How (In)Efficient is After-Hours Trading?

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Abstract—In this paper we analyze US stock market after-hours trading. This is a trading outside the regular trading hours of 09:30-16:00. During this time the market is thinly traded and the possibility of price (in)efficiency arises. Price spikes up or down sometimes reaching several percent can be observed. This pattern can be exploited by a simple automated trading strategy that buys low if market drops and closes the position high on the next day when the market reopens. An empirical study using the most liquid stocks and exchange traded funds listed in NASDAQ and NYSE exchanges for the years 2000 to 2012 is conducted. We create a portfolio of ~400 automated trading strategies. The average portfolio performance is a 23 percent per annum with a Sharpe ratio of 4. This shows that prices are inefficient during after-hours trading in the US stock market. To test for significance we run an out-of-sample test from 2012 onwards.

Algorithmic trading; automated trading; systematic trading; post-market; pre-market; after-hours trading; trading strategy;

I. INTRODUCTION

After-hours trading (AHT) refers to the buying and selling of assets listed on major stock exchanges outside of their specified regular trading hours (RTH). Investors can trade in one of the two AHT sessions - before market open (BMO) and after market close (AMC). Typical BMO hours are 04:00-09:30 am and AMC hours are 4:00-8:00 pm US ET. Having the ability to trade in AHT allows investors to react quickly on fresh information, i.e. the volume in AHT tends to be event driven. For example, after the London subway attack in July 2005, 120 million shares were traded in the NYSE Arca during the BMO session. Similarly, on January 31, 2006, when Google posted a profit that missed Wall Street targets its shares went down 19 percent in AHT - a $15 billion drop [4].

The primary focus of previous works is the examination of the immediate reaction upon the news release after-hours, or the study of liquidity and price discovery during AHT.

Reference [5] reports that the Pacific Stock Exchange transacts less than 40% of the combined regionals’ trading volume during RTH. Further, there is very little price discovery during AHT. The majority of trades take place at either the NYSE closing ask, bid, or trade price.

Reference [9] shows that high volumes in the BMO session are particularly associated with anticipated macroeconomic news releases for the U.S. economy, which occur at 8:30 am. Reference [4] reports a higher trading volume (as well as lower quoted and effective spreads) in AHT sessions containing earnings announcements than in AHT sessions without any announcements.

Our work differs from these previous works as we do not investigate the reaction upon news releases. We focus on the question whether a simple automated trading algorithm (or strategy) can exploit price jumps in the AHT session, and ask the question how (in)efficient after-hours trading is. The price efficiency theory follows from the efficient market hypothesis, which states that if markets are efficient, it is nearly impossible to "beat the market" consistently.

In general, algorithms used in financial markets aim different objectives. The two most important are 1) optimize the trade execution and 2) maximize the return to be expected, cf. [1] and [11]. Algorithmic trading (AT) focuses on 1), i.e. the execution aspect of orders, while profit seeking trading algorithms (PTA) focus on 2), i.e. determine the points of time to take a buying or selling decision [14]. AT is commonly defined as the automated, computer-based execution (submission, management and canceling) of orders via direct market-access channels. The goal is to meet a particular benchmark by defining certain aspects of an order cf. [10] and [13]. Typically the timing, quantity, and routing of orders is determined while dynamically monitoring market conditions across different securities and trading venues. Reducing the market impact by optimally and sometimes randomly breaking large orders into smaller pieces, and closely tracking benchmarks such as the volume-weighted average price (VWAP) over the execution interval are main tasks. A mix of active and passive AT strategies is used, employing both limit orders and marketable orders in order to execute the signals of the PTA best. Thus, at times these strategies function as...
liquidity demander, and at times as liquidity supplier. Further, these strategies act as smart order routers and determine where to send an order, cf. [12]. PTA aim either to buy at possibly low prices or to sell at possibly high prices, or both. The goal is to automatically determine entry point(s) before a market price rise, and exit point(s) before a market price downturn, often based on historic or predicted price movements. The starting point for the creation of a PTA is the selection of input variables likely to influence the desired outcome, i.e. to maximize the return to be expected. Every PTA consists of at least one buying rule and/or one selling rule represented by (source program) statements specifying the exact market entry and/or exit points. A typical example for a simple buying rule is the if-then statement: IF $q_t \leq x$ THEN BUY. Here, a buying signal is generated if the price $q_t$ at day $t$ is smaller than or equal to some threshold $x$. As an order, these signals can be executed on the stock market using AT. A great number of methods, attempting to predict, identify and exploit winners or trends, are used. They broadly fall in the area of either Fundamental - or Technical Analysis. Some examples can be found in [21] but for broader an overview the reader is referred to [20]. PTA based on worst-case scenarios are not considered here, cf. [22].

II. AFTER-HOURS TRADING

AHT is mainly applied by either retail traders or traders trying to react upon news released during the BMO/AMC session. Figure 1. shows a typical liquid stock (Apple, ticker: AAPL) RTH and AHT pattern, namely the day price fluctuation (RTH – light green, AHT – dark green) with volume (red). Compared to RTH, the trading volume in both the BMO and AMC session is thin.

Figure 2. shows how RHT and AHT volumes emerge from the year 2000 on. During the economic boom in 2006 and at the beginning of the crisis in 2007 and 2008 there was an increase in RTH volume. This is not that noticeable in AHT, only a slight increase can be seen around 2008.

Figure 1. RTH (light green) and AHT (dark green) pattern with volume (red)

Figure 2. Volume fluctuation of Apple (AAPL): RTH (top) and AHT (down)

Summing up, AHT corresponds to 3% of total volume traded [4]. We observe a ratio of 6% on certain stocks, which is pretty close. We also note sudden spikes in the volume traded, that likely correspond to specific news announcements that force more activity in AHT, i.e. affect stock price and volume.

III. DATA DESCRIPTION

In our analysis we used two datasets, provided by the Tradestation trading platform, ranging from 2000-01-01 to 2012-11-18. First, we performed experiments with 1297 stocks and second we increased the dataset to 2159 stocks. The most liquid US stocks and exchange traded funds (like SPY and QQQ) from NASDAQ and NYSE exchanges were selected while limiting to those with at least 150,000 traded shares per day over the last 10 day period. Stocks with a history shorter than 4 years were excluded. This is required to avoid data over-fitting. A too short history carries a certain risk to find some lucky scenario where by pure accident a strategy was successful, cf. the data-snooping bias.

Slippage and commissions: we used fixed trading costs of 0.01 USD per stock and 0.02 USD slippage per stock and leg (buying or selling transaction). Summing up, each transaction results in 0.03 USD for buying and 0.03 USD for selling. These are realistic trading costs for liquid stocks [19] that are not too high in prices (i.e. less than 100 USD). Higher priced shares may have a higher slippage. For such stocks a percentage-based slippage would be more accurate (i.e. 0.2 %). Theoretically, when buying using a limit order slippage should be zero, but to be in step with actual practice we used 0.02 USD.

IV. TRADING STRATEGY DESCRIPTION

In the AHT session, quite often, stock price jumps down and up (spikes) significantly above/below market close price. This pattern can be exploited to obtain a profit. To demonstrate how (in)efficient AHT is we constructed a simple automated PTA, denoted by strategy in the following. We try to buy in the off-market between two RTH trading sessions if the prices fall below a specific threshold $x$ (spike level), i.e. if there is an unusual spike down. We anticipate that the market will go back
up again, and that we can sell at the opening price of the next
day with some profit. This is illustrated in Figure 3.

![Figure 3. Our profit making scenario: “buy low – sell high”](image)

Note that this type of strategy is similar to a high frequency
trading liquidity provision strategy but the time frame is way
larger. We buy if someone wants to sell during AHT (supply
liquidity) and we sell in RTH (take liquidity). In doing so
liquidity from highly liquid hours is moved to less liquid hours,
thus we contribute to liquidity equalization as we move
liquidity from RHT to AHT. These types of strategies are
beneficial to the market - they reduce market volatility spikes.

Figure 4. shows the results of the 10 best strategies, each
applied to one stock. We observe a performance boost in early
2000 (dot.com bubble) and in 2008-2009 (credit crunch).

![Figure 4. The cumulative profit of the 10 best strategies](image)

A. Position sizing

Position sizing is very important in any trading environment.
The question to be answered is how many stocks should be
bought at one point of time? The simplest option is to trade
fixed amounts of stocks, for example one lot of 100 stocks.
This approach has the deficiency that if the stock price changes
so does the amount invested. At one point of time 100 stocks
may be worth 1000 USD and at a later point of time 10 000
USD. We chose a different position sizing method. We trade
stocks worth 10 000 USD by rounding to one stock. For
example, assume one Apple (AAPL) stock is worth 560 USD,
so we would buy 17 stocks (10000/560). This position
construction method is widely used. But it suffers the drawback
of data inaccuracy as historical data is usually back adjusted for
dividends. So if the stock price was 20 USD and it paid 5 USD
dividends, on the next day, the historical price is adjusted down
by 5 USD now equaling 15 USD. Stocks that paid an unusually
high dividend in the past might have near zero or negative
historical prices. This results in abnormally high position sizes.
For this reason, some data providers supply unadjusted prices
and alongside adjusted ones. We avoided this problem by
selecting data (stocks) that always had a positive historical
price.

B. Trading Strategy Variations

We explored the possibility of shorting stocks if there is an
unusual price jump up in AHT. This approach led to profitable
results as well, but in this paper we restrict to long positions
only, as borrowing stocks is sometimes problematic or shorting
is even forbidden in some countries, e.g. in Germany since
2010. Further, some stocks are easy to borrow and others not.
We leave this subtopic for future research.

We tested the option to sell an obtained stock in the same
AHT session if price jumps back up above some specific level.
Due favorable price jumps in the AHT session the results were
positive, but this scenario involves some uncertainty. When
allowing buying and selling within one AHT session, we
cannot ensure to buy at low and to sell at high. We leave this
complexity increasing modification for future research.

The liquidity of every financial instrument is usually
limited. Only a specific amount of contracts/shares/lots can be
bought with some minimum cost. With the quantity the costs
increase. We are faced with this problem: we exploit inefficient
market spikes but their volume is limited. If we observe a price
below our threshold $x$ we do not know how many shares are
traded below $x$. We only know that this amount is limited. For
a precise calculation it is essential to examine tick by tick data
instead of minute accuracy data as we did. In our setup we
bought stocks worth 10 000 USD. This relatively small amount
is easy to obtain. Bigger positions may cause a liquidity
problem. We leave this for future research.

V. PORTFOLIO OF TRADING STRATEGIES

Diversification is the main tool in financial investing. By
holding a portfolio of investments an investor can retain the
same level of return while concurrently reducing the risk.
Adding uncorrelated investments into the portfolio increases
the risk/reward ratio. Research in this field was pioneered by
Harry Markowitz [15] who created the efficient market
hypothesis and the mean/variance portfolio optimization
paradigm. This paradigm was mainly applied to stocks or other
assets, but it can also be applied to a portfolio of trading strategies. Here, the problem of data dimensionality arises, as quite often, the number of portfolio candidates is higher than the number of days in the history - the computation of covariance matrices becomes problematic [16] [17]. Further, the problem of computational complexity arises. Moreover, the computation time of the classic Markowitz portfolio increases exponentially with the number of portfolio candidates, and becomes impractical. Thus, faster heuristic/approximation methods (like a greedy algorithm) are employed in such a scenario [18].

We found that portfolio diversification benefits hold in our scenario as well. If we apply one strategy to one stock, we are not able to achieve consistent returns, but our portfolio returns are consistent. This is valid for in-sample and out-of sample data. We limit to two portfolio construction approaches: 1) simply join the best performing stocks (strategies) in one portfolio, and 2) perform the mean/variance optimization. Both approaches generated similar results in our experiments. Note that out-of-sample the performance can be worse; an example is given in Figure 5. Further, we found that a certain number of strategies is required to achieve best results. Selecting to few or too many strategies leads to an underperformance.

We computed a correlation matrix of the best performing stocks, cf. Figure 6. The light/yellow areas correspond to correlated strategies and the dark/red to uncorrelated ones. Only a few strategies are correlated (concentration of light/yellow areas on the diagonal). Hence, the construction of a portfolio would not result in an additional value. Thus, we limited to approach 1) and joined the best performing strategies in one portfolio. This is also known as the equally weighted portfolio of the best performing strategies.

We implemented the prototype of the strategy using the Tradestation trading platform. This platform allows a quick implementation and execution of trading strategies. In our experiments a buy signal is generated during AHT if the price drops below threshold level \( x = (c - e*c) \) where \( e \) denotes some pre-specified percentage level and \( c \) is the last closing price from RTH. Each open position is closed (sold) at the next day open. Figure 7. shows the logic of our strategy in EasyLanguage.

VI. EXPERIMENTS

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```
Input: e(1): //entry percentage level
var: intcrbpersist last_close_price(close);

//remember last price of the RTH
If Time >= 1400 and time[1] < 1600 then last_close_price = close;

//if AHT then try to buy lower than RTH closing price
If not (Time >= 930 and time[1] < 1600) then begin
Buy next bar last_close_price - e * close/100 limit;
end;

//if have the position sell at next RTH open session
If Marketposition = 1 and time >= 930 and time[1] < 930 then sell this bar close;
```

Figure 7. Strategy logic in EasyLanguage code (Tradestation)

Tradestation returns trading statistics as well as a performance graph. Further, the trades are illustrated in charts, cf. Figure 8. showing two trades - a losing one and winning one.

We implemented the strategy not only on the Tradestation platform but also in the Matlab environment. This allows us to conduct several automated strategy tests on arbitrary stocks.

A. Strategy Parameter Optimization

To generate good results the strategy parameters must be calibrated or in other words - optimized. The aim is to select strategy parameters in such a way that performance would be
the greatest. In our scenario we had only one parameter to optimize, the spike level \( x \). We selected \( x \) in the range of 0% and 3%. If we increase \( x \) above 3% the number of trades is too low and results are unreliable, thus we restricted to 3%. Another condition is that the strategy must be in the market at least 10% of the time. If the strategy is in the market less than 10% of the time we are utilizing capital inefficiently and the return level reduces. So, on average, within each month we want the strategy to trade at least on two days.

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As performance measure we selected the Sharpe ratio and tried to calibrate \( x \) in such a way that the Sharpe ratio is the greatest while the 10% in market condition is met. Optimization was done individually on each stock but without comparison between the stocks. This is known as absolute value type strategies. The opposite, relative value, usually compares multiple instruments and generates buy/sell signals in relation between two stocks. The optimal spike levels \( x \) for a selection of stocks. We can note that in majority of the cases \( x \) is above 1%. A lower \( x \) leads to a huge number of mostly unprofitable trades.

### TABLE I. OPTIMIZED SPIKE LEVELS \( x \) PER STOCK.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>( x )</th>
<th>Sharpe</th>
<th>In-Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADT</td>
<td>1.93</td>
<td>2.59</td>
<td>0.1</td>
</tr>
<tr>
<td>LVLT</td>
<td>2.05</td>
<td>2.76</td>
<td>0.23</td>
</tr>
<tr>
<td>LSI</td>
<td>2.99</td>
<td>2.76</td>
<td>0.12</td>
</tr>
<tr>
<td>XRX</td>
<td>2.26</td>
<td>2.38</td>
<td>0.1</td>
</tr>
<tr>
<td>AHT</td>
<td>1.28</td>
<td>2.6</td>
<td>0.1</td>
</tr>
<tr>
<td>SCHW</td>
<td>2.61</td>
<td>2.8</td>
<td>0.1</td>
</tr>
<tr>
<td>ICGE</td>
<td>1.96</td>
<td>2.26</td>
<td>0.17</td>
</tr>
<tr>
<td>MYRG</td>
<td>1.1</td>
<td>3.31</td>
<td>0.16</td>
</tr>
<tr>
<td>SY</td>
<td>1.11</td>
<td>2.51</td>
<td>0.1</td>
</tr>
<tr>
<td>AEP</td>
<td>1.07</td>
<td>2.47</td>
<td>0.1</td>
</tr>
</tbody>
</table>

### Trading Results

Each stock (out of 79) we traded with 10,000 USD, so the resulting portfolio is 790 000 USD. The average resulting portfolio profit is 177 377 USD per year. The annualized return thus equals to 177 377/790 000, i.e. 22.45 %. Note that this is a margin trading free return (no leverage). It is possible to boost the return level by trading on margin (with leverage). To demonstrate that our results are valid we used data from 2012-01-01 onward to conduct out-of-sample experiments. Tests using unseen data avoid the danger of model adaptation due to learning, also known as data over-fitting, data-snooping bias or overtraining. A strategy can adapt to the data it was optimized on, and thus produces fantastic results. In this case the results on future unseen data might be poor [17]. We optimized our strategy on data up to 2012-01-01 and tested its performance on data past this date. As our out-of-sample (2012-01-01 onwards) returns are positive, we conclude that our results cannot be inferred from the data-snooping bias.

### TABLE II. LIST OF BEST 278 PERFORMING STOCKS.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>( x )</th>
<th>Sharpe</th>
<th>In-Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRPT</td>
<td>2.55</td>
<td>1.27</td>
<td>0.1</td>
</tr>
<tr>
<td>LUV</td>
<td>1.48</td>
<td>1.94</td>
<td>0.1</td>
</tr>
<tr>
<td>GGC</td>
<td>1.64</td>
<td>2.26</td>
<td>0.1</td>
</tr>
<tr>
<td>TER</td>
<td>2.41</td>
<td>2.82</td>
<td>0.1</td>
</tr>
<tr>
<td>KVR</td>
<td>1.42</td>
<td>2.09</td>
<td>0.1</td>
</tr>
<tr>
<td>LOGM</td>
<td>1.67</td>
<td>3.26</td>
<td>0.12</td>
</tr>
<tr>
<td>HK</td>
<td>1.93</td>
<td>1.59</td>
<td>0.1</td>
</tr>
<tr>
<td>FCS</td>
<td>1.27</td>
<td>1.76</td>
<td>0.1</td>
</tr>
<tr>
<td>WMT</td>
<td>1.46</td>
<td>2.38</td>
<td>0.1</td>
</tr>
<tr>
<td>AMCC</td>
<td>2.39</td>
<td>1.91</td>
<td>0.15</td>
</tr>
</tbody>
</table>
allow (an institutional investor) to boost the return close to the 100% level.

Figure 10. shows the number of strategies in position over time. The maximum possible number is 79, as we limit to 79 stocks. We can see that we never have 79 in position. The average is 9, with a maximum of 74. The number of days when we have more than 40 in position is quite small – overall 76 days. This corresponds to an average of 7.5 days per year. Similar results we obtained in experiments using different optimization ranges. A summary of the experiments is given in Table III.

TABLE III. EXPERIMENT SUMMARY

<table>
<thead>
<tr>
<th>Total Stocks</th>
<th>Range</th>
<th>Sharpe &gt;0</th>
<th>Sharpe &gt;0.8</th>
<th>Sharpe &gt; 1</th>
<th>Portfolio Sharpe</th>
<th>Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>1297</td>
<td>2003-2012</td>
<td>346</td>
<td>98</td>
<td>71</td>
<td>3.37</td>
<td>22.85</td>
</tr>
<tr>
<td>1297</td>
<td>2009-2012</td>
<td>748</td>
<td>559</td>
<td>504</td>
<td>5.37</td>
<td>21.69</td>
</tr>
<tr>
<td>1297</td>
<td>2000-2012</td>
<td>756</td>
<td>348</td>
<td>261</td>
<td>4.18</td>
<td>19.36</td>
</tr>
<tr>
<td>2159</td>
<td>2003-2012</td>
<td>442</td>
<td>110</td>
<td>79</td>
<td>3.42</td>
<td>22.45</td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS

We showed that after-hours trading has very inefficient prices compared to regular trading hours. spikes of 3% or even more can be observed. The effect is similar for buying and selling – up and down spikes are of the same magnitude. This can be exploited by an automated trading strategy to obtain profit. We proposed a strategy that takes advance of such inefficiencies. It buys at a price lower than some threshold \( x \) during after-hours trading and sells at the next day regular trading open. The best performing 79 strategies were put in a portfolio resulting in an annual return of 23% for an optimized threshold \( x \) from \( [0.0,0.3] \).

However the drawback of such a strategy is that the trading volume is limited. As a result during AHT we can only buy a fixed number of stocks. Hence, we will not be able to trade a lot of capital using such a strategy. Further, only 1/3 of the liquid market stocks could be used. The majority of less liquid stocks have no sufficient after-hours trading activity. Thus, the probability to buy in the after-hours trading session is very small and most strategies do not satisfy our 10% in-market criteria. Reducing the threshold \( x \) could increase the number of strategies in a portfolio but the quality may suffer.

After-hours trading is getting more and more popular. This increases liquidity, and more stocks could be included in our portfolio in the future. This would increase the capacity of our strategy as well. We found that this type of strategy tends to perform better in a crisis period, where after-hours trading is also more popular as people tend to dump unwanted stocks after market close. This is reflected by a performance boost around the years 2000 and 2007-2008. The high market volatility allows greater profits.

For the future we plan to investigate more complex and hopefully more profitable variations of our strategy. A further interesting task is to apply various portfolio construction techniques as well as to employ on-line algorithms.

REFERENCES


