054	0.000071	0.000081
Average original sample	0.000329	0.000613	0.000098	0.000380	0.000126
Panel B: Hourly returns					
Average	-0.000068	-0.000107	-0.000050	-0.000048	-0.000029
Median	-0.000065	-0.000098	-0.000049	-0.000042	-0.000037
St. dev	0.000596	0.000574	0.000551	0.000697	0.000686
Average top 5%	-0.000064	-0.000103	-0.000045	-0.000043	-0.000024
Average top 1%	-0.000062	-0.000101	-0.000044	-0.000041	-0.000023
Average original sample	0.000013	0.000057	-0.000026	0.000033	-0.000023
Panel C: Returns per minute					
Average	-0.000068	-0.000107	-0.000049	-0.000048	-0.000029
Median	-0.000061	-0.000104	-0.000039	-0.000039	-0.000026
St. dev	0.000100	0.000112	0.000087	0.000109	0.000091
Average top 5%	-0.000068	-0.000107	-0.000049	-0.000048	-0.000029
Average top 1%	-0.000067	-0.000106	-0.000049	-0.000047	-0.000028
Average original sample	-0.000053	-0.000067	-0.000052	-0.000035	-0.000032
Panel D: Returns per second					
Average	-0.000050	-0.000075	-0.000039	-0.000033	-0.000026
Median	-0.000030	-0.000062	-0.000018	0.000000	0.000000
St. dev	0.000059	0.000072	0.000048	0.000060	0.000050
Average top 5%	-0.000050	-0.000075	-0.000039	-0.000033	-0.000025
Average top 1%	-0.000050	-0.000075	-0.000039	-0.000032	-0.000025
Average original sample	-0.000041	-0.000060	-0.000035	-0.000023	-0.000020

From the results, which indicate the original sample outperforms the simulated sample in nearly all instances, it can be concluded the original data contains a non-random walk which can be exploited by using technical trading rules. Moreover, samples including a one-period lag perform superior to the samples without a lag. Since incorporating a one-period lag leads to a decrease in the amount of signal changes and a decrease in transaction costs, it can be concluded the potential gain from directly anticipating to a signal change does not offset the additional transaction costs. However, in the original sample, from which the results are stated in table 2 to 5, the subsamples with no lag outperform the subsamples with a one-period lag in nearly all instances. In contrary with the bootstrap results, the gain from directly anticipating to a signal change does offset the additional transaction costs in the original sample. The latter confirms the original data contains a non-random walk which can be exploited by using moving average and momentum models.

5.3 Individual models

Table 5.8 contains summary statistics regarding the 5 best performing models for each sample, transaction costs included. An overview of summary statistics for all models is added in the appendix. Moving average models, without a lag, perform superior when applied to both daily and hourly data.

The five best performing models all comprise short-term moving averages of 1 day, a zero-period lag and long-term moving averages ranging from 15 to 40. The mean return equals 0.1377% for the five best performing models based on daily data and 0.0139% based on hourly data, compared to a mean return of 0.0329% and 0.0013% for the full sample, respectively. The majority of the models without a lag outperform the models with a lag, based on both daily and hourly data (see appendix). From the latter it follows that a signal change from positive to negative or vice versa frequently remains the same in the subsequent period, resulting in a net gain on average, when directly anticipating to a signal change.

Contrary to the application of the technical trading models on daily and hourly data, the best performing models consist of momentum models when applied to data based on observations per minute and second. In particular, models which compare exchange rates based on a relative large timeframe are among the best performing models. Transaction costs amounting to 0.02% included, all single models yield highly significant negative returns. The mean return equals respectively -0.0020% and -0.0013% for the five best performing models based on data per minute and data per second, compared to a mean return of -0.0053% and -0.0041% for the full sample, respectively.

Table 5.8
Sample statistics best performing models

This table provides an overview of the statistics for the five best performing individual models, based on observations per day, per hour, per minute and per second. MA (x, y, z) refers to a moving average model with a short-term moving average of x, long-term moving average y and lag z. MO (h, z), refers to a momentum model in which h is the timespan between observation t and the observation period which is compared to (t-h), z is the lag. In all models, a transaction cost of 0.02% per trade is incorporated.

Panel A: Models based on observations per day					
	MA (1,40,0)	MA (1,35,0)	MA (1,15,0)	MA (1,30,0)	MA (1,25,0)
Mean	0.001407	0.001395	0.001374	0.001361	0.001348
Median	0.001331	0.001323	0.001258	0.001265	0.001258
Std. dev.	0.004256	0.004258	0.004260	0.004273	0.004275
N	4,265	4,270	4,290	4,275	4,280
t-value	21.59	21.40	21.13	20.82	20.63
probability	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: Models based on observations per hour					
	MA (1,20,0)	MA (1,35,0)	MA (1,40,0)	MA (1,30,0)	MA (1,15,0)
Mean	0.000140	0.000139	0.000139	0.000138	0.000137
Median	0.000150	0.000160	0.000161	0.000158	0.000141
Std. dev.	0.001026	0.001029	0.001030	0.001029	0.001025
N	62,998	62,983	62,978	62,988	63,003
t-value	34.27	34.01	33.92	33.71	33.56
probability	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: Models based on observations per minute					
	M (40,1)	M (35,1)	M (40,0)	M (30,1)	M (35,0)
Mean	-0.000019	-0.000019	-0.000021	-0.000021	-0.000022
Median	-0.000004	-0.000004	-0.000004	-0.000004	-0.000004
Std. dev.	0.000142	0.000144	0.000155	0.000146	0.000158
N	184,384	184,389	184,384	184,394	184,389
t-value	-56.25	-57.71	-57.39	-61.95	-59.33
probability	0.0000	0.0000	0.0000	0.0000	0.0000
Panel D: Models based on observations per second					
	M (40,1)	M (35,1)	M (40,0)	M (30,1)	M (35,0)
Mean	-0.000012	-0.000012	-0.000014	-0.000014	-0.000014
Median	0.000000	0.000000	0.000000	0.000000	0.000000
Std. dev.	0.000069	0.000071	0.000076	0.000074	0.000079
N	259,157	259,162	259,157	259,167	259,162
t-value	-85.10	-88.10	-90.25	-92.34	-93.55
probability	0.0000	0.0000	0.0000	0.0000	0.0000

6. Conclusion and limitations

This section contains a conclusion. Furthermore, limitations and recommendations regarding this paper will be provided.

6.1 Conclusion

This paper examined to what extent shortening the observation length results in increasing returns when technical trading rules are applied. From the discussed literature the hypothesis, stating that shortening the observation length results in increasing returns when technical trading rules are applied, is drawn up. Moving average models and momentum models are applied to data regarding the euro/US dollar exchange rates, with observation periods varying from daily observations to observations per second.

Based on transaction costs amounting to 0.02% per trade, in line with the assumption drawn up by Schulmeister (2008a, 2008b), this paper provides evidence resulting in the rejection of the hypothesis stated above. Firstly, the results indicate no signs of significant differences in returns between the mean return of the sample based on daily observations and the mean return of the sample based on hourly observations, when adjusted to equal time periods. In addition, the application of technical trading models on both daily and hourly observations outperform the application of technical trading models on observations per minute. Furthermore, the sample consisting of observations per minute surpasses the sample consisting of observations per second, when comparing mean returns on minute basis. From the latter, it can be concluded the sample comprising of observations per second is outperformed by both the sample regarding daily observations and the sample regarding hourly observations. Contrary to aforementioned, the results provide evidence for the acceptance of the hypothesis mentioned above when transaction costs are excluded. The profitability increases when the size of the timespan between observations is smaller, being highly significant regarding the comparison of all samples. The application of technical trading models on data based on observations per second yields the largest profitability, followed by the application of technical trading models on data based on observations per minute, per hour and per day.

The full sample, comprising of 70 technical trading models regarding moving averages and momentum, both with and without a one-period large, yields significant positive returns when applied to data based on observations per day and based on observations per hour, when transaction costs are included. However, when applied to data based on observations per minute and data based on observations per second, negative mean returns are realized. The results regarding the application of technical trading models on daily observations is in contradiction with Schulmeister (2008a, 2008b), stating no excess returns can be achieved using daily data. Moreover, the results provide no evidence the adaptive market hypothesis holds with regard to the euro/dollar exchange rate. Contrary to the latter, theories stating one may benefit from information which is widely available and which is utilized by sufficient investors (De Long et al., 1987, Froot, Scharfstein and Stein, 1992), are not in contradiction with the results in this paper. When assuming no transaction costs, the full sample yields positive mean returns, significant on a 1% confidence level, when applied to data based on observations per day, per hour, per minute and per second.

Bootstrapping is applied in order to check the robustness of the results. The full sets of models based on original data per day, per hour, per minute and per second, outperform 99% of the simulated models, confirming the original data contains a non-random walk which can be exploited. The latter provides evidence in contradiction to the efficient market hypothesis (Fama, 1970) and the random walk hypothesis (Malkiel, 2012), in the short term. Furthermore, from the results it can be concluded that transaction costs limit the possibilities for shortening the observation length in which technical trading models can be applied to. In order to be able to yield positive results regarding the application of technical trading models on data based on observations per minute and observations per seconds, it is necessary to find solutions which decrease the transaction costs significantly.

Finally, when analyzing individual models, transaction costs included, it can be concluded that moving average models without a lag perform superior when applied to both daily and hourly data. In contrast, the top performing models consist of momentum models when applied to data both based on observations per minute and observations per second.

6.2 Limitations

This paper contains several weaknesses. Firstly, although bootstrapping is applied, the application of more complex testing models could strengthen the robustness and validity of the results. Brock, Lakonishok and LeBaron (1992), for example, apply several models, containing autoregressive models and models regarding generalized autoregressive conditional heteroscedastisity. Secondly, the analysis in this paper could be extended by using different trading rules. Concerning technical analysis, a wide variety of indicators is developed, from which only moving average and momentum indicators are investigated in this paper. In addition, this paper focused solely on technical analysis. The influence of other types of analysis, for example fundamental analysis, is not included in the analysis. Finally, Schulmeister (2008b) mentions both the increase of the complexity of trading rules and the increasing speed in which trading holdings are modified as potential developments. This paper investigates solely the latter, leaving the former issue to further studies.

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Appendix

Table A1

Sample statistics individual models

This table provides an overview of the statistics for the five best performing individual models, based on observations per day, per hour, per minute and per second. MA (x, y, z) refers to a moving average model with a short-term moving average of x, long-term moving average y and lag z. MO (h, z), refers to a momentum model in which h is the timespan between observation t and the observation period which is compared to (t-h), z is the lag. In all models, a transaction cost of 0.02% per trade is incorporated.

Panel A: Models based on observations per day

	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (1,5,0)	0.001259	0.001141	0.004285	0.2625	4.3779	4,300	19.2678	0.0000
MA (1,10,0)	0.001313	0.001169	0.004275	0.2772	4.3440	4,295	20.1292	0.0000
MA (1,15,0)	0.001374	0.001258	0.004260	0.2997	4.3082	4,290	21.1333	0.0000
MA (1,20,0)	0.001347	0.001258	0.004273	0.2547	4.3521	4,285	20.6315	0.0000
MA (1,25,0)	0.001348	0.001258	0.004275	0.2456	4.3611	4,280	20.6307	0.0000
MA (1,30,0)	0.001361	0.001265	0.004273	0.2717	4.3224	4,275	20.8204	0.0000
MA (1,35,0)	0.001395	0.001323	0.004258	0.2601	4.3584	4,270	21.4041	0.0000
MA (1,40,0)	0.001407	0.001331	0.004256	0.2618	4.3558	4,265	21.5941	0.0000
MA (5,10,0)	0.000350	0.000200	0.004422	0.2146	4.4668	4,295	5.1933	0.0000
MA (5,15,0)	0.000431	0.000286	0.004420	0.2239	4.4419	4,290	6.3795	0.0000
MA (5,20,0)	0.000406	0.000284	0.004426	0.1449	4.4841	4,285	6.0108	0.0000
MA (5,25,0)	0.000407	0.000263	0.004428	0.2042	4.4537	4,280	6.0091	0.0000
MA (5,30,0)	0.000440	0.000304	0.004428	0.1692	4.4649	4,275	6.4901	0.0000
MA (5,35,0)	0.000468	0.000298	0.004421	0.1906	4.4621	4,270	6.9211	0.0000
MA (5,40,0)	0.000532	0.000367	0.004416	0.1898	4.4586	4,265	7.8625	0.0000
MA (10,15,0)	0.000189	0.000108	0.004420	0.1283	4.5231	4,290	2.8059	0.0050
MA (10,20,0)	0.000188	0.000103	0.004423	0.0859	4.5350	4,285	2.7784	0.0055
MA (10,25,0)	0.000236	0.000230	0.004423	0.0729	4.5265	4,280	3.4878	0.0005
MA (10,30,0)	0.000229	0.000225	0.004428	0.0763	4.5379	4,275	3.3841	0.0007
MA (10,35,0)	0.000333	0.000295	0.004416	0.0711	4.5486	4,270	4.9250	0.0000
MA (10,40,0)	0.000400	0.000345	0.004411	0.1159	4.5283	4,265	5.9291	0.0000
MA (15,20,0)	-0.000110	-0.000055	0.004416	-0.0264	4.5666	4,285	-1.6334	0.1025
MA (15,25,0)	-0.000007	-0.000016	0.004419	0.0783	4.5466	4,280	-0.0973	0.9225
MA (15,30,0)	0.000078	0.000014	0.004422	0.1424	4.5333	4,275	1.1541	0.2485
MA (15,35,0)	0.000191	0.000113	0.004418	0.1006	4.5377	4,270	2.8226	0.0048
MA (15,40,0)	0.000263	0.000191	0.004416	0.1260	4.5281	4,265	3.8944	0.0001
MA (1,5,1)	0.000293	0.000253	0.004452	0.0255	4.4941	4,300	4.3177	0.0000
MA (1,10,1)	0.000342	0.000248	0.004448	0.1272	4.4521	4,295	5.0421	0.0000
MA (1,15,1)	0.000306	0.000248	0.004458	0.0781	4.4604	4,290	4.4933	0.0000
MA (1,20,1)	0.000271	0.000241	0.004460	0.0211	4.4801	4,285	3.9799	0.0001
MA (1,25,1)	0.000262	0.000191	0.004462	0.0268	4.4761	4,280	3.8457	0.0001
MA (1,30,1)	0.000300	0.000215	0.004460	0.0582	4.4684	4,275	4.4041	0.0000
MA (1,35,1)	0.000334	0.000247	0.004455	0.0676	4.4682	4,270	4.8968	0.0000
MA (1,40,1)	0.000352	0.000275	0.004454	0.0658	4.4709	4,265	5.1633	0.0000

Table A1 (continued)								
	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (5,10,1)	0.000104	0.000019	0.004415	0.1332	4.5564	4,295	1.5373	0.1243
MA (5,15,1)	0.000033	0.000000	0.004423	0.1002	4.5493	4,290	0.4944	0.6211
MA (5,20,1)	-0.000006	-0.000083	0.004424	0.0841	4.5448	4,285	-0.0830	0.9339
MA (5,25,1)	0.000046	-0.000032	0.004423	0.1382	4.5447	4,280	0.6805	0.4962
MA (5,30,1)	0.000071	-0.000030	0.004424	0.1816	4.5303	4,275	1.0499	0.2938
MA (5,35,1)	0.000075	-0.000023	0.004423	0.1682	4.5339	4,270	1.1025	0.2703
MA (5,40,1)	0.000099	-0.000004	0.004422	0.1990	4.5338	4,265	1.4593	0.1445
MA (10,15,1)	-0.000040	-0.000063	0.004413	0.0523	4.5640	4,290	-0.5913	0.5544
MA (10,20,1)	-0.000097	-0.000070	0.004414	0.0402	4.5671	4,285	-1.4311	0.1525
MA (10,25,1)	-0.000050	-0.000008	0.004417	0.0205	4.5610	4,280	-0.7431	0.4575
MA (10,30,1)	-0.000063	-0.000003	0.004417	0.0001	4.5658	4,275	-0.9376	0.3485
MA (10,35,1)	0.000031	0.000037	0.004416	0.0303	4.5619	4,270	0.4539	0.6499
MA (10,40,1)	0.000043	0.000025	0.004418	0.0200	4.5705	4,265	0.6339	0.5262
MA (15,20,1)	-0.000249	-0.000167	0.004402	-0.0697	4.5608	4,285	-3.6979	0.0002
MA (15,25,1)	-0.000130	-0.000102	0.004406	0.0757	4.5736	4,280	-1.9267	0.0541
MA (15,30,1)	-0.000016	-0.000028	0.004407	0.1161	4.5701	4,275	-0.2408	0.8097
MA (15,35,1)	0.000080	0.000024	0.004406	0.1174	4.5561	4,270	1.1914	0.2335
MA (15,40,1)	0.000101	0.000004	0.004408	0.1471	4.5498	4,265	1.4893	0.1365
M (3,0)	0.000693	0.000546	0.004416	0.1102	4.4597	4,302	10.2945	0.0000
M (5,0)	0.000567	0.000405	0.004416	0.1698	4.4539	4,300	8.4263	0.0000
M (10,0)	0.000420	0.000364	0.004412	0.0610	4.5469	4,295	6.2408	0.0000
M (15,0)	0.000268	0.000197	0.004421	0.0833	4.5292	4,290	3.9730	0.0001
M (20,0)	0.000310	0.000227	0.004411	0.1040	4.5314	4,285	4.6045	0.0000
M (25,0)	0.000371	0.000277	0.004404	0.1021	4.5329	4,280	5.5076	0.0000
M (30,0)	0.000340	0.000290	0.004405	0.0849	4.5385	4,275	5.0485	0.0000
M (35,0)	0.000268	0.000169	0.004405	0.0518	4.5538	4,270	3.9767	0.0001
M (40,0)	0.000215	0.000139	0.004408	0.1105	4.5413	4,265	3.1778	0.0015
M (3,1)	0.000146	0.000058	0.004436	0.1144	4.4968	4,301	2.1525	0.0314
M (5,1)	0.000126	0.000065	0.004425	0.1101	4.5266	4,299	1.8631	0.0625
M (10,1)	0.000088	0.000041	0.004416	0.0400	4.5472	4,294	1.3053	0.1919
M (15,1)	0.000031	0.000031	0.004412	0.0764	4.5476	4,289	0.4610	0.6448
M (20,1)	0.000138	0.000055	0.004406	0.1149	4.5451	4,284	2.0507	0.0404
M (25,1)	0.000220	0.000139	0.004403	0.0989	4.5486	4,279	3.2746	0.0011
M (30,1)	0.000198	0.000171	0.004404	0.0616	4.5620	4,274	2.9463	0.0032
M (35,1)	0.000149	0.000070	0.004403	0.0486	4.5645	4,269	2.2099	0.0272
M (40,1)	0.000092	0.000031	0.004405	0.0770	4.5686	4,264	1.3654	0.1722
Panel B: Models based on observations per hour								
	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (1,5,0)	0.000122	0.000114	0.001018	0.5987	10.1384	63,013	30.1249	0.0000
MA (1,10,0)	0.000133	0.000131	0.001023	0.5541	9.9548	63,008	32.5633	0.0000
MA (1,15,0)	0.000137	0.000141	0.001025	0.5761	9.8489	63,003	33.5623	0.0000
MA (1,20,0)	0.000140	0.000150	0.001026	0.5647	9.8014	62,998	34.2669	0.0000

Table A1 (continued)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (1,25,0)	0.000137	0.000153	0.001029	0.5428	9.7433	62,993	33.3527	0.0000
MA (1,30,0)	0.000138	0.000158	0.001029	0.5791	9.6697	62,988	33.7136	0.0000
MA (1,35,0)	0.000139	0.000160	0.001029	0.5876	9.6386	62,983	34.0109	0.0000
MA (1,40,0)	0.000139	0.000161	0.001030	0.6039	9.5972	62,978	33.9213	0.0000
MA (5,10,0)	0.000008	-0.000020	0.000997	0.3046	11.5795	63,008	2.1117	0.0347
MA (5,15,0)	0.000027	0.000000	0.000997	0.3989	11.4901	63,003	6.6894	0.0000
MA (5,20,0)	0.000034	0.000000	0.000996	0.3790	11.5005	62,998	8.5018	0.0000
MA (5,25,0)	0.000036	0.000000	0.000997	0.3727	11.4789	62,993	9.0796	0.0000
MA (5,30,0)	0.000040	0.000008	0.000998	0.3781	11.4508	62,988	9.9758	0.0000
MA (5,35,0)	0.000042	0.000011	0.000998	0.4237	11.3844	62,983	10.5720	0.0000
MA (5,40,0)	0.000044	0.000018	0.000998	0.4055	11.3877	62,978	11.1551	0.0000
MA (10,15,0)	0.000000	-0.000008	0.000983	0.2970	11.9781	63,003	-0.0664	0.9470
MA (10,20,0)	0.000015	0.000000	0.000981	0.2548	12.0590	62,998	3.9237	0.0001
MA (10,25,0)	0.000026	0.000000	0.000980	0.3009	12.0648	62,993	6.5528	0.0000
MA (10,30,0)	0.000024	0.000000	0.000982	0.2181	12.0966	62,988	6.1799	0.0000
MA (10,35,0)	0.000029	0.000004	0.000983	0.2531	12.0327	62,983	7.4364	0.0000
MA (10,40,0)	0.000030	0.000004	0.000984	0.2627	12.0065	62,978	7.6840	0.0000
MA (15,20,0)	-0.000024	-0.000038	0.000976	0.2057	12.1551	62,998	-6.0851	0.0000
MA (15,25,0)	0.000000	-0.000017	0.000973	0.2548	12.2081	62,993	0.0477	0.9620
MA (15,30,0)	0.000011	0.000000	0.000973	0.1405	12.3067	62,988	2.6985	0.0070
MA (15,35,0)	0.000020	0.000000	0.000974	0.2433	12.2698	62,983	5.0933	0.0000
MA (15,40,0)	0.000026	0.000000	0.000975	0.2299	12.2682	62,978	6.8066	0.0000
MA (1,5,1)	-0.000041	-0.000020	0.001020	-0.0168	10.7251	63,013	-9.9756	0.0000
MA (1,10,1)	-0.000024	0.000000	0.001017	-0.0606	10.8495	63,008	-5.8426	0.0000
MA (1,15,1)	-0.000019	0.000000	0.001016	0.0358	10.8409	63,003	-4.6191	0.0000
MA (1,20,1)	-0.000017	0.000000	0.001017	-0.0036	10.8530	62,998	-4.1923	0.0000
MA (1,25,1)	-0.000018	0.000000	0.001017	-0.0102	10.8176	62,993	-4.3258	0.0000
MA (1,30,1)	-0.000018	0.000000	0.001018	0.0420	10.7813	62,988	-4.4205	0.0000
MA (1,35,1)	-0.000015	0.000000	0.001018	0.0795	10.7553	62,983	-3.8024	0.0001
MA (1,40,1)	-0.000017	0.000000	0.001019	0.1248	10.7225	62,978	-4.0979	0.0000
MA (5,10,1)	-0.000051	-0.000055	0.000978	0.1053	12.0427	63,008	-13.1101	0.0000
MA (5,15,1)	-0.000036	-0.000038	0.000977	0.1179	12.1277	63,003	-9.2588	0.0000
MA (5,20,1)	-0.000038	-0.000038	0.000977	0.0542	12.1176	62,998	-9.7075	0.0000
MA (5,25,1)	-0.000036	-0.000038	0.000977	0.0042	12.1508	62,993	-9.1727	0.0000
MA (5,30,1)	-0.000034	-0.000038	0.000978	-0.0346	12.1490	62,988	-8.7457	0.0000
MA (5,35,1)	-0.000031	-0.000038	0.000978	0.0219	12.1286	62,983	-7.9557	0.0000
MA (5,40,1)	-0.000032	-0.000038	0.000978	0.0428	12.1016	62,978	-8.0784	0.0000
MA (10,15,1)	-0.000034	-0.000036	0.000969	0.1354	12.2791	63,003	-8.8779	0.0000
MA (10,20,1)	-0.000026	-0.000028	0.000967	0.0009	12.3583	62,998	-6.8359	0.0000
MA (10,25,1)	-0.000018	-0.000020	0.000967	0.0173	12.3943	62,993	-4.7169	0.0000
MA (10,30,1)	-0.000020	-0.000021	0.000967	0.0292	12.3650	62,988	-5.1691	0.0000
MA (10,35,1)	-0.000017	-0.000019	0.000968	0.0273	12.3660	62,983	-4.3954	0.0000

Table A1 (continued)								
MA (10,40,1)	-0.000017	-0.000019	0.000968	0.0226	12.3875	62,978	-4.4777	0.0000
MA (15,20,1)	-0.000048	-0.000041	0.000964	0.0354	12.3568	62,998	-12.4099	0.0000
MA (15,25,1)	-0.000028	-0.000035	0.000963	0.0372	12.4485	62,993	-7.1853	0.0000
MA (15,30,1)	-0.000018	-0.000031	0.000962	0.1059	12.4666	62,988	-4.7651	0.0000
MA (15,35,1)	-0.000012	-0.000020	0.000962	-0.0156	12.5296	62,983	-3.1520	0.0016
MA (15,40,1)	-0.000009	-0.000019	0.000963	0.0377	12.4731	62,978	-2.4546	0.0141
M (3,0)	0.000049	0.000038	0.001020	0.4043	10.5527	63,015	12.0343	0.0000
M (5,0)	0.000048	0.000018	0.001003	0.3694	11.2498	63,013	11.8785	0.0000
M (10,0)	0.000043	0.000008	0.000988	0.3155	11.8172	63,008	10.8299	0.0000
M (15,0)	0.000036	0.000000	0.000982	0.2931	12.0630	63,003	9.0585	0.0000
M (20,0)	0.000034	0.000000	0.000977	0.3079	12.2419	62,998	8.7048	0.0000
M (25,0)	0.000029	0.000000	0.000973	0.2476	12.4420	62,993	7.3461	0.0000
M (30,0)	0.000020	0.000000	0.000970	0.2530	12.4660	62,988	5.2342	0.0000
M (35,0)	0.000018	0.000000	0.000969	0.2735	12.5063	62,983	4.6515	0.0000
M (40,0)	0.000017	0.000000	0.000967	0.2463	12.5477	62,978	4.4994	0.0000
M (3,1)	-0.000052	-0.000069	0.000991	-0.0390	11.6846	63,014	-13.1550	0.0000
M (5,1)	-0.000035	-0.000042	0.000981	0.0926	11.9516	63,012	-8.8656	0.0000
M (10,1)	-0.000022	-0.000035	0.000972	0.0412	12.2627	63,007	-5.6691	0.0000
M (15,1)	-0.000020	-0.000035	0.000968	0.0704	12.3627	63,002	-5.0857	0.0000
M (20,1)	-0.000012	-0.000024	0.000964	0.1641	12.4480	62,997	-2.9878	0.0028
M (25,1)	-0.000015	-0.000021	0.000962	0.0248	12.5645	62,992	-3.8486	0.0001
M (30,1)	-0.000018	-0.000023	0.000960	0.0140	12.6129	62,987	-4.8053	0.0000
M (35,1)	-0.000018	-0.000027	0.000959	0.0401	12.6261	62,982	-4.6583	0.0000
M (40,1)	-0.000013	-0.000020	0.000958	0.0403	12.6535	62,977	-3.2704	0.0011
Panel C: Models based on observations per minute								
MA (1,5,0)	-0.000116	0.000008	0.000258	-1.0932	42.2776	184,419	-193.4977	0.0000
MA (1,10,0)	-0.000108	0.000015	0.000260	0.3032	39.4472	184,414	-178.6146	0.0000
MA (1,15,0)	-0.000107	0.000016	0.000261	-1.1520	40.8057	184,409	-176.7239	0.0000
MA (1,20,0)	-0.000107	0.000019	0.000262	-1.1526	40.4394	184,404	-176.0265	0.0000
MA (1,25,0)	-0.000107	0.000019	0.000262	-1.1506	40.1996	184,399	-175.5922	0.0000
MA (1,30,0)	-0.000107	0.000019	0.000262	-1.1435	39.9590	184,394	-175.6717	0.0000
MA (1,35,0)	-0.000107	0.000019	0.000263	-1.1405	39.8250	184,389	-175.6162	0.0000
MA (1,40,0)	-0.000108	0.000019	0.000263	-1.1376	39.7010	184,384	-175.7426	0.0000
MA (5,10,0)	-0.000070	-0.000004	0.000212	0.4673	87.8072	184,414	-141.6722	0.0000
MA (5,15,0)	-0.000058	0.000000	0.000206	0.4617	96.8457	184,409	-121.4697	0.0000
MA (5,20,0)	-0.000056	0.000000	0.000206	0.4251	98.0059	184,404	-116.0922	0.0000
MA (5,25,0)	-0.000054	0.000000	0.000206	0.3353	98.4974	184,399	-113.2198	0.0000
MA (5,30,0)	-0.000054	0.000000	0.000206	0.3669	98.5780	184,394	-111.8668	0.0000
MA (5,35,0)	-0.000053	0.000000	0.000206	-2.5868	106.3360	184,389	-111.3808	0.0000
MA (5,40,0)	-0.000053	0.000000	0.000206	0.3535	97.9298	184,384	-110.4682	0.0000
MA (10,15,0)	-0.000063	-0.000008	0.000197	-2.7022	125.3628	184,409	-137.4024	0.0000
MA (10,20,0)	-0.000047	-0.000004	0.000188	-3.1146	152.5543	184,404	-108.0336	0.0000
MA (10,25,0)	-0.000042	0.000000	0.000184	-3.3611	164.5119	184,399	-97.2777	0.0000

Table A1 (continued)

	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (10,30,0)	-0.000040	0.000000	0.000184	-3.3712	166.8333	184,394	-93.7345	0.0000
MA (10,35,0)	-0.000039	0.000000	0.000183	-3.3879	169.0554	184,389	-91.2042	0.0000
MA (10,40,0)	-0.000039	0.000000	0.000184	-3.3768	167.2045	184,384	-90.6221	0.0000
MA (15,20,0)	-0.000061	-0.000008	0.000192	-2.7684	137.4553	184,404	-136.7130	0.0000
MA (15,25,0)	-0.000044	-0.000004	0.000181	-3.4475	176.2195	184,399	-104.5926	0.0000
MA (15,30,0)	-0.000038	-0.000004	0.000176	-3.6075	196.0952	184,394	-92.1420	0.0000
MA (15,35,0)	-0.000035	-0.000004	0.000175	-3.7367	203.9193	184,389	-86.7024	0.0000
MA (15,40,0)	-0.000034	0.000000	0.000174	-3.7690	206.3315	184,384	-83.6170	0.0000
MA (1,5,1)	-0.000089	-0.000004	0.000232	-1.7719	58.5965	184,419	-164.2818	0.0000
MA (1,10,1)	-0.000074	0.000000	0.000224	0.1507	70.2135	184,414	-141.5733	0.0000
MA (1,15,1)	-0.000072	0.000000	0.000223	0.1474	71.3420	184,409	-137.7837	0.0000
MA (1,20,1)	-0.000071	0.000000	0.000223	0.1414	72.0517	184,404	-135.9478	0.0000
MA (1,25,1)	-0.000071	0.000000	0.000223	0.1328	71.6981	184,399	-136.4469	0.0000
MA (1,30,1)	-0.000070	0.000004	0.000223	0.1354	71.9462	184,394	-135.2535	0.0000
MA (1,35,1)	-0.000071	0.000004	0.000223	-2.0760	68.8893	184,389	-135.8558	0.0000
MA (1,40,1)	-0.000070	0.000004	0.000223	0.1347	71.6804	184,384	-135.3326	0.0000
MA (5,10,1)	-0.000063	-0.000008	0.000192	0.7750	127.4828	184,414	-141.2865	0.0000
MA (5,15,1)	-0.000052	-0.000008	0.000185	0.8791	147.8746	184,409	-121.5657	0.0000
MA (5,20,1)	-0.000050	-0.000007	0.000184	0.9086	152.7999	184,404	-116.8883	0.0000
MA (5,25,1)	-0.000049	-0.000007	0.000183	0.8495	154.1250	184,399	-114.9628	0.0000
MA (5,30,1)	-0.000049	-0.000007	0.000183	0.8922	154.3049	184,394	-114.4686	0.0000
MA (5,35,1)	-0.000049	-0.000007	0.000183	-3.1525	150.1660	184,389	-114.5586	0.0000
MA (5,40,1)	-0.000049	-0.000004	0.000183	0.8408	153.6157	184,384	-114.0200	0.0000
MA (10,15,1)	-0.000053	-0.000008	0.000180	-3.0926	158.8311	184,409	-127.2282	0.0000
MA (10,20,1)	-0.000040	-0.000004	0.000170	-3.6269	201.6161	184,404	-101.8177	0.0000
MA (10,25,1)	-0.000037	-0.000004	0.000167	-3.8846	217.2923	184,399	-94.0112	0.0000
MA (10,30,1)	-0.000035	-0.000004	0.000165	-4.0223	226.6092	184,394	-90.3783	0.0000
MA (10,35,1)	-0.000034	-0.000004	0.000165	-3.9747	229.3045	184,389	-88.9682	0.0000
MA (10,40,1)	-0.000034	-0.000004	0.000165	-4.0618	229.7731	184,384	-87.8750	0.0000
MA (15,20,1)	-0.000051	-0.000008	0.000177	-3.1942	171.0936	184,404	-123.6851	0.0000
MA (15,25,1)	-0.000037	-0.000004	0.000165	-3.9040	227.7116	184,399	-96.4207	0.0000
MA (15,30,1)	-0.000032	-0.000004	0.000160	-4.1368	253.6214	184,394	-86.7966	0.0000
MA (15,35,1)	-0.000030	-0.000004	0.000158	-4.2925	266.0607	184,389	-82.4856	0.0000
MA (15,40,1)	-0.000029	-0.000004	0.000158	-4.3487	271.9901	184,384	-79.6503	0.0000
M (3,0)	-0.000072	0.000004	0.000230	-1.9313	68.5709	184,421	-134.5853	0.0000
M (5,0)	-0.000055	0.000000	0.000209	0.3444	92.9800	184,419	-113.0085	0.0000
M (10,0)	-0.000038	0.000000	0.000186	-3.2839	160.6463	184,414	-87.9568	0.0000
M (15,0)	-0.000032	0.000000	0.000176	-3.7195	200.0066	184,409	-77.8429	0.0000
M (20,0)	-0.000028	0.000000	0.000169	-3.9749	235.1940	184,404	-70.6019	0.0000
M (25,0)	-0.000025	0.000000	0.000164	-4.1919	264.8965	184,399	-65.9998	0.0000
M (30,0)	-0.000023	-0.000004	0.000160	-4.4632	289.0876	184,394	-62.3295	0.0000
M (35,0)	-0.000022	-0.000004	0.000158	2.0145	277.3678	184,389	-59.3348	0.0000

Table A1 (continued)								
	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
M (40,0)	-0.000021	-0.000004	0.000155	-4.6856	327.3590	184,384	-57.3860	0.0000
M (3,1)	-0.000069	-0.000008	0.000203	0.5556	102.8791	184,421	-144.9097	0.0000
M (5,1)	-0.000052	-0.000008	0.000186	0.8650	146.6609	184,419	-119.0910	0.0000
M (10,1)	-0.000035	-0.000004	0.000167	-3.8986	218.4538	184,414	-90.1157	0.0000
M (15,1)	-0.000029	-0.000004	0.000158	-4.2974	267.6464	184,409	-78.8115	0.0000
M (20,1)	-0.000025	-0.000004	0.000153	-4.6464	310.2772	184,404	-70.2950	0.0000
M (25,1)	-0.000023	-0.000004	0.000149	-4.8266	345.2294	184,399	-65.5152	0.0000
M (30,1)	-0.000021	-0.000004	0.000146	-4.9799	370.7289	184,394	-61.9503	0.0000
M (35,1)	-0.000019	-0.000004	0.000144	3.2264	395.6055	184,389	-57.7133	0.0000
M (40,1)	-0.000019	-0.000004	0.000142	-5.1642	410.6571	184,384	-56.2505	0.0000
Panel D: Models based on observations per second								
MA (1,5,0)	-0.000099	0.000000	0.000177	-1.1563	2.3742	259,192	-283.4680	0.0000
MA (1,10,0)	-0.000096	0.000000	0.000176	-1.2076	2.4966	259,187	-276.6543	0.0000
MA (1,15,0)	-0.000094	0.000000	0.000175	-1.2345	2.5632	259,182	-273.1734	0.0000
MA (1,20,0)	-0.000093	0.000000	0.000174	-1.2514	2.6057	259,177	-271.0053	0.0000
MA (1,25,0)	-0.000092	0.000000	0.000174	-1.2609	2.6297	259,172	-269.8042	0.0000
MA (1,30,0)	-0.000091	0.000000	0.000173	-1.2748	2.6653	259,167	-268.0896	0.0000
MA (1,35,0)	-0.000091	0.000000	0.000173	-1.2864	2.6955	259,162	-266.6641	0.0000
MA (1,40,0)	-0.000090	0.000000	0.000173	-1.2930	2.7128	259,157	-265.8718	0.0000
MA (5,10,0)	-0.000062	0.000000	0.000148	-1.8904	4.6469	259,187	-212.1371	0.0000
MA (5,15,0)	-0.000055	0.000000	0.000141	-2.0872	5.4452	259,182	-196.8234	0.0000
MA (5,20,0)	-0.000052	0.000000	0.000138	-2.1708	5.8080	259,177	-190.8089	0.0000
MA (5,25,0)	-0.000051	0.000000	0.000137	-2.2145	6.0039	259,172	-187.7383	0.0000
MA (5,30,0)	-0.000050	0.000000	0.000136	-2.2357	6.1007	259,167	-186.2461	0.0000
MA (5,35,0)	-0.000050	0.000000	0.000136	-2.2505	6.1682	259,162	-185.2293	0.0000
MA (5,40,0)	-0.000049	0.000000	0.000136	-2.2640	6.2305	259,157	-184.2313	0.0000
MA (10,15,0)	-0.000055	0.000000	0.000140	-2.0914	5.4637	259,182	-198.2291	0.0000
MA (10,20,0)	-0.000044	0.000000	0.000128	-2.4638	7.1983	259,177	-173.9609	0.0000
MA (10,25,0)	-0.000040	0.000000	0.000124	-2.6097	7.9562	259,172	-165.5605	0.0000
MA (10,30,0)	-0.000038	0.000000	0.000121	-2.7044	8.4764	259,167	-160.4444	0.0000
MA (10,35,0)	-0.000038	0.000000	0.000120	-2.7344	8.6402	259,162	-158.7671	0.0000
MA (10,40,0)	-0.000037	0.000000	0.000119	-2.7731	8.8591	259,157	-156.8214	0.0000
MA (15,20,0)	-0.000052	0.000000	0.000137	-2.1693	5.7894	259,177	-193.5827	0.0000
MA (15,25,0)	-0.000041	0.000000	0.000124	-2.5925	7.8627	259,172	-167.3510	0.0000
MA (15,30,0)	-0.000036	0.000000	0.000117	-2.8164	9.0864	259,167	-156.0101	0.0000
MA (15,35,0)	-0.000034	0.000000	0.000114	-2.9405	9.8416	259,162	-149.7454	0.0000
MA (15,40,0)	-0.000032	0.000000	0.000112	-3.0189	10.3219	259,157	-146.4582	0.0000
MA (1,5,1)	-0.000048	0.000000	0.000133	-2.2920	6.3606	259,192	-184.3258	0.0000
MA (1,10,1)	-0.000042	0.000000	0.000126	-2.5452	7.6119	259,187	-169.5321	0.0000
MA (1,15,1)	-0.000039	0.000000	0.000122	-2.6717	8.2894	259,182	-162.6208	0.0000
MA (1,20,1)	-0.000037	0.000000	0.000120	-2.7636	8.8006	259,177	-158.1788	0.0000
MA (1,25,1)	-0.000036	0.000000	0.000118	-2.8216	9.1333	259,172	-155.0583	0.0000

Table A1 (continued)								
	Mean	Median	Std. Dev.	Skewness	Kurtosis	N	t-value	prob.
MA (1,30,1)	-0.000035	0.000000	0.000116	-2.8803	9.4787	259,167	-152.2232	0.0000
MA (1,35,1)	-0.000034	0.000000	0.000115	-2.9200	9.7182	259,162	-150.4058	0.0000
MA (1,40,1)	-0.000033	0.000000	0.000114	-2.9592	9.9552	259,157	-148.5648	0.0000
MA (5,10,1)	-0.000048	0.000000	0.000132	-2.3072	6.4198	259,187	-185.5931	0.0000
MA (5,15,1)	-0.000041	0.000000	0.000124	-2.5641	7.6952	259,182	-170.3082	0.0000
MA (5,20,1)	-0.000039	0.000000	0.000121	-2.6651	8.2306	259,177	-164.8640	0.0000
MA (5,25,1)	-0.000038	0.000000	0.000119	-2.7180	8.5263	259,172	-162.0934	0.0000
MA (5,30,1)	-0.000038	0.000000	0.000119	-2.7453	8.6763	259,167	-160.8472	0.0000
MA (5,35,1)	-0.000037	0.000000	0.000118	-2.7691	8.8135	259,162	-159.5841	0.0000
MA (5,40,1)	-0.000037	0.000000	0.000118	-2.7801	8.8772	259,157	-158.9898	0.0000
MA (10,15,1)	-0.000042	0.000000	0.000124	-2.5513	7.6338	259,182	-171.5289	0.0000
MA (10,20,1)	-0.000033	0.000000	0.000112	-2.9592	9.9294	259,177	-151.4086	0.0000
MA (10,25,1)	-0.000030	0.000000	0.000108	-3.1328	11.0185	259,172	-143.6983	0.0000
MA (10,30,1)	-0.000029	0.000000	0.000105	-3.2418	11.7444	259,167	-139.3175	0.0000
MA (10,35,1)	-0.000028	0.000000	0.000104	-3.2872	12.0484	259,162	-137.5640	0.0000
MA (10,40,1)	-0.000027	0.000000	0.000103	-3.3399	12.4074	259,157	-135.5987	0.0000
MA (15,20,1)	-0.000039	0.000000	0.000120	-2.6551	8.1742	259,177	-166.4197	0.0000
MA (15,25,1)	-0.000031	0.000000	0.000108	-3.1373	11.0650	259,172	-144.2076	0.0000
MA (15,30,1)	-0.000027	0.000000	0.000102	-3.3740	12.6348	259,167	-134.7763	0.0000
MA (15,35,1)	-0.000025	0.000000	0.000099	-3.5043	13.5969	259,162	-130.1283	0.0000
MA (15,40,1)	-0.000024	0.000000	0.000097	-3.6012	14.2755	259,157	-126.7145	0.0000
M (3,0)	-0.000043	0.000000	0.000129	-2.4832	7.2912	259,194	-169.0981	0.0000
M (5,0)	-0.000036	0.000000	0.000119	-2.8081	9.0583	259,192	-153.0262	0.0000
M (10,0)	-0.000027	0.000000	0.000105	-3.3676	12.6341	259,187	-130.6955	0.0000
M (15,0)	-0.000022	0.000000	0.000096	-3.7616	15.5238	259,182	-117.6460	0.0000
M (20,0)	-0.000019	0.000000	0.000089	-4.0994	18.2948	259,177	-108.3637	0.0000
M (25,0)	-0.000017	0.000000	0.000086	-4.3174	20.2267	259,172	-103.2034	0.0000
M (30,0)	-0.000016	0.000000	0.000082	-4.5396	22.3037	259,167	-98.2556	0.0000
M (35,0)	-0.000014	0.000000	0.000079	-4.7614	24.4976	259,162	-93.5500	0.0000
M (40,0)	-0.000014	0.000000	0.000076	-4.9378	26.3187	259,157	-90.2490	0.0000
M (3,1)	-0.000037	0.000000	0.000118	-2.7612	8.7742	259,194	-159.1323	0.0000
M (5,1)	-0.000031	0.000000	0.000109	-3.0970	10.7978	259,192	-144.1444	0.0000
M (10,1)	-0.000023	0.000000	0.000095	-3.6848	14.9332	259,187	-122.9488	0.0000
M (15,1)	-0.000019	0.000000	0.000087	-4.1257	18.5382	259,182	-110.2038	0.0000
M (20,1)	-0.000016	0.000000	0.000082	-4.4533	21.4924	259,177	-102.3195	0.0000
M (25,1)	-0.000015	0.000000	0.000078	-4.7047	23.9441	259,172	-96.9934	0.0000
M (30,1)	-0.000014	0.000000	0.000074	-4.9381	26.3504	259,167	-92.3415	0.0000
M (35,1)	-0.000012	0.000000	0.000071	-5.1603	28.7542	259,162	-88.1001	0.0000
M (40,1)	-0.000012	0.000000	0.000069	-5.3363	30.7385	259,157	-85.0950	0.0000