



## MSc Dissertation

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# **The profitability of technical analysis in a high frequency setting and its dependency on volatility**

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Submission date: 16/09/2011

This project has been submitted as part of the requirements of the award of the MSc in Quantitative Finance at Cass Business School.

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## **Abstract**

Earlier empirical studies of technical analysis have not been able to give coherent conclusions, even when looking at similar markets and assets. This study applies the same set of methods used by these studies and tries to explain the active returns given by these investment strategies by use of volatility. Applying these strategies on high frequency data we find a strong positive relationship between returns and volatility, both for individual assets and for equally weighted portfolios.

## **Executive summary**

The subject of this paper is to empirically test if active returns obtained from investment strategies based on technical analysis are related to underlying volatility. By following the methodology as outlined by Lukac, Brorsen, and Irwin (1988) and other modern papers we apply these strategies to in-sample parameter optimisation windows. These optimised parameters are then used on subsequent out-of-sample testing windows.

All strategies use high frequency data, and these out-of-sample testing windows are then summarised to daily returns. Together with other summary data we then find performance measures based on Jensen's alpha as well as raw returns compared to our benchmark portfolio.

Previous studies have typically used values like these for their conclusions. In this paper we enhance our understanding and conclusion by also incorporating the impact of volatility clustering and heteroscedasticity in the underlying assets and portfolios. In accordance with Fung and Hsieh (2001) we find that there is a significant positive relationship between active returns produced by these trend-following strategies and volatility. We do generally not find this relationship when modelling benchmark returns based on a passive buy-and-hold strategy with volatility.

The relationship between active returns and volatility allow us to decide when to deploy our strategies. When trading with transaction costs the benefit of this allows us to further increase our portfolio values in a majority of cases.

## **Acknowledgements**

Special thanks to my supervisor Dirk Nitzsche for his suggestions and feedback throughout the process of writing this paper.

## Table of Contents

1. Introduction .....	8
2. Literature review.....	10
3. Methodology.....	14
4. Data .....	16
5. Strategies .....	17
System 1: Moving average (MA).....	19
System 2: Donchian Breakout rule (DBR) .....	20
System 3, 4: Moving average based on returns.....	22
6. Ex post analysis of strategies .....	26
7. Volatility impact on performance .....	31
8. Portfolio strategies.....	33
9. Conclusions .....	38
References .....	39
Appendix .....	42

## List of Tables

Table 1: List of analysed companies.....	16
Table 2: Strategy count.....	17
Table 3: Percentage of trading days with positive out-of-sample performance measure.....	26
Table 4: Average number of trades per trading day (out-of-sample).....	27
Table 5: Coefficients from Jensen’s alpha model applied on all the trading system and transaction cost combinations using monthly returns.....	29
Table 6: Summary regression results for returns and standard deviation for c2 coefficient at a 1% significance level.....	31
Table 7: c2 coefficient values with standard errors in brackets.....	32
Appendix table 1: Monthly returns for equally weighted benchmark portfolio.....	60
Appendix table 2: Monthly returns for active strategy with equally weighted portfolio: MA, zero.....	61
Appendix table 3: Monthly returns for active strategy with equally weighted portfolio: MA, 0.001...62	
Appendix table 4: Monthly returns for active strategy with equally weighted portfolio: MA, 0.0035.....	63
Appendix table 5: Monthly returns for active strategy with equally weighted portfolio: DBR, zero....64	
Appendix table 6: Monthly returns for active strategy with equally weighted portfolio: DBR, 0.001.....	65
Appendix table 7: Monthly returns for active strategy with equally weighted portfolio: DBR, 0.0035.....	66
Appendix table 8: Monthly returns for active strategy with equally weighted portfolio: MAR, zero.....	67
Appendix table 9: Monthly returns for active strategy with equally weighted portfolio: MAR, 0.001.....	68
Appendix table 10: Monthly returns for active strategy with equally weighted portfolio: MAR, 0.0035.....	69
Appendix table 11: Monthly returns for active strategy with equally weighted portfolio: MART, zero.....	70
Appendix table 12: Monthly returns for active strategy with equally weighted portfolio: MART, 0.001.....	71

Appendix table 13: Monthly returns for active strategy with equally weighted portfolio: MART, 0.0035.....	72
Appendix table 14: Correlation between trading system portfolios and benchmark portfolio based on daily returns.....	73
Appendix table 15: Regression model coefficients for strategy returns and standard deviation.....	74
Appendix table 16: Regression model coefficients for passive returns and standard deviation.....	77

## List of Figures

Figure 1: Example of the moving average strategy.....	20
Figure 2: Example of the Donchian breakout rule strategy.....	21
Figure 3: Example of the moving average returns strategy.....	24
Figure 4: Example of the moving average returns triple strategy.....	25
Figure 5: Portfolio value of MA strategy with transaction costs equal to USD 0.001 (above), and realized volatility together with GARCH (below).....	33
Appendix figure 1: Scaled portfolio results, zero cost.....	44
Appendix figure 2: Scaled portfolio results, cost = USD 0.001.....	45
Appendix figure 3: Scaled portfolio results, cost = USD 0.0035.....	46
Appendix figure 4: Return persistence, MA, zero cost.....	47
Appendix figure 5: Return persistence, MA, cost = USD 0.001.....	48
Appendix figure 6: Return persistence, MA, cost = USD 0.0035.....	49
Appendix figure 7: Return persistence, DBR, zero cost.....	50
Appendix figure 8: Return persistence, DBR, cost = USD 0.001.....	51
Appendix figure 9: Return persistence, DBR, cost = USD 0.0035.....	52
Appendix figure 10: Return persistence, MAR, zero cost.....	53
Appendix figure 11: Return persistence, MAR, cost = USD 0.001.....	54
Appendix figure 12: Return persistence, MAR, cost = USD 0.0035.....	55
Appendix figure 13: Return persistence, MART, zero cost.....	56
Appendix figure 14: Return persistence, MART, cost = USD 0.001.....	57
Appendix figure 15: Return persistence, MART, cost = USD 0.0035.....	58
Appendix figure 16: Ratio of selected active and passive returns for N.....	59

## 1. Introduction

The purpose of this paper is to empirically test if there is a positive relationship between returns generated from trading strategies based on technical analysis and the volatility of the securities analysed. This relationship is then exploited as a method of optimising our exposure to various portfolios. Technical analysis is a securities analysis discipline in which historical data like prices and volume is used to predict the future price direction. From an efficient market hypothesis perspective this is futile as all relevant information would already be incorporated in the current price, and any future price changes would solely be dependent on new information. Still, as documented by Park and Irwin (2004), the amount of research exploring the profitability of technical analysis has been increasing steadily from 1990 onwards.

Park et al (2004) divide the studies they review into two different categories, early and modern. Modern studies are defined as those that include a more advanced and extended analysis of the results. This may include transaction cost, out-of-sample testing, statistical tests and data snooping<sup>1</sup> tests. Among a total of 92 modern studies, 58 studies found profitable results, 24 studies obtained non-profitable results, while the remaining indicated mixed results. Including some of these modern elements are important as they may significantly change the outcome.

Another aspect of this paper is that all initial analysis is performed on what is defined as high frequency data utilising high frequency trading. The definition of high frequency trading used here follow that of the FINalternatives July 2009 Technology and Trading Survey<sup>2</sup>, in which all holding periods are less than one trading day. Most previous studies' price frequency are daily or lower and the reasons for this are valid enough as high frequency data have tended to be difficult or expensive to get a hold of. In addition, the computational resources or skill required for handling high frequency data might not have been available. As both the cost has gone down and availability of high frequency data has gone up there is no reason to avoid using it. Also, computational resources and knowledge on how to utilize these resources are readily available these days.

There might be several reasons why the modern studies mentioned earlier have come to different conclusions. Many papers reference data snooping as an issue, and try to test for this bias. Among the most popular methods used we find White's reality check for data snooping (White 2000) in which a stationary bootstrap technique is used. This permits data snooping to be undertaken with

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<sup>1</sup> Data snooping, also known as data dredging or data fishing, is the inappropriate (sometimes deliberately so) use of data mining to uncover misleading relationships in data. Data-snooping bias is a form of statistical bias that arises from this misuse of statistics. Any relationships found might appear to be valid within the in-sample data set but do not guarantee statistical significance in an out-of-sample setting.

<sup>2</sup> FINalternatives July 2009 Technology and Trading Survey results: <http://www.finalternatives.com/node/8583>

some degree of confidence that one will not mistake results that could have been generated by chance for genuinely good results. This would be especially helpful in cases where available data is sparse. Another aspect might be that since the data used in these studies act on different data periods, there might be persistent features within these periods that affect profitability. Ready (2002), Kidd and Brorsen (2004) and Olson (2004) all show decreased profitability over time. As an example, Olson (2004) finds that the moving average rule generates significant profits in the Eighties, but not in the Nineties. Similar results are shown by Ready (2002) after 1986, looking at moving average rules for the Dow Jones Industrial Average. This decrease might be due to increased technical availability. Widespread “statistical arbitrage” would have eaten away at the profit potential.

Then again, it might just happen to be the case that volatility is to blame for these decreased levels of profitability in certain periods. We know that financial markets show persistence in volatility, and if there’s a link between profitability and volatility then this represents a method to choose when and how to actively use trend following strategies. Fung and Hsieh (2001) show that trend following strategies (in which most technical analysis belong) have an option-like payoff with a strong positive relationship to volatility.

This paper will analyse a set of technical analysis based strategies on the 15 most traded stocks currently part of the S&P 100 index. It will include different transaction cost levels, out-of-sample verification and both asset and portfolio based analysis of the profitability and volatility relationship.

The remaining parts are organized as follows: We start off in section 2 looking at relevant literature. Section 3 (Methodology) introduces the methods and procedures used when testing, optimising and analysing different trading strategies. Section 4 (Data) outlines any details related to the historical data used and issues related to data cleansing. Section 5 (Strategies) formally introduces the definitions of the various trading strategies deployed. Section 6 (Ex post analysis of strategies) reports the results of different ex post analysis of the results obtained from the strategies. Section 7 (Volatility impact on performance) looks into the relationship between volatility and performance, while section 8 presents and tests the portfolio selection rule. Section 9 concludes.

## 2. Literature review

This chapter will start off exploring literature available on empirical tests of technical analysis. The main parts of this paper depend heavily on the returns obtained from these methods, so it's natural to explore the development of this field.

Since Charles H. Dow introduced the Dow Theory in the late 1800s, there's been widespread use of technical analysis among market practitioners. On the academic side there are numerous papers available that have empirically tested the profitability of technical analysis, and as reported by Park et al (2004) this number has dramatically increased during the last two decades.

There's a shift present in these academic papers, where the modern studies include more advanced techniques when testing and measuring their results. This is likely due to both better understanding of potential pitfalls in addition to more computational resources available. Following Park et al (2004), modern studies typically include an extended strategy search space, transaction cost analysis, risk considerations, parameter optimisation and out-of-sample verification. They might also include various, often bootstrap based, statistical tests typically to guard against data snooping bias.

Looking first at three of the most influential papers prior to the more modern ones we find Fama and Blume (1966), Stevenson and Bear (1970), and Sweeney (1986). Three things in particular make these representative as early type papers: (a) A limited strategy search space, (b) only in-sample testing, and (c) limited focus on aspects like risk and transaction costs.

For the first point these papers tend to focus on what is known as filter rules as their active trading strategy. In its most general case a filter rule signals a long position if the asset or market has gained a defined percentage level within a historical window. This can be an absolute gain within that complete range or from a local minimum. Likewise you would obtain short signals by looking at a defined percentage decrease. Sometimes these filter rules are extended with stop-loss and take-profit levels, with the more advanced also using features like trailing stop-loss levels.

Filter rules expose at minimum one parameter, namely the percentage level. For point b, a range of these levels are tested, but only in-sample. In other words, there's little or no persistence testing on these strategies by use of parameter optimisation. Risk and transaction costs were at best very simplified, often just analysing raw returns and comparing this with a buy-and-hold benchmark. Also, as there's no parameter optimization present, transaction cost analysis was typically limited to finding a break-even level at best. Then again, as transaction cost generally have decreased over time they did play a substantially bigger role back then than they would potentially do now.

By only using an in-sample window, the chance of finding a strategy that by pure chance shows signs of abnormal returns increases as we increase our strategy search space. However, that doesn't directly imply that this would allow us to use this strategy in the future (out-of-sample) and expect continued success. These types of results are exposed to what we refer to as data snooping, and in more modern papers these issues are dealt with by various means.

Some of these means, besides out-of-sample testing, include various bootstrapping techniques to give a level of significance to the results obtained. Probably the most influential would be the one described by White (2000) in which the stationary bootstrapping technique is used. Prior block based bootstrapping is vulnerable to generating non-stationary return series, an issue fixed by the stationary bootstrap. Sullivan, Timmermann, and White (1999) apply this technique, extending the work done by Brock, Lakonishok, and LeBaron (1992). Both of these papers represent modern studies, and we may categorise them as model-based bootstrap studies. Although Brock et al (1992) do report results for different sub-periods, there's no real focus on parameter optimisation and measuring the parameter persistence in an out-of-sample setting. Sullivan et al (1999) do to some extent do this by extending the data period used, but still the main focus of these two papers is to obtain confidence intervals for their strategies.

We are in the later sections not going to follow a model-based bootstrap methodology, but rather focus on parameter optimisation and out-of-sample testing. This procedure is a significant improvement compared to earlier studies, because it's closer to actual traders' behaviour and may partially address data snooping problems (Jensen 1967; Taylor 1986). Also, with specific regards to what's being performed later on, by using high frequency data spanning over 10 years this further reduces this potential issue. Not much research has been done in this area using the frequency used here, as most of the studies use daily observations. However, from a methodology standpoint one of the earliest relevant papers is Lukac, Brorsen, and Irwin (1988). This was later expanded by Lukac and Brorsen (1990) increasing the number of trading systems, assets and test periods. In brief the approach is to test a number of strategies on an in-sample period, select the best of these based on some form of performance measure, and then apply that one selected strategy on an out-of-sample period following the in-sample period. Finally a set of statistical tests are performed on the out-of-sample results. A comprehensive review of 23 papers part of this category as conducted by Park et al (2004) conclude that in at least half of the papers there's a significant outperformance among technical analysis based trading strategies compared to a buy-and-hold benchmark. Among the remaining results these are mixed between non-significant results and significant underperformance. Overall, these trading strategies seem to work better in markets that are

dominated by more speculative trading, especially in foreign exchange markets and futures markets. These results aren't necessarily directly applicable to what's performed later however as the frequency is lower than what is used here.

As little earlier work has been done on high frequency data that makes it interesting in itself, but there's another good reason for using higher frequencies and intraday data. Given that any risk adjusted abnormal returns generated from these types of strategies would be considered an abnormality viewed from the efficient-market hypothesis, alternative market explanations would be needed. There are plenty of alternative models to choose from, but the primary focus isn't to establish any specific relationship to these. Rather, it gives a more refined and richer potential understanding as to why we obtain the results we do. The trading strategies applied are among those we call trend-following strategies. Given that these exploit trend formations that occur over time, it's interesting to bring in the following alternative market models.

Noisy rational expectation models (Treyner and Ferguson 1985; Brown and Jennings 1989; Grundy and Grundy 1989; Blume, Easley, and O'Hara 1994) argue that there's asymmetric information among market participants. This implies that there's a delay between when information is made available and when it is fully reflected in the market. This delay breaks the independence between successive asset returns as information is absorbed over a given time period instead of instantaneously. This would therefore allow trends or patterns to form, something which can be exploited by technical analysis.

Behavioural models focus more on irrational behaviour, where the underlying value is to some extent disconnected from the current price (Shiller 2003), which also would help to describe stock market bubbles. A behavioural model consists of two main types of participants; arbitrageurs (defined as investors who form fully rational expectations about security returns) and noise traders (investors who irrationally trade on noise as if it were information) (Black 1986). Noise traders, by following a positive feedback strategy (buy when prices go up, sell when prices go down) can substantially affect the price thereby contributing to trend formations (De Long et al. 1990a; De Long et al. 1990b). This then represents a situation where technical analysis, in its very existence and due to extensive usage, could be self-fulfilling.

Closely related to positive feedback effects we also find that herding behaviour of short-horizon traders can lead to informational inefficiency, as demonstrated by Froot, Scharfstein, and Stein (1992). As for the behavioural models, this type of model argues that short term investors would

benefit from technical analysis as long as it's widely adopted even if there is no fundamental connection between it and the underlying asset.

With this in mind it's obviously beneficial to use high frequency data. Higher frequencies would allow us to get a more detailed market picture as the market evolves and reacts to various market conditions and factors throughout the day.

The final sections of this paper look at the relationship between strategy returns and volatility. It's likely that this relationship might help explain some of the different conclusions given by some of the earlier mentioned papers. But there hasn't been much extensive study on if this is the case, even if quite a few of the papers mention a potential link. As referred in the introduction, Kidd and Brorsen (2004) provide some evidence that the observed reduction among managed futures fund returns in the 1990s, where technical analysis dominates, may have been caused by structural changes in the market. These include decreased price volatility and an increase in large price changes occurring while markets are closed. Also the results obtained by Fung and Hsieh (2001) (and their earlier work in Fung and Hsieh 1997a and 1997b), which the analysis in section 7 and 8 builds on, show that trend-following strategies tend to have a payoffs that follow a lookback straddle. This has several implications, first of all that linear factor models would have difficulties explaining their results. Secondly it ties in nicely with why earlier mentioned papers might have differing conclusions; we know that financial markets are heteroskedastic with prolonged periods of both higher and lower market volatility. Specifically to what they look at, trend-following funds show an uncorrelated relationship to the standard equity, bond, currency, and commodity indices. The strategies exhibit option-like payoffs that tend to be large and positive during the best and worst performing months of the underlying assets. Due to this there is systematic risk present, but not captured by our linear factor models. Betas from these linear models would either overstate or understate this risk.

### 3. Methodology

Before diving into specific details it's natural to make a few definitions and then outline the overall structures and procedures followed. First of all, this paper deals with both high and low frequency data. High frequency data always refer to one minute bars of historical market price data, or returns derived from this. Low frequency data is daily or less frequent and may consist of accumulated returns, volatility or other summary statistics. By returns, at any frequency level, we mean log returns.<sup>3</sup>

The high frequency data is used by trading strategies (also sometimes referred to as trading rules elsewhere) derived from a trading system. As defined here a trading system becomes a trading strategy once you define all input parameters made available by that system. All trading systems considered make available at least one parameter, and with a defined range of values for each parameter we obtain a finite set of parameter combinations for each system. The number of strategies equals the number of members in this parameter set.

Each trading strategy produces a set of signals that are acted upon. There are a total of three different signal types: Long, short and close. What happens on a signal change depends on the previous signal given and results in a position change. If no previous position is held (out of market) and a long (short) signal is given, we buy (sell) shares. If the previous position is long (short) and we're given a close signal we sell (buy) all shares in our current position, closing out. When dealing with transaction cost, this is given as trading cost per share traded. In the above example we went from no position to either a long or short position, or the other way around. Each example was represented by trading X shares. However, in this final example we are long (short) and change that to short (long). This requires us to trade 2\*X shares, thereby also doubling the trading cost.

After a set of trades have been performed by a strategy on high frequency data, these are summarised to daily data. Some of this daily data is used in section 6 onwards for ex post analysis and finally in section 8 for the active portfolio strategy. All results obtained from one of these strategies are referred to as values from an active strategy. There is however a final strategy which is dealt with separately, namely the passive strategy. The passive strategy does not act on the value of the price data feed, but instead acts on market open and market close, going long on market open and then closing the position on market close. The results from this passive strategy are used as a reference benchmark.

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<sup>3</sup> Log returns are calculated as  $r_{t+1} = \log_e \left( \frac{P_{t+1}}{P_t} \right) = \log_e(P_{t+1}) - \log_e(P_t)$ , which also gives us  $P_{t+1} = P_t e^{r_{t+1}}$ .

Among all the strategies given by a trading system we run an optimisation routine with the goal of finding the strategy we assume would perform well in the future. The optimisation routine tests all the strategies from the specific trading system on a defined range of high frequency data, called the in-sample period. Each strategy is then scored and sorted using what we call a performance measure. The strategy with the highest score is kept, and we have thus selected our strategy. This strategy is then used on what we call an out-of-sample data period. This out-of-sample period always follows (in time) the in-sample period, but is never part of the current in-sample period. A sample period may span more than one day, however we view each intraday as a separate data set. This has quite a few implications as to how we apply the strategies. Any technical analysis based strategy depends on historical data before a trading signal can be produced. As each intraday data set is viewed independently, no historical prices from the previous trading day can be used by the strategy. Say a strategy looks at data from the last 30 minutes. That means this strategy will not produce a trading signal we can act upon till the 31<sup>st</sup> minute, with the default behaviour of not having a position before this point. This separation also defines our first level of aggregation. Hence, any performance measure is given on a daily level. With an in-sample period spanning more than one day, the optimisation routine selects a strategy based on the average performance measure spanning this period.

Given that we view each intraday set separate and don't use prices that cross this border, it also very correctly indicates that we hold no overnight positions. All strategies are forced to close any positions at market close just as our passive strategy does. This also has implications as to how we calculate our financing costs and follows standard high frequency methods of not assuming any direct financing cost.

When analysing the final results, we're only considering the out-of-sample result of the selected strategy. Which strategy this is varies depending on the results from the in-sample period. Our out-of-sample period is one day only, so all strategies are re-estimated prior to each trading day.

## 4. Data

All the strategies use one minute bars, with each bar consisting of the open, high, low, and close price (OHLC), in addition to volume data. These bars have been constructed based on actual trades only. The data range used is from the start of 1998 till the end of February 2011. Within each intraday data set we only include price data that take place within normal trading hours (from 9:30 till 16:00).

Market data has been provided by RC Research<sup>4</sup> and have as part of their process been verified by three separate data sources. Still, as an additional check to discover obvious data issues, their data has been compared to the daily OHLC bars obtained from Bloomberg. In cases where there are obvious data discrepancies the particular minute bars affected is located and dealt with as outlined in the appendix.

There might be gaps in the data, meaning that there might not be minute bars available for each minute marker. Reasons for this might be due to a lack of trades or if the exchange halts trading. Cases representing little trading activity also poses a challenge with justifying simulated order fills, so to mitigate some of this risk only the 15 biggest companies in terms of trade volume ex post is considered. These 15 companies are shown in table 1.

<b>Company</b>	<b>Ticker</b>
Apple Inc	AAPL
Bank of America Corporation	BAC
Cisco Systems, Inc	CSCO
Citigroup Inc	C
Dell Inc.	DELL
EMC Corporation	EMC
Ford Motor Company	F
General Electric Company	GE
Intel Corporation	INTC
JPMorgan Chase & Co	JPM
Microsoft Corporation	MSFT
Oracle Corporation	ORCL
Pfizer Inc	PFE
QUALCOMM, Inc	QCOM
Texas Instruments Incorporated	TXN

*Table 1: List of analysed companies*

When the time series are delivered to the strategies there might be gaps as already mentioned. Even if the stocks chosen are among the most actively traded instruments there are still cases when this occurs. In this paper these gaps are ignored and the next available minute bar is feed in as if it would have been the next natural minute bar. In other words, we're not measuring time weighted prices or returns for, say, the moving average based strategies, but rather purely the average of prices or returns within a defined range of market observations.

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<sup>4</sup> RC Research provides a multitude of high frequency financial data, available from [www.price-data.com](http://www.price-data.com).

## 5. Strategies

As we defined in section 3, a trading strategy is a specific configuration of a trading system with four distinct trading system tested. Two of these are the well-known Moving Average (MA) and the Donchian Breakout rule (DBR). The other two experiment with using moving averages on returns rather than price data; Moving Average Returns (MAR) and Moving Average Returns Triple (MART). The complete parameters set for these four systems combined make up a total of 1588 strategies.

System	Strategies
DBR	153
MA	275
MAR	20
MART	1140
<b>Total</b>	<b>1588</b>

*Table 2: Strategy count*

Each system is optimised on 20 trading days (in-sample), before the optimal strategy per system is selected for use the next trading day (out-of-sample). The returns produced by the strategies are therefore not based on sub-optimised, or maybe rather over-fitted, reactions in a back testing environment. Instead these parameters, based on average performance within the 20 trading days are used in an out-of-sample situation. Also, whenever a strategy triggers a position change, this updated position is not changed until the next minute bar. This is because we're feeding the minute bar close price to the strategies, making it impossible to trade on that price as it's already observed. When changing positions, to address some of the uncertainty in which price the order would be filled at, the mid-price between the high and low values of the target bars are used as an average transaction price for our order. There is of course a limit as to how much one can expect to fill on an order within a one minute period. Besides only looking at the most actively traded securities and trading at the mid-price, no other considerations are taken.

In section 3 we introduced the purpose of a performance measure. We're now going to define how we calculate this performance measure, namely using one of the methods defined in Griffioen (2003): the Sharpe ratio of the active minus the Sharpe ratio of the passive strategy (from here on referred to as a relative Sharpe ratio). To recap, the passive strategy performance here is a buy on market open and hold throughout the trading day. None of these strategies use overnight positions, removing our financing costs from the formula. However, I've instead included the transaction costs as an average measure on returns. It's important that the transaction costs are included in the performance measure as we want the optimisation routine to select strategies that also take these costs into account. Transaction costs have typically not been part of parameter optimisation in earlier studies, in which transaction costs are merely applied ex post. In a high frequency setting, transaction costs play a greater role due to frequent trading. It is therefore important to include this factor in our performance measure.

$$f = \frac{\bar{r}_a - \bar{r}_{ac}}{\sqrt{\text{var}(r_a)}} - \frac{\bar{r}_p - \bar{r}_{pc}}{\sqrt{\text{var}(r_p)}}$$

$f$ : Performance measure

$\bar{r}_a$  and  $\bar{r}_p$ : Average active and passive strategy returns

$\bar{r}_{ac}$  and  $\bar{r}_{pc}$ : Average transacting cost for active and passive strategy returns

$\sqrt{\text{var}(r_a)}$  and  $\sqrt{\text{var}(r_p)}$ : Standard deviation for active and passive strategy returns

The Sharpe ratio was used since it measures mean returns per unit of risk, as measured by the standard deviation. Other performance measures could have been used, for example the difference between active and passive mean returns, ignoring the standard deviation. We could also have dealt with any non-normality in our return distributions and used a more advanced replacement for the standard deviation, but this is not considered.

As we're running back tests with each intraday data set viewed in isolation, each performance measure,  $f$ , is purely based on data from the specific day. 20 trading days was chosen as the back testing period as it represents 4 times 5 days, being close to a month on average. It could be interesting to look further into an optimal number of back testing days, but mainly due to time and resource limitations this has not been considered. 20 trading days with one minute bars represents on average about 7700 observations for one asset.

With the 20 trading days used in our back test, the average performance for this period is simply calculated as:

$$\bar{f} = \frac{1}{20} \sum_{i=1}^{20} f_i$$

$\bar{f}$ : Average performance measure over back testing period

$f_i$ : Performance measure as stated earlier for strategy on back testing day indexed by  $i$

Finally, three different levels of transaction costs are considered, with the transaction cost added as a fixed cost per share traded in the form of an average per return ( $\bar{r}_{ac}$  and  $\bar{r}_{pc}$ ). The first level of transaction cost is zero with the final level being based on public prices from Interactive Brokers<sup>5</sup> as of May 2011: USD 0.0035. A lower level, USD 0.001, is also used. Both  $\bar{r}_{ac}$  and  $\bar{r}_{pc}$  are calculated as shown next, with  $\log$  being the natural logarithm.

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<sup>5</sup> <http://www.interactivebrokers.com/>

$$\overline{r_{cost}} = \log_e \left( \frac{P - cost}{P} \right) \cdot \frac{1}{N}$$

$\overline{r_{cost}}$ : The average return impact of transaction costs

$P$ : Final trade account value at end of trading period for strategy

$cost$ : The product of transaction cost and number of trades

$N$ : Number of minute returns available in the return sequence

For completeness please notice the negative sign of  $\overline{r_{cost}}$ , a detail that must be dealt with when used in the performance measure.

### System 1: Moving average (MA)

Moving averages represent a simple indicator, where the trading strategy normally consists of two moving averages with different periods. They are among the most popular indicators used for trend following strategies (Taylor and Allen 1992; Lui and Mole 1998). There are several variants of this indicator regarding how the averaging is performed, namely simple moving average (SMA), weighted moving average (WMA) and exponentially weighted moving average (EWMA). All simulations performed here only use the SMA, defined as:

$$SMA_t = \frac{1}{N} \sum_{i=0}^{N-1} P_{t-i}$$

The parameters and variables for the above formula are:

$SMA_t$ : Value of moving average at time t

$P_t$ : The closing price at time t

$N$ : Number of time steps used when calculating average

This strategy together with the others is indifferent to the price frequency as long as we're consistent. In our case, all prices and returns are per minute when given to our various strategies.

Two moving averages would be grouped as follows to form a trading strategy:

$$N_1 < N_2$$

$$TS = MA(N_1) - MA(N_2)$$

TS denote our trading signal. If this is greater than zero we go long, otherwise short. A sign change in TS therefore denotes a position reversal, and this strategy implies always being in the market. This could further be extended to try and avoid so called "whipsaws", a condition were an assets price

heads in one direction, but then is followed quickly by a movement in the opposite direction. This extension would, in addition to a sign change in TS, also require that the absolute value of TS is greater than some defined level before a change is triggered. Alternatively we can impose the restriction that when TS changes sign, it must not change sign again within a given time period before we act on the signal.

For this study no whipsaw extensions are applied, and this is left for future research.

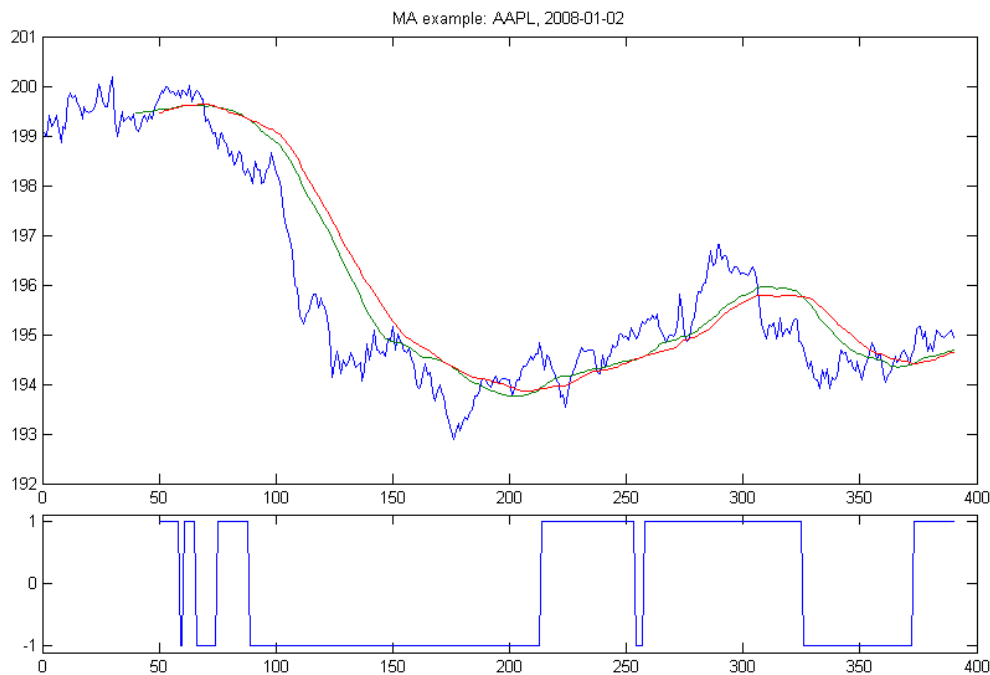


Figure 1: Example of the moving average strategy.

The above chart exemplifies the moving average strategy, here looking at the intraday price movements for Apple Inc on the 2<sup>nd</sup> of January 2008. In this instance  $N_1$  and  $N_2$  values are 40 and 50, selected as the most optimal from the preceding in-sample period. The bottom part shows the current signal, being set to 1 for long and -1 for short. We see some whipsaw tendencies with rapid signal changes. The  $N_1$  range spans from 3 or 5 to 70 minutes (with steps of 5), while the  $N_2$  range spans from 25 to 130 (depending on  $N_1$ ), also with steps of 5.

## System 2: Donchian Breakout rule (DBR)

The other indicator is price channels, known as the Donchian Breakout rule (Donchian 1957), or 'trading range break' in Brock, Lakonishok and LeBaron (1992). This indicator gives a long signal when the latest price is greater than the maximum value of  $N$  number of previous price values. Likewise, a short signal is given when the current price is lower than the minimum value of  $N$  number of previous price values.

This is formulated as given below:

$$TS_{LONG} = P_{c,t} - \max(P_{h,t-1}, \dots, P_{h,t-N1})$$

$$TS_{SHORT} = P_{c,t} - \min(P_{l,t-1}, \dots, P_{l,t-N2})$$

$TS_{LONG}$ : Trade signal value for the long signal

$TS_{SHORT}$ : Trade signal value for the short signal

$P_{c,t}, P_{h,t}, P_{l,t}$ : Closing, high, and low price for price bar at time t

$N1$  and  $N2$ : Number of steps we look back for long and short signals

Defined as this, we go long when the  $TS_{LONG}$  is positive and short when  $TS_{SHORT}$  is negative. The functional constraints also imply that we would never be out of the market, always being either long or short. Various extensions are available as with the moving average strategy, dealing with whipsaws for instance. As the high and low minute bar prices are used we already have an implied whipsaw protection, given that there tends to be a spread between these values.

There's no need to use the same values for  $N1$  and  $N2$ , even if this is sometimes linked. The DBR strategies implemented here do not link these and allow the optimisation routine to freely select different values.

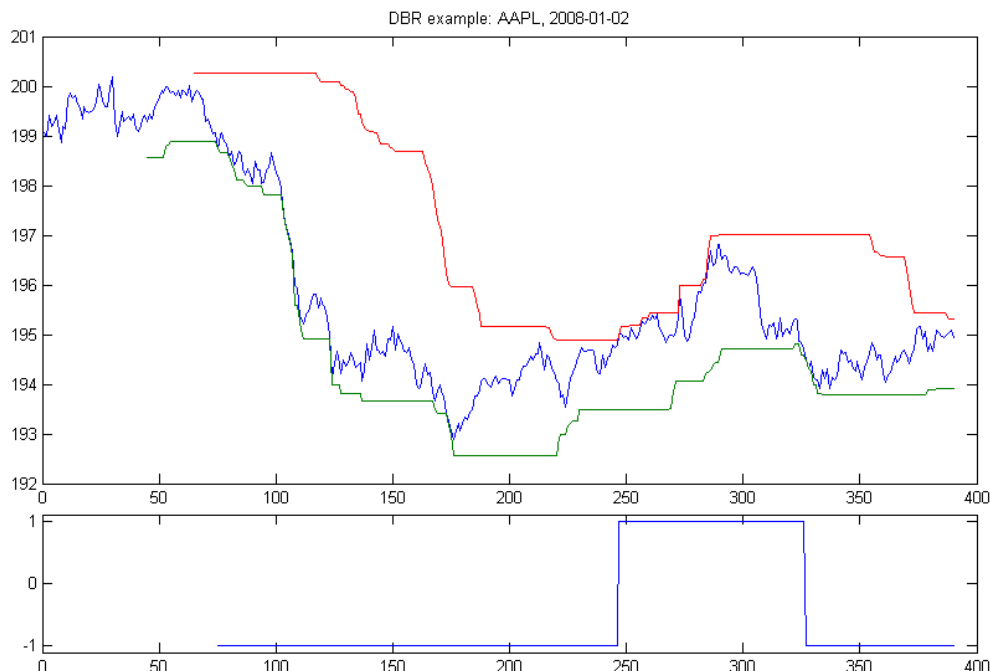


Figure 2: Example of the Donchian breakout rule strategy.

Figure 2 shows us the same intraday price movements as figure 1, but now with the DBR price channels and the trade signals they produce. In this case  $N1$  and  $N2$  have been set as 65 and 45,

again selected based on the previous in-sample period in the same fashion as for the moving average case earlier. Even if the blue line only shows us the current close price (within each minute bar), we can clearly see the effect of using the high and low prices when calculating the upper and lower price channels. Also as indicated, there is a natural whipsaw protection in the DBR strategy, with whipsaws not at all present in this example. On the negative side, this whipsaw protection makes the DBR react slower than the MA strategies. The bottom part is again the signal indicator, as used earlier. N1 and N2 are (independently) selected from a range between 5 and 120, with steps of 5.

### System 3, 4: Moving average based on returns

These are experimental systems using the simple moving average method on returns rather than prices. The first of these, Moving Average Returns (MAR) simply apply one moving average on past return values, with this being the geometric close-to-close returns per minute bar. When this value is positive it is regarded as a long signal and a short signal when we have a negative value.

$$MAR_t = \frac{1}{N} \sum_{i=0}^{N-1} R_{t-i}$$

MAR<sub>t</sub>: Average value of N returns

R<sub>t</sub>: Geometric close-to-close returns between two successive minute bars

The next one is Moving Average Returns Triple (MART). This one works in much the same way as the MAR, but we need a majority vote (2 of 3) among the moving averages to agree before concluding on a trading signal. So we have three MAR<sub>t</sub> values as defined above, but each with a different N:

$$N_1 < N_2 < N_3$$

Our trade signal function is for MART defined as:

$$TS = \text{sgn}(MAR_{t,1}) + \text{sgn}(MAR_{t,2}) + \text{sgn}(MAR_{t,3})$$

The signum function (sgn) used gives us a value of one on positive input and minus one otherwise:

$$\text{sgn}(x) = \begin{cases} -1 & \text{if } x \leq 0 \\ +1 & \text{if } x > 0 \end{cases}$$

With three MARs this is guaranteed to always give us a TS value above or below zero, interpreted as long on positive TS and short on negative TS.

The intuition for the MAR and MART is that if there is a predictable trend then this will also be exposed by the average value of the returns. Since MAR allows us to use zero as a trigger line this might allow us to react earlier than a traditional dual moving average indicator based on prices. With the MART we're also trying to react early to a starting trend, but then later on as the slower MAR catches up we want to avoid potential whipsaws by staying with the established slower trend direction. The potential downfalls with these two are that they might give too many false positives by reacting too early before the trend is established.

The next two charts exemplifies MAR and MART, again for the same intraday price period as that used earlier. As both of them apply moving averages to returns rather than prices, the middle part illustrates this.  $N$  is set to 40 for the MAR case, and  $N_1$ ,  $N_2$ , and  $N_3$  are 5, 40, and 110 for the MART case. These examples show a greater amount of whipsaw issues than shown earlier, which isn't surprising given the earlier worry about false positives.

On the parameter range, both MAR and MART share the same set of values, specifically 3 or 5 to 120, with steps of 5 between 5 and 120, with MART's  $N_1$ ,  $N_2$ , and  $N_3$  interdependencies enforced.

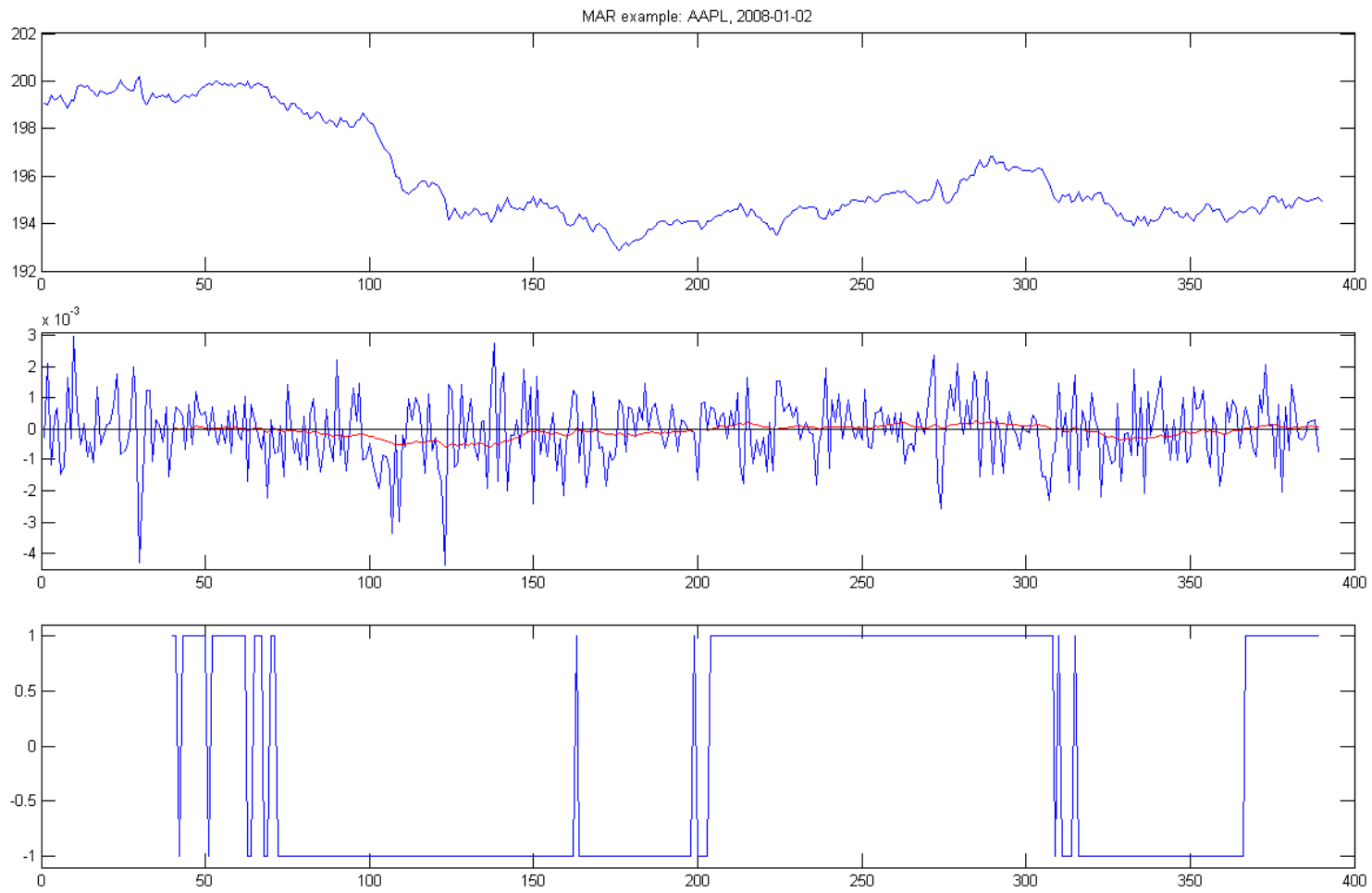


Figure 3: Example of the moving average returns strategy

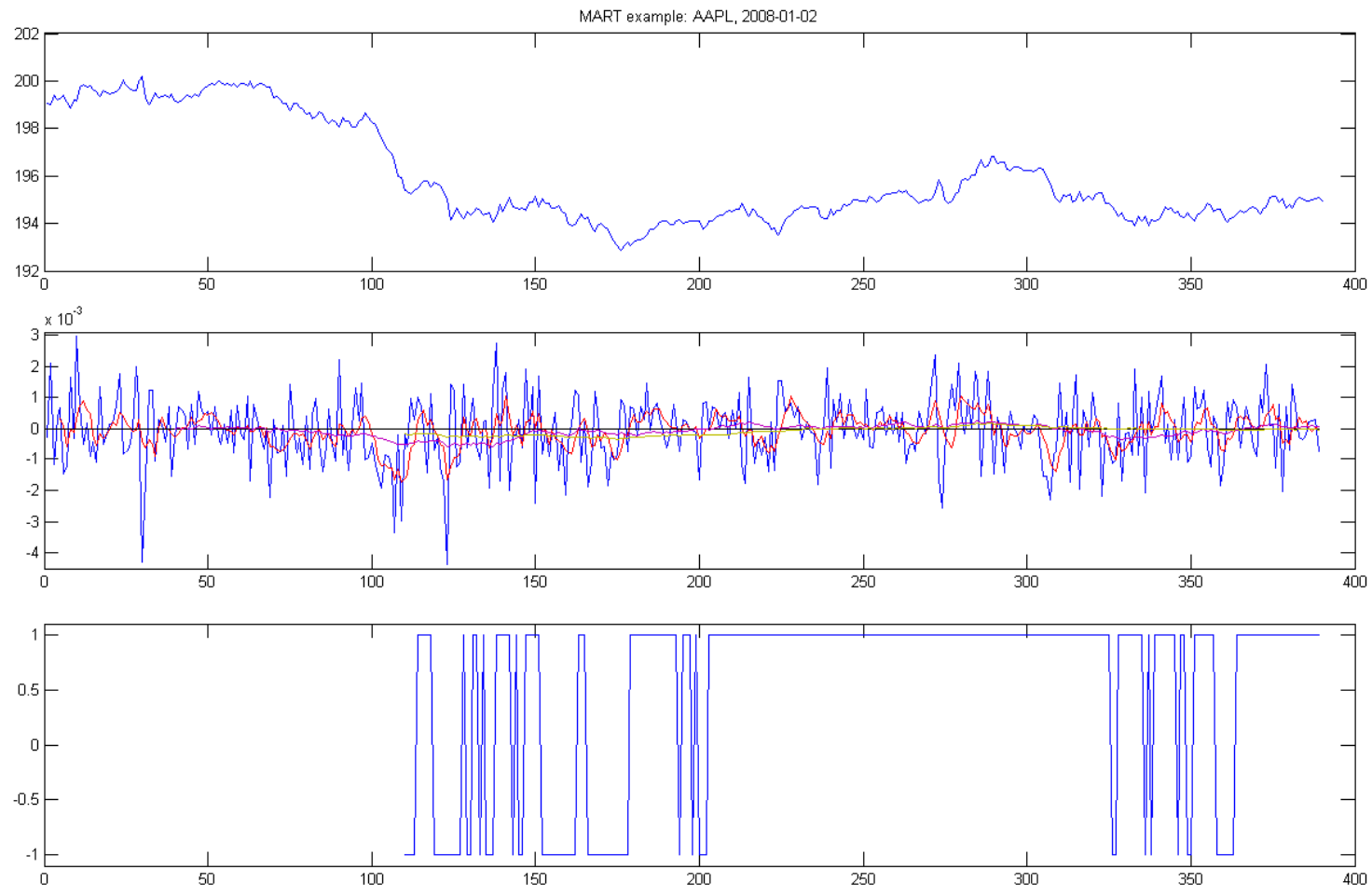


Figure 4: Example of the moving average returns triple strategy

## 6. Ex post analysis of strategies

Before continuing with a deeper analysis of the results, let's first look at some of the overall results. We're here mainly interested in how many positive performance measures we have in total. Three different scenarios are analysed: The complete data period, from the start of 1998 till the end of February 2011, consists of 3310 trading days. This period is then split into the first (1653 trading days) and second half, with the first ending on 30<sup>th</sup> of July 2004. This is the performance measure equal to that used in the in-sample calibration periods, namely the relative Sharpe ratio between the active and passive strategy. In this case however we're not looking at the in-sample results, but the same performance measure calculated for the out-of-sample results.

What these numbers tell us is simply that on about 50% of the trading days, especially for the zero transaction cost case, the active strategies are able to produce a better result than the passive buy-and-hold strategy. It's also clear, and not very surprising, that adding and increasing transaction costs decrease this number. We can however not, based on these number alone dismiss the profit potential of technical analysis as the number don't tell us anything about the difference in performance. Another observation we can make is that the strategies seem to have a harder time finding strategies that beat the benchmark in the second half. We'll look at that in more detail later, but first it's interesting to see how the optimisation routing handles different levels of transaction cost.

Transaction costs can be interpreted as a penalty since it's included in the performance measure. In any non-zero transaction cost case, the performance measure will further penalised any increase in non-profitable trading activity than compared to the zero cost case. This should cause the optimisation route to seek out strategies that tend to trade less often by increasing the parameter values. Especially in cases where no optimal in-sample strategies are found, trading as little as possible by increasing parameter values would be regarded as beneficial by the optimisation routine

Positive performance measures (complete)			
Transaction costs			
System	Zero	0.001	0.0035
MA	50.2%	47.9%	44.6%
DBR	50.3%	49.1%	47.2%
MAR	55.8%	45.8%	35.9%
MART	53.3%	44.6%	35.4%

Positive performance measures (first half)			
Transaction costs			
System	Zero	0.001	0.0035
MA	52.6%	50.5%	47.0%
DBR	53.3%	52.2%	50.2%
MAR	63.9%	53.4%	41.8%
MART	60.1%	51.4%	41.1%

Positive performance measures (last half)			
Transaction costs			
System	Zero	0.001	0.0035
MA	47.7%	45.3%	42.1%
DBR	47.3%	46.0%	44.2%
MAR	47.7%	38.2%	30.0%
MART	46.4%	37.7%	29.7%

Table 3: Percentage of trading days with positive out-of-sample performance measure

as this also implies postponing (as outlined in section 3) the first intraday trade. Unless there's an extensive case of whipsaws, increasing the parameter values will produce strategies that tend to react slower and thereby focus more on slower moving trends. Of course, there might not be any long term (intraday) slower moving trends available in which case entering the market as late as possible is the only beneficial option.

Looking at the average number of trades per trading day, as given in table 4, this confirms the expected behaviour. We see that as transaction costs increase, there's a reduction in average number of trades. Between MA and DBR we also observe that DBR is more conservative and doesn't differ as much under various trading costs. There are two probable reasons why this might be the case: Either the DBR is in general good at picking longer lasting trends than MA and thereby doesn't need to change directions as often. Or, given the number of trades, this doesn't affect the performance measure enough to drastically change the strategy selection process. With regards to the first point, we know that the DBR strategy has some protection against whipsaws which will make it react slower.

On the MAR and MART side, the concerns about too many false positives might seem to be confirmed as an average trading count of up to over 130 is high for a trend following strategy in our setting. Given that a complete intraday period consists of 390 minute bars, this doesn't give room for much trend formation and following time.

A final comment about trade counts would be the difference between the first and second half. As we saw in table 3, the second half period indicated fewer opportunities, and we see that the number of trades also go down. Again, viewed from the perspective of the optimisation routing, higher valued parameters seems to have been preferred, as a response to fewer market opportunities.

Average trading count per day (complete)			
Transaction costs			
System	Zero	0.001	0.0035
MA	22.74	18.44	13.68
DBR	13.31	11.70	9.24
MAR	136.49	84.69	54.01
MART	105.33	72.61	50.85

Average trading count per day (first half)			
Transaction costs			
System	Zero	0.001	0.0035
MA	25.60	21.86	16.50
DBR	16.11	14.52	11.57
MAR	161.53	116.14	69.32
MART	120.45	92.82	62.09

Average trading count per day (last half)			
Transaction costs			
System	Zero	0.001	0.0035
MA	19.88	15.03	10.86
DBR	10.52	8.89	6.91
MAR	111.51	53.32	38.74
MART	90.25	52.44	39.63

Table 4: Average number of trades per trading day (out-of-sample)

Given this background information it's now of interest to take a first look at the returns produced. Three different plots are available (appendix figure 1, 2, and 3), showing equally weighted portfolios of each trading system and transaction cost combination. All values have been scaled so that their different characteristics can more easily be compared. The first obvious difference is that having or not having transaction costs makes a, not surprisingly, big difference. From around trading day 1100 all strategies with transaction costs take a turn for the worst, while strategies not affected by transaction costs are either able to maintain a certain range of portfolio value or increase this value towards the end. None the less, we clearly see the shift in market conditions, indicated by the value reductions in table 3 and 4 for the second half for all three plots. It also seems to indicate that this shift occurred in around the middle of the first half period.

We haven't yet looked directly at the performance of the passive strategy, but it's natural to bring more focus on that now. Appendix table 1 tells us the story of what would have happened had we blindly followed the passive strategy, calculated using an equally weighted portfolio across the 15 companies analysed. This miserable monthly average returns of -0.69% is in accordance with what Cooper, Cliff and Gulen (2008) find in their paper, and would you have followed this from the beginning of 1998 till the end of February 2011 your total returns would have been -109.70%. We can't blame transaction costs as this is the zero transaction cost case, but including these would only further reduce the results. However, it wouldn't dramatically change the results as there's only two orders a day, and compared to the number of trades executed by the active strategies this is negligible. For those reasons these results will be used as the returns of our reference or benchmark portfolio. This is needed in the following section where we look at the results obtained when calculating Jensen's alpha.

The Jensen's alpha model typically includes the risk free rate, but again, as we don't have direct financing costs we're not including it. Transaction costs are included where applicable, so the monthly returns presented on our active portfolios are always net returns.

$$\alpha = R_a - \beta R_b$$

$\alpha$ : Jensen's alpha

$\beta$ : Beta coefficient

$R_a$ : Monthly accumulated returns on active portfolio

$R_b$ : Monthly accumulated returns on benchmark portfolio

The  $\alpha$  and  $\beta$  coefficients are estimated using standard OLS regression. Our  $R_a$  values are shown in appendix table 2 to 13. The returns follow the same pattern as we've already uncovered. The shift in

market conditions seems to occur around the second half of 2002, especially clear when looking at the more traditional technical analysis indicators (MA and DBR) applied with transaction cost. Except for the more extreme negative cases of MAR and MART they all perform better than the benchmark portfolio, when viewing average and total returns. From an alpha and beta perspective, these values are shown in the table below (in monthly terms).

System, cost	Coefficient	Value	Std.error	t-stat	p-val
<b>MA, zero</b>	Alpha	0.0455	0.0058	7.8716	0.0000
	Beta	-0.1371	0.0868	-1.5798	0.1162
<b>MA, 0.001</b>	Alpha	0.0245	0.0052	4.7276	0.0000
	Beta	-0.1761	0.0777	-2.2676	0.0247
<b>MA, 0.0035</b>	Alpha	-0.0065	0.0043	-1.5266	0.1289
	Beta	-0.154	0.064	-2.4072	0.0172
<b>DBR, zero</b>	Alpha	0.0479	0.0074	6.4486	0.0000
	Beta	-0.1284	0.1116	-1.1508	0.2516
<b>DBR, 0.001</b>	Alpha	0.0339	0.0069	4.8901	0.0000
	Beta	-0.1442	0.104	-1.3866	0.1675
<b>DBR, 0.0035</b>	Alpha	0.0099	0.006	1.6408	0.1029
	Beta	-0.1623	0.0902	-1.7999	0.0738
<b>MAR, zero</b>	Alpha	0.1619	0.0186	8.7005	0.0000
	Beta	-0.1195	0.2793	-0.4278	0.6694
<b>MAR, 0.001</b>	Alpha	0.0476	0.0161	2.9563	0.0036
	Beta	-0.2532	0.2415	-1.0486	0.2960
<b>MAR, 0.0035</b>	Alpha	-0.0996	0.0128	-7.7578	0.0000
	Beta	-0.2348	0.1928	-1.2179	0.2251
<b>MART, zero</b>	Alpha	0.1107	0.0146	7.5716	0.0000
	Beta	-0.1612	0.2195	-0.7345	0.4637
<b>MART, 0.001</b>	Alpha	0.0201	0.0131	1.5345	0.1269
	Beta	-0.2104	0.1969	-1.0683	0.2870
<b>MART, 0.0035</b>	Alpha	-0.1104	0.0115	-9.5577	0.0000
	Beta	-0.203	0.1734	-1.1711	0.2434

Table 5: Coefficients from Jensen's alpha model applied on all the trading system and transaction cost combinations using monthly returns.

Starting with the somewhat obvious, all beta values are negative. Given that the benchmark portfolio tended to favour negative returns this isn't totally unexpected. Most of these beta values are however not significant at any standard level of significance, with standard being 10%, 5% or 1%. One might attribute this result to the low correlation between our active and passive portfolios (see appendix table 14), and be tempted to conclude that there's a low or almost non-existing systematic risk present. Rather, it would probably be more accurate to conclude like Fung et al (2001) by stating that linear factor models simply aren't capable of fully explaining the relation.

With this in mind the alphas should also be interpreted with care. With three exceptions they are all significant at a 1% level. The average alpha between all systems separated on transaction cost levels are 9.15% p.m., 3.15% p.m. and -5.17% p.m. for zero, \$0.001 and \$0.0035. If we instead only include the significant values our average alphas change to 9.15% p.m., 3.53% p.m. and -10.5% p.m.

It's clear then that for the highest transaction cost level, the strategies have on average not been able to produce abnormal returns over the complete period. Also in general, the characteristics shown with exceptional returns in the beginning and then less adequate results later on aren't ideal.

## 7. Volatility impact on performance

It's at this point that most other studies (as reviewed by Park et al 2004) begin concluding. Some of them might mention something about the difference in volatility between different sub-periods within their data set. However, not too much was done to further look into these details.

Fung et al (2001) document the option like payoff of trend following strategies, specifically using lookback straddles. This payoff is non-linear and would help explain why linear factor models aren't a good fit. One could argue that these strategies are long volatility, and to test this we're going to look at the returns versus volatility relationship by running OLS regressions on the following model:

$$R_t = c_1 + c_2\sigma_t + \varepsilon_t$$

$R_t$ : Total net returns on day t

$\sigma_t$ : Standard deviation for buy and hold returns on day t

$c_X$ : Regression coefficients

The regression is run independently on each system and asset combination for both active and passive strategies, giving us 180 results for the active combinations and 15 for the passive. All of them run across the complete result period, and as in section 5 we're only looking at the out-of-sample results. All the results are available in the

appendix within appendix table 15 and 16, but to make it manageable only the summary results are presented here. Setting a significance level of 1%, we're interested in seeing first off if the majority give any significant relationship between the two, as measured by  $c_2$ . To be in line with Fung et al (2001) we need this relationship to be positive. As we can see from table 6 this is very much the case. On the passive side, this is not the case with only 20% showing a negative relationship.

When viewing this from a portfolio perspective realized volatility as described by Andersen and Benzoni (2008) is used as the volatility measure. Realized volatility is defined as:

$$h_i = \sum_{t=1}^m r_{t,i}^2$$

$h_i$ : Ex post observed volatility for day with index i

$r_{t,i}^2$ : Squared geometric returns for open-to-close on minute bar at time t for day i

$m$ : Number of minute bars in given day

	Active	Passive
<b>Positive count:</b>	144	0
<b>Negative count:</b>	10	3
<b>Avg positive:</b>	8.6525	NA
<b>Avg negative:</b>	-5.6043	-3.9147
<b>Avg pos+neg:</b>	7.7268	-3.9147
<b>% significant:</b>	85.56	20.00

Table 6: Summary regression results for returns and standard deviation for  $c_2$  coefficient at a 1% significance level

In our portfolio setting  $r_{t,i}$  is defined as:

$$r_{t,i} = \sum_{j=1}^A w_j r_{t,i,j}$$

Here the 'A' represents the number of assets in our portfolio and  $w_j$  the  $j^{\text{th}}$  weight on that asset and  $r_{t,i,j}$  being the individual asset returns. Given that we're using equally weighted portfolios the weight on all assets are positive, equal, and they all sum up to one. As not all assets have returns on each minute  $t$ , on missing cases that assets return is zero.

Again we want to test the relationship and reusing our previous model we now have

$$R_t = c_1 + c_2 h_t + \varepsilon_t$$

with  $h_t$  replacing  $\sigma_t$ .

As table 7 tells us, the results aren't as clear cut this time. On a significance level of 1%, 5% and 10% for the active portfolio strategies the percentage number of significant results for  $c_2$  are 50%, 67% and 75%. In all cases there is a positive relationship with no significant negative relationships. The benchmark portfolio shows a negative relationship at a 10% significance level with a  $c_2$  coefficient of -1.733 (0.9961). One could wonder why the benchmark portfolio shows any significant relationship at all, but this is obviously a feature of intraday data. In unreported results, no such significance (at a 10% level) was found in the relationship between daily benchmark portfolio returns and the conditional variance of a GARCH(1,1) model. Daily portfolio returns include overnight changes, measured both from open till open and the more traditional close till close.

System	Transaction costs		
	Zero	0.001	0.0035
MA	2.5357 (0.4806)	1.947 (0.4749)	1.3755 (0.4709)
DBR	1.1468 (0.5256)	0.9681 (0.5089)	-0.2329 (0.4926)
MAR	5.2552 (0.9235)	4.5674 (0.8485)	-0.1496 (0.7507)
MART	3.647 (0.7740)	2.3318 (0.7406)	-1.1215 (0.7167)

Table 7:  $c_2$  coefficient values with standard errors in brackets

## 8. Portfolio strategies

From what is seen in section 6 and 7, the essence of both of them can be summed up in the graphs below. In periods of a certain level of volatility the portfolio value increases, while the value decreases when volatility falls to the lower levels observed, especially for strategies affected by transaction costs. We see that in most of the first half part of our data period the markets exhibited a sustained level of “turbulence” before becoming very quiet until the “Great Recession”, as it’s often referred to, from around late 2007.

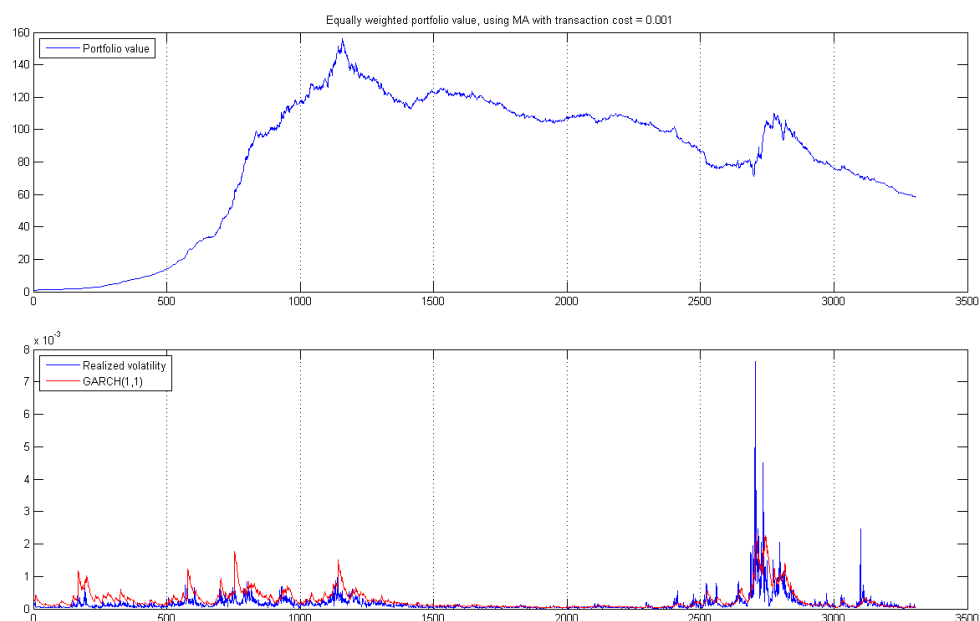


Figure 5: Portfolio value of MA strategy with transaction costs equal to USD 0.001 (above), and realized volatility together with GARCH (below)

Both realized volatility and conditional volatility obtained from a GARCH(1,1) model (here applied to intraday returns) exhibit similar properties. What is well known about financial time series is that they exhibit heteroscedasticity, and from models like GARCH and EWMA we can prove the memory or persistence of this behaviour. In unreported results, a AR(q) model also shows this persistence for our realized volatility measures. This is not surprising given the close relationship between it and what is displayed for the GARCH output above.

What makes this persistence highly interesting is the positive relationship between volatility and returns, and should allow us to formulate simple portfolio selection rules. Assume  $y_t$  represents our current selection, applied to returns on day  $t+1$ :

$$r_{sp,t+1} = y_t r_{ap,t+1} + (1 - y_t) r_{pp,t+1}$$

$r_{sp}$ : Returns on our selected portfolio

$r_{ap}$ : Returns on our active portfolio

$r_{pp}$ : Returns on our passive portfolio

$r_{pp}$  is a slightly misleading label, as it doesn't need to be a passive investment strategy. Ideally we would have an active strategy that produces positive alpha but under different circumstances than our active portfolio (i.e. low volatility conditions). As that's not available, it's natural to switch between our active portfolios and the benchmark portfolio. With 20-20 hindsight we know that the benchmark portfolio isn't a good choice, but we're assuming this is unknown for now. One could also argue that some form of risk free rate should have been selected as the passive portfolio proxy, which surely would have benefitted our overall end results.

Next we need to define the selection rule. One could assume that the level of volatility needed to produce positive returns changes over time. Then a lot of work could be put into finding and defining dynamic models that would continuously define this level, and use that with volatility forecasts as basis for our selection rule. That is however deemed out of scope for this paper, and we're defining  $y_t$  simply as:

$$y_t = \begin{cases} 1 & \text{if } s > 0 \\ 0 & \text{if } s \leq 0 \end{cases} \quad \text{with} \quad s = V_{ap,t} - \frac{1}{N-1} \sum_{i=1}^{N-1} V_{ap,t-i}$$

$N$  constitutes our backwards looking period, a value we need to define.  $V_{ap,t}$  represents the value of our active portfolio at day  $t$ . Nothing that has been looked into so far gives us any good direct indication of proper values for  $N$ . What's about to be performed next is all done at out-of-sample results, but it's of course part of the complete data set that's already been studied in section 6 and 7. Would it therefore be fair to assume that an investor could implement such a strategy prior to the start of January 1998?

Two reasons would argue in favour: Fung et al (2001) base all their analysis on data going up till the end of 1997 when concluding that trend-following strategies exhibit lookback straddle payoffs. Also, in Fung and Hsieh (1997a, 1997b) these approaches to investment strategies are shown to already exist. It's not farfetched then to assume an investor could have implemented this method going from 1998. But  $N$  is still not defined, so assuming no skill or knowledge about what  $N$  value to select we're going to test a wide range of potential values. This is then used to compare the final value of our selected portfolio versus that of the purely active based portfolio.

Utilising the out-of-sample daily active and benchmark portfolio returns available, the test is performed as follows: (1) Select a value for  $N$ . (2) Select all  $r_{sp}$  values as outlined earlier. (3) Compare

the final portfolio value of returns based on  $r_{sp}$  and  $r_{ap}$ , as a ratio between them.<sup>6</sup> This ratio would be above 1 if this portfolio selection method added value, otherwise it was futile. Given that the N value selected makes N daily data points unavailable at the beginning of the data set, these values do not contribute to the end values of the two portfolios. Ideally the period of available data reached further back in time, but as that's not available the valuation period for all portfolios start at the beginning of N+1 for our current N value.

The results of this analysis are available in appendix figures 4 to 15. Interpreting and understanding the results shown is comprehensive and requires some understanding of the earlier sections. As a means of confirming that persistence in volatility plays an important factor here, the 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples (for each N value) are also included. The bootstrapping method picks at random from the cross section of active and passive returns among available daily portfolio returns with replacement. It then applies the same method of selecting between active and passive returns as we do on the original return series. Picking single days at random will break any auto correlated relationship in volatility and hence returns if there is one.

We have 12 different combinations of trading systems and transaction costs available. These represent the active portfolios. For the alternative passive portfolio we use the same portfolio as used earlier. For each of the 12 combinations analysed there are two graphs. The first of these two graph show the ratio of end values between  $r_{sp}$  and  $r_{ap}$ , where the aim is of course to have a ratio value as far away from 1 as possible in the positive direction. Any ratio value below 1 implies that applying this additional portfolio switching mechanism was futile. The blue areas shown in this first graph represent the upper and lower percentile values from the bootstrapped return series.

In addition to merely looking at the end values of various N values we also want to see how successful this has been with regards to picking positive active returns. Remember, the core aim of this portfolio selection mechanism is to pick the positive active returns and then switch over to the alternative passive portfolio when we deem it as non-beneficial to use active returns. The second graphs show this. There are two lines, green and red, that show the ratio between the number of positive and negative active returns among the selected returns.<sup>7</sup> The green line represents this ratio for when the method chose to use active returns. The red line represents the ratio for when the

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<sup>6</sup> We'll call these portfolio values the end values (based on an equal initial value), and is calculated as

$EV = IV e^{\sum_{t=1}^T r_t}$  for all returns in their given sequence.

<sup>7</sup> The ratios of these two values on one N don't sum to 1 as they are two separate data sets. These two data sets are however constructed from the complete set of active returns, never sharing any of the daily returns between them. So in other words, we are separating all the daily active returns into two distinct groups. The first group represents when we traded on active returns, while the second group represents active returns we didn't trade on. We then find the percentage of positive active returns within each group.

method didn't choose active returns. In an extreme ideal case this would be 1 and 0 for the green and red line respectively. Also the bootstrapping results are included, represented by the blue (when using active returns) and purple (when not using active returns) areas.<sup>8</sup>

As argued in section 7 we could say that these strategies are long volatility. As there will always be some volatility in a fluctuating and liquid market the question then is at what level of volatility we begin observing positive active returns. Although not analysed here it's natural to think that our  $c_1$  coefficients from the two regression models in section 7 might be able to help in explaining this average level. If we compare the end value ratios across all the 12 results we see that for the zero transaction cost case the ratio typically stays below 1 for all (or a majority) of N values. Combining this with our results from earlier sections we can conclude that for zero transactions costs the probability of positive active returns is so high that not selecting active returns hurts our end values overall. This is distinct from the strategies that operate with transaction costs. Here the benefit of moving in and out of active returns increase as we increase this cost.

Looking at the N dimension a wide spectre of values was used starting from 10 days (two full trading weeks). The upper testing limit of N is the somewhat arbitrary and somewhat ridiculously large 1985 days (over 7.5 years of trading). Judging from appendix figure 16 we should ignore any values past about N = 800 as some of the selections begin reaching the extreme cases of only using active or passive returns at that point.

Focusing first on the bootstrapped end value results these tend to be close to but below 1, as expected. There would be no good fundamental reason why this portfolio selection rule would produce any value added benefit when we remove the volatility clustering and its relationship to our active returns. It does however serve as an indicator of significance when we compare this result to our end values based on the original return series. Clearly there is a direct relationship between active returns and volatility as shown earlier, but also that this relationship under transaction cost constraints can be exploited due to volatility clustering.

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<sup>8</sup> Please note that although included for completeness the purple area should mostly be ignored as there was a strong tendency to have very few observations in these data sets for the bootstrapped returns. This is because it tends to be an average positive return value across all the daily active returns. When bootstrapped this "drift" is spread out across the entire bootstrapped return set creating a situation where the portfolio selection method very rarely chose to use passive returns. We don't have the same issue for the original return series due to the observed return level clustering equal to that of volatility clustering. One could say the bootstrapped return series behaves more like a typical geometric Brownian motion, while the actual observed active returns do not. Also, for the MAR and MART systems on the highest transaction cost case the bootstrap results are reverted due to their negative drift.

Looking at the ratio between the number of positive and negative active returns selected (the green lines), lower values of N are preferred, but often we see the peak value not belonging to the smallest values of N. We could explain this by looking at the functional purpose of averaging out values: A simple moving average is closely related to the exponentially weighted moving average. An exponentially weighted average is what we use to describe a low pass filter.<sup>9</sup> Taking the average of these preceding active portfolio values remove higher frequency value fluctuations and gives us a less noisy signal. Remove too much of these higher frequencies (by essentially lowering you cut-off point) and you begin reducing your reaction speed, resulting in a reduced probability of picking positive active returns.

With one exception all peak values are above 60% when looking at the selected active returns, all of them above 50% and far outside the band of results we have for the bootstrapped returns. It's also interesting to see the typical stability of values below 50% for non-selected active returns (for what we deem sensible N values). As explained in an earlier foot note there are few good significance indicators available for these values, but it's fair to assume that had there been no exploitable pattern available it should be close to 50%.<sup>10</sup> We can attribute the stability of these values to a fairly certain and typically lower than 50% occurrence of positive active returns during clustering of lower volatility.

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<sup>9</sup> A low-pass filter is a filter that passes low-frequency signals but attenuates (reduces the amplitude of) signals with frequencies higher than the cut-off frequency.

<sup>10</sup> This is of course a theoretical value prior to any cost and drift bias adjustments.

## 9. Conclusions

The aim of this research was to empirically test the relationship between returns generated from technical analysis based trend-following strategies and volatility. The established methods of testing these systems were applied to high frequency data, rather than the more typical daily returns used in earlier studies. While doing this, three different levels of transaction costs were applied. These also contributed to the performance measure used, allowing the optimisation routine to adjust for some of its impact. A clear and expected negative impact of increasing transaction costs with regards to obtained returns was shown. However, the optimisation routine did adjust for this penalty and allowed the strategies to maintain profitability in a majority of cases.

We can conclude that these strategies show a highly significant positive relationship with ex post standard deviation on an asset by asset basis, applied to out-of-sample returns. We can also conclude that this relationship exists for equally weighted portfolios of these asset and strategy combinations when using realized volatility. We do not find such a relationship when looking at daily benchmark returns, but do find a negative relationship when limiting this to intraday benchmark returns. Current mainstream market models like that described by the efficient-market hypothesis are not typically able to explain these relationships, and more refined alternative market models are natural candidates.

Given the well documented aspect of heteroscedasticity and persistence of volatility in financial time series it is also shown that there is a similar persistence in our active portfolio returns. This was documented by using a selection rule that looks at historical changes in portfolio value and then assumes a continued change in the same direction. As a verification method a bootstrapping technique that breaks the persistence in volatility was applied. The bootstrapped returns, which mimics a geometric Brownian motion, were not able to reproduce the results obtained using the original return sequence.

Given the recent increase in volatility in several developed markets, further research should be applied to high frequency data spanning past what is analysed here. It would also be of interest to perform the same set of analysis on lower frequency data. This could potentially shed some light on the difference in results obtained in earlier mentioned low frequency studies. This is also of special interest as lower frequency data might not behave like higher frequency data, thereby not allowing us to apply trend-following strategies with equal success in general. Finally, the selection rule used in section 8 leaves much to be desired. More advanced methods of establishing required volatility levels paired with volatility forecasts are natural candidates to explore.

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## Appendix

### Data cleansing method

When verifying the integrity of our high frequency data, this was performed by obtaining OHLC bars from another independent and trusted source. In this case we used daily OHLC bars downloaded from Bloomberg. By comparing these daily values with an equivalently created daily OHLC bar created from our high frequency data we're first of all able to determine if these align.

Some minor differences are expected, but when massive and obvious differences are detected these are dealt with. Typically issues in our high frequency data are due to a few trade observations that are far outside what is expected. This might be due to market data capture issues, OTC trades that have incorrectly been identified as exchange traded, etc.

When this is detected the specific minute bars affected are located intraday and adjusted so that they no longer are in breach. Two factors are considered: (1) What are natural value candidates when this one observation is viewed in relation to neighbouring observations? (2) What are natural value candidates when this one observation is viewed in context of our Bloomberg data? These considerations together with the OHLC constraints are used when adjusting our data. Overall, only a minority of observations needed adjustment.

### A discussion about transaction costs and trading constraints

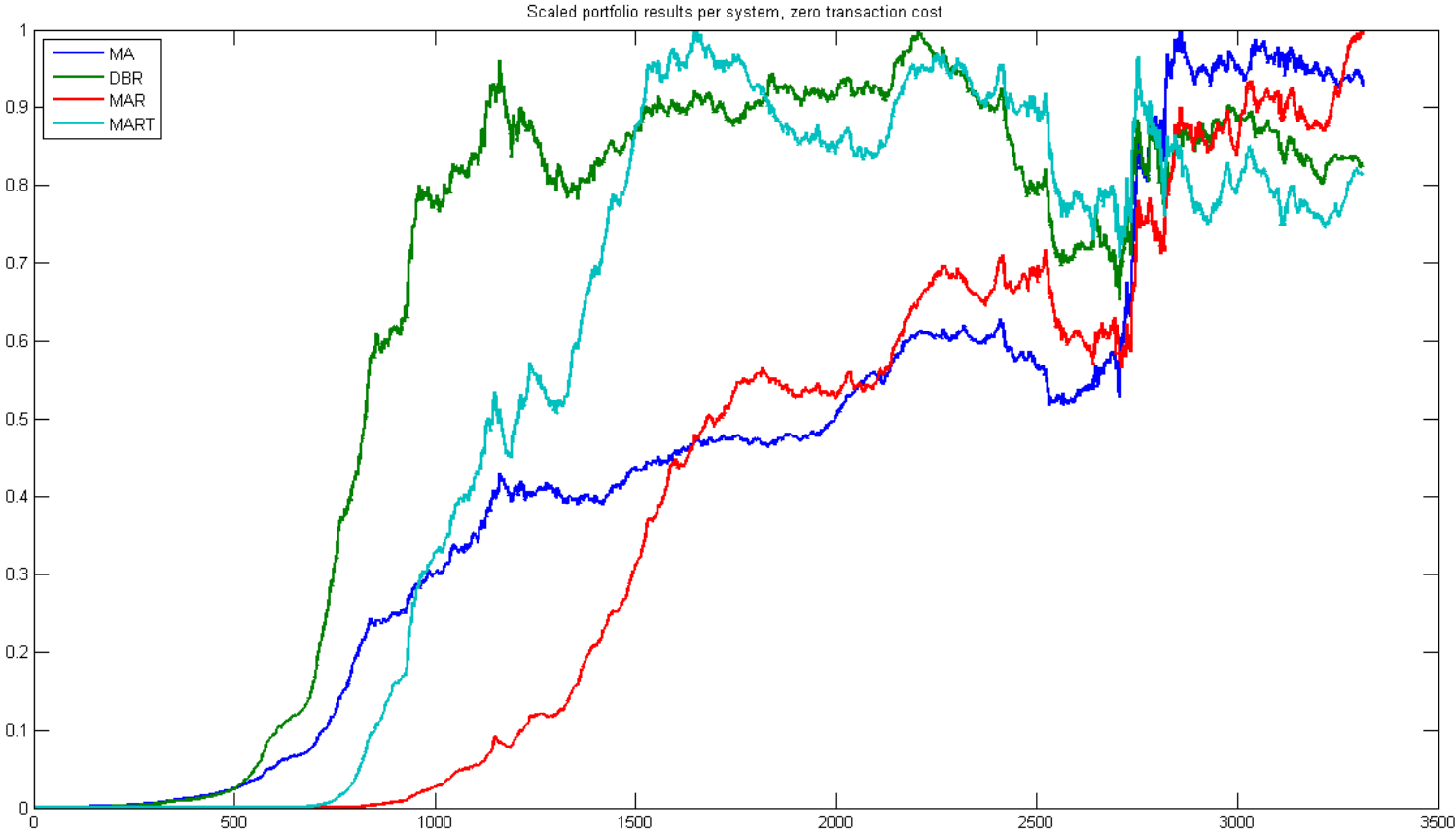
All trading performed here are for natural reasons performed in a simulated environment. Several factors have been considered to make this simulation bias as small as possible. Still, as will always be the case when working on systems that are affected by your actions, these are still only simulations. Transaction costs are one such factor, and the cost levels used here are those charged by Interactive Brokers. In addition to these costs, there are also potential costs incurred by the exchanges. These are however not always a direct cost as these exchanges would pay us if instead of removing liquidity we provide liquidity. In other words, had we used limit orders rather than market orders our total transaction costs could have been lower than what was used here.

The use of limit orders versus market orders is however out of scope for this paper. There is a huge body of research available on so called execution algorithms and still room for further research in this area. That has not been the focus of this paper, as what is typically known as alpha algorithms have been our focus.

Another important factor not considered is that of trading constraints. Throughout the historical window analysed no constraints have been applied with regards to bans on shorting. We know that

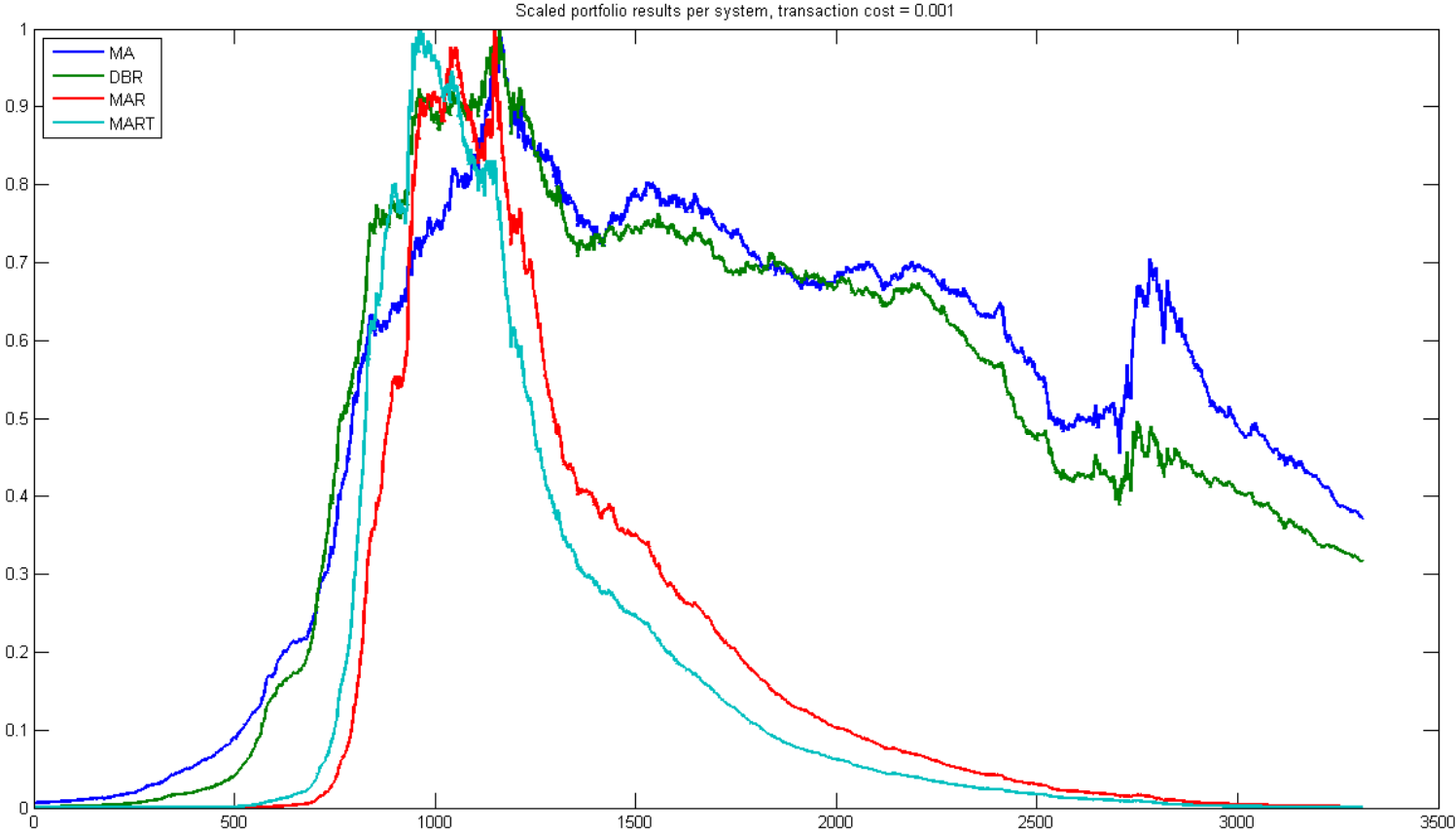
there have been bans on shorting financial stocks for certain periods, such as those adopted by the U.S. Securities and Exchange Commission (SEC) in September 2008. This would have affected our strategies for some of the stocks analysed within these periods.

Appendix figure 1: Scaled portfolio results, zero cost



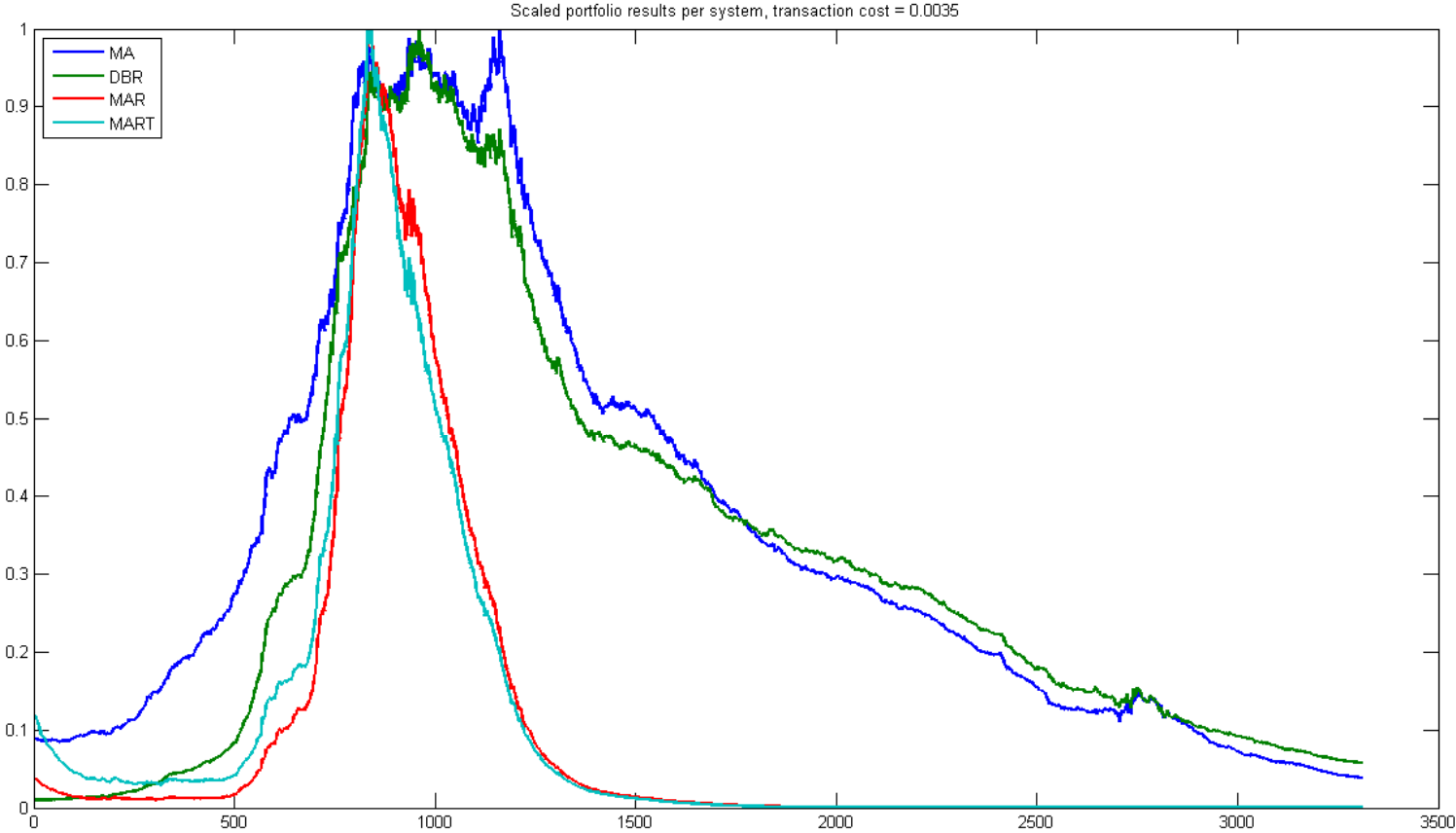
Scaled portfolio results per trading system with zero transaction cost.

Appendix figure 2: Scaled portfolio results, cost = USD 0.001



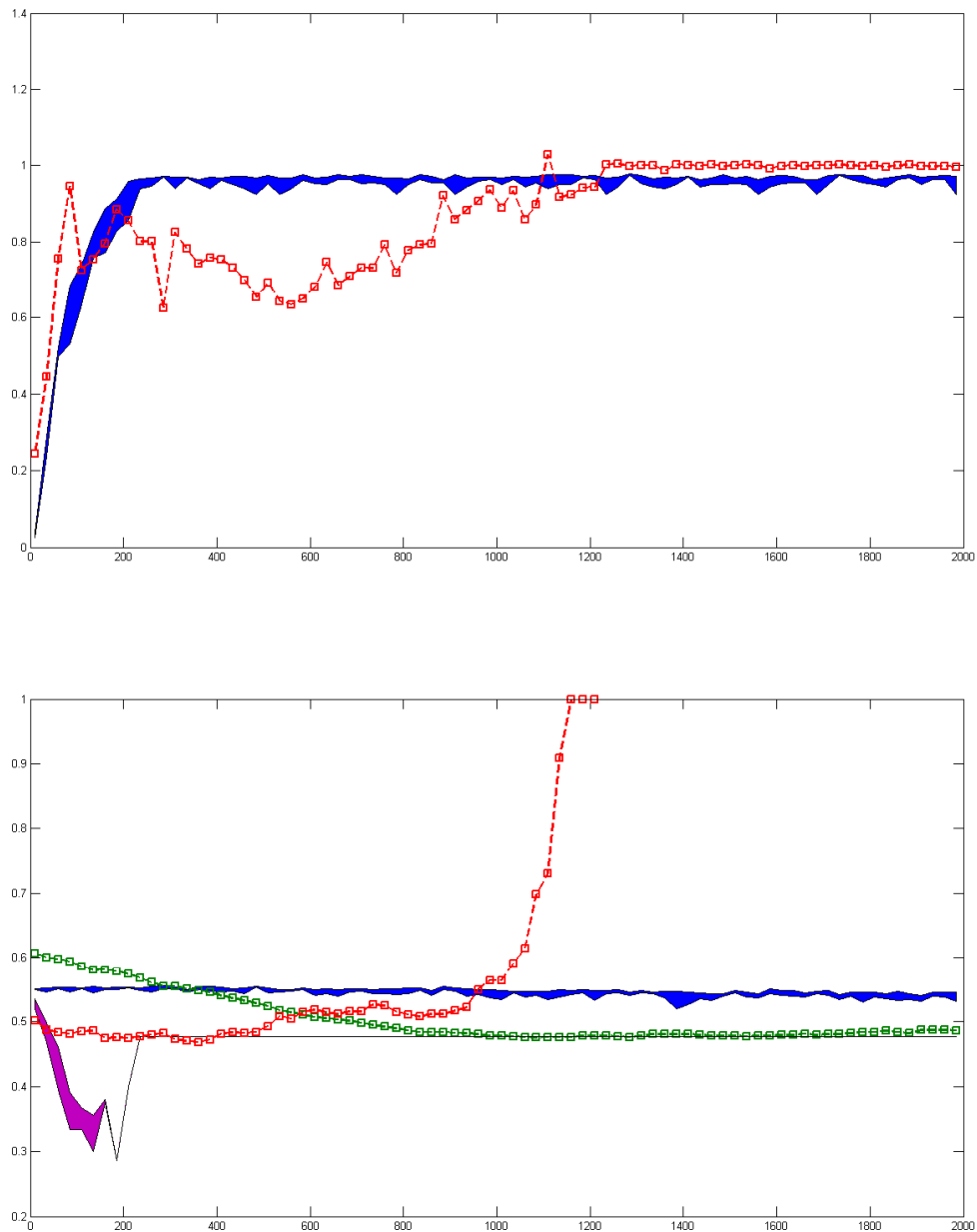
Scaled portfolio results per system with a transaction cost equal to USD 0.001

Appendix figure 3: Scaled portfolio results, cost = USD 0.0035



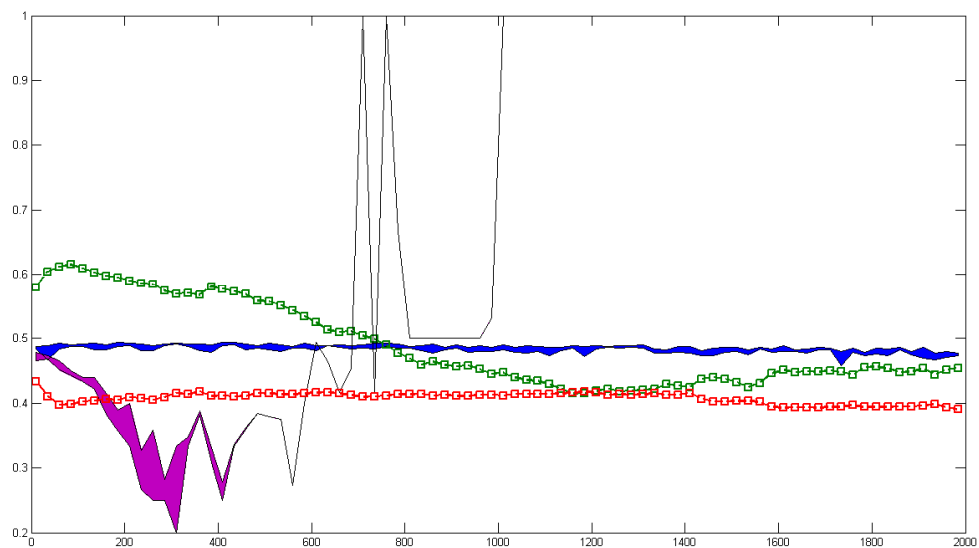
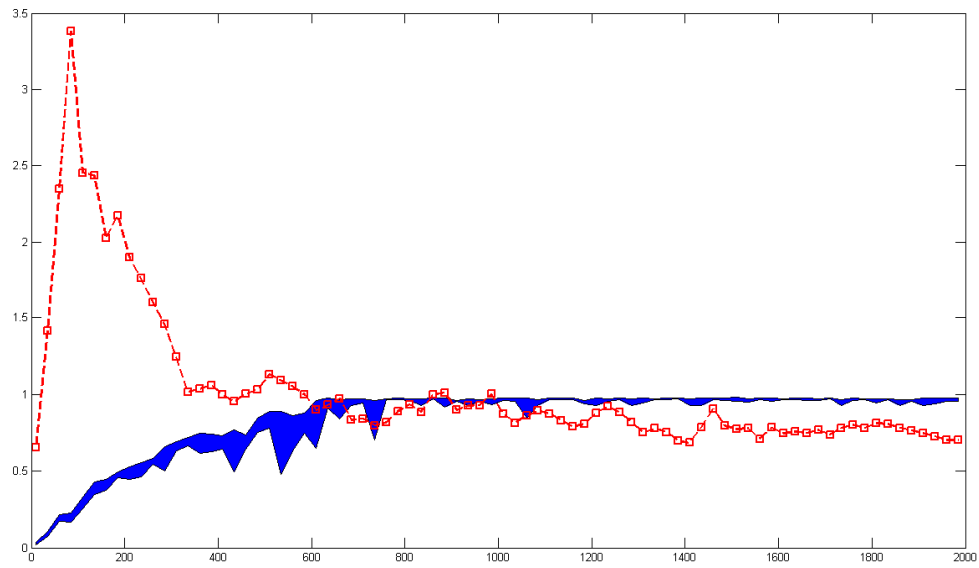
Scaled portfolio results per system with a transaction cost equal to USD 0.0035

## Appendix figure 4: Return persistence, MA, zero cost



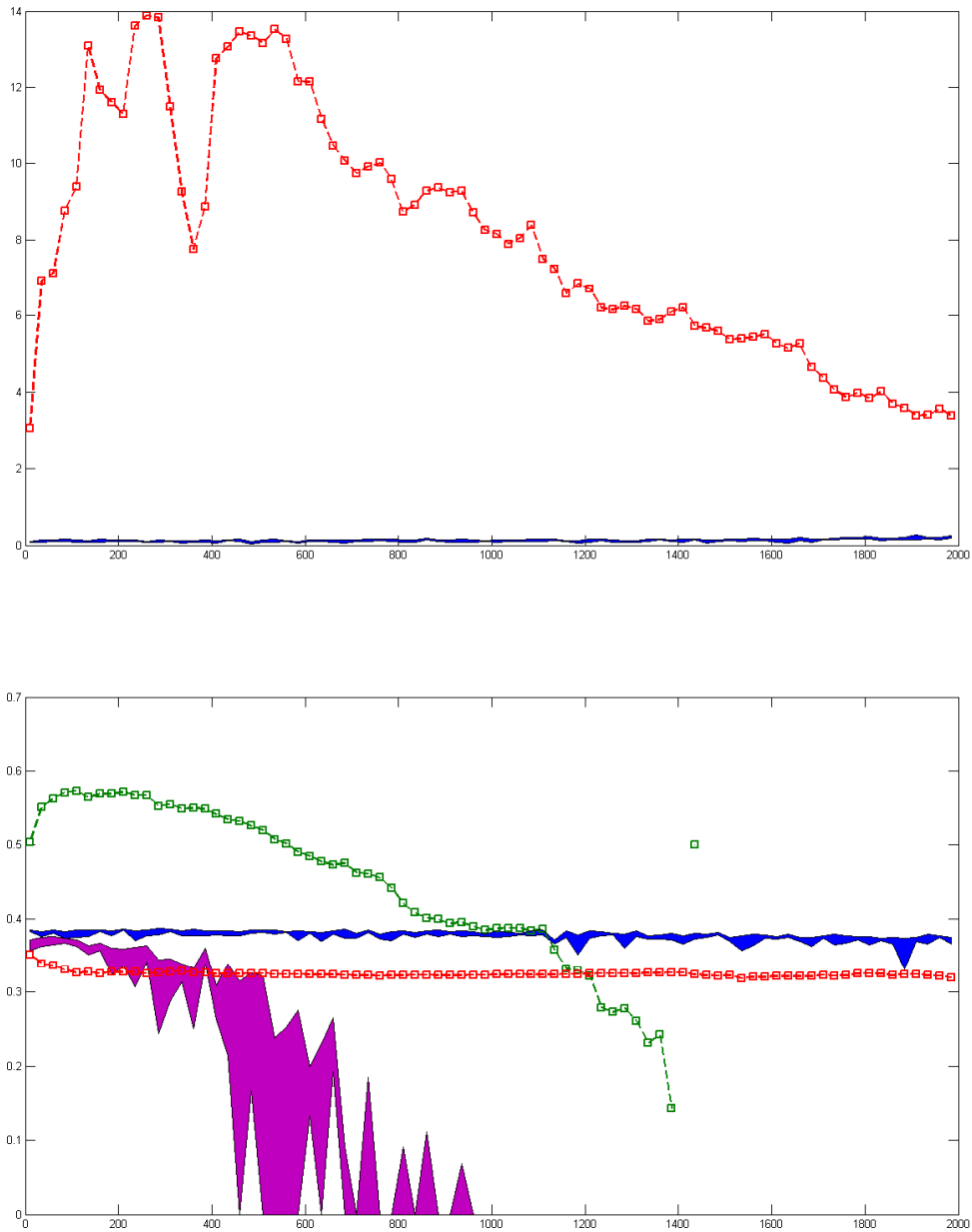
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MA system with zero transaction cost.

## Appendix figure 5: Return persistence, MA, cost = USD 0.001



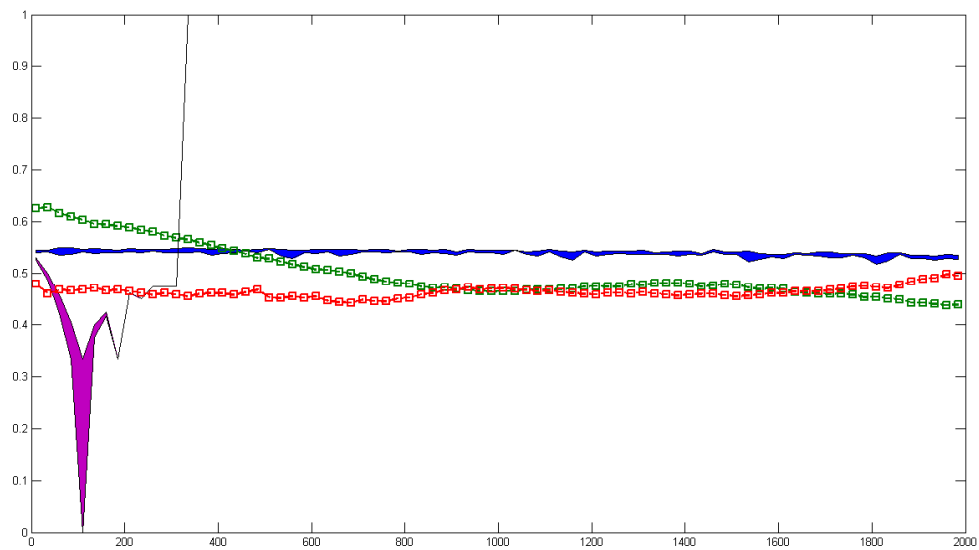
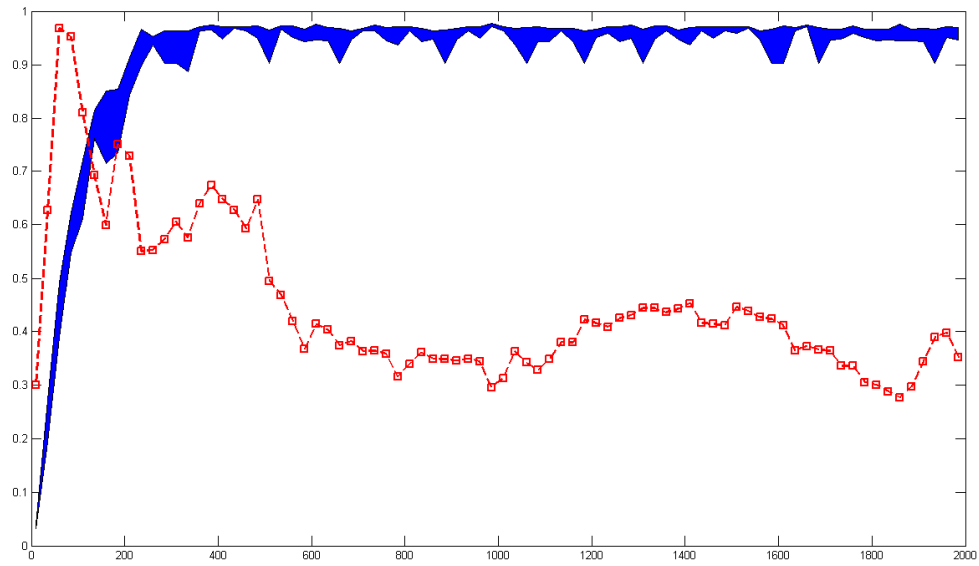
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MA system with transaction cost = USD 0.001.

Appendix figure 6: Return persistence, MA, cost = USD 0.0035



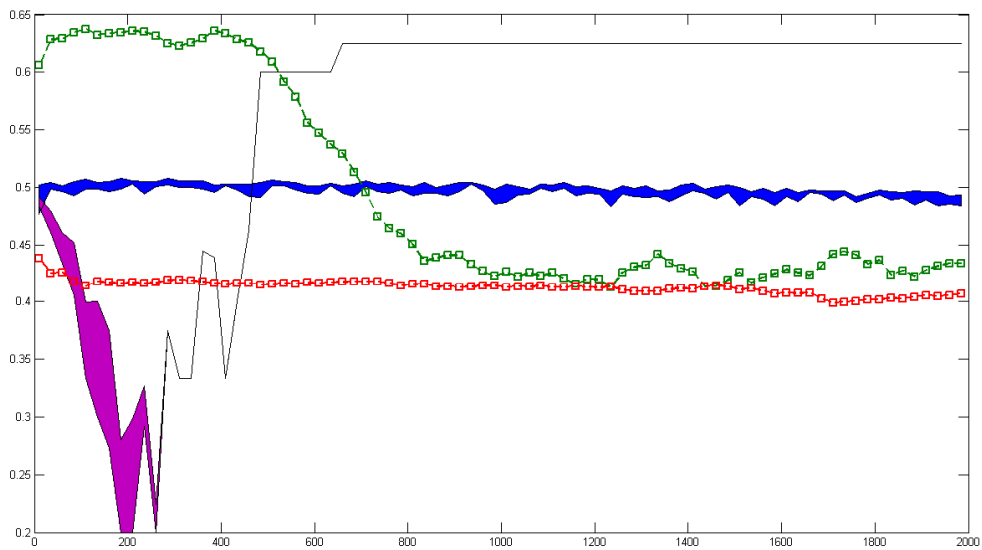
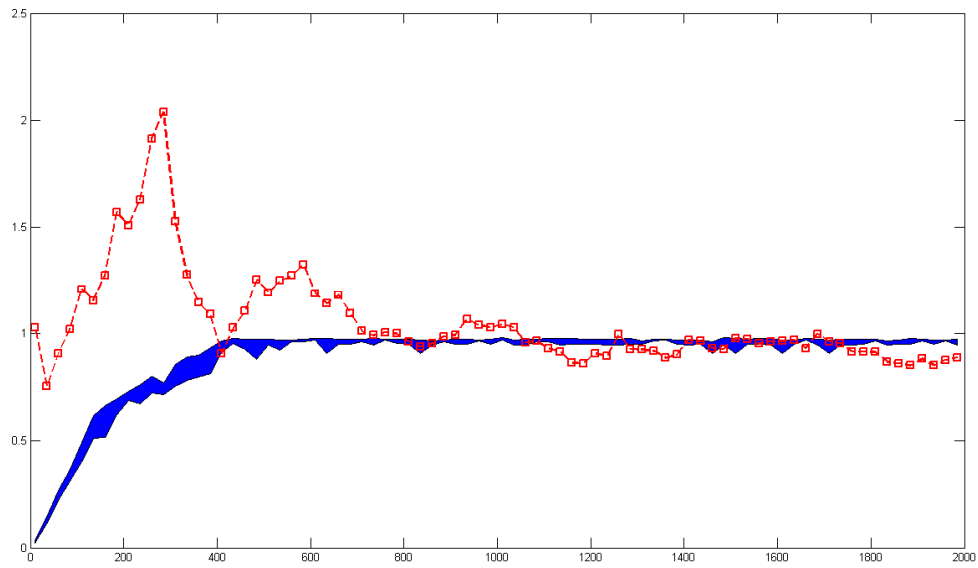
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MA system with transaction cost = USD 0.0035.

## Appendix figure 7: Return persistence, DBR, zero cost



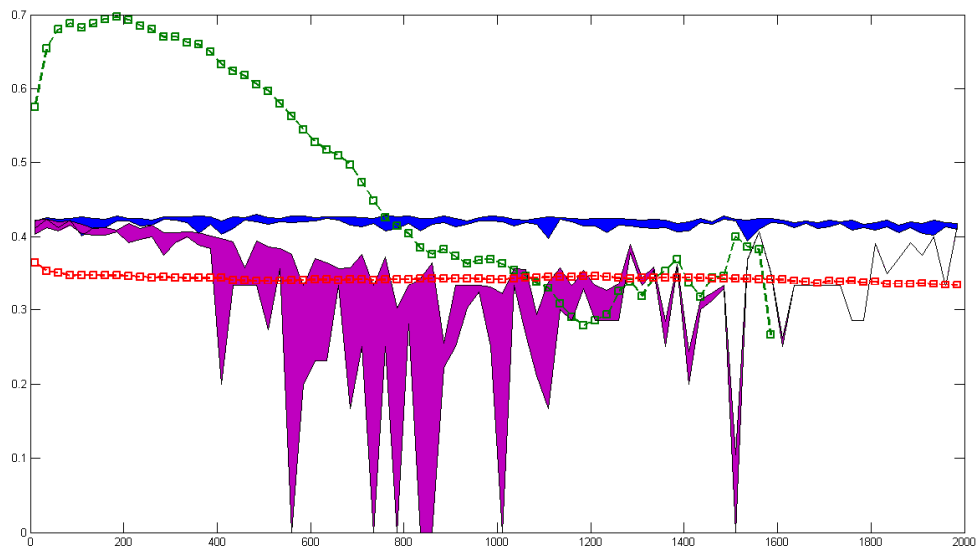
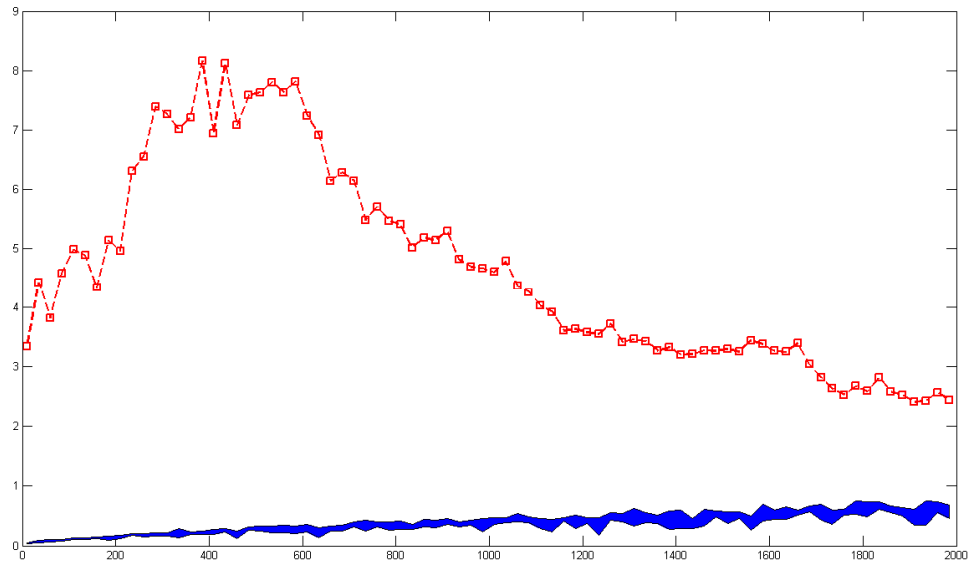
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the DBR system with zero transaction cost.

Appendix figure 8: Return persistence, DBR, cost = USD 0.001



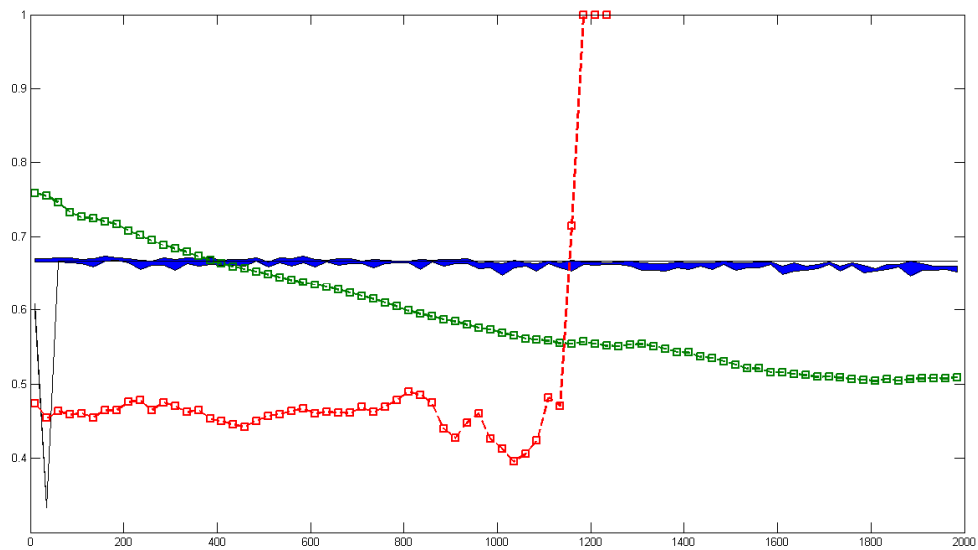
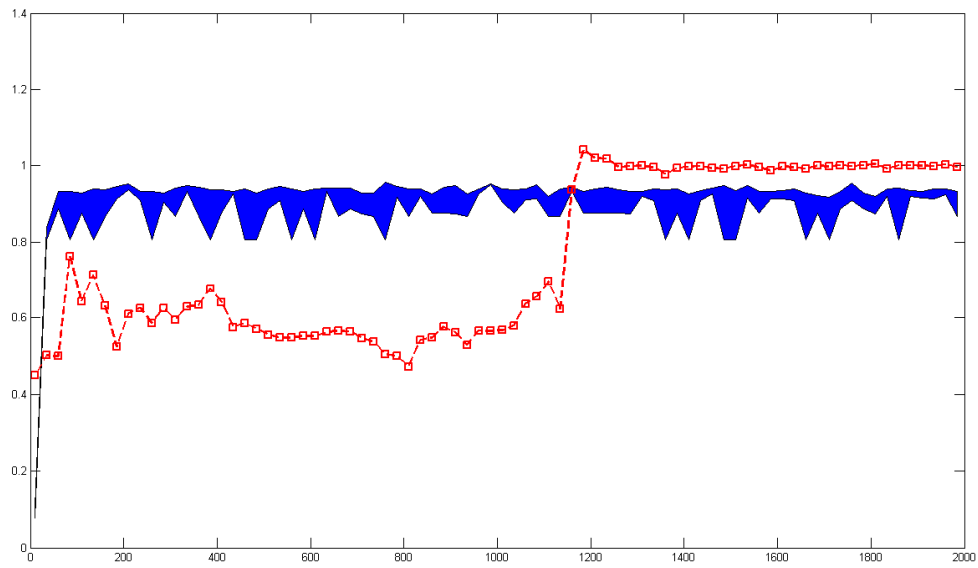
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the DBR system with transaction cost = USD 0.001.

## Appendix figure 9: Return persistence, DBR, cost = USD 0.0035



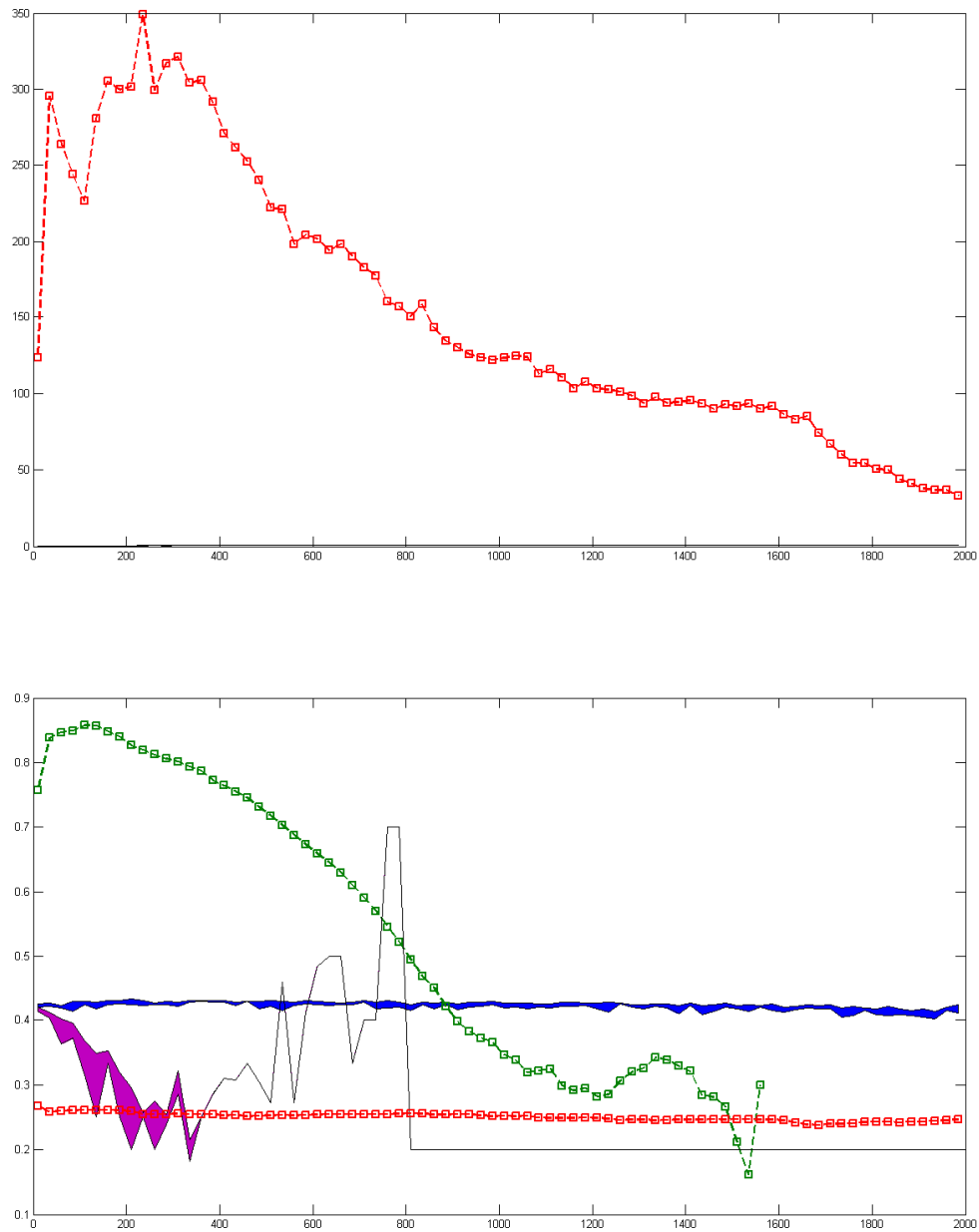
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the DBR system with transaction cost = USD 0.0035.

## Appendix figure 10: Return persistence, MAR, zero cost



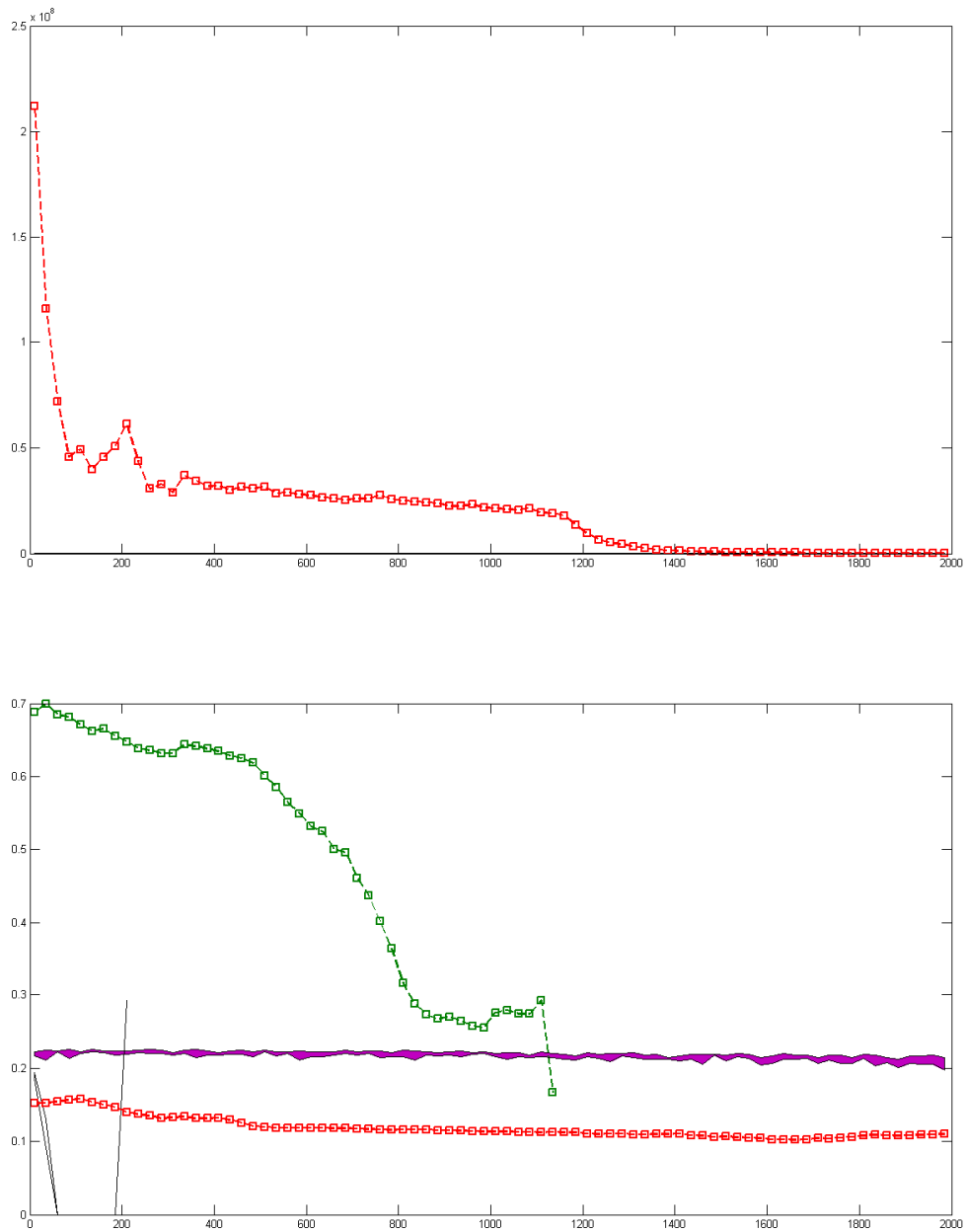
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MAR system with zero transaction cost.

## Appendix figure 11: Return persistence, MAR, cost = USD 0.001



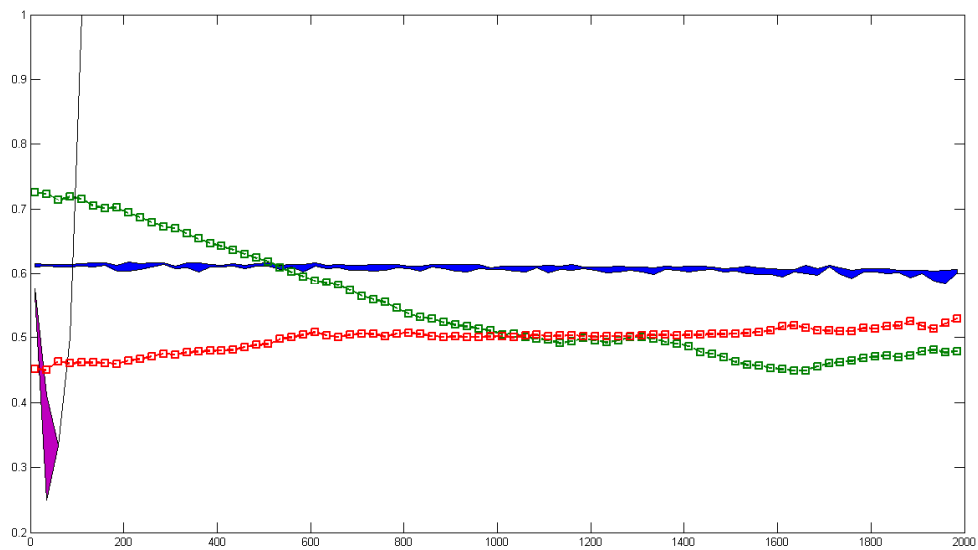
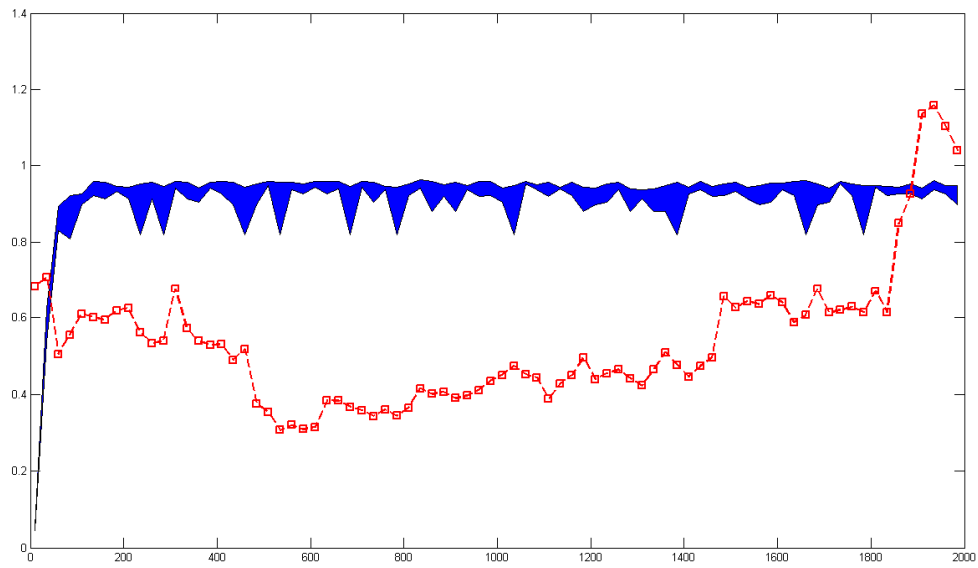
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MAR system with transaction cost = USD 0.001.

## Appendix figure 12: Return persistence, MAR, cost = USD 0.0035



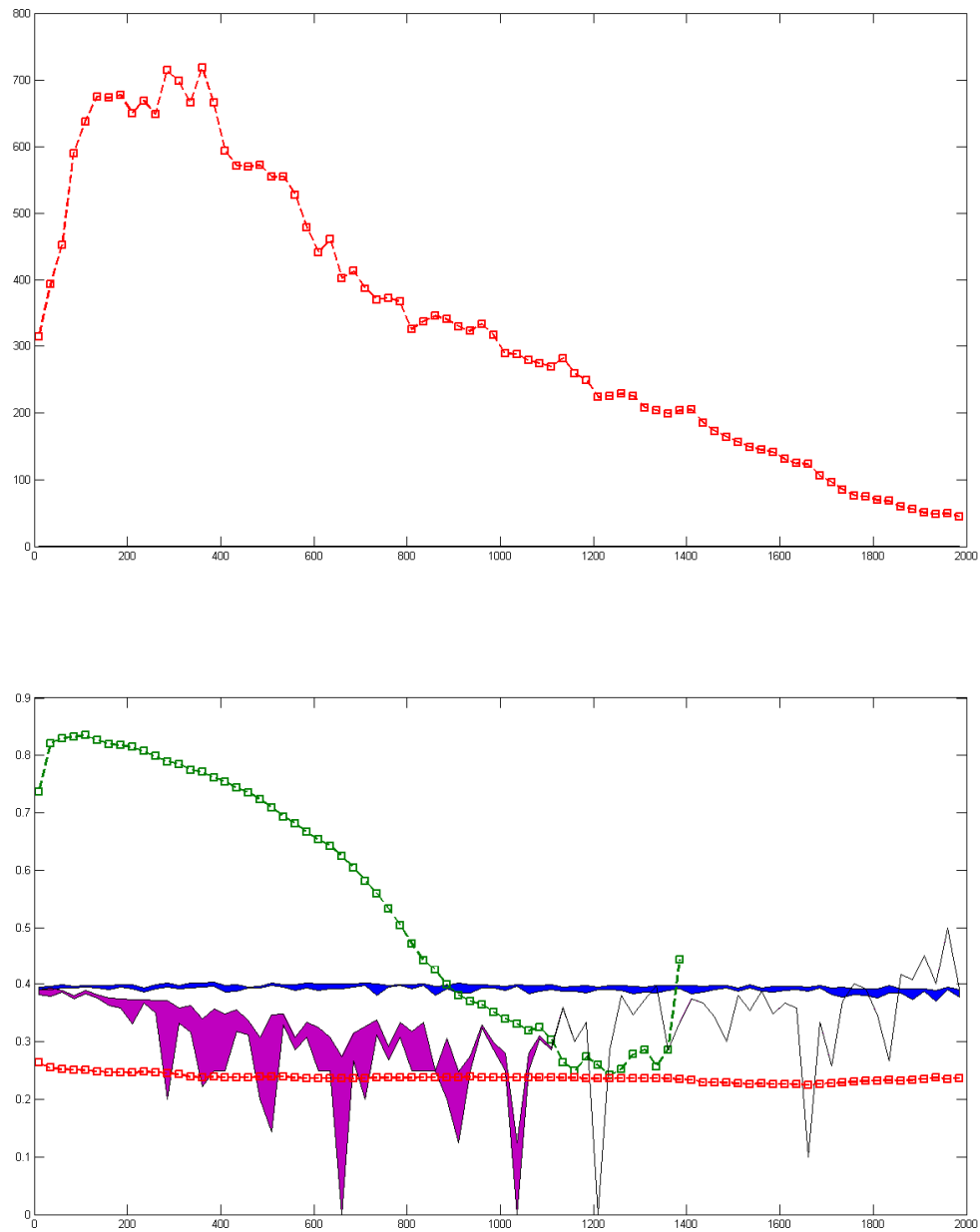
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MAR system with transaction cost = USD 0.0035.

### Appendix figure 13: Return persistence, MART, zero cost



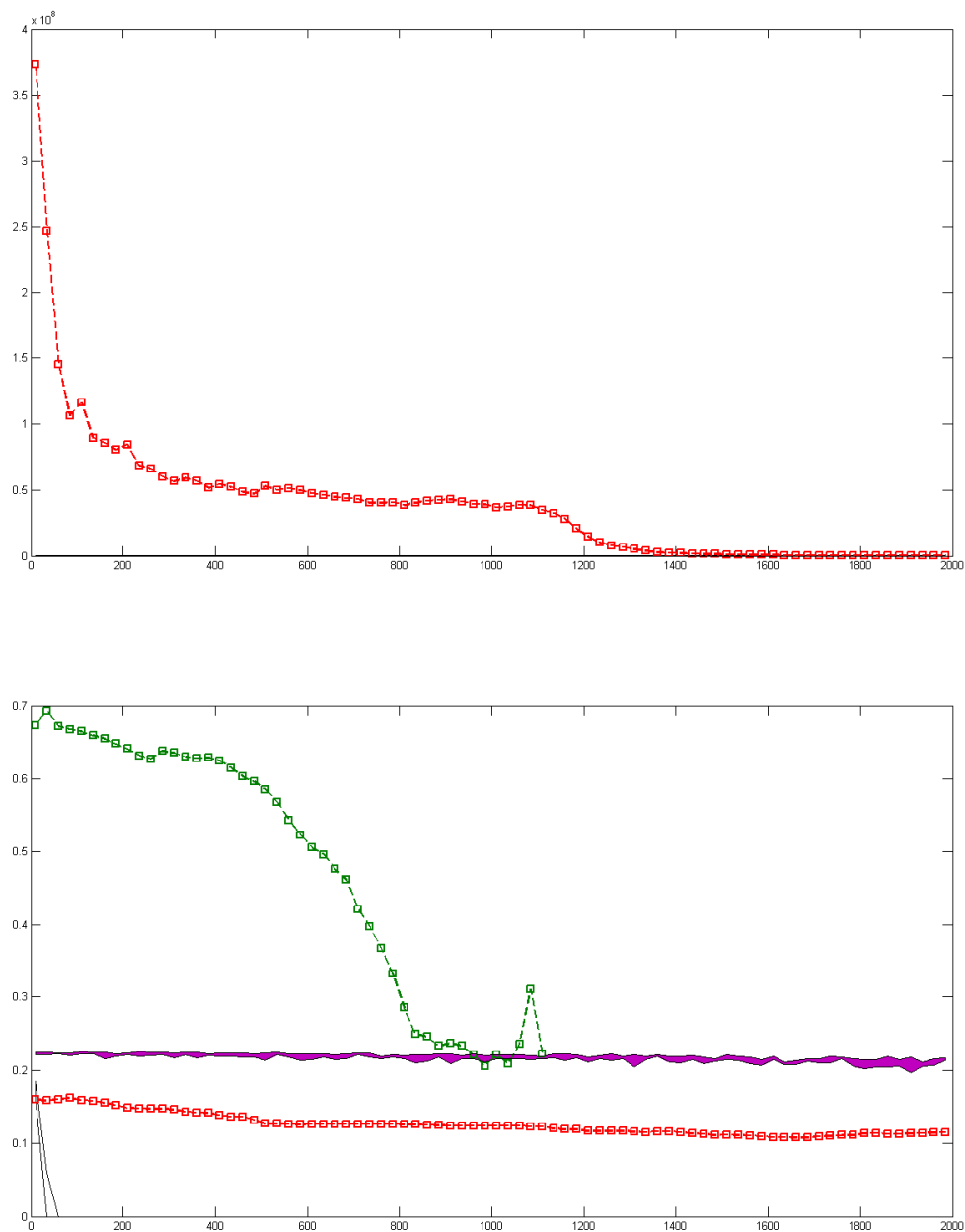
First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MART system with zero transaction cost.

## Appendix figure 14: Return persistence, MART, cost = USD 0.001



First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MART system with transaction cost = USD 0.001.

## Appendix figure 15: Return persistence, MART, cost = USD 0.0035



First figure show end value ratios between our active portfolio and our selected portfolio. Second figure show ratio of positive active returns between our selected and non-selected groups. The 10<sup>th</sup> and 90<sup>th</sup> percentile results from 500 bootstrapped samples are shown as the blue and purple area. These figures are for the MART system with transaction cost = USD 0.0035.

Appendix figure 16: Ratio of selected active and passive returns for N

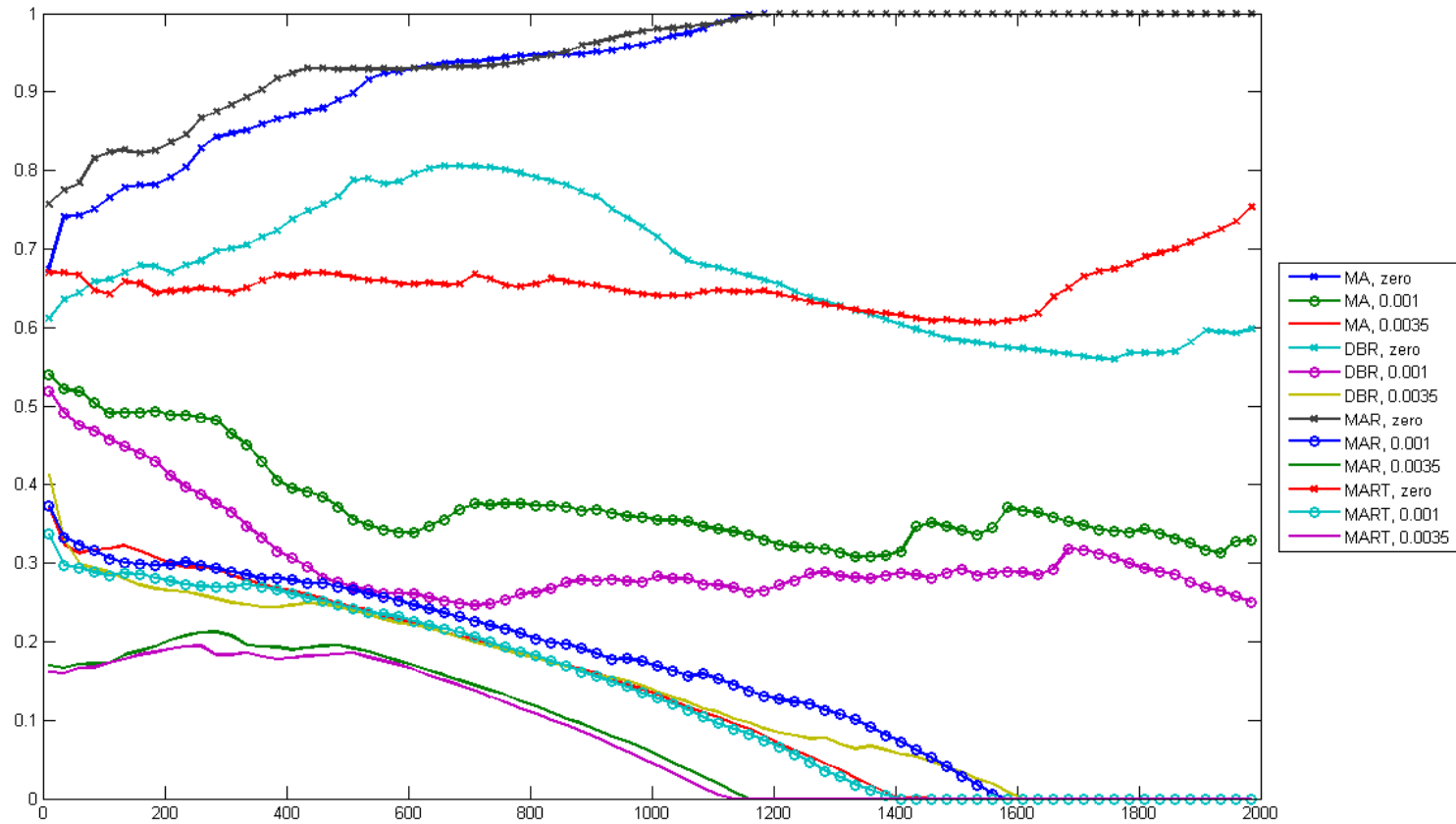


Figure show ratio of active and passive returns selected for different values of N. Note that the extreme ratios of 0 and 1 observed for some of the systems with high N values imply that we cannot trust obtained analysis in earlier figures for these values of N.

**Appendix Table 1: Monthly returns for equally weighted benchmark portfolio**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	7.82%	Jan, 2002	-3.86%	Jan, 2006	-1.16%	Jan, 2010	-8.39%
Feb, 1998	5.27%	Feb, 2002	-13.06%	Feb, 2006	0.31%	Feb, 2010	4.78%
Mar, 1998	3.37%	Mar, 2002	6.72%	Mar, 2006	0.86%	Mar, 2010	3.02%
Apr, 1998	0.27%	Apr, 2002	-9.84%	Apr, 2006	0.09%	Apr, 2010	0.09%
May, 1998	-9.05%	May, 2002	-7.30%	May, 2006	-6.16%	May, 2010	-7.54%
Jun, 1998	5.48%	Jun, 2002	7.20%	Jun, 2006	-6.26%	Jun, 2010	-10.31%
Jul, 1998	2.39%	Jul, 2002	-2.02%	Jul, 2006	-1.34%	Jul, 2010	3.67%
Aug, 1998	-19.43%	Aug, 2002	1.20%	Aug, 2006	5.05%	Aug, 2010	-1.38%
Sep, 1998	7.55%	Sep, 2002	-10.21%	Sep, 2006	3.10%	Sep, 2010	4.83%
Oct, 1998	2.87%	Oct, 2002	9.49%	Oct, 2006	5.10%	Oct, 2010	1.42%
Nov, 1998	3.40%	Nov, 2002	11.30%	Nov, 2006	1.76%	Nov, 2010	-0.04%
Dec, 1998	3.34%	Dec, 2002	-6.11%	Dec, 2006	-0.70%	Dec, 2010	3.58%
Jan, 1999	8.22%	Jan, 2003	0.22%	Jan, 2007	1.50%	Jan, 2011	0.89%
Feb, 1999	-9.28%	Feb, 2003	-1.39%	Feb, 2007	-3.45%	Feb, 2011	5.19%
Mar, 1999	-2.23%	Mar, 2003	6.76%	Mar, 2007	-0.41%	1998	13.28%
Apr, 1999	-6.46%	Apr, 2003	1.76%	Apr, 2007	3.51%	1999	-4.24%
May, 1999	-8.12%	May, 2003	9.50%	May, 2007	2.03%	2000	-36.04%
Jun, 1999	7.38%	Jun, 2003	-1.96%	Jun, 2007	-0.58%	2001	1.00%
Jul, 1999	-1.67%	Jul, 2003	-1.21%	Jul, 2007	-4.25%	2002	-16.48%
Aug, 1999	0.69%	Aug, 2003	2.11%	Aug, 2007	-0.11%	2003	23.67%
Sep, 1999	-4.05%	Sep, 2003	1.44%	Sep, 2007	1.86%	2004	2.04%
Oct, 1999	6.04%	Oct, 2003	4.56%	Oct, 2007	0.05%	2005	-13.42%
Nov, 1999	0.22%	Nov, 2003	0.19%	Nov, 2007	-10.63%	2006	0.66%
Dec, 1999	5.01%	Dec, 2003	1.70%	Dec, 2007	-4.64%	2007	-15.12%
Jan, 2000	-12.07%	Jan, 2004	0.25%	Jan, 2008	1.62%	2008	-53.88%
Feb, 2000	0.63%	Feb, 2004	-2.92%	Feb, 2008	-3.77%	2009	-10.99%
Mar, 2000	10.82%	Mar, 2004	-2.72%	Mar, 2008	-2.33%	2010	-6.25%
Apr, 2000	0.13%	Apr, 2004	-8.27%	Apr, 2008	1.19%	2011	6.07%
May, 2000	-10.05%	May, 2004	3.67%	May, 2008	-0.99%	<b>Total</b>	<b>-109.70%</b>
Jun, 2000	-0.50%	Jun, 2004	2.69%	Jun, 2008	-12.62%	<b>Average monthly:</b>	
Jul, 2000	-0.43%	Jul, 2004	-4.91%	Jul, 2008	2.62%		<b>-0.69%</b>
Aug, 2000	5.45%	Aug, 2004	2.92%	Aug, 2008	2.88%	<b>Average yearly:</b>	
Sep, 2000	-9.59%	Sep, 2004	3.82%	Sep, 2008	-4.14%		<b>-7.84%</b>
Oct, 2000	-7.51%	Oct, 2004	3.63%	Oct, 2008	-18.56%		
Nov, 2000	-8.99%	Nov, 2004	1.20%	Nov, 2008	-24.81%		
Dec, 2000	-3.93%	Dec, 2004	2.68%	Dec, 2008	5.02%		
Jan, 2001	14.93%	Jan, 2005	-8.17%	Jan, 2009	-16.66%		
Feb, 2001	-15.35%	Feb, 2005	2.38%	Feb, 2009	-12.70%		
Mar, 2001	-4.61%	Mar, 2005	-4.74%	Mar, 2009	-4.62%		
Apr, 2001	-2.38%	Apr, 2005	-4.30%	Apr, 2009	19.14%		
May, 2001	-0.96%	May, 2005	7.55%	May, 2009	-1.65%		
Jun, 2001	2.67%	Jun, 2005	-2.69%	Jun, 2009	0.12%		
Jul, 2001	-2.46%	Jul, 2005	3.80%	Jul, 2009	7.95%		
Aug, 2001	-11.60%	Aug, 2005	-1.70%	Aug, 2009	3.85%		
Sep, 2001	-1.74%	Sep, 2005	-1.44%	Sep, 2009	-1.72%		
Oct, 2001	14.57%	Oct, 2005	-3.97%	Oct, 2009	-7.32%		
Nov, 2001	11.65%	Nov, 2005	3.22%	Nov, 2009	6.69%		
Dec, 2001	-3.72%	Dec, 2005	-3.36%	Dec, 2009	-4.08%		

**Appendix table 2: Monthly returns for active strategy with equally weighted portfolio: MA, zero**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	14.20%	Jan, 2002	2.39%	Jan, 2006	3.09%	Jan, 2010	4.65%
Feb, 1998	14.94%	Feb, 2002	7.57%	Feb, 2006	1.97%	Feb, 2010	-0.43%
Mar, 1998	10.90%	Mar, 2002	-1.34%	Mar, 2006	2.47%	Mar, 2010	-1.42%
Apr, 1998	14.82%	Apr, 2002	1.88%	Apr, 2006	1.10%	Apr, 2010	0.25%
May, 1998	14.66%	May, 2002	3.41%	May, 2006	-2.13%	May, 2010	-1.76%
Jun, 1998	16.21%	Jun, 2002	6.95%	Jun, 2006	4.57%	Jun, 2010	0.11%
Jul, 1998	17.76%	Jul, 2002	6.78%	Jul, 2006	1.70%	Jul, 2010	0.00%
Aug, 1998	12.35%	Aug, 2002	4.05%	Aug, 2006	2.90%	Aug, 2010	-0.60%
Sep, 1998	8.41%	Sep, 2002	-5.69%	Sep, 2006	1.11%	Sep, 2010	0.21%
Oct, 1998	25.19%	Oct, 2002	3.38%	Oct, 2006	0.75%	Oct, 2010	0.06%
Nov, 1998	18.15%	Nov, 2002	-1.22%	Nov, 2006	-1.25%	Nov, 2010	-2.32%
Dec, 1998	15.17%	Dec, 2002	1.36%	Dec, 2006	0.26%	Dec, 2010	1.46%
Jan, 1999	25.64%	Jan, 2003	1.36%	Jan, 2007	-0.59%	Jan, 2011	0.79%
Feb, 1999	18.54%	Feb, 2003	-2.19%	Feb, 2007	1.05%	Feb, 2011	-1.84%
Mar, 1999	13.91%	Mar, 2003	-2.28%	Mar, 2007	0.39%	1998	182.74%
Apr, 1999	26.98%	Apr, 2003	0.07%	Apr, 2007	-1.12%	1999	192.43%
May, 1999	15.02%	May, 2003	-1.06%	May, 2007	-0.34%	2000	162.87%
Jun, 1999	15.16%	Jun, 2003	2.37%	Jun, 2007	0.71%	2001	84.62%
Jul, 1999	7.66%	Jul, 2003	-1.32%	Jul, 2007	3.69%	2002	29.52%
Aug, 1999	18.78%	Aug, 2003	-0.01%	Aug, 2007	-6.67%	2003	5.93%
Sep, 1999	8.16%	Sep, 2003	4.00%	Sep, 2007	-1.96%	2004	9.15%
Oct, 1999	15.59%	Oct, 2003	1.16%	Oct, 2007	-0.03%	2005	7.73%
Nov, 1999	13.48%	Nov, 2003	3.08%	Nov, 2007	-1.97%	2006	16.54%
Dec, 1999	13.53%	Dec, 2003	0.74%	Dec, 2007	0.47%	2007	-6.37%
Jan, 2000	17.44%	Jan, 2004	1.98%	Jan, 2008	-7.69%	2008	36.21%
Feb, 2000	15.20%	Feb, 2004	0.47%	Feb, 2008	0.78%	2009	13.78%
Mar, 2000	11.53%	Mar, 2004	0.25%	Mar, 2008	-1.36%	2010	0.20%
Apr, 2000	23.89%	Apr, 2004	1.79%	Apr, 2008	1.28%	2011	-1.05%
May, 2000	11.97%	May, 2004	0.58%	May, 2008	1.74%	<b>Total</b>	<b>734.29%</b>
Jun, 2000	8.90%	Jun, 2004	1.71%	Jun, 2008	-0.06%	<b>Average monthly:</b>	
Jul, 2000	6.72%	Jul, 2004	1.84%	Jul, 2008	4.80%		4.65%
Aug, 2000	5.13%	Aug, 2004	-0.68%	Aug, 2008	2.21%	<b>Average yearly:</b>	
Sep, 2000	9.77%	Sep, 2004	0.20%	Sep, 2008	-6.98%		52.45%
Oct, 2000	23.53%	Oct, 2004	1.51%	Oct, 2008	16.45%		
Nov, 2000	10.64%	Nov, 2004	-1.21%	Nov, 2008	20.07%		
Dec, 2000	18.13%	Dec, 2004	0.71%	Dec, 2008	4.97%		
Jan, 2001	15.43%	Jan, 2005	-1.73%	Jan, 2009	6.76%		
Feb, 2001	19.88%	Feb, 2005	1.23%	Feb, 2009	-0.09%		
Mar, 2001	13.72%	Mar, 2005	-1.35%	Mar, 2009	8.99%		
Apr, 2001	12.79%	Apr, 2005	1.26%	Apr, 2009	1.84%		
May, 2001	-0.90%	May, 2005	0.17%	May, 2009	-0.94%		
Jun, 2001	0.66%	Jun, 2005	1.39%	Jun, 2009	-2.96%		
Jul, 2001	3.37%	Jul, 2005	-1.55%	Jul, 2009	2.09%		
Aug, 2001	0.07%	Aug, 2005	0.84%	Aug, 2009	-2.09%		
Sep, 2001	8.99%	Sep, 2005	0.21%	Sep, 2009	3.11%		
Oct, 2001	4.17%	Oct, 2005	2.33%	Oct, 2009	-0.60%		
Nov, 2001	5.52%	Nov, 2005	1.58%	Nov, 2009	-0.45%		
Dec, 2001	0.93%	Dec, 2005	3.33%	Dec, 2009	-1.89%		

**Appendix table 3: Monthly returns for active strategy with equally weighted portfolio: MA, 0.001**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	5.44%	Jan, 2002	2.68%	Jan, 2006	0.43%	Jan, 2010	3.60%
Feb, 1998	7.96%	Feb, 2002	5.82%	Feb, 2006	0.79%	Feb, 2010	-3.15%
Mar, 1998	6.57%	Mar, 2002	-1.68%	Mar, 2006	0.62%	Mar, 2010	-3.54%
Apr, 1998	8.66%	Apr, 2002	0.29%	Apr, 2006	-0.72%	Apr, 2010	-1.46%
May, 1998	9.80%	May, 2002	2.83%	May, 2006	-3.48%	May, 2010	-3.35%
Jun, 1998	11.18%	Jun, 2002	6.81%	Jun, 2006	2.22%	Jun, 2010	-0.19%
Jul, 1998	12.14%	Jul, 2002	6.82%	Jul, 2006	-0.68%	Jul, 2010	-1.28%
Aug, 1998	7.87%	Aug, 2002	-0.25%	Aug, 2006	2.03%	Aug, 2010	-1.90%
Sep, 1998	3.54%	Sep, 2002	-7.82%	Sep, 2006	0.08%	Sep, 2010	-2.04%
Oct, 1998	17.15%	Oct, 2002	-1.07%	Oct, 2006	-0.38%	Oct, 2010	-2.14%
Nov, 1998	12.86%	Nov, 2002	-1.46%	Nov, 2006	-1.33%	Nov, 2010	-4.99%
Dec, 1998	8.79%	Dec, 2002	-1.62%	Dec, 2006	-2.11%	Dec, 2010	-0.86%
Jan, 1999	21.13%	Jan, 2003	-0.44%	Jan, 2007	-0.70%	Jan, 2011	-1.30%
Feb, 1999	14.57%	Feb, 2003	-3.54%	Feb, 2007	-0.33%	Feb, 2011	-2.27%
Mar, 1999	11.52%	Mar, 2003	-2.89%	Mar, 2007	-0.27%	1998	111.96%
Apr, 1999	20.53%	Apr, 2003	-1.04%	Apr, 2007	-1.78%	1999	152.45%
May, 1999	12.30%	May, 2003	-3.72%	May, 2007	-2.10%	2000	141.31%
Jun, 1999	12.25%	Jun, 2003	0.58%	Jun, 2007	-0.47%	2001	70.84%
Jul, 1999	5.31%	Jul, 2003	-1.73%	Jul, 2007	2.91%	2002	11.37%
Aug, 1999	16.23%	Aug, 2003	-1.01%	Aug, 2007	-7.66%	2003	-7.40%
Sep, 1999	5.35%	Sep, 2003	3.47%	Sep, 2007	-3.01%	2004	-6.33%
Oct, 1999	11.77%	Oct, 2003	-0.13%	Oct, 2007	-2.06%	2005	-7.08%
Nov, 1999	10.82%	Nov, 2003	2.85%	Nov, 2007	-2.68%	2006	-2.53%
Dec, 1999	10.66%	Dec, 2003	0.19%	Dec, 2007	-0.62%	2007	-18.78%
Jan, 2000	16.47%	Jan, 2004	2.09%	Jan, 2008	-9.12%	2008	16.03%
Feb, 2000	13.38%	Feb, 2004	-0.70%	Feb, 2008	-1.11%	2009	-31.15%
Mar, 2000	9.36%	Mar, 2004	-1.89%	Mar, 2008	-1.88%	2010	-21.31%
Apr, 2000	23.33%	Apr, 2004	0.74%	Apr, 2008	1.76%	2011	-3.58%
May, 2000	11.18%	May, 2004	-1.33%	May, 2008	0.02%	<b>Total</b>	<b>405.81%</b>
Jun, 2000	6.68%	Jun, 2004	-0.11%	Jun, 2008	-1.39%	<b>Average monthly:</b>	
Jul, 2000	5.62%	Jul, 2004	0.67%	Jul, 2008	2.56%		2.57%
Aug, 2000	2.09%	Aug, 2004	-1.65%	Aug, 2008	1.26%	<b>Average yearly:</b>	
Sep, 2000	8.45%	Sep, 2004	-1.93%	Sep, 2008	-9.57%		28.99%
Oct, 2000	20.90%	Oct, 2004	-0.37%	Oct, 2008	13.21%		
Nov, 2000	7.91%	Nov, 2004	-2.25%	Nov, 2008	17.91%		
Dec, 2000	15.95%	Dec, 2004	0.40%	Dec, 2008	2.37%		
Jan, 2001	14.28%	Jan, 2005	-3.18%	Jan, 2009	4.74%		
Feb, 2001	17.79%	Feb, 2005	-0.78%	Feb, 2009	-3.84%		
Mar, 2001	11.25%	Mar, 2005	-2.05%	Mar, 2009	0.41%		
Apr, 2001	10.12%	Apr, 2005	1.43%	Apr, 2009	-7.34%		
May, 2001	-1.80%	May, 2005	-2.32%	May, 2009	-2.55%		
Jun, 2001	0.88%	Jun, 2005	-0.21%	Jun, 2009	-4.81%		
Jul, 2001	3.13%	Jul, 2005	-1.71%	Jul, 2009	-2.94%		
Aug, 2001	0.56%	Aug, 2005	-0.03%	Aug, 2009	-6.56%		
Sep, 2001	6.67%	Sep, 2005	-0.46%	Sep, 2009	-0.52%		
Oct, 2001	3.22%	Oct, 2005	0.68%	Oct, 2009	-0.76%		
Nov, 2001	4.71%	Nov, 2005	-0.06%	Nov, 2009	-3.32%		
Dec, 2001	0.04%	Dec, 2005	1.61%	Dec, 2009	-3.66%		

**Appendix table 4: Monthly returns for active strategy with equally weighted portfolio: MA, 0.0035**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	-3.38%	Jan, 2002	0.37%	Jan, 2006	-1.25%	Jan, 2010	0.60%
Feb, 1998	-0.46%	Feb, 2002	-0.30%	Feb, 2006	-1.02%	Feb, 2010	-4.79%
Mar, 1998	-2.23%	Mar, 2002	-4.54%	Mar, 2006	-1.00%	Mar, 2010	-6.49%
Apr, 1998	2.43%	Apr, 2002	-2.88%	Apr, 2006	-2.31%	Apr, 2010	-3.01%
May, 1998	4.17%	May, 2002	0.35%	May, 2006	-4.33%	May, 2010	-3.20%
Jun, 1998	2.27%	Jun, 2002	4.68%	Jun, 2006	0.13%	Jun, 2010	-2.00%
Jul, 1998	5.07%	Jul, 2002	4.52%	Jul, 2006	-4.03%	Jul, 2010	-3.37%
Aug, 1998	1.13%	Aug, 2002	-2.87%	Aug, 2006	-0.04%	Aug, 2010	-6.64%
Sep, 1998	-3.18%	Sep, 2002	-9.01%	Sep, 2006	-0.69%	Sep, 2010	-6.24%
Oct, 1998	7.84%	Oct, 2002	-7.75%	Oct, 2006	-2.58%	Oct, 2010	-5.82%
Nov, 1998	5.83%	Nov, 2002	-2.88%	Nov, 2006	-2.17%	Nov, 2010	-6.41%
Dec, 1998	3.29%	Dec, 2002	-6.34%	Dec, 2006	-3.29%	Dec, 2010	-2.63%
Jan, 1999	11.76%	Jan, 2003	-3.71%	Jan, 2007	-3.43%	Jan, 2011	-3.34%
Feb, 1999	11.01%	Feb, 2003	-5.29%	Feb, 2007	-1.93%	Feb, 2011	-4.01%
Mar, 1999	5.74%	Mar, 2003	-4.78%	Mar, 2007	-3.31%	1998	22.79%
Apr, 1999	11.72%	Apr, 2003	-5.03%	Apr, 2007	-3.38%	1999	89.40%
May, 1999	7.46%	May, 2003	-6.11%	May, 2007	-3.35%	2000	92.06%
Jun, 1999	6.32%	Jun, 2003	-3.13%	Jun, 2007	-1.87%	2001	30.94%
Jul, 1999	1.72%	Jul, 2003	-4.31%	Jul, 2007	1.17%	2002	-26.65%
Aug, 1999	12.15%	Aug, 2003	-1.42%	Aug, 2007	-11.56%	2003	-35.72%
Sep, 1999	1.97%	Sep, 2003	1.71%	Sep, 2007	-4.54%	2004	-30.46%
Oct, 1999	5.59%	Oct, 2003	-1.29%	Oct, 2007	-3.73%	2005	-23.99%
Nov, 1999	6.24%	Nov, 2003	-0.34%	Nov, 2007	-5.01%	2006	-22.59%
Dec, 1999	7.73%	Dec, 2003	-2.03%	Dec, 2007	-3.62%	2007	-44.55%
Jan, 2000	9.35%	Jan, 2004	1.00%	Jan, 2008	-10.99%	2008	-8.54%
Feb, 2000	10.11%	Feb, 2004	-2.98%	Feb, 2008	-2.21%	2009	-71.26%
Mar, 2000	6.10%	Mar, 2004	-3.41%	Mar, 2008	-2.66%	2010	-49.99%
Apr, 2000	19.81%	Apr, 2004	-1.99%	Apr, 2008	-0.83%	2011	-7.35%
May, 2000	6.90%	May, 2004	-4.38%	May, 2008	-1.58%	<b>Total</b>	<b>-85.92%</b>
Jun, 2000	3.90%	Jun, 2004	-0.81%	Jun, 2008	-2.60%	<b>Average monthly:</b>	
Jul, 2000	3.19%	Jul, 2004	-1.81%	Jul, 2008	2.79%		-0.54%
Aug, 2000	0.69%	Aug, 2004	-4.78%	Aug, 2008	0.09%	<b>Average yearly:</b>	
Sep, 2000	5.49%	Sep, 2004	-4.03%	Sep, 2008	-8.63%		-6.14%
Oct, 2000	16.36%	Oct, 2004	-2.29%	Oct, 2008	7.59%		
Nov, 2000	2.64%	Nov, 2004	-3.31%	Nov, 2008	11.56%		
Dec, 2000	7.51%	Dec, 2004	-1.66%	Dec, 2008	-1.08%		
Jan, 2001	10.06%	Jan, 2005	-3.73%	Jan, 2009	0.01%		
Feb, 2001	15.12%	Feb, 2005	-2.38%	Feb, 2009	-6.39%		
Mar, 2001	5.86%	Mar, 2005	-3.31%	Mar, 2009	-8.09%		
Apr, 2001	3.51%	Apr, 2005	-0.04%	Apr, 2009	-6.37%		
May, 2001	-5.07%	May, 2005	-3.49%	May, 2009	-4.07%		
Jun, 2001	-1.21%	Jun, 2005	-3.59%	Jun, 2009	-8.36%		
Jul, 2001	0.51%	Jul, 2005	-1.41%	Jul, 2009	-6.00%		
Aug, 2001	0.04%	Aug, 2005	-1.93%	Aug, 2009	-11.20%		
Sep, 2001	3.19%	Sep, 2005	-1.73%	Sep, 2009	-3.57%		
Oct, 2001	0.82%	Oct, 2005	0.36%	Oct, 2009	-3.29%		
Nov, 2001	0.85%	Nov, 2005	-2.57%	Nov, 2009	-6.40%		
Dec, 2001	-2.74%	Dec, 2005	-0.18%	Dec, 2009	-7.52%		

**Appendix table 5: Monthly returns for active strategy with equally weighted portfolio: DBR, zero**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	7.89%	Jan, 2002	0.54%	Jan, 2006	0.37%	Jan, 2010	-0.16%
Feb, 1998	9.81%	Feb, 2002	4.04%	Feb, 2006	-1.69%	Feb, 2010	-1.28%
Mar, 1998	11.29%	Mar, 2002	-0.30%	Mar, 2006	1.19%	Mar, 2010	-0.36%
Apr, 1998	17.30%	Apr, 2002	1.16%	Apr, 2006	-0.73%	Apr, 2010	-1.82%
May, 1998	17.58%	May, 2002	0.64%	May, 2006	-0.32%	May, 2010	-1.50%
Jun, 1998	16.08%	Jun, 2002	6.97%	Jun, 2006	0.89%	Jun, 2010	0.44%
Jul, 1998	17.02%	Jul, 2002	1.72%	Jul, 2006	3.81%	Jul, 2010	-2.33%
Aug, 1998	20.68%	Aug, 2002	-0.24%	Aug, 2006	0.60%	Aug, 2010	-0.78%
Sep, 1998	16.54%	Sep, 2002	-5.44%	Sep, 2006	1.67%	Sep, 2010	-1.77%
Oct, 1998	32.99%	Oct, 2002	2.12%	Oct, 2006	-0.59%	Oct, 2010	2.93%
Nov, 1998	18.00%	Nov, 2002	-0.69%	Nov, 2006	-2.07%	Nov, 2010	0.60%
Dec, 1998	15.78%	Dec, 2002	-2.53%	Dec, 2006	0.19%	Dec, 2010	0.18%
Jan, 1999	24.65%	Jan, 2003	-5.05%	Jan, 2007	-1.51%	Jan, 2011	0.16%
Feb, 1999	23.36%	Feb, 2003	-1.15%	Feb, 2007	-0.14%	Feb, 2011	-1.51%
Mar, 1999	18.76%	Mar, 2003	0.58%	Mar, 2007	-2.07%	1998	200.96%
Apr, 1999	38.02%	Apr, 2003	-1.93%	Apr, 2007	-0.81%	1999	221.11%
May, 1999	12.74%	May, 2003	0.81%	May, 2007	-1.99%	2000	257.28%
Jun, 1999	8.31%	Jun, 2003	1.54%	Jun, 2007	-0.24%	2001	87.47%
Jul, 1999	10.22%	Jul, 2003	2.38%	Jul, 2007	1.76%	2002	8.01%
Aug, 1999	18.57%	Aug, 2003	0.94%	Aug, 2007	-6.43%	2003	2.17%
Sep, 1999	13.86%	Sep, 2003	1.34%	Sep, 2007	-4.76%	2004	0.97%
Oct, 1999	16.01%	Oct, 2003	-0.04%	Oct, 2007	-3.48%	2005	5.67%
Nov, 1999	18.92%	Nov, 2003	1.74%	Nov, 2007	-0.27%	2006	3.30%
Dec, 1999	17.69%	Dec, 2003	1.00%	Dec, 2007	1.08%	2007	-18.86%
Jan, 2000	34.47%	Jan, 2004	2.56%	Jan, 2008	-7.40%	2008	2.07%
Feb, 2000	24.05%	Feb, 2004	0.81%	Feb, 2008	-4.05%	2009	8.49%
Mar, 2000	31.62%	Mar, 2004	-0.52%	Mar, 2008	-1.08%	2010	-5.85%
Apr, 2000	35.40%	Apr, 2004	0.67%	Apr, 2008	2.43%	2011	-1.35%
May, 2000	15.81%	May, 2004	-0.95%	May, 2008	-0.33%	<b>Total</b>	<b>771.44%</b>
Jun, 2000	7.41%	Jun, 2004	1.33%	Jun, 2008	0.27%	<b>Average monthly:</b>	
Jul, 2000	5.99%	Jul, 2004	0.85%	Jul, 2008	0.95%		<b>4.88%</b>
Aug, 2000	8.59%	Aug, 2004	0.04%	Aug, 2008	-3.48%	<b>Average yearly:</b>	
Sep, 2000	17.48%	Sep, 2004	-2.23%	Sep, 2008	-5.89%		<b>55.10%</b>
Oct, 2000	34.67%	Oct, 2004	0.57%	Oct, 2008	10.47%		
Nov, 2000	23.18%	Nov, 2004	-2.21%	Nov, 2008	10.57%		
Dec, 2000	18.61%	Dec, 2004	0.04%	Dec, 2008	-0.39%		
Jan, 2001	13.89%	Jan, 2005	2.37%	Jan, 2009	5.39%		
Feb, 2001	10.04%	Feb, 2005	0.79%	Feb, 2009	-5.73%		
Mar, 2001	12.72%	Mar, 2005	0.06%	Mar, 2009	-0.48%		
Apr, 2001	20.31%	Apr, 2005	2.99%	Apr, 2009	6.55%		
May, 2001	2.35%	May, 2005	-1.30%	May, 2009	0.75%		
Jun, 2001	0.79%	Jun, 2005	0.41%	Jun, 2009	-1.68%		
Jul, 2001	3.53%	Jul, 2005	-1.74%	Jul, 2009	2.00%		
Aug, 2001	2.06%	Aug, 2005	0.51%	Aug, 2009	-1.48%		
Sep, 2001	12.53%	Sep, 2005	0.30%	Sep, 2009	2.04%		
Oct, 2001	9.58%	Oct, 2005	-0.30%	Oct, 2009	2.81%		
Nov, 2001	-0.29%	Nov, 2005	-0.81%	Nov, 2009	-1.61%		
Dec, 2001	-0.04%	Dec, 2005	2.40%	Dec, 2009	-0.08%		

**Appendix table 6: Monthly returns for active strategy with equally weighted portfolio: DBR, 0.001**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	4.36%	Jan, 2002	0.37%	Jan, 2006	-0.24%	Jan, 2010	-0.92%
Feb, 1998	6.70%	Feb, 2002	1.95%	Feb, 2006	-2.20%	Feb, 2010	-2.12%
Mar, 1998	7.99%	Mar, 2002	-1.29%	Mar, 2006	0.63%	Mar, 2010	-1.74%
Apr, 1998	15.09%	Apr, 2002	-0.12%	Apr, 2006	-1.06%	Apr, 2010	-2.87%
May, 1998	13.12%	May, 2002	-0.12%	May, 2006	-1.28%	May, 2010	-2.82%
Jun, 1998	11.37%	Jun, 2002	5.32%	Jun, 2006	0.23%	Jun, 2010	0.02%
Jul, 1998	13.54%	Jul, 2002	0.70%	Jul, 2006	2.07%	Jul, 2010	-2.37%
Aug, 1998	15.66%	Aug, 2002	-1.26%	Aug, 2006	-0.46%	Aug, 2010	-2.60%
Sep, 1998	9.99%	Sep, 2002	-6.27%	Sep, 2006	0.61%	Sep, 2010	-2.67%
Oct, 1998	28.30%	Oct, 2002	1.64%	Oct, 2006	-1.14%	Oct, 2010	0.13%
Nov, 1998	14.82%	Nov, 2002	-3.31%	Nov, 2006	-2.80%	Nov, 2010	-1.37%
Dec, 1998	14.30%	Dec, 2002	-4.56%	Dec, 2006	-0.76%	Dec, 2010	-1.64%
Jan, 1999	22.75%	Jan, 2003	-5.15%	Jan, 2007	-2.43%	Jan, 2011	-0.94%
Feb, 1999	19.39%	Feb, 2003	-1.56%	Feb, 2007	-0.72%	Feb, 2011	-2.16%
Mar, 1999	16.49%	Mar, 2003	-2.12%	Mar, 2007	-3.05%	1998	155.23%
Apr, 1999	34.81%	Apr, 2003	-4.71%	Apr, 2007	-1.49%	1999	193.38%
May, 1999	10.35%	May, 2003	-1.31%	May, 2007	-2.32%	2000	237.54%
Jun, 1999	6.49%	Jun, 2003	0.65%	Jun, 2007	-1.18%	2001	69.18%
Jul, 1999	8.53%	Jul, 2003	1.30%	Jul, 2007	0.03%	2002	-6.95%
Aug, 1999	17.38%	Aug, 2003	-0.27%	Aug, 2007	-6.93%	2003	-11.87%
Sep, 1999	10.51%	Sep, 2003	1.02%	Sep, 2007	-5.98%	2004	-7.71%
Oct, 1999	14.42%	Oct, 2003	-0.35%	Oct, 2007	-3.58%	2005	-1.08%
Nov, 1999	16.72%	Nov, 2003	1.03%	Nov, 2007	-2.09%	2006	-6.41%
Dec, 1999	15.53%	Dec, 2003	-0.40%	Dec, 2007	1.19%	2007	-28.54%
Jan, 2000	32.55%	Jan, 2004	1.21%	Jan, 2008	-6.46%	2008	-5.98%
Feb, 2000	22.73%	Feb, 2004	0.71%	Feb, 2008	-4.08%	2009	-11.46%
Mar, 2000	29.34%	Mar, 2004	-0.83%	Mar, 2008	-1.72%	2010	-20.96%
Apr, 2000	33.64%	Apr, 2004	-0.34%	Apr, 2008	0.63%	2011	-3.10%
May, 2000	13.70%	May, 2004	-2.01%	May, 2008	-0.47%	<b>Total</b>	<b>551.27%</b>
Jun, 2000	6.20%	Jun, 2004	0.54%	Jun, 2008	0.14%	<b>Average monthly:</b>	
Jul, 2000	3.92%	Jul, 2004	0.28%	Jul, 2008	1.12%		<b>3.49%</b>
Aug, 2000	6.53%	Aug, 2004	-1.36%	Aug, 2008	-2.53%	<b>Average yearly:</b>	
Sep, 2000	16.58%	Sep, 2004	-3.12%	Sep, 2008	-6.44%		<b>39.38%</b>
Oct, 2000	32.61%	Oct, 2004	-0.29%	Oct, 2008	8.20%		
Nov, 2000	22.57%	Nov, 2004	-2.26%	Nov, 2008	7.93%		
Dec, 2000	17.17%	Dec, 2004	-0.24%	Dec, 2008	-2.30%		
Jan, 2001	12.89%	Jan, 2005	1.75%	Jan, 2009	5.17%		
Feb, 2001	9.07%	Feb, 2005	0.03%	Feb, 2009	-5.72%		
Mar, 2001	10.19%	Mar, 2005	-0.86%	Mar, 2009	-0.45%		
Apr, 2001	19.43%	Apr, 2005	2.14%	Apr, 2009	1.35%		
May, 2001	0.69%	May, 2005	-1.20%	May, 2009	-2.34%		
Jun, 2001	-0.34%	Jun, 2005	-0.66%	Jun, 2009	-3.02%		
Jul, 2001	2.74%	Jul, 2005	-1.74%	Jul, 2009	-0.45%		
Aug, 2001	0.97%	Aug, 2005	0.04%	Aug, 2009	-3.38%		
Sep, 2001	9.19%	Sep, 2005	-0.05%	Sep, 2009	1.57%		
Oct, 2001	6.09%	Oct, 2005	-0.61%	Oct, 2009	-0.16%		
Nov, 2001	-0.54%	Nov, 2005	-1.81%	Nov, 2009	-3.38%		
Dec, 2001	-1.19%	Dec, 2005	1.91%	Dec, 2009	-0.64%		

**Appendix table 7: Monthly returns for active strategy with equally weighted portfolio: DBR, 0.0035**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	0.37%	Jan, 2002	-0.96%	Jan, 2006	-1.24%	Jan, 2010	-2.55%
Feb, 1998	2.89%	Feb, 2002	-1.01%	Feb, 2006	-3.09%	Feb, 2010	-3.88%
Mar, 1998	2.83%	Mar, 2002	-4.23%	Mar, 2006	-0.52%	Mar, 2010	-3.45%
Apr, 1998	6.89%	Apr, 2002	-2.51%	Apr, 2006	-1.80%	Apr, 2010	-4.89%
May, 1998	8.92%	May, 2002	-1.74%	May, 2006	-2.90%	May, 2010	-3.99%
Jun, 1998	2.07%	Jun, 2002	1.27%	Jun, 2006	-1.64%	Jun, 2010	-0.76%
Jul, 1998	7.25%	Jul, 2002	-2.30%	Jul, 2006	-0.29%	Jul, 2010	-3.21%
Aug, 1998	8.58%	Aug, 2002	-1.57%	Aug, 2006	-0.98%	Aug, 2010	-5.11%
Sep, 1998	-2.08%	Sep, 2002	-9.55%	Sep, 2006	-0.29%	Sep, 2010	-3.59%
Oct, 1998	19.40%	Oct, 2002	-4.15%	Oct, 2006	-2.10%	Oct, 2010	-2.69%
Nov, 1998	10.46%	Nov, 2002	-8.39%	Nov, 2006	-3.22%	Nov, 2010	-3.58%
Dec, 1998	8.55%	Dec, 2002	-5.54%	Dec, 2006	-1.94%	Dec, 2010	-2.62%
Jan, 1999	16.53%	Jan, 2003	-6.17%	Jan, 2007	-3.39%	Jan, 2011	-1.95%
Feb, 1999	14.93%	Feb, 2003	-2.69%	Feb, 2007	-1.29%	Feb, 2011	-2.68%
Mar, 1999	9.73%	Mar, 2003	-3.12%	Mar, 2007	-3.59%	1998	76.12%
Apr, 1999	25.19%	Apr, 2003	-6.76%	Apr, 2007	-1.95%	1999	136.01%
May, 1999	6.75%	May, 2003	-4.28%	May, 2007	-3.41%	2000	205.36%
Jun, 1999	4.57%	Jun, 2003	-2.33%	Jun, 2007	-1.84%	2001	35.51%
Jul, 1999	5.39%	Jul, 2003	-0.31%	Jul, 2007	-0.71%	2002	-40.69%
Aug, 1999	14.42%	Aug, 2003	-1.39%	Aug, 2007	-7.35%	2003	-30.41%
Sep, 1999	5.27%	Sep, 2003	-0.94%	Sep, 2007	-5.23%	2004	-22.04%
Oct, 1999	8.79%	Oct, 2003	-1.36%	Oct, 2007	-4.75%	2005	-14.35%
Nov, 1999	13.23%	Nov, 2003	0.62%	Nov, 2007	-4.62%	2006	-20.00%
Dec, 1999	11.22%	Dec, 2003	-1.68%	Dec, 2007	-0.20%	2007	-38.33%
Jan, 2000	28.85%	Jan, 2004	-0.41%	Jan, 2008	-7.06%	2008	-26.59%
Feb, 2000	19.99%	Feb, 2004	-1.05%	Feb, 2008	-4.34%	2009	-42.12%
Mar, 2000	26.76%	Mar, 2004	-1.87%	Mar, 2008	-2.99%	2010	-40.33%
Apr, 2000	30.50%	Apr, 2004	-1.49%	Apr, 2008	-1.39%	2011	-4.62%
May, 2000	11.37%	May, 2004	-3.92%	May, 2008	-1.78%	<b>Total</b>	<b>173.52%</b>
Jun, 2000	5.91%	Jun, 2004	0.70%	Jun, 2008	-1.04%	<b>Average monthly:</b>	
Jul, 2000	2.33%	Jul, 2004	-0.74%	Jul, 2008	-2.44%		<b>1.10%</b>
Aug, 2000	3.31%	Aug, 2004	-2.13%	Aug, 2008	-2.45%	<b>Average yearly:</b>	
Sep, 2000	15.27%	Sep, 2004	-5.89%	Sep, 2008	-8.03%		<b>12.39%</b>
Oct, 2000	26.91%	Oct, 2004	-2.36%	Oct, 2008	4.30%		
Nov, 2000	19.27%	Nov, 2004	-2.11%	Nov, 2008	5.54%		
Dec, 2000	14.89%	Dec, 2004	-0.76%	Dec, 2008	-4.92%		
Jan, 2001	8.65%	Jan, 2005	-0.67%	Jan, 2009	2.19%		
Feb, 2001	8.55%	Feb, 2005	-1.86%	Feb, 2009	-9.66%		
Mar, 2001	5.74%	Mar, 2005	-2.32%	Mar, 2009	-6.09%		
Apr, 2001	13.86%	Apr, 2005	1.15%	Apr, 2009	-3.31%		
May, 2001	-2.76%	May, 2005	-2.42%	May, 2009	-3.67%		
Jun, 2001	-1.99%	Jun, 2005	-2.68%	Jun, 2009	-5.66%		
Jul, 2001	1.35%	Jul, 2005	-1.45%	Jul, 2009	-2.05%		
Aug, 2001	-0.74%	Aug, 2005	-1.00%	Aug, 2009	-4.44%		
Sep, 2001	6.40%	Sep, 2005	-0.73%	Sep, 2009	-0.52%		
Oct, 2001	1.24%	Oct, 2005	-0.20%	Oct, 2009	-2.30%		
Nov, 2001	-2.36%	Nov, 2005	-3.17%	Nov, 2009	-4.29%		
Dec, 2001	-2.44%	Dec, 2005	1.01%	Dec, 2009	-2.33%		

**Appendix table 8: Monthly returns for active strategy with equally weighted portfolio: MAR, zero**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	41.03%	Jan, 2002	18.14%	Jan, 2006	4.20%	Jan, 2010	1.45%
Feb, 1998	24.40%	Feb, 2002	19.68%	Feb, 2006	-3.31%	Feb, 2010	-1.45%
Mar, 1998	31.26%	Mar, 2002	15.93%	Mar, 2006	0.15%	Mar, 2010	0.71%
Apr, 1998	38.38%	Apr, 2002	6.40%	Apr, 2006	0.54%	Apr, 2010	-0.64%
May, 1998	28.46%	May, 2002	5.16%	May, 2006	2.28%	May, 2010	-0.64%
Jun, 1998	40.98%	Jun, 2002	20.55%	Jun, 2006	4.30%	Jun, 2010	-0.83%
Jul, 1998	40.06%	Jul, 2002	32.05%	Jul, 2006	4.11%	Jul, 2010	-0.32%
Aug, 1998	79.46%	Aug, 2002	-13.59%	Aug, 2006	4.07%	Aug, 2010	-1.75%
Sep, 1998	77.67%	Sep, 2002	2.88%	Sep, 2006	1.86%	Sep, 2010	0.51%
Oct, 1998	88.60%	Oct, 2002	18.64%	Oct, 2006	3.40%	Oct, 2010	0.80%
Nov, 1998	31.15%	Nov, 2002	13.91%	Nov, 2006	1.96%	Nov, 2010	3.49%
Dec, 1998	32.00%	Dec, 2002	2.59%	Dec, 2006	1.19%	Dec, 2010	4.62%
Jan, 1999	43.47%	Jan, 2003	-0.14%	Jan, 2007	-0.48%	Jan, 2011	2.60%
Feb, 1999	40.01%	Feb, 2003	-0.30%	Feb, 2007	0.83%	Feb, 2011	1.40%
Mar, 1999	37.57%	Mar, 2003	7.87%	Mar, 2007	-2.79%	1998	553.46%
Apr, 1999	62.94%	Apr, 2003	15.00%	Apr, 2007	-1.10%	1999	482.67%
May, 1999	41.30%	May, 2003	11.47%	May, 2007	-1.86%	2000	692.47%
Jun, 1999	29.55%	Jun, 2003	17.15%	Jun, 2007	2.15%	2001	485.56%
Jul, 1999	24.50%	Jul, 2003	7.07%	Jul, 2007	6.36%	2002	142.34%
Aug, 1999	34.40%	Aug, 2003	10.00%	Aug, 2007	-5.74%	2003	100.40%
Sep, 1999	36.24%	Sep, 2003	8.43%	Sep, 2007	0.02%	2004	53.48%
Oct, 1999	37.10%	Oct, 2003	4.58%	Oct, 2007	1.38%	2005	-1.86%
Nov, 1999	43.78%	Nov, 2003	9.55%	Nov, 2007	1.52%	2006	24.75%
Dec, 1999	51.80%	Dec, 2003	9.71%	Dec, 2007	0.54%	2007	0.83%
Jan, 2000	79.83%	Jan, 2004	12.86%	Jan, 2008	-4.83%	2008	8.25%
Feb, 2000	52.90%	Feb, 2004	3.14%	Feb, 2008	-5.24%	2009	18.32%
Mar, 2000	74.88%	Mar, 2004	6.34%	Mar, 2008	-4.83%	2010	5.93%
Apr, 2000	63.41%	Apr, 2004	9.27%	Apr, 2008	2.23%	2011	4.00%
May, 2000	45.54%	May, 2004	-0.08%	May, 2008	-2.45%	<b>Total</b>	<b>2570.62%</b>
Jun, 2000	30.42%	Jun, 2004	3.72%	Jun, 2008	-3.55%	<b>Average monthly:</b>	
Jul, 2000	42.99%	Jul, 2004	4.69%	Jul, 2008	8.24%		16.27%
Aug, 2000	35.61%	Aug, 2004	4.16%	Aug, 2008	-1.72%	<b>Average yearly:</b>	
Sep, 2000	47.93%	Sep, 2004	-0.84%	Sep, 2008	-4.75%		183.62%
Oct, 2000	92.31%	Oct, 2004	2.48%	Oct, 2008	1.23%		
Nov, 2000	57.31%	Nov, 2004	3.61%	Nov, 2008	14.63%		
Dec, 2000	69.33%	Dec, 2004	4.13%	Dec, 2008	9.29%		
Jan, 2001	68.25%	Jan, 2005	0.02%	Jan, 2009	-0.51%		
Feb, 2001	65.79%	Feb, 2005	1.81%	Feb, 2009	-3.47%		
Mar, 2001	76.19%	Mar, 2005	0.51%	Mar, 2009	9.78%		
Apr, 2001	63.23%	Apr, 2005	-1.17%	Apr, 2009	8.97%		
May, 2001	25.75%	May, 2005	-2.43%	May, 2009	0.29%		
Jun, 2001	34.14%	Jun, 2005	-0.51%	Jun, 2009	-2.10%		
Jul, 2001	24.10%	Jul, 2005	-0.98%	Jul, 2009	0.49%		
Aug, 2001	17.26%	Aug, 2005	0.99%	Aug, 2009	-1.73%		
Sep, 2001	42.87%	Sep, 2005	0.10%	Sep, 2009	2.85%		
Oct, 2001	36.34%	Oct, 2005	-0.32%	Oct, 2009	1.28%		
Nov, 2001	16.08%	Nov, 2005	-0.84%	Nov, 2009	-4.45%		
Dec, 2001	15.57%	Dec, 2005	0.96%	Dec, 2009	6.91%		

**Appendix table 9: Monthly returns for active strategy with equally weighted portfolio: MAR, 0.001**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	5.75%	Jan, 2002	1.34%	Jan, 2006	-3.05%	Jan, 2010	-3.65%
Feb, 1998	0.75%	Feb, 2002	4.31%	Feb, 2006	-6.23%	Feb, 2010	-8.07%
Mar, 1998	3.99%	Mar, 2002	-3.44%	Mar, 2006	-4.25%	Mar, 2010	-10.05%
Apr, 1998	12.13%	Apr, 2002	-4.85%	Apr, 2006	-4.88%	Apr, 2010	-7.65%
May, 1998	5.83%	May, 2002	-5.41%	May, 2006	-7.61%	May, 2010	-4.76%
Jun, 1998	15.91%	Jun, 2002	4.84%	Jun, 2006	-1.76%	Jun, 2010	-6.35%
Jul, 1998	20.31%	Jul, 2002	10.58%	Jul, 2006	-4.10%	Jul, 2010	-7.23%
Aug, 1998	50.67%	Aug, 2002	-18.96%	Aug, 2006	-4.57%	Aug, 2010	-10.31%
Sep, 1998	46.95%	Sep, 2002	-8.63%	Sep, 2006	-3.13%	Sep, 2010	-9.52%
Oct, 1998	59.52%	Oct, 2002	-1.35%	Oct, 2006	-5.04%	Oct, 2010	-8.76%
Nov, 1998	12.15%	Nov, 2002	-4.97%	Nov, 2006	-6.56%	Nov, 2010	-10.59%
Dec, 1998	15.36%	Dec, 2002	-11.72%	Dec, 2006	-6.11%	Dec, 2010	-6.25%
Jan, 1999	23.45%	Jan, 2003	-11.80%	Jan, 2007	-6.66%	Jan, 2011	-4.61%
Feb, 1999	23.00%	Feb, 2003	-10.00%	Feb, 2007	-3.89%	Feb, 2011	-7.02%
Mar, 1999	21.55%	Mar, 2003	-10.05%	Mar, 2007	-5.47%	1998	249.32%
Apr, 1999	38.82%	Apr, 2003	-3.06%	Apr, 2007	-5.62%	1999	303.82%
May, 1999	26.47%	May, 2003	-7.78%	May, 2007	-6.95%	2000	566.30%
Jun, 1999	14.26%	Jun, 2003	0.22%	Jun, 2007	-1.42%	2001	307.96%
Jul, 1999	13.42%	Jul, 2003	-4.37%	Jul, 2007	-1.40%	2002	-38.27%
Aug, 1999	23.20%	Aug, 2003	-1.92%	Aug, 2007	-12.74%	2003	-58.59%
Sep, 1999	22.29%	Sep, 2003	-1.38%	Sep, 2007	-8.10%	2004	-57.97%
Oct, 1999	24.30%	Oct, 2003	-5.32%	Oct, 2007	-7.38%	2005	-64.87%
Nov, 1999	32.83%	Nov, 2003	-1.20%	Nov, 2007	-2.87%	2006	-57.29%
Dec, 1999	40.25%	Dec, 2003	-1.92%	Dec, 2007	-4.77%	2007	-67.25%
Jan, 2000	69.43%	Jan, 2004	-1.72%	Jan, 2008	-12.50%	2008	-66.07%
Feb, 2000	41.52%	Feb, 2004	-6.27%	Feb, 2008	-10.14%	2009	-133.09%
Mar, 2000	63.75%	Mar, 2004	-8.26%	Mar, 2008	-7.30%	2010	-93.17%
Apr, 2000	56.54%	Apr, 2004	-3.33%	Apr, 2008	-1.84%	2011	-11.63%
May, 2000	37.59%	May, 2004	-5.56%	May, 2008	-6.49%	<b>Total</b>	<b>779.20%</b>
Jun, 2000	21.83%	Jun, 2004	-1.75%	Jun, 2008	-7.81%	<b>Average monthly:</b>	
Jul, 2000	34.90%	Jul, 2004	-1.78%	Jul, 2008	0.63%		4.93%
Aug, 2000	24.36%	Aug, 2004	-5.59%	Aug, 2008	-6.01%	<b>Average yearly:</b>	
Sep, 2000	36.47%	Sep, 2004	-7.29%	Sep, 2008	-12.37%		55.66%
Oct, 2000	79.97%	Oct, 2004	-6.20%	Oct, 2008	-3.68%		
Nov, 2000	43.84%	Nov, 2004	-4.21%	Nov, 2008	5.40%		
Dec, 2000	56.08%	Dec, 2004	-6.01%	Dec, 2008	-3.95%		
Jan, 2001	54.19%	Jan, 2005	-6.68%	Jan, 2009	-10.28%		
Feb, 2001	51.07%	Feb, 2005	-4.68%	Feb, 2009	-13.48%		
Mar, 2001	57.12%	Mar, 2005	-6.76%	Mar, 2009	-15.24%		
Apr, 2001	49.24%	Apr, 2005	-6.45%	Apr, 2009	-8.12%		
May, 2001	13.98%	May, 2005	-6.87%	May, 2009	-14.04%		
Jun, 2001	21.66%	Jun, 2005	-6.17%	Jun, 2009	-14.91%		
Jul, 2001	10.35%	Jul, 2005	-4.17%	Jul, 2009	-11.60%		
Aug, 2001	3.52%	Aug, 2005	-3.75%	Aug, 2009	-9.42%		
Sep, 2001	28.22%	Sep, 2005	-5.74%	Sep, 2009	-7.02%		
Oct, 2001	18.93%	Oct, 2005	-4.27%	Oct, 2009	-8.02%		
Nov, 2001	0.51%	Nov, 2005	-6.22%	Nov, 2009	-10.14%		
Dec, 2001	-0.83%	Dec, 2005	-3.11%	Dec, 2009	-10.83%		

**Appendix table 10: Monthly returns for active strategy with equally weighted portfolio: MAR, 0.0035**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	-25.02%	Jan, 2002	-7.94%	Jan, 2006	-9.66%	Jan, 2010	-13.99%
Feb, 1998	-20.50%	Feb, 2002	-10.06%	Feb, 2006	-14.68%	Feb, 2010	-19.62%
Mar, 1998	-21.86%	Mar, 2002	-14.05%	Mar, 2006	-13.24%	Mar, 2010	-25.20%
Apr, 1998	-15.61%	Apr, 2002	-14.57%	Apr, 2006	-12.01%	Apr, 2010	-17.73%
May, 1998	-17.45%	May, 2002	-12.83%	May, 2006	-17.37%	May, 2010	-14.40%
Jun, 1998	-12.33%	Jun, 2002	-7.83%	Jun, 2006	-10.65%	Jun, 2010	-16.84%
Jul, 1998	-7.48%	Jul, 2002	-14.11%	Jul, 2006	-12.43%	Jul, 2010	-16.90%
Aug, 1998	0.13%	Aug, 2002	-28.02%	Aug, 2006	-13.67%	Aug, 2010	-29.86%
Sep, 1998	-3.56%	Sep, 2002	-22.53%	Sep, 2006	-8.40%	Sep, 2010	-28.25%
Oct, 1998	11.62%	Oct, 2002	-25.21%	Oct, 2006	-16.71%	Oct, 2010	-20.38%
Nov, 1998	-5.67%	Nov, 2002	-18.29%	Nov, 2006	-13.50%	Nov, 2010	-24.89%
Dec, 1998	-9.83%	Dec, 2002	-25.55%	Dec, 2006	-12.98%	Dec, 2010	-18.28%
Jan, 1999	3.63%	Jan, 2003	-18.99%	Jan, 2007	-14.25%	Jan, 2011	-13.06%
Feb, 1999	3.13%	Feb, 2003	-15.93%	Feb, 2007	-11.55%	Feb, 2011	-17.22%
Mar, 1999	-3.39%	Mar, 2003	-19.17%	Mar, 2007	-13.75%	1998	-127.56%
Apr, 1999	15.54%	Apr, 2003	-18.68%	Apr, 2007	-12.34%	1999	49.76%
May, 1999	1.74%	May, 2003	-19.66%	May, 2007	-14.29%	2000	314.18%
Jun, 1999	-2.27%	Jun, 2003	-14.98%	Jun, 2007	-8.10%	2001	34.28%
Jul, 1999	-6.26%	Jul, 2003	-13.01%	Jul, 2007	-5.80%	2002	-200.99%
Aug, 1999	5.12%	Aug, 2003	-13.98%	Aug, 2007	-21.34%	2003	-176.43%
Sep, 1999	0.40%	Sep, 2003	-10.41%	Sep, 2007	-15.41%	2004	-143.67%
Oct, 1999	-0.36%	Oct, 2003	-12.90%	Oct, 2007	-12.02%	2005	-151.18%
Nov, 1999	14.66%	Nov, 2003	-6.72%	Nov, 2007	-8.92%	2006	-155.32%
Dec, 1999	17.83%	Dec, 2003	-11.99%	Dec, 2007	-10.18%	2007	-147.94%
Jan, 2000	46.91%	Jan, 2004	-5.91%	Jan, 2008	-26.21%	2008	-188.04%
Feb, 2000	22.36%	Feb, 2004	-10.82%	Feb, 2008	-14.79%	2009	-379.08%
Mar, 2000	39.52%	Mar, 2004	-14.17%	Mar, 2008	-13.99%	2010	-246.35%
Apr, 2000	41.71%	Apr, 2004	-11.36%	Apr, 2008	-9.29%	2011	-30.29%
May, 2000	21.37%	May, 2004	-12.69%	May, 2008	-12.16%	<b>Total</b>	<b>-1548.62%</b>
Jun, 2000	4.66%	Jun, 2004	-8.03%	Jun, 2008	-14.92%	<b>Average monthly:</b>	
Jul, 2000	16.26%	Jul, 2004	-10.20%	Jul, 2008	-7.12%		<b>-9.80%</b>
Aug, 2000	5.87%	Aug, 2004	-12.77%	Aug, 2008	-12.32%	<b>Average yearly:</b>	
Sep, 2000	16.49%	Sep, 2004	-15.53%	Sep, 2008	-24.69%		<b>-110.62%</b>
Oct, 2000	50.42%	Oct, 2004	-14.13%	Oct, 2008	-22.01%		
Nov, 2000	19.13%	Nov, 2004	-13.32%	Nov, 2008	-7.30%		
Dec, 2000	29.47%	Dec, 2004	-14.75%	Dec, 2008	-23.24%		
Jan, 2001	29.31%	Jan, 2005	-15.06%	Jan, 2009	-26.95%		
Feb, 2001	24.50%	Feb, 2005	-11.24%	Feb, 2009	-37.72%		
Mar, 2001	21.56%	Mar, 2005	-14.44%	Mar, 2009	-79.68%		
Apr, 2001	15.14%	Apr, 2005	-12.00%	Apr, 2009	-37.28%		
May, 2001	-8.41%	May, 2005	-14.73%	May, 2009	-27.37%		
Jun, 2001	-2.09%	Jun, 2005	-12.04%	Jun, 2009	-28.93%		
Jul, 2001	-8.56%	Jul, 2005	-10.04%	Jul, 2009	-27.70%		
Aug, 2001	-12.33%	Aug, 2005	-11.94%	Aug, 2009	-21.27%		
Sep, 2001	5.51%	Sep, 2005	-12.60%	Sep, 2009	-17.65%		
Oct, 2001	-6.06%	Oct, 2005	-11.83%	Oct, 2009	-20.01%		
Nov, 2001	-12.16%	Nov, 2005	-13.93%	Nov, 2009	-24.91%		
Dec, 2001	-12.15%	Dec, 2005	-11.32%	Dec, 2009	-29.60%		

**Appendix table 11: Monthly returns for active strategy with equally weighted portfolio: MART, zero**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	26.57%	Jan, 2002	4.66%	Jan, 2006	1.13%	Jan, 2010	1.45%
Feb, 1998	22.02%	Feb, 2002	7.46%	Feb, 2006	-3.34%	Feb, 2010	-2.84%
Mar, 1998	27.18%	Mar, 2002	6.60%	Mar, 2006	0.57%	Mar, 2010	-2.71%
Apr, 1998	28.99%	Apr, 2002	1.95%	Apr, 2006	-0.67%	Apr, 2010	-0.84%
May, 1998	24.57%	May, 2002	6.15%	May, 2006	1.66%	May, 2010	-2.42%
Jun, 1998	31.41%	Jun, 2002	13.74%	Jun, 2006	4.43%	Jun, 2010	1.40%
Jul, 1998	33.74%	Jul, 2002	6.24%	Jul, 2006	3.10%	Jul, 2010	0.66%
Aug, 1998	54.36%	Aug, 2002	-11.82%	Aug, 2006	2.47%	Aug, 2010	-1.88%
Sep, 1998	51.04%	Sep, 2002	1.95%	Sep, 2006	0.13%	Sep, 2010	-0.68%
Oct, 1998	67.24%	Oct, 2002	8.17%	Oct, 2006	0.89%	Oct, 2010	-0.61%
Nov, 1998	26.01%	Nov, 2002	8.66%	Nov, 2006	0.98%	Nov, 2010	0.65%
Dec, 1998	28.38%	Dec, 2002	-3.13%	Dec, 2006	-0.67%	Dec, 2010	3.47%
Jan, 1999	38.37%	Jan, 2003	-3.08%	Jan, 2007	-0.78%	Jan, 2011	3.39%
Feb, 1999	33.12%	Feb, 2003	-3.34%	Feb, 2007	1.60%	Feb, 2011	-0.04%
Mar, 1999	34.09%	Mar, 2003	1.53%	Mar, 2007	-1.87%	1998	421.50%
Apr, 1999	55.29%	Apr, 2003	7.78%	Apr, 2007	-2.42%	1999	388.22%
May, 1999	31.35%	May, 2003	6.86%	May, 2007	-1.55%	2000	535.55%
Jun, 1999	22.39%	Jun, 2003	9.65%	Jun, 2007	1.21%	2001	331.11%
Jul, 1999	19.40%	Jul, 2003	3.84%	Jul, 2007	4.11%	2002	50.62%
Aug, 1999	30.99%	Aug, 2003	5.84%	Aug, 2007	-4.99%	2003	48.11%
Sep, 1999	30.23%	Sep, 2003	6.82%	Sep, 2007	-1.87%	2004	8.39%
Oct, 1999	25.66%	Oct, 2003	0.70%	Oct, 2007	0.82%	2005	-11.54%
Nov, 1999	32.52%	Nov, 2003	4.85%	Nov, 2007	0.14%	2006	10.69%
Dec, 1999	34.83%	Dec, 2003	6.67%	Dec, 2007	-1.09%	2007	-6.69%
Jan, 2000	60.17%	Jan, 2004	6.62%	Jan, 2008	-6.74%	2008	-0.07%
Feb, 2000	37.98%	Feb, 2004	1.48%	Feb, 2008	-5.37%	2009	-7.83%
Mar, 2000	55.10%	Mar, 2004	-1.60%	Mar, 2008	-3.58%	2010	-4.35%
Apr, 2000	53.43%	Apr, 2004	2.96%	Apr, 2008	3.52%	2011	3.35%
May, 2000	33.50%	May, 2004	-1.82%	May, 2008	-3.00%	<b>Total</b>	<b>1767.06%</b>
Jun, 2000	25.22%	Jun, 2004	1.62%	Jun, 2008	-4.73%	<b>Average monthly:</b>	
Jul, 2000	34.79%	Jul, 2004	2.33%	Jul, 2008	8.30%		<b>11.18%</b>
Aug, 2000	26.78%	Aug, 2004	-2.14%	Aug, 2008	-0.12%	<b>Average yearly:</b>	
Sep, 2000	39.64%	Sep, 2004	-1.99%	Sep, 2008	-10.80%		<b>126.22%</b>
Oct, 2000	70.59%	Oct, 2004	-0.24%	Oct, 2008	7.10%		
Nov, 2000	44.36%	Nov, 2004	0.55%	Nov, 2008	14.42%		
Dec, 2000	53.98%	Dec, 2004	0.62%	Dec, 2008	0.94%		
Jan, 2001	53.69%	Jan, 2005	-2.73%	Jan, 2009	-2.58%		
Feb, 2001	49.10%	Feb, 2005	-0.65%	Feb, 2009	-2.29%		
Mar, 2001	58.14%	Mar, 2005	-1.97%	Mar, 2009	-0.83%		
Apr, 2001	45.00%	Apr, 2005	-1.39%	Apr, 2009	-0.19%		
May, 2001	15.23%	May, 2005	-2.82%	May, 2009	-1.73%		
Jun, 2001	23.60%	Jun, 2005	-0.04%	Jun, 2009	-7.17%		
Jul, 2001	14.21%	Jul, 2005	-2.17%	Jul, 2009	-0.70%		
Aug, 2001	6.74%	Aug, 2005	0.67%	Aug, 2009	-0.62%		
Sep, 2001	34.23%	Sep, 2005	0.50%	Sep, 2009	2.89%		
Oct, 2001	22.00%	Oct, 2005	-1.10%	Oct, 2009	4.87%		
Nov, 2001	3.75%	Nov, 2005	-0.77%	Nov, 2009	-3.33%		
Dec, 2001	5.42%	Dec, 2005	0.92%	Dec, 2009	3.84%		

**Appendix table 12: Monthly returns for active strategy with equally weighted portfolio: MART, 0.001**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	3.01%	Jan, 2002	-2.64%	Jan, 2006	-5.07%	Jan, 2010	-3.80%
Feb, 1998	1.05%	Feb, 2002	0.41%	Feb, 2006	-7.39%	Feb, 2010	-9.31%
Mar, 1998	3.04%	Mar, 2002	-5.79%	Mar, 2006	-4.94%	Mar, 2010	-10.84%
Apr, 1998	9.02%	Apr, 2002	-5.55%	Apr, 2006	-5.80%	Apr, 2010	-9.09%
May, 1998	4.56%	May, 2002	-3.26%	May, 2006	-7.52%	May, 2010	-7.09%
Jun, 1998	11.47%	Jun, 2002	2.50%	Jun, 2006	-2.17%	Jun, 2010	-5.96%
Jul, 1998	16.74%	Jul, 2002	-1.21%	Jul, 2006	-2.69%	Jul, 2010	-6.75%
Aug, 1998	36.40%	Aug, 2002	-17.97%	Aug, 2006	-5.49%	Aug, 2010	-9.82%
Sep, 1998	27.98%	Sep, 2002	-12.42%	Sep, 2006	-2.83%	Sep, 2010	-9.31%
Oct, 1998	42.24%	Oct, 2002	-5.53%	Oct, 2006	-7.25%	Oct, 2010	-9.71%
Nov, 1998	9.87%	Nov, 2002	-8.01%	Nov, 2006	-6.59%	Nov, 2010	-9.68%
Dec, 1998	12.51%	Dec, 2002	-14.13%	Dec, 2006	-5.51%	Dec, 2010	-7.06%
Jan, 1999	23.13%	Jan, 2003	-9.75%	Jan, 2007	-5.67%	Jan, 2011	-4.24%
Feb, 1999	17.70%	Feb, 2003	-8.78%	Feb, 2007	-4.77%	Feb, 2011	-6.99%
Mar, 1999	21.88%	Mar, 2003	-8.38%	Mar, 2007	-5.38%	1998	177.90%
Apr, 1999	36.82%	Apr, 2003	-5.22%	Apr, 2007	-6.14%	1999	245.25%
May, 1999	21.38%	May, 2003	-8.20%	May, 2007	-6.20%	2000	441.37%
Jun, 1999	11.77%	Jun, 2003	-3.04%	Jun, 2007	-1.31%	2001	209.52%
Jul, 1999	8.55%	Jul, 2003	-3.10%	Jul, 2007	-0.88%	2002	-73.60%
Aug, 1999	21.05%	Aug, 2003	-3.85%	Aug, 2007	-12.67%	2003	-63.73%
Sep, 1999	17.10%	Sep, 2003	-2.00%	Sep, 2007	-7.35%	2004	-69.11%
Oct, 1999	16.10%	Oct, 2003	-6.54%	Oct, 2007	-4.42%	2005	-68.82%
Nov, 1999	23.72%	Nov, 2003	-1.96%	Nov, 2007	-3.98%	2006	-63.25%
Dec, 1999	26.07%	Dec, 2003	-2.90%	Dec, 2007	-5.94%	2007	-64.72%
Jan, 2000	52.55%	Jan, 2004	-2.42%	Jan, 2008	-12.86%	2008	-75.80%
Feb, 2000	31.04%	Feb, 2004	-5.87%	Feb, 2008	-9.63%	2009	-144.20%
Mar, 2000	47.02%	Mar, 2004	-7.91%	Mar, 2008	-8.07%	2010	-98.42%
Apr, 2000	48.42%	Apr, 2004	-5.19%	Apr, 2008	-1.90%	2011	-11.23%
May, 2000	28.41%	May, 2004	-6.45%	May, 2008	-6.89%	<b>Total</b>	<b>341.18%</b>
Jun, 2000	17.40%	Jun, 2004	-3.00%	Jun, 2008	-9.51%	<b>Average monthly:</b>	
Jul, 2000	27.23%	Jul, 2004	-5.53%	Jul, 2008	2.06%		2.16%
Aug, 2000	17.75%	Aug, 2004	-6.00%	Aug, 2008	-5.46%	<b>Average yearly:</b>	
Sep, 2000	32.34%	Sep, 2004	-6.83%	Sep, 2008	-12.39%		24.37%
Oct, 2000	61.30%	Oct, 2004	-7.45%	Oct, 2008	-5.07%		
Nov, 2000	34.82%	Nov, 2004	-5.40%	Nov, 2008	3.39%		
Dec, 2000	43.09%	Dec, 2004	-7.06%	Dec, 2008	-9.47%		
Jan, 2001	43.46%	Jan, 2005	-7.33%	Jan, 2009	-14.20%		
Feb, 2001	40.64%	Feb, 2005	-4.85%	Feb, 2009	-11.97%		
Mar, 2001	45.08%	Mar, 2005	-9.15%	Mar, 2009	-26.02%		
Apr, 2001	37.10%	Apr, 2005	-5.67%	Apr, 2009	-10.71%		
May, 2001	6.18%	May, 2005	-8.08%	May, 2009	-12.17%		
Jun, 2001	14.23%	Jun, 2005	-5.11%	Jun, 2009	-16.53%		
Jul, 2001	4.18%	Jul, 2005	-5.30%	Jul, 2009	-10.43%		
Aug, 2001	-5.09%	Aug, 2005	-4.61%	Aug, 2009	-9.64%		
Sep, 2001	20.18%	Sep, 2005	-4.30%	Sep, 2009	-5.59%		
Oct, 2001	8.49%	Oct, 2005	-5.07%	Oct, 2009	-7.41%		
Nov, 2001	-2.22%	Nov, 2005	-5.76%	Nov, 2009	-9.06%		
Dec, 2001	-2.72%	Dec, 2005	-3.58%	Dec, 2009	-10.48%		

**Appendix table 13: Monthly returns for active strategy with equally weighted portfolio: MART, 0.0035**

Period	Returns	Period	Returns	Period	Returns	Period	Returns
Jan, 1998	-27.43%	Jan, 2002	-5.53%	Jan, 2006	-10.93%	Jan, 2010	-14.17%
Feb, 1998	-17.89%	Feb, 2002	-10.13%	Feb, 2006	-15.72%	Feb, 2010	-23.83%
Mar, 1998	-22.71%	Mar, 2002	-16.15%	Mar, 2006	-12.56%	Mar, 2010	-27.04%
Apr, 1998	-16.43%	Apr, 2002	-15.33%	Apr, 2006	-12.37%	Apr, 2010	-17.35%
May, 1998	-16.38%	May, 2002	-14.68%	May, 2006	-16.67%	May, 2010	-17.44%
Jun, 1998	-13.24%	Jun, 2002	-7.41%	Jun, 2006	-11.04%	Jun, 2010	-19.11%
Jul, 1998	-4.37%	Jul, 2002	-14.51%	Jul, 2006	-11.66%	Jul, 2010	-16.86%
Aug, 1998	-3.39%	Aug, 2002	-26.09%	Aug, 2006	-14.02%	Aug, 2010	-27.06%
Sep, 1998	-9.72%	Sep, 2002	-23.07%	Sep, 2006	-9.71%	Sep, 2010	-26.65%
Oct, 1998	9.74%	Oct, 2002	-23.49%	Oct, 2006	-17.42%	Oct, 2010	-21.39%
Nov, 1998	-9.78%	Nov, 2002	-20.31%	Nov, 2006	-13.49%	Nov, 2010	-26.36%
Dec, 1998	-8.91%	Dec, 2002	-24.01%	Dec, 2006	-12.73%	Dec, 2010	-18.71%
Jan, 1999	4.90%	Jan, 2003	-21.96%	Jan, 2007	-12.44%	Jan, 2011	-13.42%
Feb, 1999	2.57%	Feb, 2003	-16.73%	Feb, 2007	-11.76%	Feb, 2011	-16.13%
Mar, 1999	-4.45%	Mar, 2003	-18.36%	Mar, 2007	-11.80%	1998	-140.53%
Apr, 1999	13.39%	Apr, 2003	-18.33%	Apr, 2007	-12.81%	1999	34.19%
May, 1999	1.90%	May, 2003	-18.99%	May, 2007	-13.99%	2000	242.34%
Jun, 1999	-1.31%	Jun, 2003	-15.74%	Jun, 2007	-8.42%	2001	6.31%
Jul, 1999	-6.20%	Jul, 2003	-13.35%	Jul, 2007	-7.21%	2002	-200.72%
Aug, 1999	7.13%	Aug, 2003	-14.07%	Aug, 2007	-20.85%	2003	-179.62%
Sep, 1999	0.60%	Sep, 2003	-9.79%	Sep, 2007	-15.36%	2004	-151.43%
Oct, 1999	-1.03%	Oct, 2003	-13.36%	Oct, 2007	-10.37%	2005	-160.70%
Nov, 1999	7.54%	Nov, 2003	-7.51%	Nov, 2007	-11.39%	2006	-158.30%
Dec, 1999	9.15%	Dec, 2003	-11.43%	Dec, 2007	-13.46%	2007	-149.84%
Jan, 2000	36.51%	Jan, 2004	-7.17%	Jan, 2008	-25.70%	2008	-200.98%
Feb, 2000	17.47%	Feb, 2004	-11.69%	Feb, 2008	-13.95%	2009	-376.98%
Mar, 2000	30.00%	Mar, 2004	-14.04%	Mar, 2008	-15.83%	2010	-255.98%
Apr, 2000	35.83%	Apr, 2004	-12.08%	Apr, 2008	-11.21%	2011	-29.55%
May, 2000	13.08%	May, 2004	-13.60%	May, 2008	-13.26%	<b>Total</b>	<b>-1721.79%</b>
Jun, 2000	1.44%	Jun, 2004	-9.28%	Jun, 2008	-16.81%	<b>Average monthly:</b>	
Jul, 2000	10.40%	Jul, 2004	-12.36%	Jul, 2008	-8.74%		<b>-10.90%</b>
Aug, 2000	2.55%	Aug, 2004	-14.83%	Aug, 2008	-12.68%	<b>Average yearly:</b>	
Sep, 2000	15.91%	Sep, 2004	-16.10%	Sep, 2008	-23.13%		<b>-122.99%</b>
Oct, 2000	41.63%	Oct, 2004	-13.74%	Oct, 2008	-19.25%		
Nov, 2000	15.46%	Nov, 2004	-13.46%	Nov, 2008	-14.58%		
Dec, 2000	22.07%	Dec, 2004	-13.08%	Dec, 2008	-25.82%		
Jan, 2001	22.43%	Jan, 2005	-14.87%	Jan, 2009	-30.27%		
Feb, 2001	21.47%	Feb, 2005	-13.03%	Feb, 2009	-29.39%		
Mar, 2001	18.79%	Mar, 2005	-15.99%	Mar, 2009	-78.36%		
Apr, 2001	10.90%	Apr, 2005	-12.19%	Apr, 2009	-37.76%		
May, 2001	-8.70%	May, 2005	-15.74%	May, 2009	-24.92%		
Jun, 2001	-5.09%	Jun, 2005	-13.38%	Jun, 2009	-31.36%		
Jul, 2001	-10.82%	Jul, 2005	-12.18%	Jul, 2009	-27.21%		
Aug, 2001	-15.05%	Aug, 2005	-13.33%	Aug, 2009	-22.99%		
Sep, 2001	1.07%	Sep, 2005	-12.92%	Sep, 2009	-18.78%		
Oct, 2001	-8.04%	Oct, 2005	-12.51%	Oct, 2009	-21.92%		
Nov, 2001	-10.40%	Nov, 2005	-13.35%	Nov, 2009	-24.98%		
Dec, 2001	-10.25%	Dec, 2005	-11.22%	Dec, 2009	-29.03%		



Appendix table 15: Regression model coefficients for strategy returns and standard deviation

	AAPL		BAC		CSCO		C		DELL		EMC	
	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2
<b>MA, zero</b>	-0.0044 (0.0008)	5.0624 (0.4765)	-0.0011 (0.0005)	2.7571 (0.3834)	-0.0059 (0.0007)	8.2132 (0.5639)	-0.0054 (0.0005)	6.382 (0.3200)	-0.0078 (0.0007)	9.2295 (0.5569)	-0.0044 (0.0008)	5.9313 (0.5416)
<b>MA, 0.001</b>	0 (0.0008)	1.4191 (0.4834)	-0.0019 (0.0005)	3.0733 (0.3737)	-0.0059 (0.0007)	7.282 (0.5611)	-0.0043 (0.0005)	4.1883 (0.3205)	-0.0078 (0.0007)	8.4553 (0.5598)	-0.0047 (0.0008)	5.3314 (0.5338)
<b>MA, 0.0035</b>	0 (0.0007)	0.6259 (0.4711)	-0.003 (0.0005)	3.367 (0.3705)	-0.006 (0.0007)	5.7981 (0.5506)	-0.0033 (0.0005)	2.1344 (0.3257)	-0.0083 (0.0007)	7.7889 (0.5556)	-0.0054 (0.0008)	4.1786 (0.5181)
<b>DBR, zero</b>	-0.0014 (0.0008)	2.2944 (0.4819)	0.0016 (0.0005)	0.035 (0.3952)	-0.0066 (0.0007)	9.559 (0.5883)	-0.0032 (0.0005)	3.5487 (0.3307)	-0.0083 (0.0008)	10.1071 (0.5924)	-0.0053 (0.0009)	6.8331 (0.5775)
<b>DBR, 0.001</b>	-0.0013 (0.0008)	1.9369 (0.4787)	0.0007 (0.0005)	0.8398 (0.3939)	-0.0064 (0.0007)	8.677 (0.5843)	-0.0033 (0.0005)	3.2887 (0.3281)	-0.0075 (0.0008)	8.9119 (0.5838)	-0.0059 (0.0009)	6.4778 (0.5709)
<b>DBR, 0.0035</b>	-0.001 (0.0007)	1.4055 (0.4707)	0.0005 (0.0005)	0.454 (0.3942)	-0.0066 (0.0007)	7.6664 (0.5766)	-0.0026 (0.0005)	2.0344 (0.3364)	-0.0075 (0.0008)	7.6563 (0.5695)	-0.0054 (0.0008)	4.9316 (0.5442)
<b>MAR, zero</b>	-0.0099 (0.0010)	11.2852 (0.6007)	-0.0011 (0.0006)	6.5717 (0.4407)	-0.0188 (0.0010)	27.7168 (0.7863)	-0.0021 (0.0007)	4.2778 (0.4049)	-0.0175 (0.0010)	23.8906 (0.7567)	-0.0144 (0.0011)	19.7637 (0.7143)
<b>MAR, 0.001</b>	-0.0059 (0.0009)	5.0029 (0.5780)	-0.002 (0.0006)	4.6378 (0.4338)	-0.0214 (0.0010)	25.3431 (0.7626)	-0.0033 (0.0007)	0.7767 (0.4062)	-0.0191 (0.0010)	21.2212 (0.7370)	-0.0157 (0.0011)	14.0353 (0.6995)
<b>MAR, 0.0035</b>	-0.0028 (0.0009)	-0.6063 (0.5460)	-0.0044 (0.0006)	2.7092 (0.4286)	-0.0212 (0.0009)	18.353 (0.7469)	0.0034 (0.0013)	-13.7276 (0.8277)	-0.018 (0.0009)	13.8356 (0.7060)	-0.0154 (0.0010)	7.2378 (0.6569)
<b>MART, zero</b>	-0.0081 (0.0009)	8.6083 (0.5528)	-0.0008 (0.0005)	4.4241 (0.4046)	-0.0181 (0.0009)	24.7404 (0.7041)	-0.0037 (0.0006)	4.5963 (0.3442)	-0.0159 (0.0009)	20.772 (0.6899)	-0.0109 (0.0010)	14.0144 (0.6444)
<b>MART, 0.001</b>	-0.0074 (0.0009)	5.6056 (0.5391)	-0.0014 (0.0005)	2.7821 (0.4036)	-0.0193 (0.0009)	21.9407 (0.7092)	-0.0029 (0.0006)	-0.0853 (0.3805)	-0.0179 (0.0009)	19.2269 (0.6807)	-0.0132 (0.0010)	10.9849 (0.6323)
<b>MART, 0.0035</b>	-0.003 (0.0008)	-0.5603 (0.5160)	-0.0044 (0.0006)	2.3141 (0.4292)	-0.0189 (0.0009)	15.7909 (0.7229)	0.0019 (0.0012)	-12.1092 (0.7244)	-0.0181 (0.0009)	13.6511 (0.6718)	-0.0147 (0.0010)	6.2383 (0.6325)

Standard errors are provided in brackets

Appendix table 15: Regression model coefficients for strategy returns and standard deviation

	F		GE		INTC		JPM		MSFT		ORCL	
	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2
<b>MA, zero</b>	-0.0019 (0.0007)	3.7231 (0.4003)	-0.0004 (0.0005)	0.4202 (0.4396)	-0.0022 (0.0007)	4.751 (0.6075)	0.0005 (0.0006)	0.9365 (0.4622)	-0.0027 (0.0006)	5.2631 (0.6056)	-0.0058 (0.0007)	6.261 (0.5038)
<b>MA, 0.001</b>	-0.0003 (0.0006)	1.2321 (0.3840)	0.0005 (0.0005)	-1.5578 (0.4435)	-0.0023 (0.0007)	3.9109 (0.5963)	0.0001 (0.0006)	0.7831 (0.4570)	-0.003 (0.0006)	4.4998 (0.6019)	-0.0058 (0.0007)	5.1933 (0.4948)
<b>MA, 0.0035</b>	-0.0027 (0.0006)	1.0836 (0.3740)	-0.0001 (0.0005)	-1.7708 (0.4420)	-0.0023 (0.0007)	2.3277 (0.5806)	-0.0006 (0.0006)	0.1891 (0.4577)	-0.0029 (0.0006)	2.76 (0.5905)	-0.0053 (0.0007)	3.1836 (0.4997)
<b>DBR, zero</b>	-0.0003 (0.0007)	2.4891 (0.4068)	0.0002 (0.0005)	-0.6426 (0.4769)	-0.0059 (0.0008)	9.403 (0.6516)	0.0006 (0.0006)	-0.2965 (0.4480)	-0.005 (0.0006)	8.3873 (0.6617)	-0.0095 (0.0008)	10.1217 (0.5484)
<b>DBR, 0.001</b>	0.0001 (0.0007)	1.2807 (0.3986)	-0.0001 (0.0005)	-0.9267 (0.4659)	-0.0059 (0.0008)	8.7205 (0.6433)	0.0004 (0.0006)	-0.3213 (0.4457)	-0.0046 (0.0006)	7.2249 (0.6535)	-0.0086 (0.0008)	8.7485 (0.5430)
<b>DBR, 0.0035</b>	0.0004 (0.0006)	-0.2915 (0.3840)	0.0004 (0.0005)	-1.9737 (0.4538)	-0.0054 (0.0008)	6.8555 (0.6370)	-0.0001 (0.0006)	-0.3265 (0.4469)	-0.0043 (0.0006)	5.5603 (0.6301)	-0.0069 (0.0008)	5.7902 (0.5350)
<b>MAR, zero</b>	-0.0004 (0.0008)	7.2548 (0.4920)	0.0012 (0.0006)	2.789 (0.6217)	-0.0161 (0.0010)	23.833 (0.8110)	-0.0003 (0.0007)	1.864 (0.5156)	-0.0137 (0.0008)	24.5754 (0.8369)	-0.0207 (0.0011)	24.4942 (0.7408)
<b>MAR, 0.001</b>	-0.0011 (0.0008)	-0.1675 (0.4700)	-0.0023 (0.0006)	1.9045 (0.5716)	-0.0177 (0.0009)	22.226 (0.7866)	-0.002 (0.0006)	1.2191 (0.4913)	-0.0142 (0.0008)	20.495 (0.8120)	-0.0206 (0.0011)	17.83 (0.7324)
<b>MAR, 0.0035</b>	-0.0021 (0.0009)	-7.4711 (0.5503)	-0.0036 (0.0006)	-1.6453 (0.5340)	-0.0178 (0.0009)	16.0562 (0.7442)	-0.0038 (0.0006)	0.2157 (0.4757)	-0.0135 (0.0007)	12.5532 (0.7629)	-0.0204 (0.0012)	10.4302 (0.7983)
<b>MART, zero</b>	0.0001 (0.0007)	4.7824 (0.4367)	0.0008 (0.0005)	0.9514 (0.5226)	-0.0137 (0.0009)	19.8556 (0.7231)	-0.0005 (0.0006)	1.1043 (0.4642)	-0.0112 (0.0007)	19.0114 (0.7645)	-0.018 (0.0010)	20.3129 (0.6907)
<b>MART, 0.001</b>	0.0001 (0.0007)	-1.7055 (0.4372)	-0.0006 (0.0005)	-1.1188 (0.5144)	-0.0146 (0.0009)	17.7178 (0.7148)	-0.0021 (0.0006)	0.9192 (0.4622)	-0.0124 (0.0007)	16.9034 (0.7463)	-0.0184 (0.0010)	15.1532 (0.6973)
<b>MART, 0.0035</b>	0.0007 (0.0009)	-10.4304 (0.5671)	-0.0025 (0.0005)	-3.6513 (0.5117)	-0.0152 (0.0008)	12.6071 (0.7021)	-0.0046 (0.0006)	0.8689 (0.4602)	-0.0136 (0.0007)	12.5072 (0.7127)	-0.0185 (0.0012)	8.2748 (0.7789)

Standard errors are provided in brackets

Appendix table 15: Regression model coefficients for strategy returns and standard deviation

	PFE		QCOM		TXN	
	c1	c2	c1	c2	c1	c2
<b>MA, zero</b>	-0.0014 (0.0005)	2.0381 (0.5299)	-0.004 (0.0008)	3.9404 (0.4818)	-0.003 (0.0008)	3.965 (0.5728)
<b>MA, 0.001</b>	-0.0018 (0.0005)	1.8186 (0.5217)	-0.0037 (0.0007)	3.1085 (0.4679)	-0.0038 (0.0008)	3.9765 (0.5770)
<b>MA, 0.0035</b>	-0.0023 (0.0005)	1.5987 (0.5185)	-0.0041 (0.0007)	2.3666 (0.4713)	-0.0041 (0.0008)	3.1661 (0.5647)
<b>DBR, zero</b>	-0.0014 (0.0005)	2.1387 (0.5360)	-0.0059 (0.0008)	5.2726 (0.5092)	-0.0053 (0.0009)	6.3719 (0.6209)
<b>DBR, 0.001</b>	-0.0017 (0.0005)	2.1396 (0.5321)	-0.0052 (0.0008)	4.1151 (0.5019)	-0.0056 (0.0009)	5.8915 (0.6156)
<b>DBR, 0.0035</b>	-0.0021 (0.0005)	1.9375 (0.5295)	-0.0036 (0.0008)	2.0701 (0.4833)	-0.0056 (0.0008)	4.8527 (0.5993)
<b>MAR, zero</b>	-0.0065 (0.0007)	11.1115 (0.6831)	-0.0192 (0.0010)	19.7666 (0.6432)	-0.014 (0.0011)	18.4492 (0.7698)
<b>MAR, 0.001</b>	-0.0071 (0.0006)	7.6414 (0.6333)	-0.0173 (0.0010)	14.156 (0.6584)	-0.0164 (0.0010)	16.3722 (0.7348)
<b>MAR, 0.0035</b>	-0.0072 (0.0006)	2.3353 (0.5934)	-0.013 (0.0011)	5.2955 (0.7141)	-0.015 (0.0010)	10.0241 (0.6775)
<b>MART, zero</b>	-0.0045 (0.0006)	6.5614 (0.5783)	-0.0128 (0.0009)	12.5652 (0.5696)	-0.0101 (0.0010)	12.6608 (0.6840)
<b>MART, 0.001</b>	-0.0056 (0.0005)	4.7216 (0.5536)	-0.0118 (0.0009)	8.3737 (0.5772)	-0.0127 (0.0009)	11.5857 (0.6715)
<b>MART, 0.0035</b>	-0.0079 (0.0006)	2.9751 (0.5786)	-0.0105 (0.0010)	2.9137 (0.6286)	-0.0134 (0.0009)	7.9916 (0.6477)

Standard errors are provided in brackets

**Appendix table 16: Regression model coefficients for passive returns and standard deviation**

<b>AAPL</b>		<b>BAC</b>		<b>CSCO</b>		<b>C</b>		<b>DELL</b>		<b>EMC</b>	
c1	c2	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2
0.0001	0.2692	0.002	-2.4685	0.0011	-1.6379	0.0051	-5.9323	-0.0002	0.5065	0.0003	0.2239
(0.0010)	(0.6203)	(0.0007)	(0.5395)	(0.0009)	(0.7454)	(0.0008)	(0.4739)	(0.0009)	(0.6995)	(0.0011)	(0.7224)
<b>F</b>		<b>GE</b>		<b>INTC</b>		<b>JPM</b>		<b>MSFT</b>		<b>ORCL</b>	
c1	c2	c1	c2	c1	c2	c1	c2	c1	c2	c1	c2
0.0026	-3.3435	0.0007	-1.1646	0.0005	-0.8558	-0.0012	1.1916	0.0005	-0.6823	0.0011	-0.886
(0.0008)	(0.5057)	(0.0006)	(0.5816)	(0.0009)	(0.7811)	(0.0008)	(0.6141)	(0.0007)	(0.7665)	(0.0010)	(0.6847)
<b>PFE</b>		<b>QCOM</b>		<b>TXN</b>							
c1	c2	c1	c2	c1	c2						
-0.001	0.7054	0.0013	-0.48	-0.0014	1.101						
(0.0007)	(0.7032)	(0.0010)	(0.6373)	(0.0010)	(0.7384)						

Standard errors are provided in brackets