Estimation of performance and execution time effect on high frequency statistical arbitrage strategies

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Abstract

This research is designed to help quantify one of the "slippages" which are often recognized in quant strategies. The idea is that whenever the actual executed prices are away (both time and size) from the model prices, the realized returns will suffer. The slippage for a particular statistical arbitrage strategy is quantified. It is shown that portion of the loss is due to using different prices for estimating the parameters of the strategy. The main source of the loss is the use of intraday in place of market on close prices. Five years of intraday transaction data from NYSE TAQ database are used. Analysis shows that on average the daily loss due to intraday prices accounts for 0.03% of the initial capital. For the period 2003 - 2006 the accumulated loss is approximately 30%. The described approach can be of use to new quantitative analysts who create and backtest trading strategies. It could also be used during the due diligence process of a fund that is interested in investing in a statistical arbitrage strategy. The recommendation from this research is to require a backtest done by using intraday and market on close prices in order to identify the size of such loss.

During the last 10 years the number of hedge funds has reached the total number of over 8,000, representing more than $1.1 trillion in net assets. Many of them hire scientists who have training in mathematics, physics, or statistics, to name a few quantitative areas of interest. Other potential employers are the program trading desks at the main brokerage firms and the research/risk groups of major investment banks.

When a quant joins the trading team in one of the above institutions one of the tasks he might be asked to do is to create a profitable trading strategy. This process involves several steps. First a compelling idea must be presented. The idea should be financially sound, i.e. it must make sense from the financial markets point of view. The expectation is that very few people are currently using it for active trading or asset allocation. This idea in general will come from published academic research, for instance if it identifies a market anomaly that could lead to an arbitrage opportunity. The research will have a collection of tests all statistically significant to support the arbitrage hypothesis and (usually) this evidence is derived in a static setup.

The next step is to show the performance of this strategy over time. The backtest usually covers several years and market regimes like recessions, market crashes, bear and bull markets. The backtest is dynamic in nature and involves many assumptions and parameters' decisions that were not part of the original research. For instance, a publication can show evidence for market’s inefficiency by using 20 years of monthly data. The backtest is like a sliding window crawling over these 20 years that executes the theoretical model and shows the strategy performance as if it was traded in the past. Questions like, how big the window size should be, are usually not answered in the original academic paper and very often questions as simple as this one can make or break the strategy's performance. Trying to be consistent with the financial theoretical concept and in the same time not getting trapped in a data mining exercise could be a very challenging task.

Assume that the backtest confirms that the strategy would have been profitable. The next step is to show that there is still evidence that the same anomaly continues in the future. A trading platform is then created and the *paper trading* of the strategy is initiated. The paper trading process helps to clear up programming glitches that always exist in any computer implementation as well as add more relevant performance information that may lead to the adjustment of some of the parameters. As part of this process one can estimate what is the difference in the performance of the strategy if the prices used for estimating the parameters of the model are not the closing prices but some “snapshot intraday” prices taken before the closing. Additionally, question like what will be the impact of the difference between execute on close vs. market order can be addressed as well.

The objective of this research is to walk the reader through some of the steps of creating a trading strategy. The main goal is to identify some important implementation issues associated with using different prices, in particular intraday vs. market on close. Our results show numerical evidence for one of the "slippages" which are often and well recognized in the quant strategies. The idea is that whenever the actual executed prices are away (both time and size) from the model prices, the realized returns will suffer. We were able to quantify this slippage for a particular strategy. Our results may not be directly applicable for other statistical arbitrage strategies. The value of the estimated “slippage” may depend on how much "mean-reversion” the strategy tries to capture; the liquidity of the individual stock, or whether the stock is short-able. However, we believe that the suggested approach can be of use to new quants who enter the field of creating and backtesting statistical arbitrage strategies.

What follows is a description of an imaginable path taken by a quant on Wall Street that leads to a numerical estimation of the possible problem that could arise in implementing and trading statistical arbitrage strategies.

Suppose that a new quant is given the task to design a strategy that switches between momentum and contrarian positions by using daily stock prices. The main idea behind his task is rooted in the very well known empirical fact that there is a negative serial autocorrelation for individual stock returns and positive cross-autocorrelations across securities. These phenomena have been researched from a market microstructure point of view as well as from an equilibrium point of view where investors have different access and ability to analyze information. The goal of the quant is not to confirm or reject the validity of any of the published research.

If one wants to design a trading strategy based on serial autocorrelation, it is clear that the random walk hypothesis will not be valid. Lo and MacKinlay [1988] test the random walk hypothesis for weekly stock market returns by comparing variance estimators derived from data sampled at different frequencies. If the stock returns follow a random walk than the variance should grow with the square root of time. They reject the random walk hypothesis and show that the rejection is due largely to the behavior of small stocks. Additionally they show that the autocorrelations of individual securities are generally negative and the autocorrelations for equally weighted CRSP index are positive.

Search into the serial autocorrelation literature leads to a large set of publications. Brown and Jennings [1989] show that technical analysis, or use of past prices to infer private information, has value in a model in which prices are not fully revealing and traders have rational conjectures about the relation between prices and signals. Lo and MacKinlay [1990] show how to use a contrarian strategy by selling winners and buying losers and produce positive expected returns. Studies by Fama and French [1988] and Lo and MacKinlay [1988] suggest that there may exist significant serial correlation in stock returns. Jegadeesh and Titman [1995] explain the short-term negative serial covariances for stock returns from a market microstructure point of view. Conrad and Kaul [1998] analyze a wide range of trading strategies in the 1926-1989 period. They show that momentum and contrarian strategies are equally likely to be successful.

Campbell, Grossman and Wang [1993] analyze the relationship between trading volume and the serial correlation of daily stock returns. They found that the first order daily return autocorrelation tends to decline with volume. The paper explains this phenomenon by using a model in which risk – averse "market makers" accommodate buying or selling pressure from "liquidity" or "noninformational" traders. Authors test a variety of regression models by using lagged serial correlation, volume and different measures of volatility to explain daily stock returns. Having two types of traders – informed and uninformed - and how their trades influence prices – is a very compelling story that can be used to attract potential investors in statistical arbitrage fund since one of investors' biggest fears is the concept of a "black box". Being able to explain how the trades are made without giving the actual details could be a big advantage in attracting potential investors. Suppose that the quant settles on that concept and decides to use the simplest version of the Campbell, Grossman and Wang [1993] model presented in Table I of their paper. Note that the above model is just a starting point for building the strategy.

Transforming a Theoretical Idea into a Dynamic Trading Strategy

In this paper the universe of stocks comprising S&P 500 index is used to create and test a strategy, in particular its composition as of January 2007. Ideally, one would like to backtest a strategy by using a universe of stocks that is relevant for a particular point in time. For example, starting from January 1995 one can move forward by selecting stocks from a universe that dynamically changes as stocks get included or excluded from the S&P 500 index. Such an approach is not taken here; as a result there may be a potential survivorship bias introduced into the analysis.

For every stock in the selected universe the daily closing prices from 1995 – 2007 were obtained. Zero stock prices is substituted for the stocks that did not have prices back to 1995. Starting from January 1995, a 252 day (trading days) sliding window for parameter computation is used. This leads to an estimate of the performance of the strategy from January 1, 1996 to December 31 2007, a total of 3,020 trading days. On a daily basis, the past 252 days historical prices are used to estimate the parameters of the model and produce daily trading signals.

The proposed strategy generates 5 different trading signals:

- Momentum Long - Appreciating stocks that are expected to continue to appreciate.
- Contrarian Short - Appreciating stocks that are expected to mean-revert.
- Momentum Short - Declining stocks that are expected to continue to depreciate.
- Contrarian Long - Declining stocks that are expected to mean-revert.
- No Trade - Stocks with weak signals or too much noise to identify.

Denote by P_i^j the closing price for stock j on day i, for $i = 1, \cdots, 252$ and $j = 1, \cdots, 500$j=1. The daily stock returns are denoted by R_i^j, where $R_i^j = \frac{P_i^j - P_{i-1}^j}{P_{i-1}^j}$ for $i = 2, \ldots, 252$. Let's denote by Y_i^j the one day ahead stock return, i.e. $Y_i^j = R_{i+1}^j$.

The following regression model is used to obtain estimates for the parameters needed to design the trading strategy that is used for illustration in this paper (this is the first model tested by Campbell, Grossman and Wang [1993]):

$$Y_i^j = c_0 + c_1 R_i^j + \varepsilon^j, \text{ for } i = 2, \ldots, 252, \text{ and j = 1, …500} \quad (1)$$

Where c_0 and c_1 are the regression coefficients and ε^j ej is Normally distributed with mean 0 and standard deviation sigma. The coefficient c_1 corresponds to the autocorrelation of stock returns. Assume that the strategy will create a trading signal only if the estimator of the coefficient c_1, $\hat{c}_1$, is statistically significant. Denote the t-statistics for $\hat{c}_1$ by t_{c_1}. Therefore the trading signals will be generated based on the following rules, call this strategy Momentum-Contrarian-Switch (MCS):

If $|t_{c_1}| > 1.65$ (1.65 represents significance at 95%)

1. If $\hat{c}_1 > 0$ than the trading direction is momentum

a. If $R_i^j > 0$ the stock trading signal is momentum long. The generated trading signal is Buy. (if the daily stock return is positive this is a stock that is expected to continue to appreciate in value)

b. If $R_i^j < 0$ the stock trading signal is contrarian short. The generated trading signal is Sell. (if the daily stock return is negative this is a stock that is expected to revert in value)

2. If $\hat{c}_1 < 0$ than the trading direction is contrarian

a. If $R_i^j > 0$ the stock trading signal is momentum short. The generated trading signal is Sell. (if the daily stock return is positive this is a stock that is expected to continue to depreciate in value)

b. If $R_i^j < 0$ the stock trading signal is contrarian long. The generated trading signal is Buy. (if the daily stock return is negative this is a stock that is expected to revert in value)

If $\left|t_{c_1}\right| \leq 1.65$ there is no trading signal generated.

Empirical Backtest Using Equally Weighted Portfolios

Given the rules for generating buy or sell signals the historical price information is used to backtest the strategy. To backtest a strategy usually means to start at some date in the past and pretend to generate trades based on the chosen rules. Since the whole history is available, one can evaluate how well the strategy would have performed in the past. In practice, one of the most frequently looked and analyzed performance tools are the plot of the historical P&L (Profit & Loss), risk/return ratios and several valuation measures: Sharpe ratio, Sortino ratio, maximum gain, loss, longest losing streak, etc.

While backtesting the strategy, one of the main objectives is to identify parameters that may have a potential big influence on its performance.

The MCS strategy generates trading signals on a daily basis. To evaluate its performance, an equally weighted portfolio is constructed from the chosen stocks. The initial capital is $10M and there is no additional leverage. This means that $10M is used to purchase stocks and $10M was received from selling short. As a result, the portfolio is dollar neutral. The strategy opens and closes the positions on a daily basis. Such frequent rebalancing will overestimate the trading costs but will produce a conservative estimate of strategy’s performance. The number of shares purchased or sold short is always in round lots of 100 shares. The extra cash left due to the use of round lots is kept as cash and there is no interest accumulated on it. The transaction cost used is 2 cents per share each way. Two cents per share is a conservative estimate regarding transaction costs. For example (from personal trading experience) a top Wall Street brokerage house has given the following costs to execute trades produced by a real statistical arbitrage daily trading strategy: commission of 25 mills (1 mil = 1/10 cent) per share; $5 ticket charge and SEC fee charged on the sell trades computed by SEC fee = Traded Shares ×Executed Price ×46.8/1,000,000.

Exhibit 1 shows the actual average execution cost per share for 36 days of real execution of a proprietary statistical arbitrage trading strategy.

Insert Exhibit 1 here

Based on 36 days real execution of the strategy, the average transaction cost per share (commission, ticket charge and SEC fee if applicable) was 90 mills. Since this is a very small sample, to be on the conservative side 2 cents per share will be used in all of the backtest presented in this paper. (Note that such costs are possible since the decimalization that occurred in 2000. The costs were much higher in earlier periods and the backtest results in the time period before year 2000 will be optimistic and should be interpreted very cautiously.)

Exhibit 2 shows statistical information regarding the number of trading signals generated by the strategy.

Insert Exhibit 2 here.

On average, there are 50 long and 50 short signals generated on a daily basis. The number of signals can vary significantly during the covered period. For example, the maximum number of signals is 183 long and 193 short.

Exhibit 3 shows the actual annual returns of the strategy and the S&P 500 index for the time period 1996-2007.

Insert Exhibit 3 here

Exhibit 4 shows a comparison between different performance measures of the MCS strategy and S&P500. The Sharpe Ratio computed at risk free rate of 5% is 0.11 for S& 500 and 1.02 for the MCS strategy. The Sortino Ratio computed at 5% risk free rate is 0.15 for S&P500 and 5.12 for the MCS strategy. The Highest Monthly Return for S&P500 is 8.97% and 25.39% for the MCS strategy. The Lowest Monthly Return is -15.46% for SP 500 and -4.22% for the MCS strategy. The Skewness is -0.12 and 1.15, kurtosis is 3.14 and 6.09 respectively for S&P500 and the MCS strategy.

Insert Exhibit 4 here

Exhibit 5 shows the profit and loss (P&L) plot of the MCS strategy compared with the S&P 500 index.

Insert Exhibit 5 here

Estimate on Intraday "Snapshot" Price and Execute on Close

The presented backtest used closing prices on a particular day to produce the trading signals and assumed that a trade execution can be performed at the same price. In practice such an execution is impossible to achieve. In this section a more realistic estimation and trading procedures are performed. The parameters of the model are estimated at a snapshot of the intraday prices and the actual execution occurs on closing.

For this test, 5 years of intraday data for the period 2002-2006 from the NYSE TAQ database are used. The Trade and Quote (TAQ) database contains intraday transactions data (trades and quotes) for all securities listed on the New York Stock Exchange and American Stock Exchange, as well as Nasdaq National Market System and SmallCap issues. The 5 year TAQ database occupies approximately 2 TB (1Tera Byte = 1000GB) of space. For every day and every stock in the sample, all recorded trades for a 5 min interval from 3.30pm to 3.35pm are extracted. The first observed price in this 5 min interval is used for the daily estimation of the model. For most of the stocks, there is a price recorded at 3.30. For less liquid stocks, the first price after 3.30 is used. If there is no recorded price for the time interval from 3.30pm to 3.35pm, the stock is not included in the analysis for that day. This happens rarely for some stocks for trading days around major holidays.

The above described data gathering process produced daily stock prices that were used to estimate the model in equation (1) and to produce the daily trading signals by the MCS strategy. Given the size of the estimation window - 252 trading days - the daily parameter estimates for the period January 2003 – December 2006 total to 1,005 trading days.

Exhibit 6 shows a comparison between the numbers of signals produced when using closing prices vs. intraday prices.

Insert Exhibit 6 here.

Based on the statistics of the number of generated signals, it appears that using intraday data does not affect the process of signal generation. For example, the average, median, min and max number of daily long signals produced by using closing prices is 50, 42, 12 and 183. The corresponding numbers when intraday prices are used are 51, 43, 14 and 183.

The next objective is to identify if there is any loss or gain when intraday data is used to estimate the parameters of the model presented in equation (1). To do this two sequences of daily P&L are computed. The first one uses closing prices to estimate the parameters and executes the trades at the same closing prices. This is a repeat of the procedure described in the previous section but this time over the period of time 2003 - 2006. The second time series of daily P&L is obtained by using the intraday prices to obtain estimates of the parameters of the model but the actual execution is done on closing prices. In terms of time difference between estimation and execution, on average it is about 25 minutes. If one wants to implement and trade such a strategy having 20-25 minutes to run the models and obtain the list of trades is a reasonable assumption. Of course, keep in mind that on a daily basis during the 20-25 munities time interval one needs to run only one set of parameter estimates. This task is achievable given the modern computer speed.

Insert Exhibit 7 here.

Exhibit 7 shows the performance of the two scenarios. One dollar invested under the first scenario (estimate on close, execute on close) grows to $1.65 and to $1.34 under the second scenario (estimate on intraday, execute on close). Translating this numbers with an initial capital of $10M, the average daily loss due to intraday estimation is about $3,024 or 0.03% of the initial capital. The accumulated loss for the time interval January 2003-December 2006 is approximately 30%.

The presented numerical results show that backtests should be interpreted very carefully. It is advisable that investment funds with major business into "seeding" new hedge funds require similar intraday analysis for statistical arbitrage and in general for high frequency trading strategies. It is possible that a great performance is reduced to mediocre depending on how the estimation is done and what prices are used to illustrate the strategy.

Conclusion

This article presents the effect of using intraday vs. market on close prices when backtesting a statistical arbitrage strategy. Depending on the stock prices used, a statistical arbitrage strategy may lose some of its potential return shown in a backtest based on market on close prices only. In the presented strategy this loss is 0.03% of the initial capital invested. The presented analysis could be useful for "quants" whose job is to create and backtest statistical arbitrage strategies. In could also have a wider implication in the general question of estimating risk premium. If the trades are not made on market on close, the expected risk premium may need to be adjusted accordingly.

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Exhibit 1

Transaction Costs per Share

Exhibit 1 shows the actual average execution cost per share for 36 days of real execution of a proprietary statistical arbitrage trading strategy. The costs are based on an actual transaction cost offer made from a top Wall Street brokerage house. The commission is 25 mills per share; $5 ticket charge and SEC fee.

	Transaction Cost per Share Sell	**Transaction Cost per Share Buy**	**Transaction Cost per Share**
6/5/2003	$ 0.00312	$ 0.00331	$ 0.00322
6/6/2003	$ 0.00790	$ 0.00715	$ 0.00753
6/9/2003	$ 0.01129	$ 0.00924	$ 0.01026
6/10/2003	$ 0.00680	$ 0.00398	$ 0.00539
6/11/2003	$ 0.00803	$ 0.00613	$ 0.00708
6/12/2003	$ 0.00460	$ 0.00851	$ 0.00655
6/13/2003	$ 0.01197	$ 0.00916	$ 0.01057
6/16/2003	$ 0.01054	$ 0.01108	$ 0.01081
6/17/2003	$ 0.01171	$ 0.01101	$ 0.01136
6/18/2003	$ 0.00828	$ 0.00796	$ 0.00812
6/19/2003	$ 0.00866	$ 0.00628	$ 0.00747
6/20/2003	$ 0.00743	$ 0.00613	$ 0.00678
6/23/2003	$ 0.00715	$ 0.00636	$ 0.00676
6/24/2003	$ 0.01100	$ 0.00653	$ 0.00876
6/25/2003	$ 0.00969	$ 0.00978	$ 0.00973
6/26/2003	$ 0.00891	$ 0.00728	$ 0.00809
6/27/2003	$ 0.00862	$ 0.00676	$ 0.00769
6/30/2003	$ 0.00961	$ 0.00874	$ 0.00918
7/1/2003	$ 0.00755	$ 0.00830	$ 0.00792
7/2/2003	$ 0.00828	$ 0.00595	$ 0.00711
7/3/2003	$ 0.00800	$ 0.00805	$ 0.00802
7/7/2003	$ 0.00862	$ 0.00658	$ 0.00760
7/8/2003	$ 0.01043	$ 0.00809	$ 0.00926
7/9/2003	$ 0.01293	$ 0.00892	$ 0.01092
7/10/2003	$ 0.01239	$ 0.01008	$ 0.01124
7/11/2003	$ 0.01348	$ 0.01119	$ 0.01234
7/14/2003	$ 0.01319	$ 0.00986	$ 0.01153
7/15/2003	$ 0.01637	$ 0.00891	$ 0.01264
7/16/2003	$ 0.00988	$ 0.00870	$ 0.00929
7/17/2003	$ 0.01106	$ 0.00841	$ 0.00973
7/18/2003	$ 0.01080	$ 0.00722	$ 0.00901
7/21/2003	$ 0.00952	$ 0.00731	$ 0.00841
7/22/2003	$ 0.01067	$ 0.01084	$ 0.01075
7/23/2003	$ 0.01278	$ 0.00883	$ 0.01080
7/24/2003	$ 0.01162	$ 0.00827	$ 0.00994
7/25/2003	$ 0.01464	$ 0.00937	$ 0.01201

Exhibit 2

Number of Long and Short Signals Produced by the MCS Strategy

Exhibit 2 shows statistical information regarding the number of trading signals generated by the MCS strategy. The universe of stocks comprising S&P 500 index as of January 2007 is used to create the trading signals. The corresponding statistics are computed over 3,020 trading days during the time period January 1996 to December 2007.

	Long Signals	**Short Signals**
Average	51	51
Median	48	47
Standard Deviation	19	19
Min	12	15
Max	183	193

Exhibit 3

Cumulative Annual Returns for S&P 500 and the MCS Strategy

Exhibit 3 shows a comparison between the actual annual returns by the MCS strategy and S&P 500 index.

Year	S&P 500	Strategy
1996	18.45%	-7.08%
1997	21.06%	34.30%
1998	23.64%	67.65%
1999	17.84%	69.93%
2000	-10.69%	97.84%
2001	-13.98%	42.88%
2002	-26.61%	62.51%
2003	23.41%	-14.60%
2004	8.61%	9.32%
2005	2.96%	16.97%
2006	12.77%	41.61%
2007	4.01%	47.10%

Exhibit 4

Backtest Performance Statistics for S&P 500 and the MCS Strategy

Average annual return is computed by averaging the 12 annual returns presented in Exhibit 3. The annual volatility is computed by using the sample standard deviation for the 12 annual returns in Exhibit 3. Sharpe ratio is computed by dividing the (Average annual return - 5%) to the Annual volatility. Sortino ratio is computed similar to the Sharpe ratio, except that instead of using standard deviation as the denominator, it uses downside deviation from the chosen risk - free rate of 5%. Highest/Lowest monthly return is the max/min over the period January 1996 to December 2007.

	S&P 500	**MCS Strategy**
Average Annual Return	6.79%	39.04%
Annual Volatility	16.34%	33.39%
Sharpe Ratio at 5%	0.11	1.02
Sortino Ratio at 5%	0.15	5.12
Highest Monthly Return	8.97%	25.39%
Lowest Monthly Return	-15.46%	-4.22%
Skewness	-0.12	1.15
Kurtosis	3.14	6.09

Exhibit 5

Daily P&L from January 1996 - December 2007

Exhibit 5 plots the daily profit and loss for the strategy and SP 500. The initial investment is $1 made at January 2, 1996. The graph shows the growth of this initial investment.

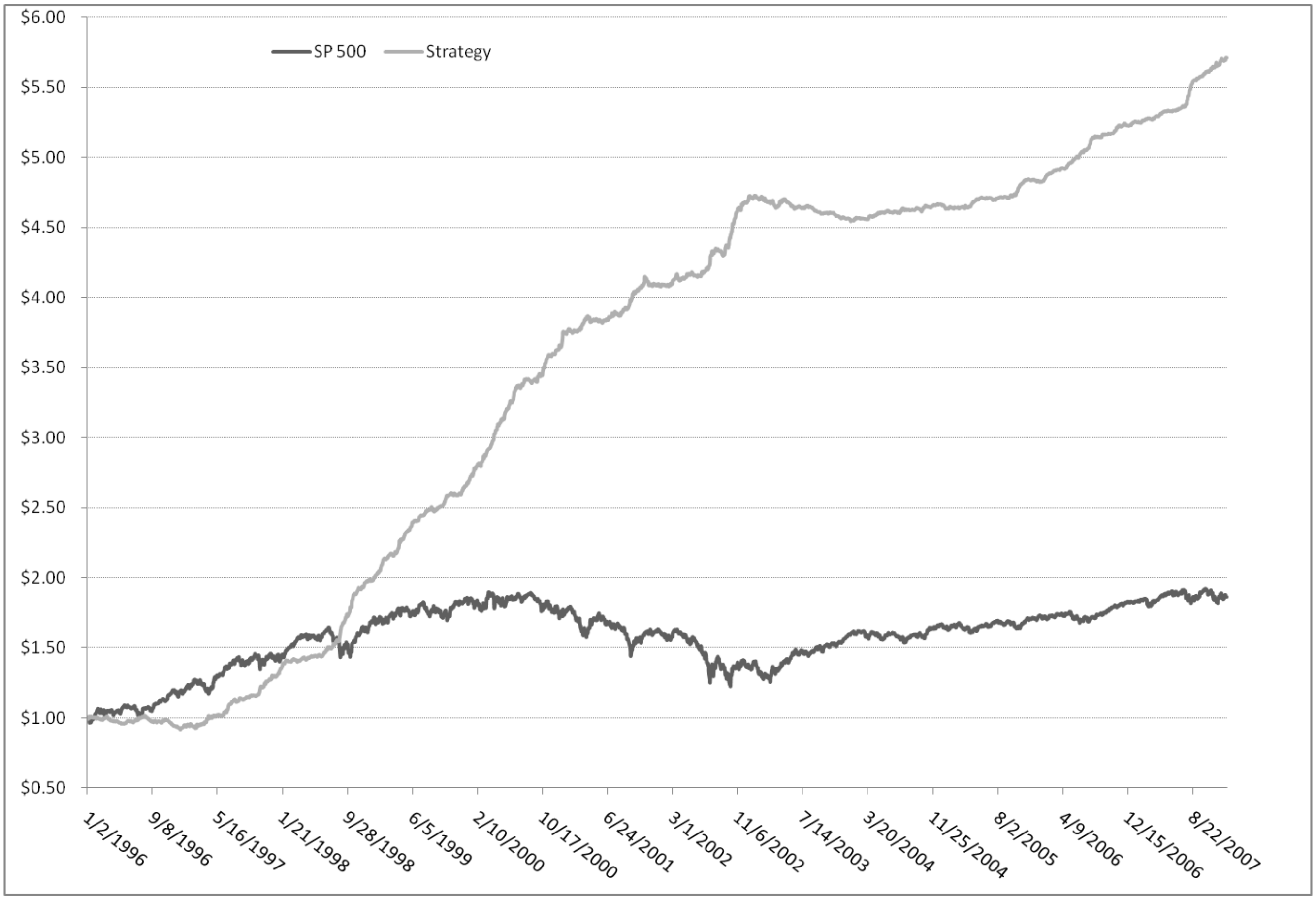

Exhibit 6

Intraday Effect: Number of Long and Short Signals Produced by the MCS Strategy

Exhibit 6 shows statistical information regarding the number of trading signals generated by the MCS strategy. The universe of stocks comprising S&P 500 index as of January 2007 is used to create the trading signals. The corresponding statistics are computed over January 2003 – December 2006 for a total of 1,005 trading days.

	Long signals on close	**Short signals on close**	**Long signals on intraday**	**Short signals on intraday**
Average	50	51	51	52
Median	42	42	43	44
Standard Deviation	25	27	25	27
Min	12	15	14	16
Max	183	193	183	194

Exhibit 7

Intraday Effect: Daily P&L from January 2003 - December 2006

Exhibit 7 shows the performance of the strategy under two estimation scenarios. One dollar invested under the first scenario (estimate on close, execute on close) grows to $1.65 and to $1.34 under the second scenario (estimate on intraday, execute on close). Translating this numbers with an initial capital of $10M, the average daily loss due to intraday estimation is about $3,024 or 0.03% of the initial capital. The accumulated loss for the time interval January 2003-December 2006 is approximately 30%.